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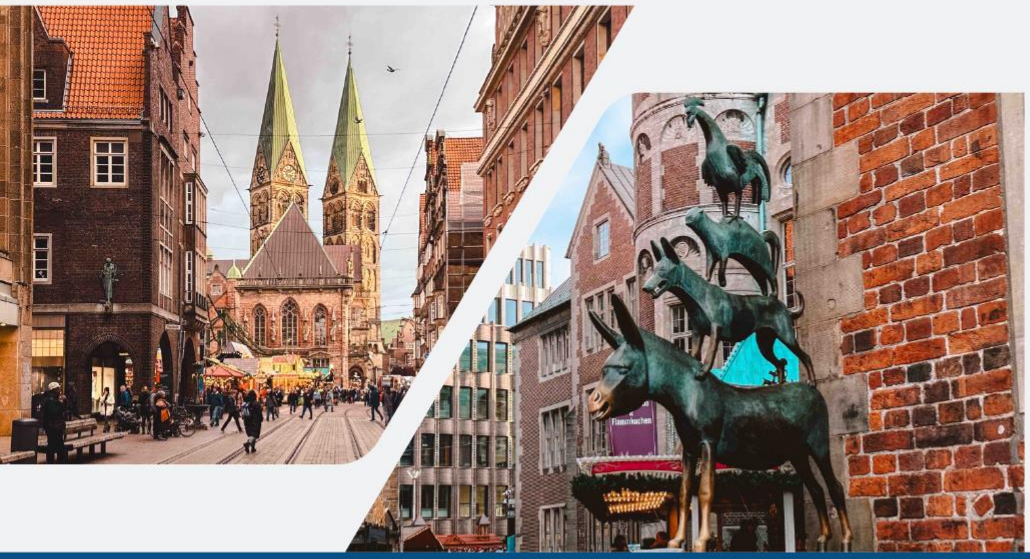
6. ULUSLARARASI EĞİTİM TEKNOLOJİLERİ VE ÇEVRİMİÇİ ÖĞRENME KONFERANSI

[FULL PAPER PROCEEDINGS]

[TAM METİN BİLDİRİ KİTABI]

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Preface

The 6th International Conference on Educational Technology and Online Learning (ICETOL 2026) was held on 17–20 August 2026 at Constructor University in Bremen, Germany, under the theme "Education for Uncertain Futures: Learning, Resilience and Responsibility." The hybrid programme brought together 1,365 participants from 76 countries, of whom 385 attended in person and 980 joined online. A total of 685 papers were presented in 11 parallel tracks, six in-person and five virtual, in four languages: English, Turkish, German and Spanish. Compared with the 54 countries represented at ICETOL 2025, the 2026 edition reached participants from 22 additional countries, confirming that the conference continues to grow as a truly international meeting place for educational technology research.

The theme of this year's conference reflects the conditions under which education now operates. Technological change is fast, information is harder to verify, and institutions, teachers and learners are asked to make decisions without knowing what the next few years will bring. Complexity science offers one useful vocabulary for this situation, and a recent scoping review of peer-reviewed articles shows how it has begun to enter educational research (Durak, Çankaya, & Öncü, 2026b). The papers in this volume take up the same challenge from many directions, asking how learning can be designed to be resilient and how those who design, teach and assess it can act responsibly, a concern that recent work on the implications of AI for policymakers, researchers and practitioners shares (Ifenthaler et al., 2024).

Generative artificial intelligence (AI) is the most visible source of this uncertainty, and a large share of the contributions to ICETOL 2026 address it. Large language models open real opportunities for education but also bring serious challenges (Kasneci et al., 2023), and systematic reviews of AI in higher education have repeatedly called for greater attention to ethics, collaboration and rigour (Bond et al., 2024) and to the role of educators themselves (Zawacki-Richter et al., 2019). Using AI critically depends on what learners can do and how confident they feel doing it, which is why instruments that assess text-based generative AI literacy from a self-efficacy perspective are needed (Durak, Çankaya, & Öncü, 2026a). Teachers stand at the centre of this process, and the knowledge they need is itself being rethought (Mishra et al., 2023). Recent work in the *Journal of Educational Technology and Online Learning* (JETOL) examines teachers' technopedagogical competence and their perspectives on AI in education (Araycı & Özyurt, 2026), and measures the trust that teachers place in AI-based educational technologies (Yüksel et al., 2026). Responsible use is not only a matter of competence. It also concerns the emotional side of teaching with AI (Abdoli, 2026), the ethical dilemmas of AI-driven education across cultures (Al-bannay, 2026), and the need for a community-wide framework for the ethics of AI in education (Holmes et al., 2022).

AI also forces the field to reconsider what is assessed. When a system can produce the output, the question becomes what assessment should measure, and a conceptual framework for human-centered assessment in online education offers one answer (Aydemir, 2026). Related work argues that learners need to develop evaluative judgement for a time of generative AI (Bearman et al., 2024). The same concern for human-centred practice runs through the studies presented in Bremen, from learning analytics and adaptive systems to virtual reality, robotics and language learning.

Resilience also has a structural side. Flexible and stackable learning pathways, such as micro-credentials, are increasingly seen as a way of supporting lifelong learning in unpredictable labour markets and societies, a topic discussed in depth in the conference panel on micro-

credentials and lifelong learning. Responsibility, in turn, requires attention to who benefits from these developments. Research on equity, diversity and inclusion in blended learning reminds us that technology-enhanced education can widen gaps as easily as it closes them (Durak, Çankaya, Öncü, & Rienties, 2025). Many of the papers in this volume come from contexts that are often under-represented in the literature, and we see this diversity as one of ICETOL's main strengths.

This volume presents 143 full papers from the ICETOL 2026 programme. All papers are published as open access under the Creative Commons Attribution (CC BY 4.0) licence, and each paper has its own DOI and is deposited in the ICETOL 2026 community on Zenodo. ICETOL is also connected to JETOL, whose ICETOL 2025 special issue (Volume 8, Issue 4) published peer-reviewed articles that grew out of the conference, such as the study on multimedia design and digital training preferences by Gürsoy (2025). The ICETOL 2026 special issue (Volume 9, Issue 4) is currently in preparation.

Looking Ahead

ICETOL 2027 will be held on 6–8 July 2027, hosted by the University of Malaga, Spain. We look forward to welcoming the ICETOL community there and to continuing the conversation about how educational technology can serve learners with care, evidence and responsibility.

We thank all authors, reviewers, members of the International Scientific Advisory Board, session chairs, technical teams and our host, Constructor University, for making ICETOL 2026 possible. With deep appreciation, we present the ICETOL 2026 Full Paper Proceedings.

Prof. Dr. Gürhan Durak
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From Open Education to Open Democracy: How OER Strengthen Digital Citizenship

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Abstract

The introduction of artificial intelligence tools into our lives and the rapid rise of digital technologies can both serve and undermine the democratization of the process, while somehow affecting the inclusion of individuals in democratic processes. While social media and online platforms in particular promise greater accessibility and connectivity, they can also serve to spread misinformation, algorithmic bias and the exclusion of marginalized groups. The digital divide that prevents individuals with low technological literacy or fluency from becoming digital citizens is growing increasingly. This study explores how Open Educational Resources (OER)—freely accessible, adaptable, and participatory learning materials—can serve as a critical tool for rebuilding digital citizenship and promoting democratic flexibility. The study adopts a literature review methodology and analyzes the role of OER in the process toward open democracy. In this context, the study outlines how open educational resources can strengthen digital citizenship and serve open democracy in three key aspects. These important aspects are: a) combating digital misinformation by imparting media and digital literacy skills, b) enabling participatory policy-making through the co-creation of open knowledge, and c) developing practical recommendations for policymakers, educators, and civil society to leverage OER as a digital public infrastructure for inclusive democracy. OER, eliminating the barriers of permission related to cost and sharing in the learning process, provides opportunities for learning, creating, and participating in governance for every young, old, and disadvantaged individual in society. It is particularly important for all responsible stakeholders to work together to strengthen digital citizenship, increase individuals' participation in democratic processes, and build open and accessible democratic structures. Addressing OER on digital public infrastructure such as open data or broadband networks for a governance approach based on transparency will be quite effective in creating a resilient civic ecosystem. Therefore, it is recommended that policymakers adopt the mandatory use of OER in public education and establish funds for citizenship literacy.

Keywords: Open educational resources, open democracy, digital citizenship, digital literacy, digital democracy.

Introduction

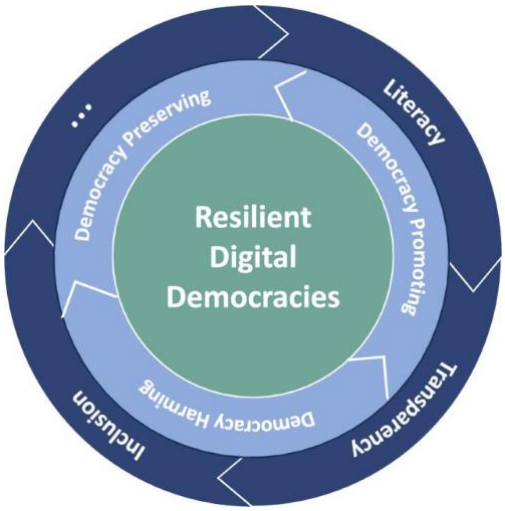
When we look at the concepts of OER, open democracy, and digital citizenship, it can be seen that they are frequently used and concern people from different groups in many areas of life. The concept of digital citizenship, on the other hand, has been a concept on the agenda in recent years, as information and communication technologies have rapidly become an indispensable part of daily life. While this concept aims to enable citizens to benefit more easily from the advantages of digital technologies, it also aims to ensure conscious and safe use by making them aware of their rights and responsibilities. Digital citizenship means the ability to act safely in digital environments and to use these technological tools in an ethical and responsible manner (Althibyani & Al-Zahrani, 2023). In addition, it can be considered an umbrella concept that encompasses many skills, such as digital rights, digital literacy, digital security, and digital communication and access (Richardson & Milovidov, 2019). Digital citizenship is considered to have nine dimensions, which are listed as follows: digital communication, digital security, digital culture, digital rights and responsibilities, digital health, digital law, digital commerce, digital access, and digital etiquette.

Open Educational Resources (OERs) are defined as learning materials that embody the philosophy of "openness," are openly and freely accessible to everyone, and have an open license for use, distribution, and modification (UNESCO, 2012; Wiley et al., 2014). OERs are also considered learning resources that include printed resources such as books and journals, as well as all types of digital learning materials containing images, audio, text, and video, to be used by all users in learning processes without paying any copyright or licensing fees (Butcher, 2015; Orr et al., 2015). When looking at the concept of open democracy, it can be defined as a dynamic process based on citizens' sharing of information, active participation, continuous deliberation, and lifelong learning. In this context, OER can be considered a learning infrastructure that supports democratic processes and facilitates citizens' lifelong access to information and learning. OERs serve not only as a means of accessing information but also facilitate the sharing of accurate and reliable learning resources with different social groups and enable the liberation of knowledge. In their study on the understanding of OERs in a public institution, Mikroyannidis and

https://doi.org/10.5281/zenodo.24338678

Papastilianou (2021) show that OERs can be considered not only as educational materials that support individual learning but also as an open infrastructure that supports information sharing, collaboration, and collective knowledge production within public institutions.

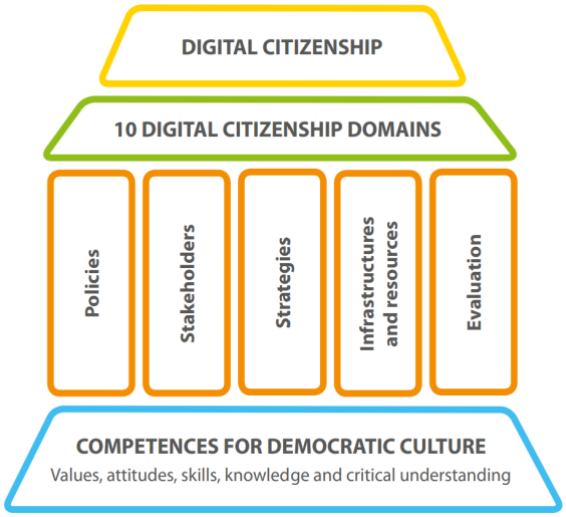
Figure 1. Resilient digital democracies (Weinhardt et al., 2024).



As shown in the image above, Weinhardt et al. (2024) have identified the concepts of transparency, inclusivity, and digital literacy as the cornerstones of a resilient digital democracy. Transparency supports the principle of open governance and is vital because it holds institutions accountable to citizens, while the principle of inclusivity is considered fundamental to ensuring that technology empowers all segments of society equally. Digital literacy, meanwhile, is considered essential for equipping citizens with the necessary skills to effectively navigate, critique, and contribute to the digital sphere. These three fundamental principles are valued for ensuring that the digital age strengthens rather than weakens democratic values and for helping democracies remain robust and resilient in an increasingly digital world (Weinhardt et al., 2024).

In the digital competence development model developed by the Council of Europe, digital citizenship is shown to contribute to the creation of a democratic culture in society through the core areas it encompasses. The visual representation of this model is provided below, and each column and color within the model represents a different context.

Figure 2. The Council of Europe model for digital competence development (Richardson & Milovidov, 2019)



It has been argued that five concepts—policies, stakeholders, strategies, infrastructure and resources, and evaluation, as shown by the orange columns in the figure below—are crucial for the development of effective digital citizenship practices (Richardson & Milovidov, 2019). While these five building blocks underpin the entire structure of digital citizenship development, the democratic culture-related competencies listed below—values, attitudes, skills, knowledge, and critical understanding—also form the foundation of digital citizenship. Policy and

evaluation constitute the two framing pillars of the model, and progress in the field of education is largely shaped by policies. At the center of the model are strategies designed to guide practical applications aimed at enabling learners of all ages to develop their full potential as active citizens in the democracies of today and tomorrow. In the context of this study, the focus is on how digital citizenship and an understanding of open democracy can be fostered through the support of and awareness regarding OERs.

Methodology

Since the research topic falls within a niche field and to evaluate the context from a comprehensive framework, a literature review was adopted in this study. By examining the relevant literature, the study set out to explore how the topics of open democracy and digital citizenship can develop in the context of OERs and what role OERs play in this regard, and it included current studies on the subject. Therefore, a traditional literature review was adopted to achieve the study's objective, and by evaluating studies in the relevant literature (Baumeister & Leary, 1997), the study investigated the effects of OERs on the development of digital citizenship and flexible democratic understanding. By examining relevant studies in literature, this type of research enables current conclusions to be drawn on the identified topic (Webster & Watson, 2002)—allows for interpreting the situation from a holistic framework and establishing connections among disparate research findings (Cronin et al., 2008).

Research Objective and Questions

The primary objective of this study is to investigate how OERs can serve to support the concepts of digital citizenship and open democracy. In line with this objective, the research questions have been formulated as follows:

- *What critical role do OERs play in the development of digital citizenship?*
- *How can OERs be used to promote an open and inclusive democracy?*

In line with the above research questions, relevant studies were reviewed to examine the impact and potential of OERs on the processes of open democracy and digital citizenship. Therefore, this study highlights the power of OERs in strengthening digital citizenship, increasing individual participation in democratic processes, and building democratic processes that are open and accessible to all. In particular, the research explores how OERs can play a role—not merely as learning materials, but also in fostering equality, participation, and trust for the sake of open democracy.

Results

As a result of the literature review adopted in this study, the process leading to open democracy and the development of digital citizenship through OERs was examined. In this context, the study focuses on three key areas regarding how open educational resources can strengthen digital citizenship and contribute to open democracy. These key areas are: combating digital misinformation by fostering digital literacy skills; enabling participatory policymaking through the co-creation of open knowledge; and developing actionable recommendations for policymakers, educators, and civil society on how to leverage OERs as a digital public infrastructure for inclusive democracy.

In a study linking OER to open democracy, e-government, and the digital transformation of public administration, public sector employees were found to be actively participating in a platform developed to create, share, reuse, and adapt OER (Mikroyannidis & Papastilianou, 2021). The same study suggests that, in the context of developing digital citizenship, OERs can be viewed not only as an educational tool that equips individuals with digital skills but also as a digital public infrastructure that facilitates access to information, information sharing, and collaborative knowledge production among citizens and public actors (Mikroyannidis & Papastilianou, 2021). Another study on digital citizenship education argues that digital citizenship should be approached not merely as a matter of individuals' ability to use technological tools, but rather as an educational approach that takes into account the inequalities faced by different social groups in the digital sphere and supports participatory democracy (Choi & Cristol, 2021). Therefore, the structure of OER—which supports the production of open knowledge as well as social sharing and collaboration—reinforces the research's finding that open education can strengthen participatory and transparent governance mechanisms in the transition to open democracy.

Estellés and Doyle's (2025) review emphasizes the need to move beyond traditional approaches focused on teaching safe behavior in digital environments and instead foster critical digital citizenship. The emphasis in this study indicates that the role of OER in supporting digital citizenship should be evaluated not only in terms of imparting technical skills but also through individuals' abilities to critically assess online information environments, recognize digital risks, and consciously participate in online social processes. In another study

supporting this view, Aydoğan (2022) argues that defining digital citizenship solely in terms of individuals' ability to use digital technologies or possess technical competencies is insufficient, noting that digital transformation requires a critical examination of knowledge production processes, technological decisions, and their social consequences. The structure of OER, based on open access, reuse, adaptation, and knowledge sharing, has the potential to transform individuals from mere consumers of digital content into active participants who question how knowledge is produced, shared, and reshaped (Aydoğan, 2022). Therefore, OER can be evaluated in terms of fostering critical digital citizenship—which goes beyond technical digital literacy—and steering digital transformation in a more democratic and socially just manner.

Parvin (2015) emphasizes in the research that democratic decision-making processes cannot be strengthened merely by creating spaces where citizens can participate; rather, the necessary knowledge, capacity, trust, and social conditions must also be established for participation to occur. Based on this research, the existence of OERs, digital platforms, or online participation mechanisms does not, on its own, guarantee democratic participation. For the public to participate meaningfully in these environments, they must have access to information, develop digital and media literacy, and possess the competence to make informed decisions on public issues. At this point, the role of OERs is to support one of the prerequisites of digital citizenship by ensuring that the knowledge and skills necessary for democratic participation are made available to different social groups in an open and low-cost manner. Therefore, the democratic value of OERs should be assessed not merely in terms of "providing open resources for participation," but through their capacity to enhance participation. In his research, Kobayashi (2023) approaches democracy as a dynamic process that is constantly evolving and renegotiating its internal tensions; the "democracy as perpetual revolution" approach argued in the study maintains that democracy should never be viewed as a completed system but must instead constantly seek a balance among dimensions such as equality, freedom, and ethical citizenship. Building on this context, it is crucial to ground the concept of "open democracy" not as a static democratic model but as a process of continuous learning, participation, and knowledge production. OERs, meanwhile, can be positioned as an infrastructure that supports the continuity of the democratic process and civic capacity by enabling individuals, within this continuous learning process, to access knowledge throughout their lives, reinterpret existing content, produce new content, and share knowledge with different social groups. When we focus on the question of why and how OERs can serve as a democratic tool, the table below illustrates how society can achieve an open and participatory democratic outcome based on the characteristics of OERs.

Table 1. OER as a democratic infrastructure

OERs Features	Personal Outcome	Democratic Outcome
Open access	Access to information	More equal citizenship
Free to reuse	Reduced learning costs	Lower barriers to participation
Adaptability	Learning adapted to local needs	Inclusive participation
Remix	Actively generating knowledge	Collective knowledge
Sharing	The circulation of knowledge	The public knowledge ecosystem
Collaboration	Collaborative learning	Deliberative participation

As shown in the table above, the focus is on how the fundamental characteristics of OERs first impact outcomes at the individual level from a societal perspective, and second, on what the democratic outcomes of these fundamental characteristics are. The table begins by addressing the open access feature of OERs, highlighting its impact on access to information at the individual level and, as a democratic outcome, the development of more equal citizenship. Looking at the individual outcomes in order, they are listed as follows: access to information, reduced learning costs, learning adapted to local needs, actively generating knowledge, the circulation of knowledge, and collaborative learning. The democratic outcomes are listed as follows: more equal citizenship, lower barriers to participation, inclusive participation, collective knowledge, the public knowledge ecosystem, and deliberative participation.

Conclusions

In conclusion, it is believed that OERs play a significant role in reshaping the concept of digital citizenship with greater awareness within a societal structure where the digital divide is widening—particularly in a context where artificial intelligence tools are becoming more prevalent and digital transformation is gaining momentum. OERs facilitate the democratization of knowledge and the creation of inclusive platforms for collaborative policy dialogue. Additionally, they help citizens develop their digital skills and participate confidently in online

environments. By their very nature, OERs support open education and digital equity, thereby contributing to the strengthening of open democratic structures. By offering open-access tools that allow for offline use and supporting digital equity (Open Development & Education, 2022), OERs foster broader participation and transparency, building resilience against misinformation and propaganda, and thereby helping to advance the principles of open democracy (Open Science Coordination in Finland, Federation of Finnish Learned Societies, 2021). On the other hand, the potential of OERs to strengthen digital citizenship should not be assessed solely based on their provision of open and free materials; designing OERs to facilitate access to information for individuals of different ages, socioeconomic statuses, and levels of digital literacy can make the context of digital citizenship more inclusive (Choi & Cristol, 2021). Thus, OERs can become more functional in terms of open democracy by contributing to broader and more equitable civic participation, beyond merely the development of digital skills. In line with this perspective, OERs can be positioned not only as a means of "open participation" in open democracy, but also as an infrastructure that supports the continuous learning and civic capacity necessary for sustainable participation.

To build a strong and resilient sense of digital citizenship and ensure it serves the principles of open democracy, policymakers must consider promoting the use of OERs and evaluating regulatory measures that would make OERs mandatory in public education. In addition, the development of high-quality, context-appropriate OERs that cater to a diverse audience to foster civic literacy in society, as well as the creation of special funds to disseminate them, should be supported. In terms of the widespread adoption of OERs, governance strategies that embrace open data, broadband infrastructure, and transparency are crucial for an inclusive and open democracy. To strengthen citizen participation in democratic processes, building such a robust and integrated system should be viewed as an essential step at all levels of society.

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Beyond Visual Literacy: A Visual–Algorithmic Literacy Framework for Education in the Age of AI

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Abstract

Images in education are now often made or selected with the help of algorithms. A student can produce a strong visual result without being able to explain how it was made, what it suggests, or whether it should be shared. This paper proposes the Visual–Algorithmic Literacy Framework (VALF) as a simple way to connect these questions. The study is a conceptual synthesis of work on visual literacy, AI literacy, visual culture, and responsible use of technology. It identifies four related layers: visual–aesthetic literacy, algorithmic visual awareness, critical and ethical visual judgement, and meaning-making and responsible visual practice. Each layer asks a different question about an image, while all four contribute to a thoughtful visual decision. A short classroom example shows how the framework may guide discussion and learning activities. The framework is a proposal; it has not yet been tested with learners.

Keywords: visual literacy, generative AI, algorithmic awareness, art and design education, responsible visual practice

Introduction

People learn to read images through experience and education. They notice colour, framing, symbols, and the way these choices shape a message. Visual literacy gives students a language for discussing such features and for making their own visual work (Avgerinou & Pettersson, 2011). It also invites them to ask where an image comes from, who sees it, and how its meaning may change in different settings (Rose, 2016).

Generative AI adds another part to this work. A prompt can produce several images in seconds, but the images do not simply carry the user's intention. Their content is affected by training material, model design, and the choices offered by a platform. Learners may select an attractive result without asking why certain people, places, or roles appear in it. Research on image datasets and generated images shows why representation deserves attention (Crawford & Paglen, 2021; Bianchi et al., 2023). Recent discussion of visual literacy also argues that generative AI changes the knowledge needed to interpret and create images (Brumberger, 2025).

This paper asks what students should learn when they work with such images. Its answer is VALF, a four-layer framework that joins visual understanding with awareness of algorithmic processes and responsibility for the final use of an image. The paper first explains how the framework was developed, then presents the four layers and a brief educational example. The aim is to offer clear concepts for teaching and future research, not to report an intervention or claim that the framework has already been validated.

The question matters beyond courses devoted to art or technology. Learners meet images in news, social media, and everyday communication. They may need to decide whether an image is an illustration, evidence, or an attempt to persuade. In this setting, knowing how to use a generator is only one small part of visual learning. Students also need to ask what an image invites them to believe and what responsibility they take when they pass it on to others. A framework for education should make these questions manageable without asking every teacher to become a technical expert.

Methodology

This is a conceptual study. We brought together selected ideas from visual literacy, visual culture, AI literacy, and guidance on responsible AI in education. The sources were chosen because they clarify what a learner might need to notice, understand, judge, or do when working with an algorithmically mediated image. Work on AI literacy provides a wider account of understanding and evaluating AI (Long & Magerko, 2020; Ng et al., 2021), while visual literacy and visual culture keep attention on the image and its audience.

We compared these ideas and organised them around four educational questions: What does the image show and communicate? How might algorithmic processes have shaped it? What concerns arise for people and audiences? How should the learner act on these judgements? This process produced the four layers described below. It was a

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selective synthesis rather than a systematic review. No participants were recruited, and no learning outcomes were measured. The example in this paper illustrates possible teaching use; it is not a record of a classroom study.

In forming the layers, we looked for a distinct purpose for each one. An observation about composition, for example, is different from a claim about the way a model generated the composition. Both differ from deciding whether the image is suitable for a public audience. These distinctions help teachers ask clearer questions and notice where a student needs support. They do not describe fixed stages of development or a tested scale of ability. The value of the framework lies in the links among the questions as well as in their differences.

Results

The main outcome of the synthesis is VALF. Its layers can be considered separately, but a real visual task may require a learner to move between them. The framework does not assume that students must complete one layer before beginning another.

Visual–Aesthetic Literacy

The first layer concerns what learners can see and explain in an image. They consider composition, colour, scale, perspective, and visual symbols. They ask how these features guide attention and support a particular meaning. For example, a figure placed at the centre of a poster may appear more important than others. A student should be able to point to the visual features that support this reading, while allowing for other interpretations.

This layer keeps established visual knowledge at the centre of the framework. AI can change how an image is produced, but it does not remove the need to judge whether the image communicates well. At the same time, visual appearance cannot by itself prove who made an image, where its material came from, or whether its use is fair. Those questions require other forms of inquiry.

A useful classroom question is, “What in the image supports your interpretation?” Students can answer by marking a feature and explaining its effect. They may also compare how different viewers could read the same feature. This makes visual judgement open to discussion rather than leaving it as a personal preference. It also gives a starting point for later questions about the image’s origin and use.

Algorithmic Visual Awareness

The second layer asks learners to think about the system involved in making or selecting an image. A prompt, model, platform settings, and available source material may all affect what appears. Students do not need to know every technical detail. They do need to understand that a generated image is shaped by more than a single human request and that some parts of the process may be hidden from them.

A simple comparison can support this awareness. Students might change one part of a prompt and compare the results. They can describe what changed, what stayed similar, and what they still cannot explain. A few examples cannot reveal an entire training dataset or establish how a model works internally. Recognising that limit is part of the learning, because it helps students avoid confident claims based on too little evidence.

Teachers can ask learners to separate three things: the instruction they gave, the result they observed, and their explanation of that result. A system may respond in an unexpected way, and the reason may remain unclear. Saying “I do not know” can therefore be a good answer when it is paired with careful observation. This layer aims for informed curiosity, not a claim of complete access to a hidden system.

Critical and Ethical Visual Judgement

The third layer asks whether an image is appropriate for its purpose and audience. Learners consider whose perspective is visible, who is missing, and whether an image could reinforce a stereotype or create a false impression. They also consider sources, permission, and whether viewers should be told that AI was used. These are questions about a specific use, not only about the image in isolation.

For instance, an invented scene may work well as an illustration but mislead viewers if presented as a photograph of a real event. A responsible judgement therefore connects a concern to an action: revising the image, changing its caption, using a different source, or deciding not to publish it. Guidance for education likewise stresses human agency and careful consideration of risks when generative AI is used (Miao & Holmes, 2023).

The audience and purpose should shape the discussion. An image made for private experimentation may be judged differently from one used in a school website or a public campaign. Students can ask what a viewer is likely to assume and whether the image gives a fair account of the people or situation it depicts. Such questions help them move from a general statement that “AI can be biased” to a reasoned decision about the image before them.

Meaning-Making and Responsible Visual Practice

The fourth layer brings the other three into the learner's own work. Students choose a purpose, review possible images, make changes, and explain why the final version is suitable. They can identify which parts were generated, which were made or edited by a person, and which sources informed the work. This account helps others understand the decision behind the image.

Responsible practice is more than adding an AI label at the end. It means using visual interpretation, knowledge of the tool, and ethical judgement while the work is being developed. A short note about a rejected option or a changed caption can show how thinking affected the result. The same principle applies when a student decides that an AI-generated image is unnecessary for the task.

The explanation should be brief enough to be useful. A learner could keep the original idea, one or two alternatives, and a note on the main change. This does not prove everything about the process, but it makes a key decision visible. It also allows a teacher to respond to the student's reasoning, instead of judging only the appearance of the final product. The fourth layer therefore links making an image to being answerable for it.

Bringing the Layers Together

Consider a class preparing a poster for a school reading event. Students first discuss how the people, text, and colours in a draft poster guide attention. They then compare a small set of generated options and note what changes when the prompt is revised. Next, they ask whether the images represent the intended audience fairly and whether the poster could be mistaken for a record of an actual event. Finally, they select or revise an image and explain the choice in a short production note.

This activity is only an illustration. It shows how one task can connect the four layers without turning the lesson into a technical course on AI. Teachers could use brief annotations, comparisons, and discussion to make students' reasoning visible. The quality of the finished poster would still matter, but it would not be the only evidence of learning.

The four layers may appear in a different order during the activity. A concern about representation may send students back to examine the visual arrangement of the poster. A new image from the generator may change their original message. A classmate's interpretation may lead them to revise the caption. VALF is intended to support this movement. It gives a name to each kind of question while leaving room for learners to return to an earlier decision.

Discussion

VALF can help teachers plan a manageable visual task. Instead of asking students to "use AI responsibly" without further guidance, a teacher can give one question for each layer. Students might describe a visual choice, compare two generated options, identify a possible problem for viewers, and explain one change they made. These short pieces of evidence can support feedback about thinking as well as about the final image. They can also be used when students analyse supplied images rather than generating their own.

The framework does not require a single tool or a single kind of assignment. A drawing, a photograph, and an AI-generated illustration can all be discussed through visual and ethical questions. The algorithmic layer becomes especially important when a system creates, filters, recommends, or changes visual material. Teachers may adapt the depth of technical discussion to the learners and the course aim. The common expectation is that students distinguish what they observed from what they are only guessing.

There are limits to this proposal. The four layers were developed from selected literature, and their boundaries have not been tested with learners. A lesson may also be affected by access to tools, language, privacy rules, and the time available for discussion. Students should not be asked to upload personal images to an unfamiliar service simply to complete an activity. Future studies should examine whether teachers and learners understand the four questions in similar ways and whether the suggested activities lead to better visual decisions in real settings.

Conclusions

VALF offers a way to teach visual literacy when images are increasingly shaped by algorithms. The four layers keep attention on how an image looks, how it may have been mediated, what its use means for others, and how a learner makes a responsible choice. Together, they give teachers and students a shared set of questions for examining visual work.

The framework remains a conceptual proposal. Its value in different subjects, age groups, and learning environments still needs to be studied. Future work can test whether the four layers are clear to learners and teachers, and whether activities based on them help students explain and improve their visual decisions. Until then, VALF can serve as a practical starting point for discussion and course design.

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Data-Related Skills and Mathematical Literacy of Pre-Service Mathematics Teachers Within the K12 Framework

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Abstract

This study examined pre-service mathematics teachers' statistics self-efficacy and mathematical literacy self-efficacy, and the direction and strength of the relationship between these constructs. Data-related skills in the K12 framework provided the curricular context, while statistics self-efficacy was the construct measured in relation to statistical tasks. A quantitative correlational survey design was used. Participants were 100 pre-service teachers enrolled in elementary and secondary mathematics teacher education programmes at a public university in the Marmara Region of Türkiye. Data were collected using the 14-item Statistics Self-Efficacy Belief Scale and the 25-item Mathematical Literacy Self-Efficacy Scale. Descriptive statistics and Pearson's correlation were used to analyse the scores. Mean statistics self-efficacy was 3.71 (SD = 0.271), and mean mathematical literacy self-efficacy was 3.72 (SD = 0.286). The latter corresponded to a high level under the interpretive intervals used for the five-point scale. The two variables showed a statistically significant, very strong positive correlation (r = .944, p < .001). Participants who reported greater confidence in statistical tasks also tended to report greater confidence in using mathematics in real-life contexts. The findings concern self-efficacy beliefs and do not establish actual competence or a causal relationship. The magnitude of the correlation should be considered alongside the conceptual overlap between the constructs and their measurement through self-report scales.

Keywords: Data-related skills, mathematical literacy, pre-service mathematics teachers, statistics self-efficacy, self-efficacy

Introduction

Mathematical literacy involves using mathematical knowledge to understand situations, formulate problems and evaluate solutions in context. The PISA 2022 framework places mathematical reasoning, formulation, application and interpretation at the centre of this capacity (OECD, 2023). Mathematical competence similarly concerns a person's readiness to respond appropriately to the mathematical demands of a situation (Niss & Højgaard, 2019). These perspectives draw attention to how knowledge is used, as well as to whether concepts and procedures are known. For mathematics teacher education, they raise questions about how pre-service teachers perceive their ability to connect mathematical knowledge with situations beyond routine exercises.

Many everyday situations are presented through tables, graphs, percentages and statistical summaries. Making sense of this information requires attention to how data were obtained, what the results represent and which conclusions they support. Gal (2002) describes statistical literacy in relation to interpreting, critically evaluating and communicating statistical information. The GAISE II framework likewise treats statistical investigation as a connected process of posing questions, collecting or considering data, analysing data and interpreting results (Bargagliotti et al., 2020). These processes provide a conceptual link between statistical tasks and the contextual use of mathematics.

In Türkiye, the Türkiye Yüzyılı Maarif Modeli (Century of Türkiye Education Model) gives curricular prominence to working with data and making data-based decisions as a mathematics domain skill. This skill includes identifying statistical problems, obtaining and preparing data, reaching findings and interpreting them (Millî Eğitim Bakanlığı [MEB], 2024). Its place within the K12 framework makes pre-service teachers' beliefs about statistical tasks relevant to teacher education. However, a curriculum skill and self-efficacy in that skill are different constructs. The present study approaches this curricular context through statistics self-efficacy and mathematical literacy self-efficacy; it does not directly assess the full range of K12 data-related skills.

Self-efficacy refers to beliefs about one's capacity to organise and carry out the actions required for a particular task (Bandura, 1997). Such beliefs can influence the effort devoted to a task and persistence when difficulties arise, but they are not equivalent to demonstrated performance. Mathematical literacy self-efficacy concerns perceived capability to use and interpret mathematics in real-life situations (Özgen & Bindak, 2008). Statistics self-efficacy concerns confidence in carrying out statistical tasks, including understanding concepts, analysing data and interpreting results (Finney & Schraw, 2003; Sevimli & Aydın, 2017). The two domains differ in scope, although both involve making sense of quantitative information and evaluating conclusions.

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Research with pre-service teachers has examined mathematical literacy self-efficacy alongside several related variables. Dinçer et al. (2016) identified a small but significant relationship with mathematics teaching efficacy beliefs. Özçakır Sümen and Çalışır (2016) examined mathematical literacy self-efficacy, metacognitive awareness and problem-solving skills together and reported significant relationships involving problem-solving scores. More recently, Türk et al. (2025) found a moderate positive association between mathematical literacy self-efficacy and mathematical thinking. These studies support considering mathematical literacy self-efficacy in relation to other aspects of pre-service teachers' learning, without treating those aspects as interchangeable.

Studies on statistical tasks and data use provide a related body of evidence. Aydın et al. (2019) reported low to moderate statistics self-efficacy among Palestinian pre-service mathematics teachers. Research on data literacy interventions has considered both knowledge about data and beliefs about using it. Reeves and Honig (2015) examined a classroom intervention in pre-service teacher education, while Wurster et al. (2023) investigated the effects of a data-use intervention on data literacy and motivational beliefs. Data literacy, statistics self-efficacy and beliefs about data use overlap conceptually, but their measurement and scope differ. This distinction is necessary when these studies are used to contextualise statistics self-efficacy.

The research considered here has generally related mathematical literacy self-efficacy to problem solving, mathematical thinking or teaching efficacy, while work on statistical tasks has emphasised statistics self-efficacy and data use. Examining the two self-efficacy constructs within the same group can clarify whether confidence in statistical tasks is associated with confidence in the contextual use of mathematics. The present study therefore aimed to describe statistics self-efficacy and mathematical literacy self-efficacy among pre-service elementary and secondary mathematics teachers, and to determine the direction and strength of their relationship. It addressed three questions: What are participants' statistics self-efficacy scores? What is their mathematical literacy self-efficacy level? Is there a statistically significant relationship between the two variables, and what are its direction and strength?

Methodology

Research design and participants

A quantitative correlational survey design was used to examine the relationship between statistics self-efficacy and mathematical literacy self-efficacy. The variables were measured without an instructional intervention. The study therefore provides descriptive and correlational evidence rather than evidence about the effects of a particular teaching approach. The target population comprised students enrolled in elementary and secondary mathematics teacher education programmes in faculties of education at public universities in Türkiye. The accessible population was limited to the corresponding programmes at one public university in the Marmara Region.

The sample consisted of 100 pre-service teachers who participated voluntarily and were enrolled in the first, second, third or fourth year of these programmes. Of the participants, 43 were male and 57 were female. Table 1 presents their distribution by year of study and gender. Second-year students constituted 70% of the sample. The distribution describes the composition of the group and should be taken into account when considering the extent to which the findings represent other cohorts or universities.

Table 1. Distribution of participants by year of study and gender

Year of study	Male	Female	Total
First year	8	3	11
Second year	25	45	70
Third year	5	5	10
Fourth year	5	4	9
Total	43	57	100

Data collection instruments

Statistics self-efficacy was measured using the Statistics Self-Efficacy Belief Scale developed by Finney and Schraw (2003) and adapted into Turkish by Sevimli and Aydın (2017). The instrument contains 14 items with a six-point response format. It asks respondents to judge their confidence in performing statistical tasks. The Turkish adaptation retained the 14 items and provided evidence concerning the validity and reliability of the instrument. In the present study, statistics self-efficacy was used as a measure of perceived capability in statistical processes, rather than as a direct measure of data literacy or the complete K12 data-related domain skill.

Mathematical literacy self-efficacy was measured using the scale developed by Özgen and Bindak (2008). This instrument comprises 25 items with a five-point Likert response format and concerns perceived capability to use, interpret and evaluate mathematical knowledge in everyday situations. The original development study provided validity and reliability evidence for the scale. Both instruments measure self-efficacy beliefs. Consequently, the resulting scores indicate how participants evaluate their own capabilities; they do not show how successfully participants would perform corresponding mathematical or statistical tasks.

Data analysis

Before analysis, the data were examined for missing values and distributional characteristics. The scores were described using the mean, median, standard deviation, minimum and maximum. Skewness and kurtosis were also calculated. Pearson's correlation coefficient was used to determine the direction and strength of the linear association between the two variables, with the significance level set at .05 (Field, 2018). The positive skewness and kurtosis values reported in the results indicate departures from a symmetric distribution; these values should be considered when interpreting the correlation and its statistical significance.

For mathematical literacy self-efficacy, the five-point scale was interpreted using the following intervals: 1.00–1.80, very low; 1.81–2.60, low; 2.61–3.40, moderate; 3.41–4.20, high; and 4.21–5.00, very high. These intervals were used as descriptive interpretive categories. They were not applied to the statistics instrument, which has a six-point response format. Statistics self-efficacy is therefore described through its score distribution. The different response formats also mean that numerical proximity between the two means should not be interpreted as equality of self-efficacy across the domains.

Results

Self-efficacy scores

Table 2 presents the descriptive statistics for both variables. Mean statistics self-efficacy was 3.71 (SD = 0.271), with a median of 3.69. The observed scores ranged from 3.15 to 5.00. Mean mathematical literacy self-efficacy was 3.72 (SD = 0.286), with a median of 3.70 and an observed range of 3.14–5.00. The standard deviations indicate relatively limited dispersion within the sample. The observed maximum of 5.00 for statistics self-efficacy is a sample value and should not be confused with the upper response category of the six-point instrument.

Table 2. Descriptive statistics for the two self-efficacy variables

Statistic	Statistics self-efficacy	Mathematical literacy self-efficacy
N	100	100
Mean	3.71	3.72
Median	3.69	3.70
Standard deviation	0.271	0.286
Minimum	3.15	3.14
Maximum	5.00	5.00
Skewness	1.24	1.26
Kurtosis	4.48	3.71

The mean of 3.72 for mathematical literacy self-efficacy falls within the 3.41–4.20 interval and was classified as high. This finding suggests that participants generally evaluated their ability to use and interpret mathematical knowledge in everyday contexts favourably. Statistics self-efficacy had a mean of 3.71 and a median close to that value. These scores describe perceived capability in statistical tasks, without establishing actual statistical performance. Since the two instruments use different response formats, the means were not used to rank participants' confidence in one domain relative to the other.

The distributions were positively skewed, with coefficients of 1.24 for statistics self-efficacy and 1.26 for mathematical literacy self-efficacy. The corresponding kurtosis coefficients were 4.48 and 3.71. These findings indicate that neither distribution was fully symmetric. The proximity of the mean and median does not, by itself, establish normality. The distributional characteristics are relevant to the interpretation of the association, particularly because a correlation coefficient can be influenced by the pattern and extremity of individual observations (Field, 2018).

Relationship between the two variables

The Pearson correlation analysis indicated a statistically significant, very strong positive relationship between statistics self-efficacy and mathematical literacy self-efficacy ($r = .944$, $p < .001$, $N = 100$). Table 3 summarises the result. Higher statistics self-efficacy scores were associated with higher mathematical literacy self-efficacy scores. Thus, participants who considered themselves more capable of carrying out statistical tasks also tended to consider themselves more capable of using mathematical knowledge in different contexts.

Table 3. Pearson correlation between the self-efficacy variables

Variables	*N*	*r*	*p*
Statistics self-efficacy and mathematical literacy self-efficacy	100	.944	< .001

The correlation describes the co-variation of the scores within this sample. It does not indicate that increasing confidence in statistics would cause an increase in mathematical literacy self-efficacy, or that the two scales measure an identical construct. Both domains involve interpreting quantitative information and evaluating results, which may help to account for their association. However, this conceptual explanation remains an interpretation of the finding rather than a mechanism tested by the research design.

Conclusions

This study identified a very strong positive association between pre-service mathematics teachers' statistics self-efficacy and mathematical literacy self-efficacy. Mathematical literacy self-efficacy was high under the five-point interpretive intervals, while statistics self-efficacy was described by a mean of 3.71 on the instrument used. The findings show that beliefs about carrying out statistical tasks and using mathematics in real-life contexts were closely related within the study group. They provide a basis for considering these beliefs together in mathematics teacher education, while keeping self-efficacy distinct from performance.

The mathematical literacy self-efficacy result differs from the moderate level reported by Türk et al. (2025). Such differences should be considered in relation to the samples and research contexts, rather than treated as evidence of a general change in pre-service teachers' beliefs. Earlier findings concerning mathematics teaching efficacy and problem solving also show that mathematical literacy self-efficacy can be related to other educationally relevant constructs (Dinçer et al., 2016; Özçakır Sümen & Çalışır, 2016). The present research adds statistics self-efficacy to this consideration. It does not establish that the relationships reported across separate studies have the same source or magnitude.

Aydın et al. (2019) reported low to moderate statistics self-efficacy in a different national context. Direct comparison with the present mean requires attention to the response format, scoring and interpretive criteria used in each study. Research on classroom data literacy and data-use interventions further indicates that beliefs about data can be examined alongside structured learning experiences (Reeves & Honig, 2015; Wurster et al., 2023). No intervention was implemented here, and the study does not determine which academic or instructional experiences contributed to participants' beliefs. The findings therefore concern the relationship between the two measured variables, rather than the effectiveness of the teacher education programme.

The correlation of .944 requires cautious interpretation. Statistics self-efficacy and mathematical literacy self-efficacy share processes such as interpreting quantitative information, evaluating results and drawing conclusions in context. This overlap may contribute to the association. At the same time, both variables were measured through self-report scales, and a shared measurement approach may also have contributed to the magnitude of the relationship. The design does not distinguish between these possibilities. A very strong correlation should therefore prompt further examination of the empirical distinctness of the constructs, rather than an assumption that confidence in one domain fully represents confidence in the other.

Limitations and implications

The findings are limited to 100 volunteers from one public university, and the concentration of second-year students restricts their representation of different stages of teacher education. Self-report measurement does not establish actual mathematical literacy or statistical competence. In addition, the positive skewness and kurtosis of the score distributions warrant caution in interpreting the Pearson analysis. Larger studies across several universities could examine whether the association persists in more varied samples. Inspection of individual scores and comparison with a rank-based correlation would also help assess the sensitivity of the result to distributional characteristics and influential observations.

Performance-based tasks and interviews could be used alongside self-efficacy scales to examine how participants' confidence relates to their actual responses to data and mathematical problems. Such work could also explore

whether pre-service teachers understand the two domains as separate areas or draw on similar experiences when judging their capabilities. Including statistics achievement, problem solving, mathematical thinking or data literacy would extend the analysis beyond two self-report variables. These directions would help clarify the very strong relationship observed here without assigning a causal explanation to the present result.

Within the K12 curricular context, teacher education activities could bring the interpretation of data and the contextual use of mathematics together. Tasks involving the analysis of data, evaluation of competing interpretations and justification of conclusions may offer a setting in which the two self-efficacy domains can be considered jointly (Bargagliotti et al., 2020; MEB, 2024). Whether such activities strengthen either form of self-efficacy or improve performance remains a question for intervention research. The contribution of the present study is to identify the close association between these beliefs in the same group of pre-service mathematics teachers.

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Artificial Intelligence in Project Management Decision-Making for Uncertain Futures: Bias, Accountability, and Responsible Governance

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Abstract

Artificial intelligence (AI) now supports project portfolio selection, resource allocation, risk assessment, and performance evaluation. Its analytical capacity can improve decisions, yet project environments combine limited information with futures that historical data may not represent. Research documents efficiency gains and ethical risks, while offering limited guidance for connecting institutional principles, project routines, and technical controls. This conceptual study integrates research on AI-enabled project management, bounded rationality, sociotechnical systems, meaningful human control, and responsible AI. It also examines the European Union Artificial Intelligence Act, Türkiye's Personal Data Protection Law, and the NIST AI Risk Management Framework as reference points. Accountability requires active, authorised human oversight. Decision makers must understand system limits, possess authority to reject recommendations, document reasons, and remain identifiable throughout the system lifecycle. The article proposes a three-layer Responsible AI Governance Model. The strategic layer sets risk tolerance, assigns responsibilities, and authorises use cases through an interdisciplinary ethics and risk committee. The tactical layer embeds ethical impact assessment, human review, and accessible appeal procedures in project decisions. The operational layer supports these processes through bias monitoring, explainable outputs, data governance, and auditable records. Feedback from operational monitoring and appeals informs tactical adjustment and strategic revision. The model positions AI as accountable decision support under uncertainty and specifies how abstract ethical commitments can become coordinated organisational practice. The contribution links responsible AI governance to organisational resilience and learning. It also identifies AI literacy as a professional and educational requirement for project managers who must interpret, challenge, and govern algorithmic recommendations.

Keywords: Artificial intelligence, project management, responsible artificial intelligence, meaningful human control, algorithmic accountability

1. Introduction

Project managers make interdependent decisions — such as portfolio selection, resource allocation, risk prioritisation, and performance evaluation — under constraints of limited time and information. Artificial intelligence (AI) supports these decisions by processing patterns in large datasets to provide prediction, classification, and optimisation. Systematic reviews in the field of project management show that applications are concentrated in particular on securing efficiency in planning, cost, and schedule, as well as in risk analysis and resource management (Taboada et al., 2023; Hashfi & Raharjo, 2023). This analytical capacity can shorten decision time and render visible options that a human could not evaluate simultaneously.

Project environments also involve situations in which future probabilities cannot be reliably calculated. New technologies, shifting stakeholder expectations, and unexpected external shocks reduce the representativeness of historical data. In such an environment, a model that projects an appearance of high accuracy may lead the decision maker to perceive uncertainty as measured risk. Inequalities in training data can be carried over into resource allocation and performance evaluation; complex models can obscure the rationale behind a decision; and excessive trust in automated recommendations can narrow human judgement (Mehrabi et al., 2021; Parasuraman & Manzey, 2010). Moreover, when a decision proves erroneous, the distribution of responsibility among the project manager, the developer, the data owner, and the institution may remain unclear (Matthias, 2004).

Research in the field of responsible AI shows a broad consensus on the principles of fairness, transparency, non-maleficence, privacy, and accountability (Jobin et al., 2019). Nevertheless, the existence of a principle does not by itself produce the institutional order that puts it into effect in a project decision. General ethical frameworks may remain at the institutional level, while technical measures may become detached from the organisational context of the decision (Dignum, 2019). The project management literature, for its part, largely concentrates on the functions, adoption, and performance contributions of AI (Taboada et al., 2023; Hashfi & Raharjo, 2023). At the

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intersection of these two lines of research lies a governance gap that would connect institutional responsibility to the project workflow and to technical control.

The article's guiding question is the following: through which governance mechanisms can AI-supported decision processes embedded in project management under conditions of uncertainty be conducted responsibly? In seeking an answer, uncertainty and bounded rationality are read together with sociotechnical systems theory and meaningful human control. This reading yields the Responsible AI Governance Model, which connects institutional authority to in-project review and to technical evidence. In the model, appeals and monitoring findings return to decision makers along the same channel. The contribution of the article is to translate ethical principles into examinable mechanisms such as decision authority, impact assessment, explainability, and audit records.

2. Theoretical Framework

2.1 Uncertainty, bounded rationality, and automation

Knight (1921) distinguishes risk, in which the possible outcomes and their probabilities are known, from uncertainty, in which a reliable distribution cannot be established. Simon's (1997) account of bounded rationality holds that, because of limits on information, time, and cognitive capacity, the decision maker cannot evaluate all available options. Taken together, these two perspectives imply that AI cannot be regarded as a tool that eliminates uncertainty. An AI model can compare options on the basis of the patterns visible in the data available to it. Responsibility for assessing developments that lie beyond the data, and the ethical consequences of the decision, rests with the human.

Human decision making, too, is affected by systematic biases. Heuristics facilitate rapid decision making under uncertainty but may lead to the misinterpretation of probabilities and samples (Tversky & Kahneman, 1974). AI support can compensate for some of these limitations, yet automation creates a new distribution of attention. As the level of automation rises, the human task shifts from generating information to monitoring outputs and managing exceptions (Parasuraman et al., 2000). Automation bias arises when the decision maker accepts the system's recommendation without sufficient scrutiny, and it can intensify as the perceived reliability of the system increases (Parasuraman & Manzey, 2010). For this reason, leaving decision authority with the human does not by itself constitute a sufficient safeguard. The human must be able to access an explanation, to reject the recommendation, and to monitor the consequences of the decision.

2.2 Sociotechnical systems and meaningful human control

The sociotechnical systems approach treats the outcomes of an information system as the joint product of technology and organisational order. When user roles, workflows, rules, data practices, and technical components are not designed together, a local technical improvement can generate new problems at the system level (Baxter & Sommerville, 2011). Adapted to project management, this approach explains bias, opacity, and the responsibility gap through the relationships among the algorithm, the data, and the organisational order. The form these risks take is determined by how the data are produced, which decisions the model is bound to, how much authority the user holds, and how the institution handles appeals.

Meaningful human control defines the human's role in the decision loop through more precise criteria. Santoni de Sio and van den Hoven (2018) propose the conditions of tracking and tracing for such control. Tracking denotes the responsiveness of the system's behaviour to the relevant human and institutional reasons. Tracing requires that the system's output be traceable back to responsible persons who understand the system's capacities and effects. In project management, the first condition ensures that a resource-assignment model responds to defined criteria such as equity, competence, and project requirements. The second condition renders visible who evaluated the recommendation, on what grounds it was accepted, and who will account for the outcome.

Within this framework, the place of explainability in governance acquires a more limited and concrete meaning. Explainable AI techniques can render model output interpretable and facilitate error analysis (Barredo Arrieta et al., 2020). However, unless a space for intervention is opened to the user, an explanation goes no further than an informative display. The institution must define the legitimate limits of use and the responsible actors; the project manager must be able to modify the recommendation; and the technical system must record, in a traceable manner, both the grounds and the outcomes of the decision. The three layers of the model are derived from this relationship.

3. Method

This study is conceptual research that does not collect empirical data. In conceptual articles, the choice of theory, the logic of integration, and the anticipated contribution must be shown explicitly (Jaakkola, 2020). To this end,

the literature was examined through the foci of AI-supported project management, the relationship between uncertainty and human–automation interaction, AI ethics and accountability, and AI literacy. Recent systematic reviews were taken as the basis for identifying project management and AI applications. For uncertainty, bounded rationality, and automation, foundational works were consulted. The regulatory analysis draws on the official texts of the European Union Artificial Intelligence Act, the Personal Data Protection Law, and the Artificial Intelligence Risk Management Framework developed by the National Institute of Standards and Technology (NIST).

The sources are not arranged so as to form a sequential summary of the literature. Each line of research was examined from the perspective of the same decision event: under what conditions can a system recommendation count as evidence, who may make the decision, and by what record can the outcome be re-examined? The sociotechnical approach was used to explain the organisational context of the decision, meaningful human control to explain the relationship between authority and traceability, and the regulatory texts to explain minimum obligations. Related problems cluster around institutional authority, in-project review, and technical evidence, and the connections among them were transformed into a governance model. Because of this selective synthesis, the study makes no claim to being a systematic review or an exhaustive survey of the literature.

4. Regulatory and Ethical Framework

Rather than assessing all AI applications at the same level of risk, the European Union Artificial Intelligence Act adopts a graduated approach based on the purpose and likely effects of use. Certain systems used for the purposes of employment, worker management, task allocation, and performance monitoring fall within this scope among the high-risk applications (Regulation (EU) 2024/1689, 2024, Annex III, Art. 4). Such a classification gives rise, for the institution using the system, to obligations such as risk management, data governance, technical documentation, record-keeping, transparency, and human oversight (Regulation (EU) 2024/1689, 2024, Arts. 9–15). The legal status of a tool used in project management, too, should be determined less by the general name of the software than by which decision it actually affects. For instance, a system that merely proposes meeting times and one that ranks employees for critical tasks or career opportunities do not carry the same level of impact. Tools that perform resource allocation, performance evaluation, or task prioritisation may, depending on how they are used, be associated with the high-risk provisions. Taking into account the Act's phased timetable of application, each use scenario should be assessed separately against the current criteria.

For project applications in Türkiye, Personal Data Protection Law No. 6698 provides the fundamental legal framework governing the purposes for which, and the extent to which, employee data may be processed. Article 11 of the Law grants the individual the right to object to an outcome that arises to their detriment as a result of being analysed solely by automated systems (Personal Data Protection Law, 2016, Art. 11/1-g). This provision does not mean that every AI recommendation automatically produces the same legal outcome. Even so, in applications that may create marked effects on employees — such as performance scoring, task allocation, and resource allocation — an accessible channel through which the decision can be re-examined is required. The affected person's ability to understand which data were used and how the decision was formed likewise facilitates the practical exercise of the right to object. Furthermore, the scope of the data transferred to the model should be determined not by a desire to construct a more detailed profile but by the principle of being purpose-related, limited, and proportionate (Personal Data Protection Law, 2016, Art. 4/2-ç).

Although the Artificial Intelligence Risk Management Framework developed by the National Institute of Standards and Technology (NIST) is not a binding legal text, it offers a practice-oriented path for how these obligations can be managed within an institution. The framework links the functions of governing, mapping the context, measuring, and managing across the system's life cycle (Tabassi, 2023). Risk assessment thereby ceases to be a one-off procedure completed before the system is deployed and becomes a recurring institutional activity throughout the period of use. Whereas the European Union Artificial Intelligence Act and the Personal Data Protection Law set the legal limits, the NIST framework provides a more operational structure for monitoring and managing risks. The principles of fairness, transparency, and accountability shared across international ethical guidelines also help to set the direction of this structure (Jobin et al., 2019). The view that responsible AI should be addressed across institutional roles and decision processes, for its part, places the responsibility for implementation on the institution (Dignum, 2019). The task, control, and feedback relationships at the project level cannot be taken ready-made from any of these texts. They must be designed separately according to the impact of the decision, the data used, and the institution's structure of responsibility. The proposed governance model relates these expectations to tasks, records, and feedback channels that can be tracked in project practice.

5. Responsible AI Governance Model

In Figure 1, the AI-supported project decision is addressed within a cycle formed by three mutually reinforcing foci. The institution defines the purpose of use, the responsible parties, and the limits of intervention. The project

manager evaluates the system recommendation in light of the prevailing conditions, records the rationale for the decision, and keeps the appeal process open. The technical team, in turn, maintains records concerning the data used, the model's behaviour, and how the decision was formed. When monitoring results or appeals reveal a new problem, both the project practice and the institution's risk approach are re-examined.

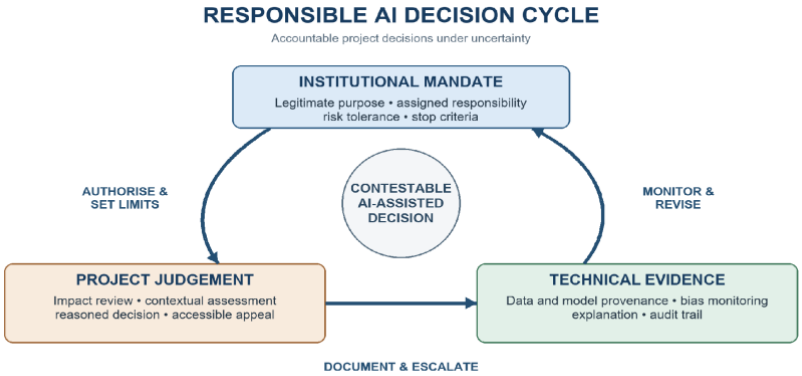


Figure 1. The responsible AI decision cycle: institutional authority, project judgement, and technical evidence.

5.1 Strategic layer

The principal actor of the strategic layer is an interdisciplinary AI ethics and risk committee with senior-management support. The committee represents competencies in project management, law, data science, information security, and human resources. The permitted purposes of use and the institution's risk tolerance are determined here. For each system, the business owner, the model owner, the data controller, the decision authority, and the appeal body are assigned in advance. The view that responsible AI should be addressed within institutional roles extending from design to use supports this distribution (Dignum, 2019; Tabassi, 2023). Should harm arise, responsibility can thus not be attributed to an indeterminate system.

The committee's work is not completed with the approval of a system. Suspension thresholds are set in advance for performance decline, discriminatory impact, insufficient explanation, or appeals concentrated on the same issue. In high-risk systems, the regulation of record-keeping and human oversight as separate obligations supports this requirement of continuous review (Regulation (EU) 2024/1689, 2024, Arts. 12 and 14). When a threshold is exceeded, use may be suspended. The renewed assessment considers not only the model's performance but also whether the project conditions have changed.

5.2 Tactical layer

The tactical layer regulates the decision flow of the Project Management Office and the project managers. In every use scenario involving AI, the purpose of the decision, the affected groups, the data sources, the potential harms, and the appeal channel are recorded in an ethical impact assessment. The significance of the decision determines the human review required. If the project manager can see the grounds for the recommendation, evaluate the alternatives, and depart from the recommendation, human control can satisfy the conditions of tracking and tracing (Santoni de Sio & van den Hoven, 2018). An unauthorised approval screen does not provide the same assurance.

During resource assignment, the system produces a candidate ranking based on skills, suitability, and workload. The project manager examines the criteria, adds to the decision record information not visible in the data within the team context, and departs from the recommendation where necessary. The employee affected by the decision must be able to understand the data on which the system output is based and how it was formed, must be able to request the correction of erroneous data, and must be able to request that the decision be re-examined by a human (Erduran & Demir, 2026). The right to object to an adverse outcome arising from automated analysis is one of the legal bases for such a request (Personal Data Protection Law, 2016, Art. 11/1-g).

5.3 Operational layer

The operational layer encompasses the data, model, and record infrastructure. The representativeness and quality of the dataset are documented on a version basis. Model outputs are regularly compared across the relevant groups, and bias indicators are monitored throughout the period of use (Mehrabi et al., 2021). The explanation method is selected according to the decision maker's question and the impact of the decision. A technical ranking of feature importance can help the project manager understand which data influenced the recommendation. In high-impact

decisions such as the distribution of tasks and opportunities, counterfactual explanations and scenario comparisons may be more functional (Barredo Arrieta et al., 2020).

When a decision is examined afterwards, it is not sufficient that only the final outcome has been recorded. The model and data version used, the inputs given to the system, the system recommendation, the explanation provided, the manager's decision and its rationale, and any appeal and its outcome must be traceable within the same chain of records. These records must be stored in accordance with the rules on personal data protection and information security, and access permissions must be restricted. When a significant change is observed in the model's behaviour or in the project's conditions, the system must be re-validated. In this way, the technical team not only reports on the model's performance but also supplies the evidence necessary for the project manager and the institutional committee to reassess their decisions.

6. Discussion

The three layers of the model demonstrate that accountability cannot be achieved merely by naming those responsible. In the formation of a project decision, the institution's rules, the project's particular conditions, and the technical infrastructure used all play a part together (Baxter & Sommerville, 2011). Nor is the presence of a human in the decision process sufficient on its own for meaningful control. The decision maker must be able to intervene in the system recommendation and must assume responsibility for the decision made (Santoni de Sio & van den Hoven, 2018). When it can be clearly seen who holds authority, on what grounds a decision rests, and how the process was recorded, how a contested outcome came about can subsequently be traced and evaluated.

With respect to uncertainty, the model's most important implication is that decision support requires a regime of oversight that varies according to the level of confidence. Under new conditions in which past patterns have weakened, the decision authority allotted to the model output should be reduced, and scenario assessment and human review should be strengthened. This proposal does not treat bounded rationality as a human failing. Humans and automation carry different limitations. An appropriate division of tasks combines analytical capacity with contextual knowledge and responsibility (Parasuraman et al., 2000; Shneiderman, 2020).

This governance responsibility does not require making the project manager a technical expert. AI literacy encompasses, beyond the steps of operating the tool, the capacity to assess the model's limits, its data sources, and its ethical consequences (Long & Magerko, 2020). In project management and management information systems programmes, case analysis, objection to algorithmic recommendations, impact assessment, and the design of audit records can be studied together. Such training helps ensure that the authority to explain and to reject a recommendation is genuinely exercised in everyday decisions.

The limitations of the study stem from the nature of the proposal. The model is conceptual and has not been tested through application in different sectors. Regulatory requirements vary according to the purpose of use and the jurisdiction. Moreover, because the selected literature rests on a purposive theoretical synthesis, there is no claim to cover all relevant works. Future research could translate the model's mechanisms into measurement scales, conduct case studies in different types of projects, and examine the effect of the appeal, model-suspension, and policy-update cycles on decision quality.

7. Conclusion

Approval of an AI system's recommendation by the project manager does not, by itself, render the decision accountable. First, the institution must clarify for what purpose and within what limits the system is to be used. The manager must be able to compare the recommendation with the prevailing project conditions, to reject it where necessary, and to record the rationale for their choice. The existence of an appeal channel to which those affected by the decision can turn, and the technical team's keeping of the decision's grounds traceable, are likewise parts of the same process. The model proposed in this study addresses these responsibilities through the relationships among institutional authority, managerial judgement, and technical evidence. Accountability, in this respect, is not an abstract principle recalled after the decision but an institutional practice sustained during the preparation, implementation, and review of the decision.

This arrangement should not be expected to remain unchanged. An unexpected decline in model performance, a change in the data structure, or appeals repeated on similar grounds may require the re-examination of a use previously deemed appropriate. Carrying the findings obtained from the project team up to the institutional level makes it possible to modify both the mode of implementation and the risk limits in line with new conditions. Only within such a regime of review can AI function as a tool that supports the project manager's contextual judgement. That said, the proposed model is conceptual in nature. Empirical studies conducted in different sectors should determine which governance mechanisms contribute to trust, fairness, and project performance, and under what conditions this contribution arises.

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A Dynamic Approach of Artificial Intelligence to Inculcate Algorithmic Thinking in Language Learning

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Abstract

This research study aims at inculcating a dynamic approach of artificial intelligence for inculcation of algorithmic thinking in learning of language. It includes dynamicity of automated systems which are involved in rapidity of language learning. This trend has a dynamic approach; hence this trend keeps on improving changes and procedures of learning. The objectives of the research are to demonstrate automated systems, illustrate dynamicity of artificial intelligence and express algorithmic thinking for language learning through artificial intelligence. The research study is facilitated through a hypothesis. In the hypothetical statement it has a dependent and an independent variable. Algorithmic thinking is an independent variable and learning language is a dependent variable. The research methodology for this research study is a quantitative research approach. The questionnaire is a research instrument and consists of ten items based on thematic perception called discreet variables. The research is analyzed through SPSS (Statistical Package of Social Sciences). The research is further analyzed through ANOVA achieving numerical values of mean square and Sig. The values of mean and standard deviations of discreet variables are also calculated through Statistical Package of Social Sciences. Hence, it was found that nowadays, there is an AI revolutionization of language. Turboscribe is an application of language learning and is an online for reading and listening. Gliglish is an AI-powered assistant of language learning and design fluency. Jenni.AI, an automated system for writing skills. There are automated systems which are multimodal, spoken and written. These are speech recognition devices for pronunciation in a language. Gamification utilization is for language learning. There are intelligent systems for learning and thinking. Hence, there is a dynamicity of algorithmic thinking which promotes operations of thinking such as thoughts of computer and computations. CALL (Computer Assisted Language Learning) is used for investigating language partners by using computers. These systems include dialogue systems, chatbots, and intelligent personal assistants. Therefore, it implies that curriculum is an algorithmic implementation for design and development of teaching outcomes.

Keywords: dynamic, algorithm, automated systems, language, learning

1. Background of Study

Wing (2006) proposed that CT (Computational Thinking) is considered as a basic skill after writing, reading and arithmetic. BMBWF (2018) argued that Austria is included in countries who earns education compulsory in several countries. There is a transformation of the model of CT and CS. They have found their ways in a classroom teaching a foreign language. There is an implementation of diagrams from computer science as one of the strategies of teaching and learning for fostering thinking of computation in an education with a foreign language (Yin, 2009). The structures of data bases and systems of software are having diagrams which are dependent on Unified Modelling Language (UML) (Seidl, 2015). Chen (1976) proposed that there is a use of systems of software and structures of database having notations. The use of these diagrams in varied contexts is one of the strategies of learning and teaching in which the authors are having many goals. Rottenhofer (2021) and Meusel (2020) proposed that CS modelling of diagrams is easier for showing diagrams for a convenient visualization of learners of various ages. This strategy can be acquired quite easily and is consisted of teachers and students. Hence, its applicability is in many subjects. Papert (1980) argued that he was the first mentioner of thinking of the computation in his teaching work which was based on the literacy of computer in his early time. CT was a result of his theory of learning for constructionism. After twenty-six years, there was an attitude and a set of skill which was to boost the scientists of computer and there was an emergence of various definitions. It can be learnt and used. Voogt (2015) proposed that a focus on programming can lead to an assumption of programming as an essential teaching tool for teaching of CT. National Research Council (2009) argued that an acquisition of CT is for everyone. It is not for programmers and hence, should be exposed to CT before programming. There is a coincidence of pattern of style of brain and an approach which is creative. It permits students for connection of information with memories which are already stored, discovered and having an information cluster. Hence, the data is sorted and stored (Willis, 2007). Sousa (2017) said that the usefulness of CT models is fostering skills with problem resolution. Moreover, this technology is useful for students for facing difficulties in learning. Schneider (2012) proposed that the dyslexics can also frame good abilities in intellectualism. Therefore, the similarities notice distinctiveness in

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vocabulary and patterns of formation of word. Crombie (2012) proposed that in processing of semantics, there is a comparison of foreign language with native language.

1.1 Problem Statement

Bull and Mabbott (2007) proposed that teaching and learning are moved away from a defined precision having questions which are close ended. This is to have questions which are open ended. Students are affected by their involvement in the real-world problems and their resolution. Petzne (2022) proposed that because of what there is an enhancement of applicability and relevance in the learning. It is conceptualized to be a system which is adaptive to the conceptualizations (Larson Freeman, 2015). Such perspective has an alignment with a developed thinking of algorithm. Where flexibility is prioritized. There are skills of problem resolution and adaptability. Language is comprised of complexity in system apart from set of rules. Interactions and experiences are constructed by learners. Gu (2025) proposed that computational thinking is based on principles. They are recognition of pattern, decomposition, algorithmic thinking and abstraction. There is a framework which is cognitive and is structured. It can support a complexity in processes involving writing and learning of language. Computational thinking having research on education of language for learners who are individual is proposed by recent research. There is a huge collaborative outcome, which is based on studies of computational writing. Jeong (2023) proposed that there is not any incorporation of strategies of computational thinking. He further proposed that apart from computational thinking and computational writing, there still is a scarcity of resources for remaining writing at the school levels of secondary as well as, in collaborative writing of EFL. Li (2023) proposed that there is a promotion of both development in linguistic and socio-cognition for computational writing.

2. Research Hypothesis

Algorithmic thinking includes automated systems for language learning. These automated systems increase learning level of students. This algorithmic thinking is one of the basic outcomes of Artificial Intelligence in learning a language.

…if algorithmic thinking is inculcated from a dynamic approach of Artificial Intelligence, then, the frequency of language learning is increased in students preceded by fluency…

Algorithmic thinking is an independent variable comprised of automated systems for learning a language. It is independent of language learning which is a dependent variable.

Learning is a dependent variable which is dependent on algorithmic thinking and hence, may lead to an increase in learning processes through automated systems.

Hence, algorithmic thinking is an independent variable, and learning is a dependent variable for increasing learning in students of languages.

3. Research Objectives

This research study aims at:

- Demonstrating automated systems for language learning in education.
- Illustrating dynamicity of artificial intelligence for language learning in education.
- Expressing algorithmic thinking for language learning in education.

4. Research Methodology

4.1 Research design

The data is analyzed through a quantitative approach in which the research study is hypothesized. The research instrument used for the research is a questionnaire based on the themes of algorithmic thinking in language teaching. There are ten discreet variables which are technology, AI tools, advanced technologies, AI content, AI assistant tools, instructions, assessment tools, voice recognition systems, interactionism, and chatbots and has been emphasized by the research instrument as ten items. This questionnaire was, then, distributed through a purposive sampling to a population sample of 50 people for getting the opinion of algorithmic thinking in language learning. The respondents were given ample time of one week and the respondents responded to the questionnaire within a week, and the research presented the results of analysis. The data sampling and demographic is displayed in the following table:

Table 1

Demography and Sampling

Gender	Age:	17-25	26-35	36-40
Males		9	8	5
Females		8	11	9

The reliability of the questionnaire was tested by SPSS (Statistical Package of Social Sciences). The reliability calculated was 0.658. Hence, the value is:

Cronbach alpha value = +0.658

It proves that the research instrument was a reliable instrument.

5. Results, Discussion and Implications

6.1 Results

The results obtained from the research questionnaire are presented in the following table given below:

Table 2

Values by Analysis of Variance

Variables	Mean square	F	Sig.
1	.22	.9	.47
2	.38	.4	.71
3	3.1	3.9	.72
4	1.2	.9	.49
5	3.7	3.9	.7
6	3.2	1.1	.41
7	2.0	.26	.84
8	.92	.22	.87
9	3.9	.23	.88
10	.91	.62	.6

Table 2 consists of an analysis of discreet variables by inculcating mean square, F and sig. values of the questionnaire through SPSS (Statistical Package of Social Sciences). Table 2 indicates mean square values of discreet variable are .22, .38, 3.1, 1.2, 3.7, 3.2, 2.0, .92, 3.9 and .91. The F values of the discreet variables are .9, .4, 3.9, .9, 3.9, 1.1, .26, .22, .23, and .62. The sig. values are .47, .71, .72, .49, .7, .41, .84, .87, .88 and .63. The highest value of mean squares is 3.7 and the lowest value is .22. The highest value of F is 3.9 and the lowest value is .4. The highest value for sign. is .72 and the lowest value is .41. Hence, there are fluctuations in the values from highest to low. None of the values are equal, which indicates the frequency of likert scale values from 1-5. The results in the table represent the values of mean squares, F and Sig.

The values of mean and standard deviation are presented in the following table. These are the values of discreet variables.

Table 3

Mean and St. Deviation Values of Questionnaire

Variables	Mean	St. Dev
Technology	1.3	.48
AI- tools	3.0	.81
Advanced Technology	3.6	1.3
AI-content	3.8	1.1
AI-tools	4.1	1.7
Instruction	3.6	2.4
NLP-tools	2.9	1.2
VRS	2.4	1.7
Interactionism	2.5	1.3
Chatbots	1.8	1.2

Table 3 indicates values of mean and standard deviation of discreet variables. The mean values are 1.3, 3.0, 3.6, 3.8, 4.1, 3.6, 2.9, 2.4, 2.5 and 1.8. The values of standard deviation are .48, .81, 1.3, 1.1, 1.7, 2.4, 1.2, 1.7, 1.3 and 1.2. The themes are fluctuations in technology, AI tools, Advanced technology, AI content, AI tools, Instruction, NLP tools, Voice Recognition system, interactionism and chatbots.

6.2 Discussion

Selwyn (2023) proposed that education is being revolutionized by Artificial Intelligence. If the learning is accessible and flexible, then there can be removal of limitations, space and time. The practices of education are reshaping the digital transformation due to an enhancement of automating making of decisions. The environment is professional and having an access of data of high-quality. Agley (2022) argued that automation and AI are emergent tools of essentiality in education in future. The learner is at the position for making a core decision. Automation is facilitated by individual accommodation for learning individual styles and generating contexts of EFL (English as a Foreign Language). Smutny (2020) said that automated learning of language, hence, encompasses the varied tools for designing an enhancement, as well as, personalizing the experience of education. It involves tutors of AI and chatbots. There are offered the practices of conversation in real-time and a software of a recognition of speech. There are improved translation of automation, pronunciation, and tools for correction of grammar for supporting accuracy of language, the platforms of learning adaptiveness. Hence, the lessons are tailored which are based on the progress of individuality. Schriebrova (2020) said that the applications of gamification and systems of repetition which are spaced are utilized for an improvement in retention of vocabulary. The process of learning is automated and are streamlines. The levels are proficiency are different and are accessible, efficient and having an engagement of learners. Nof (2009) proposed that automation is a discipline which is penetrated in systems of intelligence and systems of theory of control. This is predated to the theory of control and the development is formal. As the techniques are advanced, there are foundations of theory which have models which are basic. It also involves systems of communication which are having systems ranged from environments of virtuality and sensors. There is inclusion of roles of human during automation and there are functions of controllers which are intelligent.

7 imilarly, Vygotsky's Zone of Proximal Development (ZPD) supports the use of

8 Gamification, inspired by Deci and Ryan's Self-Determination Theory (1985, p. 43)

6. Findings

6.1 **AI Revolutionization in Language Learning**

7. .Conversational Interaction AI bots interact with the user through messages or voice and act as actual people in everyday
8. life. This way, users establish communication with other people, work on their language abilities, may ask questions and
9. get answers[6].
10. B. Natural Language Processing (NLP) NLP is adopted by the AI bots to interpret and understand the input from
11. humans in natural language. This can comprise language processing and deciphering including sentiment analysis and
12. intent identification for the bots to discern user inputs and respond correspondingly[1][7].
13. C.Personalized Learning Intelligent assistant bots provide customized knowledge acquisition processes according to the
14. learners' specific needs. To do this they seek to implement language proficiency level, learning goals, and performance
15. metrics based on data from its users[8].
16. E.Instant Feedback During language practice sessions, the AI bots Notify users on the go the feedback they have received.
17. These delete wrong forms of words, propose synonyms and antonyms and provide simple explanations of the right way
18. to use and/or write words in an appropriate context[9].
19. F.Adaptive Learning Teaching tools used in interacting AI bots incorporate reinforcement algorithms in order to modify
20. the teaching methodology in relation to the user's actions and vice-versa. It changes the level of difficulty of the exercises,
21. offers enhanced help in areas, which are difficult for students, and monitors progress made at different times to enhance
22. learning[10].

7.1.1 Turboscribe

Romero (2024) argued that it is an application of language learning which is online for reading and listening. It is an AI powered application for converting into text video and audio files. The students and educators can generate a free account for transcribing the files for a day and files which are in thirty minutes. Rifa and Vu (2024) proposed that an accuracy is delivered by transcriptions. This application is having an ability of transcribing. These languages are translated widely in transcriptions and in subtitles for languages in hundred. There is an identification of varied speakers and there is an ensured of privacy of data and handling a secured file. Gardner (2024) proposed that this tool of an AI is utilized by scholars and it is also expressed in its use and easiness for their research papers.

7.1.2 Gligish

Ariawan (2024) proposed that AI-powered assistant of learning of language is to design and enhances fluency of user, as well as confidence for speaking different languages. The features which are intelligent are offered by the rates of speaking to be customized. There are systems of recognition of voice which is multilingual, and feedback of grammar. There is an array of language s which are France, German, English, Russian, Spanish and Portuguese. The tool of deliver which is an alternative to budget-friendly of an instruction of language is Gligish. It includes self-practice aiding to confidence gaining in scenarios which are diverse. Moreover, there is a regular refreshens of software having new function for an enhancement of a journey of learning for saviour of money and time. It has an adjustable speed where feedback is provided by pronunciation and grammar users, and a translation is offered by it.

8. Conclusion

The study is limited to algorithmic thinking and automated systems for acquisition and learning of language. This research study is effective in its limitations for artificial intelligence instruments for learning and acquisition of language. There is no inculcation in learning languages and their acquisition. The research study is significant for:

- Language teachers who want to guide students to dynamicity of automated systems for learning a language.
- Research in computational linguistics may lead to new advents of swift language learning.
- Technology driven language systems for an involvement of learning a language and its importance in the life of language learners.

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Preservice Teachers' Experiences with Computational Breakdown and Repair in Visual Programming

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Abstract

Block-based visual programming environments reduce several syntax-related demands by letting learners construct executable programs through graphical commands, yet successful block assembly does not ensure a program will produce its intended output. This study examined computational breakdowns and repairs that occurred as preservice teachers programmed geometric shapes and patterns in Scratch. A qualitative multiple-case design was used with preservice elementary teachers working on tasks involving triangles, squares, joint-square patterns, and debugging. Data included screen and video recordings, successive programming artifacts, visual outputs, and process documentation. Analysis focused on breakdown-repair episodes in which program execution, output, or sprite state diverged from the intended geometric result. Five recurring breakdown categories were identified: parameter coordination, sequencing and block placement, repetition and nesting, spatial state, and pattern integration and automation. Repairs included parameter adjustments, repeated executions, block relocations, sequence revisions, loop restructuring, and sprite repositioning. Local changes often sufficed for isolated parameter or state problems, whereas breakdowns during pattern extension more often required structural changes to the organization of repeated commands. The findings provide a descriptive account of computational difficulties that can remain hidden behind the syntactic accessibility of block-based programming and of the repair practices used to regain control over program execution.

Keywords: visual programming, block-based programming, computational breakdowns, debugging, preservice teachers

Introduction

Visual programming environments provide graphical commands that learners can select, connect, execute, and revise without producing the full syntax of a text-based programming language. This design can reduce some barriers to entry in programming, but it does not eliminate conceptual difficulties associated with control structures and program behavior. For example, misconceptions concerning loops occur in both block-based and text-based programming contexts (Mladenović et al., 2018). A sequence of blocks may be accepted by the programming environment while still containing unsuitable parameter values, an incorrect order of actions, or a loop configuration that does not produce the intended result.

Programming difficulties are visible during debugging. Debugging is more than correcting a detected error; it requires understanding the program, locating a possible source of failure, generating a possible correction, and evaluating the result (McCauley et al., 2008). Debugging develops through repeated interactions among code, execution, and output. Learners may revise block configurations, execute the program, inspect the resulting behavior, and use that feedback to evaluate or further modify the repair (DeLiema et al., 2024; C. Kim et al., 2018, 2023). Such practices direct attention to the sequence between an observed problem and the actions taken to repair it.

The visible output in block-based environments serves as a distinctive source of information during this process. Scratch, for example, allows a programmer to execute movement, turning, drawing, and repetition commands and immediately inspect the resulting trajectory. Research on visual programming for geometry shows that program feedback can make geometric relationships inspectable as learners construct and modify code (Crisci et al., 2024; Dinç & Kim, 2025). In Scratch-based polygon game development, some students also reported difficulties realizing their planned designs (Övez & Acar, 2022). The correspondence between code and output can expose errors.

In teacher education, teachers may encounter programming challenges while simultaneously considering how computational activity can be translated into teaching practice. This interaction has been documented between learning to program and pedagogical design. Preservice teachers engaged in robot programming and troubleshooting alongside lesson design (Dinç & Zhang, 2026), and teachers learning Scratch encountered technical difficulties that informed their decisions about scaffolding and reducing programming demands for learners (E. Kim & Dinç, 2025). Construction-oriented programming activities can support preservice teachers' development of computational thinking when they have opportunities to design, test, and revise programs (Butler

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& Leahy, 2021). Debugging deserves specific attention within these experiences. Kim et al. (2022) found differences in preservice teachers' debugging behaviors depending on the scaffolding available to them, showing that teacher candidates' programming activity involves identifiable strategies for locating and addressing errors rather than a simple distinction between correct and incorrect code.

Much of the literature on programming errors has examined learners' misconceptions and recurring difficulties in introductory programming (e.g., Qian & Lehman, 2017). In Scratch-based mathematical programming, some students have similarly reported difficulties translating their intended procedures into code and positioning code blocks (Çelik & Sevgi, 2025). A complementary question concerns the computational location of the breakdown itself. In geometric programming, a visible mismatch may originate from an unsuitable numeric value, the structural placement of an otherwise appropriate command, the boundary of a repeated sequence, the sprite's execution state, or the coordination of several routines during automation. Treating these conditions as a single category of *error* obscures differences in what should be repaired. In this study, a computational breakdown refers to an observable divergence between an intended geometric result and the program's execution, visual output, or sprite state. A repair is a modification to code or execution conditions intended to reduce or eliminate that divergence. The analysis was guided by two research questions: (a) What types of computational breakdowns occurred as preservice teachers programmed geometric shapes and patterns in a block-based environment? and (b) What repair practices did preservice teachers use to address these breakdowns as programs were tested, revised, and extended?

Methodology

Design and participants

A qualitative multiple-case design was used to examine breakdowns and repairs across collaborative programming activities. Participants were drawn from a cohort of sixteen preservice elementary teachers recruited at a public university in the northeastern United States. No prior programming experience was required for participation. The present analysis reported findings across cases rather than for individual pairs.

Programming activities and data sources

The programming activities formed part of a 110-minute in-person collaborative session. Participants first completed a nonprogramming geometric pattern activity and then received a 15-minute introduction to Scratch. During this introduction, they explored the block interface and programmed the Scratch sprite to draw a triangle. They subsequently spent approximately 40 minutes programming square patterns, reviewed their code, and completed a 25-minute debugging activity involving square patterns. The programming sequence increased the coordination required in the code. Participants moved from drawing an individual geometric shape to creating adjacent squares and larger joint-square patterns. The debugging activity involved faulty code for square patterns and required participants to modify the program so that the visual output corresponded to the intended configuration (see Dinç & Kim (2025) for task details). Data sources included screen and video recordings, successive Scratch code states, visual output on the Scratch stage, and written process documentation. The screen recordings preserved changes in block selection, parameter values, loop organization, sprite position, and program execution. Video recordings provided contextual information about decisions made during collaborative programming.

Data analysis

Analysis focused on breakdown-repair episodes. An episode began when execution, visual output, or sprite state diverged from the intended result and ended when the mismatch was resolved, replaced by another computational problem, or abandoned. Successive program states were compared to identify what changed immediately before and after each breakdown. Initial coding addressed movement and turning parameters, repeat values, block order, block placement, loop boundaries, nesting, sprite position and direction, stage constraints, and coordination across repeated geometric units. Repair actions were coded separately so that a single repair practice could be applied to different breakdowns. Codes were compared iteratively across episodes and refined against the screen recordings and successive code states.

Findings

The first research question concerned the types of computational breakdowns that occurred during geometric programming. Five categories were identified. The second research question concerned the actions used to repair

these breakdowns. Table 1 summarizes the relationship between the observable breakdowns and the main repair practices.

Table 1. Computational breakdowns and associated repair practices.

Computational breakdown	Observable manifestation	Main repair practices
Parameter coordination	Distorted or incomplete shapes; unsuitable turning or movement; gaps; excessive or insufficient repetition	Adjust movement, turn, coordinate, or repeat values; execute and compare output
Sequencing and block placement	Relevant commands execute at an unsuitable point or structural location	Reorder or relocate commands; restore omitted blocks
Repetition and nesting	Missing or excessive repetition; incorrect grouping of actions; separated or incomplete repeated shapes	Revise repeat values and boundaries; restructure nested loops
Spatial state	Incorrect starting position or direction; displaced output; insufficient stage space	Reposition sprite; revise coordinates or direction; reset execution state
Pattern integration and automation	Local routines fail when extended; gaps, overlap, displacement, or incomplete automated patterns	Separate local and pattern-level actions; revise transitions; restructure repeated routines

Computational breakdowns

Parameter coordination breakdowns occurred when numerical values in otherwise usable blocks did not operate in a manner compatible with the intended geometry. Movement distance, turning angle, coordinate values, and repetition counts functioned as related parameters rather than independent settings. During polygon construction, inappropriate combinations resulted in outputs that either failed to close or failed to resemble the target shape. In pattern tasks, movement values affected the spacing between adjacent shapes, while repetition values determined whether a routine stopped at the intended point. The breakdown could appear to stem from a single value, even when the visible result depended on several parameters working together.

Sequencing and block-placement breakdowns occurred when the relevant blocks were available, but their order or structural position changed their effect. Movement and turning commands were especially sensitive to their position relative to repeat blocks. A movement command within a shape-level loop operated during every repetition of that loop; the same movement positioned between an inner and outer loop could instead control the transition between completed shapes. In several episodes, changing numeric values did not resolve the problem until the command itself was moved to another position in the program. Omitting or relocating drawing-state commands could similarly alter whether the intended geometric path appeared.

Repetition and nesting breakdowns involved a mismatch between the intended unit of repetition and the code enclosed by a repeat structure. At a basic level, an unsuitable repeat value produced too few or too many repeated actions. At a structural level, nested loops created separate units of repetition that had to remain coordinated. The inner loop could control the construction of a single square, while the outer loop controlled how that square was repeated across the pattern. When commands for these functions were grouped within an unsuitable loop boundary, execution resulted in isolated shapes, incomplete sequences, excessive repetition, or patterns that could not be extended as intended.

Spatial-state breakdowns originated from the location or orientation from which the sprite executed the code. A block sequence could be internally consistent yet produce unsuitable output if the sprite began at a different coordinate or in a different direction. Earlier runs could leave the sprite in a state that changed the next execution. Stage dimensions created a related constraint: as a repeated pattern expanded, a configuration that fit on the stage for a small case could place later shapes partly outside the visible area. Repairs to these breakdowns involved controlling the initial state rather than changing the geometric routine itself.

Pattern integration and automation breakdowns became more apparent as programs were extended from individual shapes to repeated structures. Code that produced one square did not automatically include the transition required to begin another adjacent square. Similarly, a configuration that produced a small joint-square case could fail when several local routines were repeated. Gaps, overlaps, displacement, and incomplete patterns appeared when the shape-producing routine and the between-shape movement were no longer compatible. Debugging tasks involving two geometric patterns introduced further coordination because side length, repetition, positioning, and movement values in one pattern affected its alignment with the other.

In response to the first research question, the observed breakdowns were associated with five different parts of executable logic: parameter relationships, command sequence and placement, repetition structure, execution state, and integration of routines during automation. The categories overlapped in some episodes. For example,

relocating a movement command could expose a second breakdown in its movement value, requiring a structural repair followed by parameter adjustment.

Repair practices

The most immediate repair practice was *parameter adjustment followed by re-execution*. Participants modified movement distances, turn values, repeat counts, or coordinates, then inspected the resulting output. This approach worked when the breakdown stemmed from an inaccurate value, but sometimes several executions were needed to determine which parameter drove the visible discrepancy. Re-execution provided information by making the consequence of each modification observable.

A second repair practice involved *block relocation and sequence revision*. When adjustments to values did not correct the output, participants changed where a command operated within the program. Moving a block into, out of, or between repeat structures altered its scope. Such repairs addressed the relation among commands rather than the value assigned to an individual block.

A third practice was *loop restructuring*. Participants changed repeat boundaries, dismantled an existing nested structure, reconstructed loops around different groups of commands, or placed a local shape routine within a higher-level repetition. These repairs appeared when the output problem involved several repeated geometric units. The repaired code had to indicate which commands belonged to a single square and which governed movement across the entire pattern.

Participants also used *spatial reset and repositioning*. Participants revised coordinates and direction to establish a suitable starting state and cleared the stage before additional executions. These practices reduced ambiguity from previous runs and became more prominent as larger patterns approached the limits of the Scratch stage.

Timing controls appeared primarily as *execution-monitoring aids*. Participants sometimes slowed execution or requested pauses to inspect where the sprite moved and how successive commands affected the drawing. In the records examined here, temporal control was more closely associated with observing a breakdown than with a distinct timing failure.

The findings for the second research question can be summarized in terms of two levels of repair. *Local repairs* changed a parameter or execution state, including a movement value, turn value, repeat count, coordinate, or direction. *Structural repairs* changed relationships among commands through block relocation, resequencing, loop-boundary revision, or reorganization of nested structures. Both were used throughout the activities, but structural repair became more prominent when programs were extended beyond individual shapes.

Breakdowns during pattern scaling

Pattern scaling cut across the five breakdown categories. Errors that stayed local while constructing a single geometric figure had broader consequences when the same code repeated. A small spacing difference could recur across consecutive squares, a misplaced command could operate at every iteration of an outer loop, and an unsuitable coordinate could become problematic only when the pattern reached the edge of the stage.

Scaling also changed the organization the program required. One square could be represented through a short movement-turn sequence and a repeat structure. Several joint squares required a second computational function to transfer the sprite from a completed square to the starting state of the next square. Larger and overlapping patterns added further coordination among side length, repeat values, spatial position, and transition commands. Breakdowns at these higher levels were less likely to be resolved by changing a single parameter. They more often required participants to revise the organization and scope of repeated commands.

Discussion

Computational breakdowns in visual programming were heterogeneous. Some originated from incorrect numerical parameters, while others arose from the position of a correct command, the boundary of a loop, or the sprite's current state. Block-based programming can constrain the forms in which commands are assembled, yet it does not eliminate misconceptions about the operation and scope of repetition structures (Mladenović et al., 2018), and successful debugging can depend on learners attending to the changing state of program execution (Lewis, 2012). The present findings extend this observation to geometric programming by showing that executable blocks can remain incompatible with an intended visual result at several levels of the program.

The relation between breakdown type and repair type is another concern. Parameter changes addressed local mismatches, but structural problems often persisted until participants changed block placement or loop organization. Debugging in block-based environments has been characterized as an iterative process of testing

possible causes and evaluating resulting program behavior (C. Kim et al., 2018). Among preservice teachers, this process can involve successive parameter changes followed by execution and observation, with an initially plausible repair being revised or abandoned when the resulting behavior does not support it (C. Kim et al., 2021). The current analysis adds a descriptive distinction between local repair, which modifies an individual value or execution state, and structural repair, which modifies the relationships among executable commands.

Pattern scaling further clarified this distinction. A local routine could generate an acceptable geometric unit while remaining poorly coordinated with the routines needed to extend the pattern. When repetition propagated an inappropriate value or structural placement, the visible consequences accumulated across later shapes. Repair then required attention to how a local geometric routine interacted with a pattern-level routine. The role of visible program output in this process is consistent with work showing that Scratch-based geometric activities allow learners to inspect the consequences of computational decisions through the produced figure (Crisci et al., 2024).

For preservice teacher education, the findings support programming activities in which computational breakdowns are intentionally available for inspection. Research with practicing teachers has identified differences in programming self-efficacy and efficacy for teaching programming across subject areas (Mumcu et al., 2025), providing a broader rationale for attending to programming-related preparation. Debugging tasks can ask preservice teachers to differentiate whether a mismatch originates from a parameter, sequence, loop boundary, starting state, or interaction among repeated routines. Kim et al. (2022) showed that scaffolding influences preservice teachers' debugging behavior, while Butler and Leahy (2021) demonstrated the value of sustained construction-oriented computational experiences in preservice teacher education. A useful instructional extension would require learners to identify the level of a breakdown before changing the code and to state what part of the output should change if the proposed repair is appropriate.

These findings also suggest that debugging activities can be designed to distinguish between local and structural repair. Learners can first determine whether a mismatch can be addressed by changing a parameter or execution state, or whether it requires reconsidering block placement, loop boundaries, or the organization of repeated routines. Repeated opportunities to code and debug have been shown to support novice preservice teachers' development of block-based programming skills (Umutlu, 2022). Such experiences could be extended by prompting learners to align a proposed repair with the computational level at which the breakdown occurs.

The tasks were restricted to geometric drawing and pattern programming in Scratch, so other programming contexts may produce different breakdown configurations. The collaborative format also means that repairs reflected interaction between participants as well as interaction with the program. The categories provide a vocabulary for describing where breakdowns occurred and what kinds of actions followed; questions about the cognitive or theoretical mechanisms underlying shifts among repair practices require more detailed analysis.

Conclusions

This study examined computational breakdowns and repair practices during preservice teachers' block-based programming of geometric shapes and patterns. Five recurring breakdown categories were identified: parameter coordination, sequencing and block placement, repetition and nesting, spatial state, and pattern integration and automation. These categories show that an executable program can diverge from its intended output for reasons beyond an incorrect numeric value. Repairs were made at both the local and structural levels. Parameter revision and spatial reset addressed relatively bounded problems, while block relocation, sequence revision, and loop restructuring addressed relationships among commands. Pattern scaling amplified these relationships by requiring local shape routines to remain compatible with the movement and repetition needed for larger automated structures. Programming activities that make such breakdowns visible can give preservice teachers opportunities to examine executable logic through systematic testing and repair, rather than treating successful visual output as the only criterion for completion.

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Collaborative learning in virtual environments: teacher and student perceptions in a pre-university program

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Abstract:

This study focused on analyzing teachers' and students' perceptions of collaborative learning as a teaching and learning strategy in virtual environments and its impact on a pre-university education program. The research was conducted using a mixed-methods approach with a case study design. Data were collected through focus groups with teachers and students, with group sizes ranging from four to six participants. In addition, online questionnaires were administered to a sample of 31 teachers and 28 students. The analysis of the focus group data was performed using Atlas.ti version 8 software. Quantitative data from the questionnaires were automatically processed using Google Forms , while open-ended responses were analyzed qualitatively. In this context, collaborative learning emerges not only as a determining factor in academic performance but also as a fundamental element for mitigating the inherent lack of physical interaction in virtual environments, thus fostering a social and shared construction of learning.

Keywords: Collaborative learning, Online learning, Non-formal education, Educational technology

Introduction:

In recent years, virtual learning environments have grown steadily, transforming into an educational modality that allows interaction between students and teachers through digital platforms, overcoming the geographical barriers of face-to-face education. Within these virtual environments, collaborative learning is configured as a key pedagogical strategy and an ongoing challenge, to promote the joint construction of knowledge and the development of cognitive skills . Thus, meaningful interaction between the participants in the educational process becomes fundamental, as stated by Carrasco and Delfín (2023), who point out:

This type of learning is made up of collaboration (when necessary) facilitated by a participant to direct the communication, so that when all participants are involved and accept the role that concerns them, the possibility of achieving the objectives increases, and the exchange of ideas, analysis and discussion between participants becomes meaningful (p. 141)

This collaborative approach, mediated by digital technologies in virtual environments, constitutes a particularly relevant pedagogical guideline in educational programs operating outside the traditional classroom setting, where technological mediation is fundamental for achieving academic objectives. This approach promotes the shared construction of knowledge through systematic peer interaction, which helps reduce the isolation characteristic of virtual environments and strengthen academic cohesion (Hernández-Selles et al., 2024). Furthermore, the implementation of collaborative learning methods in virtual classrooms has demonstrated a positive impact on students' academic performance by fostering active participation , shared responsibility in the learning process, and the achievement of common goals (Erwin & Ariani, 2023).

In Chile, online education has gained prominence in both formal education and non-formal educational initiatives aimed at preparing students for higher education. Within this context lies the CPECH pre-university program , an institution with a national presence through 31 locations that offers training programs for those preparing to take the University Entrance Exam (PAES) 1. CPECH's experience in online environments provides a relevant case study for analyzing how collaborative learning practices, mediated by digital platforms, are perceived by teachers and students in a non-university educational setting that is nonetheless highly focused on demanding academic results.

In this context, the present research aimed to analyze the perceptions of teachers and students on collaborative learning strategies in virtual environments and their impact on student training in a pre-university program.

1 Currently called the Higher Education Access Test (PAES), it is a standardized test administered to Chilean students who wish to apply to higher education. It covers four areas of knowledge: reading comprehension, mathematical comprehension (M1) (M2), science elective, and history and social science elective.

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In this sense, we can state a priori that collaborative learning in virtual environments is a pedagogical strategy that promotes learning, increases participation, and contributes positively to academic performance and student retention in pre-university programs.

Methodology

This study is based on a mixed-methods research approach, a strategy that systematically integrates qualitative and quantitative methodologies to transcend the individual limitations of each paradigm. According to Medina et al., (2023), the central purpose of this combination is “to leverage the strengths of both methods to obtain a more complete and enriching understanding of the phenomena studied” (p. 16), achieving data triangulation that strengthens the validity of the findings through the convergence of evidence. In this way, statistical trends and numerical metrics acquire greater analytical depth when contrasted with the narrative and social context, offering a multidimensional view of the observed reality. From this perspective, the methodology is grounded in pragmatism, allowing researchers to use all available approaches to understand the problem, thus bridging the gap between quantitative and qualitative paradigms (Dawadi , 2021). Ultimately, this methodological architecture not only compensates for the weaknesses inherent in each method separately, but also guarantees a more comprehensive scientific interpretation that is closer to the complexity of the object of study.

As a research strategy, we used the case study approach, which allows for a thorough and in-depth examination of a specific unit—in this case, a pre-university educational institution—with the aim of understanding the intrinsic dynamics of collaborative learning. According to Stake (2007), this approach is justified when the object of analysis has a "very special interest in itself" (p. 11), which requires prioritizing the details of its interaction with the environment. Under this premise, the methodology favors obtaining detailed information (Asenahabi , 2019, cited in Calderón et al., 2023), prioritizing analytical depth over statistical breadth. By integrating multiple sources of evidence, both qualitative and quantitative, this strategy facilitates the resolution of questions about the how and why of phenomena, establishing itself as an essential tool in the social sciences for evaluating contemporary situations in real-world contexts (Harrison et al., 2017). Thus, the case study offers a holistic understanding that is fundamental to interpreting complex pedagogical processes where the limits of the phenomenon and its context are not fully defined.

With the aim of gaining a deep and informed understanding of collaborative learning in virtual environments, this research was conducted with a sample of primary and secondary informants. The primary informants were experienced teachers with at least three years of service at the institution who managed virtual classrooms during the 2023 academic year. This group, aged between 30 and 50, contributed the technical and pedagogical perspective based on their teaching practice. The research was further enriched by the experiences of the students enrolled in the 2023 cohort, who served as secondary informants. These students completed their entire coursework virtually, representing the institution's geographic reach across the country.

The research instruments used in this study were rigorously selected based on their alignment with the mixed-methods approach. Two main tools were employed: virtual focus groups and online questionnaires. In accordance with the methodological design of our research, we opted for focus groups, understood not only as a data collection technique but also as social constructs through dialogic narratives (Benavides et al., 2021, p. 165). Under this premise, focus group discussions are established as a strategic tool within qualitative and mixed-methods paradigms, widely applied to obtain in-depth collective perspectives on a phenomenon (Alam, 2025). Based on this theoretical framework, the study included the design of two guides for conducting the focus groups, one specifically for teachers and the other for students. This distinction allowed for a precise exploration of the experiences and visions of the key actors who led the virtual educational model at the CPECH pre-university, guaranteeing a situated understanding of their pedagogical experience.

Data collection through focus groups was carried out in four sessions: two groups of four teachers each, and two groups of students (one of five people and the other of six). For data processing, verbatim transcripts were used, taking care not to alter the idioms or colloquial language of the participants, a crucial factor in preserving the fidelity of the original discourse.

In addition , the data collection process relied on the use of questionnaires. In this regard, Medina et al. (2023) state that “mixed instruments combine both quantitative and qualitative measurement. For example, a questionnaire containing closed-ended questions with multiple choices (quantitative) along with open-ended questions (qualitative)” (p. 17). This duality in design allows the instrument to play a strategic role within the study, since, essentially, “a research questionnaire is an instrument used to collect data and opinions from a group of people in order to answer a specific research question” (Medina et al., 2023, p. 39).

The questionnaires were administered via Google Forms , yielding a total of 59 responses (31 from teachers and 28 from students). It should be noted that, of the 50 teachers who taught virtual classes in 2023, a 62% response

rate was achieved. Regarding the student body, the institution's privacy restrictions prevented access to the total number of enrolled students, thus limiting the calculation of statistical representativeness. Therefore, snowball sampling was chosen. The implementation of this technique proved crucial in obtaining a more representative student sample. In this context, snowball sampling is understood as a non-probabilistic procedure highly useful for reaching hard-to-access groups. In this scheme, the initial subjects become key informants who facilitate contact with other members of the population (Gierczyk et al., 2023). This data collection strategy allowed the collection process to flow naturally among the students of the Pre-University program.

Results

The results obtained reveal a series of trends and challenges in the implementation of collaborative learning in virtual environments. Generally speaking, most respondents emphasize the importance of activating prior knowledge, fostering reflective discussion, and linking content to everyday life situations. However, these pedagogical aspirations face constant tension with the institution's curricular structures and external pressure to prepare for the PAES standardized tests.

In this context, all the teachers consulted highlighted the importance of information and communication technologies (ICTs) not only as technical support but also as mediating tools to mitigate the sense of distance between teacher and student that characterizes virtual environments and to enable collaborative learning. The implementation of digital resources such as synchronous Zoom voting , debates via chat or verbally, and the joint analysis of responses and group conclusions is consolidated as a fundamental axis for fostering student participation, as well as the development of collaborative learning strategies. In this way, the communicative dimension of collaborative learning is enhanced by the strategic use of technological mediation tools. The use of platforms like Zoom has made it possible to break down participation barriers that often arise in the traditional classroom, especially for students with more introverted profiles. The possibility of interacting through chats, the implementation of anonymous voting during exercises, and the ability to speak without showing one's face create a safe and comfortable space for learning. These features not only increase the volume of participation, but also reduce the fear of public error, strengthening the sense of belonging and the student's security within the virtual classroom.

For their part, the analysis of the experience of students at the CPECH pre-university program reveals that collaborative learning transcends mere technical interaction, becoming the structuring axis of the virtual educational process. All those consulted agree that collaborative dynamics were fundamental in mitigating the limitations inherent to virtual learning, such as the lack of non-verbal communication, noting that pedagogical effectiveness depends, to a large extent, on the articulation of strategies that promote participation and the collective construction of knowledge.

In line with the above, the collective construction of learning is evident in the development of the classes, where students assume an active role. The ability to contribute prior knowledge to resolve doubts as a group is described by the students as a dynamic where ″ everyone ended up doing the class together . ″ In this context, constant practice, especially through solving problems in the PAES format and critically analyzing distractors, is consolidated as an essential complement to collaboration, promoting strategic preparation for academic demands. Other methodologies, such as debate, appear as valuable alternatives that, although mentioned less frequently, diversify the collaborative pedagogical experience.

A deeper examination of pedagogical strategies highlights self-directed learning and the promotion of student collaboration. This data reveals a view of the teacher as a guide and facilitator of the metacognitive process. Thus, teaching practice in the virtual environment is not only geared towards the transmission of knowledge, but also towards strengthening student autonomy, allowing them to reflect on their own thought processes and information searches, as well as the collaboration that can be generated among peers.

Finally, the findings demonstrate a significant correlation between academic performance and student retention, mediated by the quality of collaborative interaction. In this regard, the majority of faculty and students surveyed maintain that satisfaction with the teaching methodology, particularly that which fosters collaborative work, is a fundamental pillar for student retention and academic performance. This reaffirms that methodological innovation based on collaborative learning transcends the pedagogical objective, establishing itself as a key strategy for ensuring student continuity and success in virtual environments. In this sense, constant practice emerges as a fundamental pedagogical strategy. This perspective suggests that practice and peer review of work guides foster the development of cognitive skills and greater student autonomy.

Discussion

The results obtained corroborate the initial hypothesis, which stated that collaborative learning in virtual environments is a pedagogical strategy that promotes learning, increases participation, and contributes positively to academic performance and student retention in pre-university programs.

In line with previous studies, our findings highlight that ICTs are not merely technical supports, but fundamental mediating tools for mitigating the teacher-student divide and combating isolation in virtual environments. In this sense, the implementation of collaborative learning strategies, supported by synchronous and asynchronous tools, is vital for fostering interaction and academic success, coinciding with the findings of Mesa et al. (2023), who concluded that "collaborative learning strengthens communication processes in digital learning environments and promotes the formation of virtual communities and networks for academic and emotional support among members of the educational community" (p. 259). Thus, the implementation of collaborative strategies is consolidated as a determining factor in ensuring student persistence in their educational processes.

In turn, students' perceptions of collaborative learning strategies reveal that they are not only a methodology for developing a lesson, but also an essential element for socialization and knowledge construction. Under this approach, the classroom is transformed into an active learning space, where knowledge ceases to be a product transmitted unidirectionally by the teacher and becomes a dynamic and shared process. In this scenario, the teacher's role evolves or transforms, abandoning the position of sole source of knowledge to become a guide or facilitator of the process, thus placing the leading role on the students. It is they who, through debate, the exchange of perspectives, and teamwork, manage to give profound meaning to the content. By discussing, questioning, and proposing ideas together, students not only retain information, but also develop critical and social skills and competencies that arise from direct interaction. In this vein, collaborative learning not only promotes content acquisition but also fosters active student participation in the educational process, generating opportunities for constant peer interaction. In this way, the classroom becomes a space for socialization where, through cooperation, students develop social, communicative, and teamwork skills, fundamental for the meaningful construction of learning (Arrocha & Esteves, 2025).

Likewise, collaborative learning strategies, particularly guided and collaborative problem-solving, are emerging as an added value within virtual classrooms. In this context, there is a prioritization of the use of structured guides and practical exercises aimed at strengthening comprehension and mastery of the content. These practices not only complement collaborative work but also foster more strategic preparation for academic demands. Similarly, other methodologies, such as debate, are emerging as relevant alternatives that, although less frequent, contribute to enriching and diversifying the pedagogical experience in collaborative learning environments. As Hernández-Sellés et al. (2024) argue, constant interaction among students promotes deeper learning processes, since knowledge is constructed through exchange, discussion, and peer feedback. In this way, virtual environments cease to be passive spaces for content transmission and become dynamic scenarios where active participation and collaboration become central elements of the learning process.

Finally, a correlation between academic performance and student retention is evident, mediated by collaborative interaction strategies. In this scenario, teaching methodologies, especially those that prioritize collaborative work, are consolidated as strategic elements for reducing student dropout. Thus, collaborative learning emerges as a key pedagogical strategy in online education to enhance academic performance and mitigate student dropout, moving beyond traditional individualistic approaches. Through the integration of fundamental pillars such as positive interdependence, individual accountability, and group processing, this methodology not only fosters the development of cognitive, socio-emotional, and self-regulation skills, but also strengthens students' sense of belonging and social integration, improving their academic performance (Pillajo et al., 2025).

Conclusion

Collaborative learning in virtual environments transcends its role as a pedagogical support tool, becoming a key pillar of academic performance and student retention. In this sense, strategies such as collective participation transform the act of learning into a social commitment, where individual success is intertwined with the progress of the group, thus mitigating the inherent isolation of the virtual modality.

Furthermore, it is evident that technological mediation and collaborative learning strategies enrich the collective construction of knowledge, allowing the class to become an instance of critical and practical problem-solving oriented towards the demands of current education.

Therefore, prioritizing collaborative learning fosters a culture of self-directed learning and peer collaboration that directly impacts academic outcomes. Ultimately, the consolidation of a virtual learning community, based on

communicative trust and consistent collaborative practice, emerges as the most robust strategy for ensuring student retention and success in online education programs.

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Generative AI in Deaf Higher Education: Students' Attitudes and Ethical Challenges

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Abstract

Generative artificial intelligence (GenAI) offers new opportunities for learning in higher education, but its value for Deaf students depends on accessibility, usability, digital competence, and responsible use. This study examined Deaf students' attitudes toward GenAI, accessibility and usability perceptions, ethical concerns, and differences by GenAI experience and computer skills. A quantitative survey of 135 Deaf students at King Abdulaziz University, Saudi Arabia, was conducted from March to July 2026 using an Arabic questionnaire with embedded Saudi Sign Language video translations. Students reported positive attitudes ($M = 3.90$, $SD = 0.545$) and high accessibility/usability ($M = 3.88$, $SD = 0.625$). Attitudes differed significantly by GenAI experience, $\chi^2(4) = 27.87$, $p < .001$, and computer skills, $\chi^2(4) = 11.74$, $p = .019$. Ethical and privacy concerns were moderate ($M = 3.12$, $SD = 0.520$). The findings highlight the need for accessible AI literacy, inclusive design, institutional guidance, and Deaf student involvement in AI development and evaluation.

Keywords: generative artificial intelligence; Deaf students; higher education; accessibility; usability; ethical AI; Universal Design for Learning; Technology Acceptance Model

Introduction

GenAI is increasingly used in higher education to support brainstorming, summarizing, clarification, feedback, academic writing, and personalized learning (Chiu, 2024). Recent research has also explored its potential to enhance learner support in open and distance learning, particularly through continuous, natural, and personalized responses to learners' inquiries (Gevher et al., 2025). In higher education, students' experiences with ChatGPT have also highlighted its potential to encourage engagement, support confidence, and provide immediate feedback, while raising concerns about overreliance and learner autonomy (Öksüz Gül, 2025). Despite these opportunities, the use of GenAI raises concerns about academic integrity, inaccurate information, overreliance, privacy, and the changing role of instructors (Dwivedi et al., 2023; Bretag et al., 2024). Effective adoption therefore requires not only access to these technologies but also the ability to critically evaluate AI-generated content. For Deaf students, access alone does not guarantee an inclusive GenAI experience. Captioning, transcription, translation, visual communication, and multimodal interfaces may improve access, but challenges remain in usability, reliability, linguistic diversity, and cultural responsiveness (Levesque et al., 2023). Although research on GenAI in higher education is expanding, Deaf students remain underrepresented in empirical studies.

Universal Design for Learning (UDL) emphasizes designing learning environments around learner variability and supporting multiple ways of accessing and engaging with information (Saborío-Taylor & Rojas, 2024). For Deaf learners, this includes accessible written and visual content, captions, transcription, translation, and multimodal resources. Building on this perspective, the present study combines UDL with the Technology Acceptance Model (TAM), which highlights perceived usefulness and ease of use (Venkatesh & Davis, 2000), and Responsible AI principles concerning transparency, privacy, fairness, accountability, and academic integrity (Dwivedi et al., 2023).

Against this background, the study examines Deaf students' attitudes toward GenAI and its educational value, accessibility and usability, and perceptions of ethical use, privacy, and fairness in Saudi higher education. It also investigates whether attitudes differ according to prior GenAI experience and computer skills. By integrating technology acceptance, accessibility, and responsible AI, the study aims to provide a more inclusive understanding of GenAI adoption among Deaf university students.

Methodology

A quantitative cross-sectional survey was conducted with 135 Deaf students at King Abdulaziz University, purposively selected from an estimated population of 200. The sample included 58 males (43.0%) and 77 females (57.0%); 91.1% were bachelor's students. GenAI use ranged from always (14.8%) to never (16.3%), while computer skills were mainly good (45.2%) or very good (25.2%).

Data were collected using an Arabic questionnaire with embedded Saudi Sign Language video translations, comprising eight attitude, eight accessibility/usability, and six ethical/privacy items on a five-point Likert scale. A

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pilot with 30 Deaf students and review by six specialists supported the instrument's clarity and validity (93.7% agreement; item–dimension correlations = .313–.831). Cronbach's alpha was .836, .880, and .711 for the three dimensions, respectively.

Ethical approval was obtained (REC-FAH-KAU-2026-021). Data were collected via Google Forms from March–July 2026 with voluntary electronic consent and no identifying information. SPSS was used for descriptive statistics and, due to non-normality, Kruskal–Wallis and Mann–Whitney U tests for group comparisons.

Results

Students reported highly positive attitudes toward GenAI (M = 3.90, SD = 0.545), particularly its contribution to academic success (M = 4.09), study organization (M = 4.06), and understanding course content (M = 4.05). Accessibility and usability were also rated highly (M = 3.88, SD = 0.625), although ease of use received the lowest rating (M = 3.69). Ethical and privacy concerns were moderate (M = 3.12, SD = 0.520), while students strongly endorsed safe and ethical AI use (M = 4.05). Attitudes differed significantly according to GenAI experience, $\chi^2(4) = 27.87$, $p < .001$, and computer skills, $\chi^2(4) = 11.74$, $p = .019$. These findings indicate that students generally perceive GenAI as a useful learning support, but familiarity, digital competence, and ease of use may influence adoption. Because the study was cross-sectional, these relationships should be interpreted as associations rather than causal effects.

Table 1. Summary of Key Findings on Deaf Students' Attitudes Toward Generative AI.

Dimension / Finding	Result
Attitudes toward GenAI	M = 3.90, SD = 0.545
Accessibility and usability	M = 3.88, SD = 0.625
Ethical and privacy concerns	M = 3.12, SD = 0.520
GenAI experience	$\chi^2(4) = 27.87$, $p < .001$
Computer skills	$\chi^2(4) = 11.74$, $p = .019$
Academic success	M = 4.09
Access to AI tools	M = 4.03
Safe and ethical AI use	M = 4.05
Ease of use	M = 3.69

The findings are consistent with TAM, as experience and computer skills were associated with more positive attitudes, and with UDL, as accessibility requires more than simply providing technological access. The lower ease-of-use rating and strong need for training suggest that accessible AI should also be understandable and practical for Deaf learners. Universities should therefore provide accessible AI literacy through Saudi Sign Language, captions, visual demonstrations, and clear written materials, alongside guidance on prompting, verifying AI-generated information, privacy, academic integrity, and responsible use. Deaf students should be involved in the design and evaluation of AI technologies to ensure culturally and linguistically responsive solutions. Human support from instructors and accessibility professionals should remain central, with GenAI complementing rather than replacing teaching and communication support. These implications also reflect Responsible AI principles concerning privacy, fairness, transparency, and accountability.

Conclusions

GenAI shows clear potential to support Deaf students in higher education, but effective integration requires more than technological access. Although students reported positive attitudes and high perceptions of accessibility and usability, lower ease-of-use ratings and strong demand for training suggest that access alone does not ensure inclusive use. Students also showed awareness of ethical and safe AI use, while privacy and fairness concerns were comparatively lower. Universities should therefore adopt a human-centered, accessibility-by-design approach that includes accessible AI literacy, clear responsible-use guidance, and meaningful Deaf student involvement in AI design and evaluation. Successful adoption should be measured not only by AI use, but by whether Deaf students can access, understand, evaluate, and use these technologies equitably.

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Curtailing the Cognitive Miser Phenomenon: To Use or Not to Use Generative-AI for Writing Assignments

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Abstract

The notion of cognitive miser refers to human beings' basic tendency to prefer cognitive operations with low computational demands (shortcuts). The popularity of AI generative tools has led educators to be concerned about the potential impact on students' cognitive functioning. Namely, students' excessive reliance on AI, such as for writing homework assignments, may reinforce this human tendency to the point at which the writing product is good, but the student cannot thoroughly explain its content. The present field study examined the consequences of writing assignments in class or at home on test performance for questions involving level 4 of the Bloom taxonomy (analysis). Sections of freshman-year general education courses (Introduction to Psychology and World Civilizations, 1500 – Present) offered during separate semesters were randomly assigned to one of two conditions: control and treatment. In the control condition, students wrote the assignments at home under specific instructions not to use generative AI. In the treatment condition, they wrote the assignments in class with the aid of the materials that would have been available at home (i.e., the textbook and selected readings). All students were instructed to prepare for assignments by relying on their textbook and/or selected readings while avoiding generative AI tools. Two assignments were written before the midterm test, and two were written after it. All assignments involved level 2 (understanding) and level 3 (application) of the Bloom taxonomy. Tests engaged level 4 (analysis). In this study, students who wrote assignments in class exhibited higher test grades on analysis questions than students who wrote the assignments at home. Attendance rates, which measured behavioral engagement, did not differ. Scores for in-class participation activities, which indexed cognitive engagement, also did not differ. Yet, in the treatment condition, students' expectations for their final test performance tended to be less inflated. It was concluded that preventing the use of AI in writing by monitoring students' assignment completion may foster deeper levels of learning, ultimately benefiting test performance based on higher-order critical thinking skills and metacognition.

Keywords: critical thinking, Bloom taxonomy, deep learning, Global South

Introduction

Among educators, no day goes by without coming across concerns about the overuse of AI tools and the dangers that they may represent for human cognition. Improper reliance on AI tools may take many forms. For instance, it may entail searching for the answers to an online test, as reported by Ludwig and Achtziger (2021). In their experiment, Ludwig and Achtziger created two versions of the Cognitive Reflection Test (CRT), a popular test of intuitive versus analytical thinking styles: one with standard items, for which answers could be found online, and one with paraphrased items, for which no answers existed online. They found that students' performance was higher for the standard version of the test, but simply because students searched for the correct answers online. Improper reliance on AI tools may escalate to asking generative AI to produce homework assignments to be written for a course. Besides being a grave example of cheating, this behavior may have long-term consequences if it becomes a habit. Generative AI refers to "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio" (Feuerriegel et al., 2024, p. 111). Since AI detection tools are less than effective, being plagued by false alarms and misses (Alexander et al., 2023; Chaka, 2023; Elkhatat et al., 2023), educators' concern is that overuse indulges the cognitive miser that is in all of us. In students, it sets a habit that deprives them of the opportunity to develop and practice the critical thinking competencies that define academic attainment as well as professional endeavors (Lindebaum & Fleming, 2024). It may also lead students to be overly dependent on generative AI, thereby detracting from their sense of agency, a key aspect of engagement in human endeavors (Shogren et al., 2015), and ultimately impairing metacognition (i.e., self-awareness of one's cognitive processing) and performance (Revesai, 2025; Shabir, 2025). Lastly, students may experience a misleading sense of confidence in the quality of the information produced by generative AI tools since the likelihood that such tools produce 'hallucination effects' is not negligible. The term refers to erroneous outputs that are so convincing as human products that their true origin and value are difficult to detect at first glance (O'Dea & O'Dea, 2023).

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Human beings have been described as cognitive misers because they tend to rely more on fast, intuitive processes (shortcuts) when analyzing information and making decisions, and less on deliberate processes that are slower and effortful. Although fast and effortless intuitive processing can be useful, it can also negatively impact human reasoning. Consider the following problem presented to university-level students: "A pencil and an eraser together cost $1.10. The pencil costs $1 more than the eraser. How much does the eraser cost?" (De Neys et al., 2013). Compared with the control version of the problem ("A pencil and an eraser together cost $1.10. The pencil costs $1. How much does the eraser cost?"), most students misread "the pencil costs $1 more than the eraser" as if it said "the pencil costs $1", thereby answering "10 cents". By substituting the relational statement with an absolute statement, they failed to produce the correct response (i.e., the eraser costs 5 cents, whereas the pencil costs $ 1.05). This error is an instance of the attribute substitution bias and a glaring indicator of the cognitive miser phenomenon at work.

Deliberative processes, which include the modes of processing outlined by the Bloom taxonomy in the cognitive domain (Krathwohl, 2002), require practice to develop and be maintained (Gelder, 2005). The Bloom taxonomy includes cognitive processes organized in a hierarchy of increasing complexity: knowledge (i.e., remembering; level 1), comprehension (level 2), application (level 3), analysis (level 4), synthesis (level 5), and evaluation (level 6). In this hierarchy, higher-order critical thinking skills (Mulnix, 2012) are usually those that include levels 3-6. There is little controversy about the support that AI tools may provide to lower-order skills during studying, such as remembering and understanding (Essien et al., 2024). If a student does not remember or understand a concept, AI can describe it to aid memory retrieval and offer examples to aid comprehension. There is, however, concern about higher-order skills, which define the deliberative processes inherent to critical thinking as "reflective thinking aimed at deciding what to believe or do" (Ennis, 1993, p. 180), including the "conceptualization, application, analysis, synthesis, and evaluation of information gathered from observation, experience, reflection, reasoning, or communication" (Essien et al., 2024, p. 867).

While the broader role of AI in education has been extensively discussed (Lim et al., 2023), there is a dearth of empirical research investigating the impact of generative AI on higher-order critical thinking skills, especially from student populations of the Global South. The present research consists of a field study in which students enrolled in different sections of the same general education courses completed assignments at home (control condition) or in class (treatment condition). Sections were assigned to home or in-class assignments during separate semesters to minimize carryover effects. The potential impact of the assignment mode on higher-order critical thinking was measured on students' test performance. Evidence of students' deeper learning was gathered from answers to test questions at level 4 of the Bloom taxonomy. In the research, participation in class activities (i.e., written answers to questions related to materials discussed in class) served as an index of cognitive engagement, whereas attendance was treated as an index of behavioral engagement.

Notwithstanding the prohibition on using generative AI for assignments, it was assumed that usage would be greater among students in the control condition than among students in the treatment condition. Namely, treatment-condition students could only use generative AI to prepare for assignments, whereas control-condition students could use it for both preparation and completion of assignments. Thus, it was hypothesized that if the in-class assignment mode fostered deeper learning, students in the treatment condition would exhibit higher grades in midterm and final tests for questions that involved level 4 of the Bloom taxonomy (H-a). Furthermore, if the in-class assignment mode fostered not only deeper learning but also greater engagement, students in the treatment condition would exhibit higher scores for participation (cognitive engagement) and greater attendance (behavioral engagement; H-b). Thus, in the present study, engagement (Reeve et al., 2025) was broken down into cognitive engagement (i.e., the mental investment in a course as evidenced by the quality of in-class participation performance) and behavioral engagement (i.e., the action of attending class regularly).

Of course, a key ingredient of deep learning is the awareness of one's performance. Such awareness is an aspect of metacognition, which is a building block of students' self-regulation during learning. Thus, it was predicted that if in-class assignments fostered deeper learning, students would be able to accurately predict their performance on the final test (H-c). Yet, evidence exists that students' estimates of their test performance vary with their actual performance (Dunning–Kruger effect; Dunning et al., 2004). That is, poor performers tend to overestimate how well they performed. Instead, higher performers are either accurate or err in the opposite direction (i.e., generate underestimates). Thus, in the present study, instances of poor performance would not only index poor deep learning but also inflated estimates of performance. Curiously, there are two explanations for the Dunning–Kruger effect: either poor performers lack awareness of their deficiencies, or they are aware, but they engage in wishful thinking to deal with expected undesirable outcomes (Miller & Geraci, 2011; Pilotti et al., 2023; Pilotti et al., 2024). Thus, in the present study, instances of inflated estimates of actual poor performance should be expressed with high confidence if unawareness is the source of inflation (Dunning et al., 2004; H-d1). Alternatively, if the source of inflated estimates is wishful thinking, doubts about their accuracy should emerge (Pilotti et al., 2024; H-d2). These hypotheses are tested through the methodology presented below.

Methodology

Participants

The participants were 884 female undergraduate students enrolled in one of two freshman-year courses of the general education curriculum, Introduction to Psychology and History (World Civilizations: 1500–Present), at an English-medium institution of higher education located in Saudi Arabia. They were bilingual speakers with Arabic as their first language and English as their second language. Their English language competency, which was deemed equal to that of a competent English user, was assessed through standardized testing as a precondition for enrollment in an undergraduate program. Their ages ranged from 18 to 28 years. The courses were selected for the present study because they enrolled students from different majors (Computer Science, Engineering, Architecture, Design, Business, and Law).

Procedure and Materials

The study was conducted over two years. Each semester, sections of Introductory Psychology and History were assigned to either the control or the experimental condition. In the control condition ($n = 418$), students were given homework assignments to be carried out at home. In the treatment condition ($n = 466$), students were asked to complete the same assignments in class. All were asked to rely on their textbook or selected readings to carry out assignments. Thus, students in the treatment condition were allowed to use their textbook or key readings while completing assignments in class. However, cell phones, laptops, and smartwatches were not permitted. Proctors monitored students' behavior to ensure compliance. All students were repeatedly told not to rely on generative AI tools to prepare for or complete assignments. In the control condition, students were informed that their work would be submitted to an AI detector tool (Turnitin). If instances of plagiarism were detected, the assignment would need to be entirely rewritten. To ensure equity in the assessment of written products between the treatment and control conditions, the evaluation of all students' work was based on content. Content-based rubrics guided the scoring of assignments.

Each course entailed two assignments written before the midterm test, and two assignments written before the final test. During class meetings, students carried out activities (i.e., writing answers to specific open-ended queries at levels 2 and 3 of the Bloom taxonomy), which were used to measure their degree of participation (i.e., cognitive engagement). Behavioral engagement was measured through attendance records (i.e., number of class meetings attended / number of class meetings offered x 100). All assignments entailed queries at level 3. Assignments and class activities were primarily intended to promote understanding, memory consolidation, and applications of class materials. Midterm and Final exams contained open-ended questions at level 4 of the Bloom taxonomy. That is, assignments and in-class activities offered students opportunities for reiteration and practical applications of the information upon which tests were built. Thus, tests were not mere reiteration of learned materials and tasks. Exams were timed: 90 minutes for the midterm test, and 120 minutes for the final test. For each of the in-class and at-home assignments, students were advised to spend approximately 60-90 minutes on writing. Preparation time for assignments was left to the individual students to determine.

Immediately after students completed the final exam, they were asked to realistically estimate their grade on a scale from 0 to 100 to measure their awareness of performance. Next to their estimations, students were to report on a 5-point Likert scale from "very unsure" (coded as -2) to "very sure" (coded as +2) how confident they were in their estimates. On this scale, the middle value ("I do not know") was coded as 0.

The University where the study was conducted followed a U.S. curriculum, language, and mode of instruction (student-centered teaching). The data-collection process was approved by the Deanship of Research to comply with the guidelines of the Office for Human Research Protections of the U.S. Department of Health and Human Services (PMU-DoR-2023-2025-1).

Results

Descriptive statistics (median, *Med.*, and interquartile range, *IQR*) are displayed in Table 1. All scores were translated into percentages. For each participant, the median of the scores of assignments completed before the midterm (MT; 1-2) was computed to quantify the potential initial influence of AI-free composition on the midterm test. Similarly, for each participant, the median of the scores of assignments completed after the midterm test and before the final test (FT; 3-4) was computed to quantify the potential influence of AI-free composition on the final test. The Independent-Samples Mann-Whitney *U* Test, a non-parametric statistic, was used to assess whether there were differences between treatment and control conditions. All results were considered significant at $p < 0.05$. Preliminary analyses indicated that there were no unique patterns for course type. Thus, the data from Introduction

to Psychology and History were merged. In Table 1, significant differences between control and treatment conditions are marked in bold characters.

Table 1. Median (*Med.*) and Interquartile Range (*IQR*) of students' scores.

	Control Cond.		Treatment Cond.	
	Med.	***IQR***	***Med.***	***IQR***
Before-MT Assign.	82.50	16.50	82.50	12.63
Midterm Test	73.00	30.00	74.00	22.00
Before-FT Assign.	**81.50**	13.13	**87.50**	13.50
Final Test	**59.50**	25.50	**79.00**	26.50
Participation	90.00	20.00	90.00	16.00
Attendance	88.00	13.00	88.00	16.00

H-a predicted that if the in-class assignment mode fostered deeper learning, students in the treatment condition would exhibit higher grades in the midterm and final tests for questions that involved level 4 of the Bloom taxonomy. There were no differences between conditions in the grades for assignments completed before the midterm test [$U = 104609.00$, *ns*] and for the midterm test [$U = 100800.50$, *ns*]. Grades differed between conditions for the assignments carried out after the midterm [$U = 71133.00$, $p < 0.001$, with a mean rank equal to 498.85 for the treatment condition and 379.67 for the control condition], and for the final tests [$U = 50915.00$, $p < 0.001$, with a mean rank equal to 542.24 for the treatment condition and 331.31 for the control condition]. That is, grades were higher for the students assigned to the treatment condition, suggesting that, at the end of the semester, writing assignments in class had a positive influence.

H-a was partially supported. It is reasonable to assume that preparation for assignments in the treatment condition required students to understand (level 2) and retain (level 1) concepts for later use. Understanding and retention were then the basis for successful in-class applications (level 3). Combined, these cognitive activities led to extra effort put into processing class materials, ultimately leading to greater final test performance. Yet, the impact of assignments on test performance was delayed. There might be two reasons for the delayed impact of preparing for in-class assignments. On one side, treatment-condition students might have needed time to adapt to the novelty of the preparatory activities for assignments written in class. On the other side, the generative-AI prohibition prompts might have made some control-condition students less likely to use generative AI.

H-b predicted that if the in-class assignment mode fostered not only deeper learning but also greater engagement, students in the treatment condition would exhibit higher scores for participation and greater attendance. There was no difference between conditions in the grades for participation activities, which indexed cognitive engagement [$U = 100785.00$, *ns*], and for attendance, which indexed behavioral engagement [$U = 96921.50$, *ns*]. H-b was not supported. A reasonable explanation for these null findings is that students' concerns about grades (Pilotti et al., 2022), a common preoccupation in this student population, might have overridden potential engagement differences between conditions.

H-c predicted that if indeed in-class assignments fostered deeper learning, students would be able to accurately predict their performance on the final test. Performance estimates minus final test grades for open-ended questions at level 4 of the Bloom taxonomy created three degrees of accuracy: overestimation (+1), correct estimation (0), or underestimation (-1). Whether the control and the treatment condition differed was determined through a Chi-Squared Test for independence with degree of accuracy and condition as variables (see Table 2). In the control condition, overestimations abounded, whereas in the treatment condition, there was a mixture of underestimations and overestimations [$\chi^2(2) = 81.98$, $p < 0.001$].

Table 2. Degrees of accuracy by condition

Accuracy	Under Est. %	Correct Est. %	Over Est. %
Control Cond. ($n = 418$)	14%	3%	83%
Treatment Cond. ($n = 488$)	41%	4%	55%

Instances of poor performance were expected not only to index inadequate deep learning but also to be accompanied by inflated estimates of performance. Two conflicting predictions were made. If the source of inflated estimates was unawareness of one's performance, such estimates would be expressed with a sense of certainty (Dunning et al., 2004; H-d1). Alternatively, if their source was wishful thinking, inflated estimates would be expressed with a sense of uncertainty (Pilotti et al., 2024; H-d2). As a precondition for testing these conflicting hypotheses, final test performance was categorized into unsatisfactory (≤ 70%; i.e., C) and satisfactory (> 70%).

In the control condition, 72% of the grades were unsatisfactory, most of which (96%) were overestimations [$\chi^2(2) = 121.41$, $p < 0.001$]. In the treatment condition, 33% of the grades were unsatisfactory, most of which (92%) were overestimations [$\chi^2(2) = 123.49$, $p < 0.001$]. Thus, poor final test performance, although more prevalent in the control condition, was accompanied by inflated expectations in both conditions.

To test H-d1 and H-d2, we considered the confidence with which estimates of unsatisfactory performance were made. Three categories of confidence were created: certain (including +2 and +1), unknown (0), and uncertain (including -2 and -1). In the control condition, students with unsatisfactory performance rated 65% of their overestimations as uncertain or unknown. In the treatment condition, students with unsatisfactory performance rated 100% of their overestimations as either uncertain or unknown. The challenges of writing assignments in class might have created a broad sense of indecision in metacognition. H-d2 was supported. Yet, the findings of the treatment condition suggested that a remedy for wishful thinking might be a protocol that prevents students from using generative AI.

Conclusions

The findings of the present study suggest that there are benefits in AI-free performance, which may take some time before they become visible in students' performance and metacognition. These benefits are likely to reflect the extra effort that students need to invest in their preparatory activities. They may also reflect students' practice of specific cognitive processes (e.g., understanding of concepts and their application to different contexts), which may serve as building blocks for the effective use of higher-order critical-thinking skills, such as analysis. Another relevant benefit of AI-free performance on tests is the enhanced accuracy of test takers' grade expectations, potentially reducing grade haggling at the end of the semester. Of course, it is important to remember that the participants of our study were second-language learners from the Global South, thereby questioning the extent to which the current results generalize to student populations for whom English is the first language. Their responses to the AI-free mode may also differ from those of other students, depending on socio-cultural factors that have remained unexamined in our study.

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Understanding Generative-AI Use In Higher Education: Evidence From Nigeria

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Abstract

The rapid evolution of Generative Artificial Intelligence (Gen AI) has significant transformative impact on higher education systems universally. This study investigated lecturers' and students' awareness, accessibility, intention, and use behaviour of Generative AI tools in universities in Borno State, Nigeria. Grounded on two theories, the Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB), the research adopted a descriptive survey design and analysed data using Partial Least Squares Structural Equation Modelling (PLS-SEM). Findings revealed moderate awareness but limited accessibility and low actual utilisation of Gen AI for academic practices. Perceived usefulness and perceived ease of use significantly predicted lecturers' intention to use Gen AI, while behavioural intention strongly influenced actual use behaviour. Accessibility also had a direct impact on utilisation. The major constraints identified include infrastructural deficits, limited training for the lecturers, high subscription costs, ethical concerns, and absence of institutional policies governing AI use in the universities. Consequently, the study concludes that structured institutional frameworks, AI literacy programmes, and infrastructural investment are critical to fostering responsible and effective Gen AI adoption in Nigerian universities.

Keywords: Generative AI, Technology Acceptance Model, Awareness, Perceived Usefulness, Perceived Ease of Use, Behavioural Intention, Higher Education, Nigeria

Introduction

Generative Artificial Intelligence (Gen AI) tools including ChatGPT, Gemini, Copilot, and DeepSeek have redefined possibilities for content generation, research workflows, and student engagement in higher education globally (Wu, Wang & Wang, 2024; Monib et al., 2025). In Nigerian universities, particularly in Borno State, institutions face competing pressures to embrace digital transformation while navigating persistent infrastructural and pedagogical constraints. Yet, many lecturers appear either unaware of Gen AI tools or face access barriers that hinder meaningful integration into teaching and research.

Evidence on Gen AI awareness among academics is mixed. Studies by Fasola (2024) and Joseph et al. (2024) found high AI awareness among Nigerian educators, whereas Uygun et al. (2024), Madu and Musa (2024), and Almisad and Aleidan (2025) reported only moderate awareness. Regarding perceived usefulness, Van Wyk (2024), Ofoegbu et al. (2025), and Akanzire et al. (2025) reported high perceived utility among academics. Similarly, Nathaniel et al. (2021) and Alshamsy et al. (2025) found high PEOU ratings, though operational reliability remains a concern. On behavioural intention, Gapol et al. (2025) and Alshamsy et al. (2025) documented strong intentions to adopt Gen AI, with Shahzad et al. (2024) demonstrating that awareness significantly mediates adoption intention. Regarding predictors of intention, Wu et al. (2024) and Alshurideh et al. (2024) confirmed that PU and PEOU positively influence intention, while Osman (2025) found PEOU to have limited direct impact. Despite these insights, empirical evidence from North-East Nigeria particularly Borno State remains scarce, limiting the capacity of universities and policymakers to design contextually appropriate interventions.

This study is grounded in the Technology Acceptance Model (TAM), proposed by Davis (1986) and refined by Venkatesh and Davis (2002), which posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the primary determinants of users' behavioural intention to adopt technology. TAM is extended in this study by incorporating Awareness as an antecedent, recognising that knowledge of Gen AI tools and their academic relevance is a prerequisite for forming meaningful adoption intentions. Complementarily, the Theory of Planned Behaviour (TPB) (Fishbein & Ajzen, 2009) bridges the gap between intention and actual behaviour through Perceived Behavioural Control operationalised here as accessibility and institutional support which moderates whether high intentions translate into actual Gen AI use. Together, these dual-theoretical frameworks enable a holistic investigation of Gen AI adoption dynamics in the Borno State context.

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Objectives and Research Questions

Specifically, this study aims to:

i. Assess the levels of Gen AI awareness, PU, PEOU, and behavioural intention among lecturers in universities in Borno State, Nigeria; and

ii. Determine the influence of awareness, PU, and PEOU on lecturers' behavioural intention to use Gen AI.

The corresponding research questions are:

iii. What are the levels of Gen AI awareness, PU, PEOU, and behavioural intention among lecturers in universities in Borno State?

iv. To what extent do awareness, PU, and PEOU influence lecturers' behavioural intention to use Gen AI?

Methodology

A descriptive survey research design was adopted (Creswell & Creswell, 2018). The population comprised 2,095 lecturers across four universities in Borno State. A multistage sampling technique was used to select 322 respondents from three universities: purposive sampling for university selection, proportionate sampling for representation, and simple random sampling for individual lecturers. Data were collected via a validated, adapted five-point Likert-scale questionnaire measuring Awareness (AWR), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioural Intention (INT). Expert validation and a pilot study (n = 30) yielded a Cronbach's alpha of .791, confirming acceptable reliability. Descriptive statistics addressed RQ1; PLS-SEM with 5,000 bootstrapped subsamples was used for hypothesis testing at $\alpha = .05$.

Results

3.1 Descriptive Results

Table 1. Descriptive Summary of TAM Constructs

Construct	Grand Mean	SD	Interpretation
Awareness (AWR)	3.97	1.08	High Level
Perceived Usefulness (PU)	3.97	1.08	High Level
Perceived Ease of Use (PEOU)	4.02	1.05	High Level
Behavioural Intention (INT)	4.00	1.09	High Level

Table 1 shows that all four constructs were rated at high levels. Lecturers reported the highest awareness of specific Gen AI tools (M = 4.14) and familiarity with the term 'Generative AI' (M = 4.10), with contextual academic engagement slightly lower (M = 3.71). Perceived usefulness was highest for instructional content enhancement (M = 4.14) and teaching material creation (M = 4.10). For PEOU, ease of learning (M = 4.19) and interface intuitiveness (M = 4.10) scored highest, while technical reliability scored lowest (M = 3.79). Behavioural intention was strongest for academic use (M = 4.10) with consistent high scores across all intention items.

3.2 Measurement Model Assessment

Table 2. Construct Reliability and Validity

Construct	α	CR (ρa)	AVE
Awareness (AWR)	0.876	0.885	0.671
Perceived Ease of Use (PEOU)	0.857	0.869	0.635
Perceived Usefulness (PU)	0.889	0.902	0.696
Behavioural Intention (INT)	0.870	0.877	0.661

Results in Table 2 indicated that all constructs exceeded the 0.7 threshold for Cronbach's alpha and composite reliability, confirming high internal consistency. AVE values ranged from .635 to .696 (threshold > .50), confirming convergent validity. Discriminant validity was established using the HTMT criterion; all HTMT values fell below the 0.85 threshold, confirming that the four constructs are empirically distinct.

3.3 Hypotheses Testing

Table 3. Structural Path Analysis Results

Hypothesis	Path	β	SD	t-stat	p-value	f^2	Decision
H1	AWR → INT	0.684	0.048	14.211	< .001	0.898	Supported
H2	PEOU → INT	0.015	0.068	0.217	.828	0.000	Not Supported
H3	PU → INT	0.161	0.075	2.154	.031	0.015	Supported

Note. AWR = Awareness; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; INT = Behavioural Intention; β = standardised path coefficient; f^2 = Cohen's effect size.

From Table 3, H1 was strongly supported: Awareness was the dominant predictor of behavioural intention (β = 0.684, $p < .001$), with an exceptionally large effect size ($f^2 = 0.898$), far exceeding Cohen's (1988) large-effect benchmark ($f^2 \geq 0.35$). H2 was not supported: PEOU showed a negligible and non-significant path (β = 0.015, p = .828, $f^2 = 0.000$), indicating no direct influence on intention. H3 was supported: PU significantly but modestly predicted intention (β = 0.161, p = .031), with a small effect size ($f^2 = 0.015$).

Discussion

All four TAM constructs — awareness, perceived usefulness, perceived ease of use, and behavioural intention — were rated at high levels, consistent with findings by Fasola (2024), Van Wyk (2024), Nathaniel et al. (2021), and Alshamsy et al. (2025). The high awareness confirms that Borno State lecturers are engaged with global Gen AI discourse despite regional challenges, while high PU scores indicate they view Gen AI primarily as a productivity tool rather than a transformative pedagogical instrument. The lower PEOU score for technical reliability (M = 3.79) points to infrastructural deficits as an underlying constraint.

The dominance of Awareness in predicting behavioural intention (β = 0.684, $f^2 = 0.898$) strongly corroborates Shahzad et al. (2024) and extends the original TAM by establishing that knowledge about Gen AI precedes and outweighs perceptions of its usability in driving adoption intentions. The non-significant effect of PEOU (β = 0.015, p = .828) aligns with Osman (2025), suggesting that in the Borno State context, understanding what Gen AI can do is a stronger driver of intent than how easy it is to use — an important signal for institutional intervention design. The modest but significant role of PU (β = 0.161) confirms findings by Ma and Li (2024) and Alshurideh et al. (2024) that perceived utility remains a meaningful, if secondary, predictor.

Critically, despite high intentions, actual utilisation remains low. This intention–use gap is consistent with TPB's Perceived Behavioural Control framework: infrastructural deficits, high subscription costs, limited training, ethical concerns, and absent institutional AI policies collectively moderate whether strong intentions translate into sustained Gen AI use.

Conclusions and Recommendations

This study established high levels of Gen AI awareness, perceived usefulness, perceived ease of use, and behavioural intention among lecturers in Borno State universities. Awareness emerged as the dominant predictor of intention (β = 0.684, $f^2 = 0.898$), followed by perceived usefulness (β = 0.161), while perceived ease of use exerted no significant direct influence. The study's principal theoretical contribution is the empirical validation of Awareness as a powerful TAM antecedent in the Nigerian higher education context, and its documentation of a critical intention–use gap attributable to institutional and infrastructural constraints.

Based on these findings, it is recommended that: (i) university managements organise regular Gen AI workshops and seminars to convert high awareness into skilled, purposeful use; (ii) training should advance beyond basic literacy toward critical AI output evaluation, bias detection, and discipline-specific application; (iii) universities should leverage high PU to institutionalise wider Gen AI adoption across teaching and research; (iv) governments and university management should urgently address infrastructural deficits, high subscription costs, and the absence of institutional AI policies to bridge the intention–use gap.

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AI-Mediated Hospitality English Labs: Repositioning English as a Professional Working Language in Vocational Tourism Education

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Abstract

Artificial intelligence is rapidly reshaping tourism and hospitality workplaces, yet English language instruction in many vocational education contexts remains disconnected from these evolving professional realities. This paper introduces AI-Mediated Hospitality English Labs, an innovative pedagogical model developed and implemented at a vocational tourism high school in Türkiye. The model integrates English language learning, vocational simulation, and AI-supported task design through realistic hospitality scenarios such as welcoming international guests, managing front-office communication, handling reservations, and responding to customer complaints. Rather than treating AI as a separate technical subject, the model positions AI tools as pedagogical scaffolds that support meaningful professional communication. Drawing on task-based language teaching (TBLT), English for Specific Purposes (ESP), and digital literacy frameworks, the study presents the theoretical rationale, learning design, sample task structures, and early classroom reflections from the implementation process. Findings suggest that AI-mediated vocational language learning promotes not only linguistic competence but also digital awareness, adaptability, and professional confidence in learners. The paper contributes to current discussions on AI-driven innovation in teaching and learning, AI-supported language education, and teacher professional development for digitally enriched vocational contexts.

Keywords: AI-mediated language learning, vocational English education, hospitality English, task-based language teaching, digital literacy, tourism education

1. Introduction

The rapid integration of artificial intelligence (AI) into tourism and hospitality industries is fundamentally altering how professionals communicate, deliver services, and interact with customers. From AI-powered reservation systems and virtual concierges to automated complaint management platforms and multilingual chatbots, the contemporary hospitality workplace demands a workforce that is not only linguistically proficient in English but also digitally literate and adaptable to AI-augmented environments (Buhalis & Sinarta, 2019; Gursoy et al., 2019).

Despite these transformations, English language instruction in many vocational education settings continues to follow traditional academic models that prioritize grammar exercises, reading comprehension, and decontextualized vocabulary activities. The gap between what is taught in classrooms and what is needed in AI-driven hospitality workplaces represents a significant pedagogical challenge — one that calls for curriculum innovation grounded in authentic professional contexts (Basturkmen, 2010; Dudley-Evans & St John, 1998).

This paper responds to this challenge by presenting AI-Mediated Hospitality English Labs, a vocational language education model developed and implemented in a tourism-focused high school in Türkiye. The model draws on principles from Task-Based Language Teaching (TBLT), English for Specific Purposes (ESP), and digital literacy education to create a practice-oriented, future-responsive learning environment. Rather than introducing AI as a standalone technical topic, the model embeds AI tools as scaffolding mechanisms within professionally authentic tasks, enabling learners to engage with realistic hospitality scenarios while simultaneously developing language competence and digital workplace readiness.

The paper presents the theoretical foundations of the model, its instructional design, sample task structures, and preliminary reflections from classroom implementation. It argues that AI-supported vocational language learning offers an inclusive and contextually meaningful pathway for preparing the next generation of tourism professionals in an era of digital transformation.

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2. Theoretical Background

2.1 English for Specific Purposes and Vocational Language Education

English for Specific Purposes (ESP) has long argued for the alignment of language instruction with learners' professional and academic needs (Hutchinson & Waters, 1987). In vocational contexts, this alignment is particularly critical, as students are preparing for specific occupational roles where language serves as a primary tool for professional performance (Basturkmen, 2010). Hospitality English, as a sub-field of ESP, focuses on the communicative competencies required in tourism-related roles, including customer service interactions, complaint resolution, reservation management, and intercultural communication (Blue & Harun, 2003).

Vocational language education has increasingly emphasized the importance of authentic tasks and workplace simulation as means of bridging classroom learning and professional practice. Task-Based Language Teaching (TBLT), as developed by Willis (1996) and Long (2015), provides a pedagogically sound framework for this approach, organizing instruction around meaningful tasks that mirror real-world communicative demands. Within TBLT, language acquisition occurs through purposeful engagement with tasks, rather than through isolated grammatical practice.

2.2 AI in Language Education

The role of artificial intelligence in language education has expanded significantly in recent years. AI tools such as conversational agents, intelligent tutoring systems, and generative language models have been explored as resources for language practice, feedback, and learning support (Godwin-Jones, 2022; Huang et al., 2023). Research in this area has examined applications including automated writing evaluation, intelligent tutoring, vocabulary learning, pronunciation support, and personalised learning systems (Huang et al., 2023).

However, much of the existing literature treats AI as a supplementary resource rather than an integrated pedagogical tool. In vocational language education, the potential of AI to simulate professional scenarios, provide role-play partners, and model workplace communication patterns has remained underexplored. The present model addresses this gap by embedding AI tools within task-based vocational language instruction, positioning them as authentic components of the professional environment rather than as external add-ons.

2.3 Digital Literacy and Vocational Education

Digital literacy has emerged as a core competency in contemporary vocational education, encompassing not only technical skills but also critical thinking, adaptability, and the capacity to work effectively within digitally mediated environments (Eshet-Alkalai, 2004; Lankshear & Knobel, 2008). For future tourism and hospitality professionals, digital literacy intersects with professional communication in increasingly complex ways, as AI tools become embedded in everyday workplace operations. The AI-Mediated Hospitality English Labs model responds to this intersection by cultivating both linguistic and digital competencies through integrated task design.

3. The AI-Mediated Hospitality English Labs Model

3.1 Pedagogical Rationale

The AI-Mediated Hospitality English Labs model is founded on three interconnected principles. First, vocational language education should reflect the authentic communicative demands of the professional environment students are preparing to enter. Second, AI tools, rather than being treated as objects of study, should function as pedagogical scaffolds that enable learners to engage with professional tasks in meaningful ways. Third, language learning in vocational contexts should develop not only linguistic competence but also broader professional capabilities, including problem-solving, adaptability, intercultural awareness, and digital confidence.

These principles align with the concept of "authenticity" in language education (Gilmore, 2007), which argues that learners benefit most from engagement with tasks and materials that reflect genuine communicative purposes. In the hospitality context, authentic tasks include managing a guest check-in, responding to a dissatisfied customer, recommending local attractions, or coordinating a group reservation — all of which require specific linguistic resources and professional judgment.

3.2 Learning Design

The model is implemented through a sequence of three-phase lab sessions, each organized around a specific hospitality scenario. The three phases — Orientation, Task Performance, and Reflection — follow a broadly task-based instructional arc.

In the Orientation phase, learners are introduced to the professional context of the task through authentic materials, including hotel websites, reservation platforms, guest complaint forums, and AI-generated service scripts. Vocabulary and communicative functions relevant to the task are pre-taught through embedded activities, with AI tools used to generate model dialogues and scenario variations.

In the Task Performance phase, learners engage in simulated professional interactions. Scenarios are designed to require the use of specific communicative competencies, such as formal greetings, complaint management language, or travel recommendation strategies. AI tools serve dual roles in this phase: as interlocutors with whom learners practice (simulating guests, customers, or colleagues) and as feedback mechanisms that draw learners' attention to linguistic form and appropriateness.

In the Reflection phase, learners review their task performance, analyse AI-generated feedback, and identify areas for linguistic and professional development. Reflective activities include comparing their own responses with AI-modelled alternatives, evaluating the cultural appropriateness of their communication, and discussing how the task relates to their future professional roles.

3.3 Sample Task Structures

Table 1 presents an overview of representative task structures used within the model, illustrating the range of professional scenarios addressed and the AI scaffolding mechanisms employed.

Hospitality Scenario	Language Focus	AI Scaffolding Role
Welcoming international guests at reception	Formal greetings, check-in procedures, politeness conventions	AI as guest interlocutor; model dialogue generation
Handling a guest complaint about room conditions	Apology language, problem resolution, empathy expressions	AI as dissatisfied customer; feedback on tone and appropriateness
Managing an online reservation enquiry	Written professional correspondence, availability language, pricing discourse	AI drafts customer email; learner responds and compares outputs
Designing personalised travel suggestions	Descriptive language, persuasive register, cultural sensitivity	AI generates sample itineraries; learner adapts and personalises
Front-office communication during peak hours	Concise professional language, multitasking communication, brevity under pressure	AI simulates simultaneous guest requests; learner prioritises responses

Table 1. Sample task structures in the AI-Mediated Hospitality English Labs model.

4. Methodology

The research was conducted over one academic semester in a vocational tourism high school in Türkiye and involved 52 students enrolled in Grades 11 and 12, who participated in mixed-grade professional English learning groups.

Data collection methods included classroom observation notes, semi-structured teacher reflection journals, student feedback surveys administered at the end of each lab cycle, and samples of student task outputs (written and oral). Student feedback was collected using a 5-point Likert scale instrument supplemented by open-ended questions addressing perceived relevance, confidence, and engagement. Teacher reflection journals were maintained weekly and addressed challenges, adaptations, and observed learner responses.

Data were analysed thematically following Braun and Clarke's (2006) framework for thematic analysis. Themes were derived inductively from teacher and student data, and subsequently cross-referenced with the theoretical frameworks underpinning the model. Member checking and peer debriefing were employed to strengthen the trustworthiness of interpretations.

5. Results and Discussion

5.1 Learner Engagement and Perceived Relevance

Student feedback surveys indicated that 87% of the 52 participants perceived the hospitality scenarios as relevant to their future professional roles, while 81% reported greater confidence in English communication following lab participation. Qualitative responses suggested that learners valued opportunities to interact with AI-generated interlocutors and to practise in a simulated, low-stakes environment. These findings represent participants' reported perceptions within this classroom implementation and should not be interpreted as evidence of causal effects.

The findings point to the perceived relevance of professionally situated language practice and the potential value of AI-supported activities as additional opportunities for communication practice. They also align with broader discussions of AI applications in language education, while highlighting the need for further research using systematic measures of language development and learner experience (Godwin-Jones, 2022; Huang et al., 2023).

5.2 Language Development and Professional Competence

Analysis of student task outputs indicated measurable growth in the use of professional register, domain-specific vocabulary, and communicative functions associated with hospitality English. Students demonstrated increasing ability to deploy apology language, recommendation strategies, and formal correspondence conventions across successive task cycles. Teacher reflection journals noted a progressive shift from decontextualized language production to contextually embedded professional communication, with learners increasingly drawing on hospitality-specific scripts and adapting them to scenario-specific demands.

Beyond linguistic development, teacher observations documented growth in learners' digital confidence and their capacity to critically evaluate AI-generated outputs. Learners reported developing awareness of the limitations of AI-generated communication — including cultural inappropriateness, excessive formality, and lack of personalisation — which prompted critical reflection on the role of human judgment in AI-augmented workplaces. This dimension of the model aligns with broader digital literacy objectives in vocational education (Eshet-Alkalai, 2004).

5.3 Teacher Perspectives and Professional Development

Teacher reflection journals revealed that the implementation process itself functioned as a form of professional development, prompting the participating teacher to reconsider established assumptions about language instruction and to develop new competencies in AI tool selection, task design, and formative assessment within technology-rich environments. Initial challenges included uncertainty about how to evaluate learner performance in AI-mediated interactions and the need to establish clear criteria for task appropriateness. Over the course of the implementation, these challenges were addressed through iterative refinement of task rubrics and through peer consultation with colleagues in the school's digital education working group.

6. Conclusions

This paper has presented AI-Mediated Hospitality English Labs as an innovative response to the growing misalignment between traditional vocational English instruction and the realities of AI-augmented tourism workplaces. By embedding AI tools within task-based, professionally authentic learning scenarios, the model offers a pedagogically coherent approach to developing both linguistic competence and digital workplace readiness in vocational learners.

The early findings from the implementation process suggest that the model holds significant promise for inclusive, practice-oriented, and future-responsive vocational language education. Learners demonstrated increased engagement, professional confidence, and critical digital awareness, while the implementation process supported teacher professional growth in the design of AI-integrated instruction.

The study contributes to current scholarship on AI-driven innovation in teaching and learning, AI-supported language education, and the preparation of educators for digitally enriched vocational contexts. Future research directions include longitudinal assessment of the model's impact on learner language development, comparative studies across different vocational contexts, and investigation of the transferability of the model to other ESP domains. As AI continues to transform professional environments, vocational language education must evolve to prepare learners not merely to use language in workplaces, but to communicate effectively and thoughtfully within AI-augmented professional realities.

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From Anthropocentric Human Learner to Postanthropocentric Posthuman Learner: The Impact of ChatGPT Plus on L2 Learners' Speaking Skills

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Abstract

Since the launch of ChatGPT's beta version in November 2022, there has been significant debate about the use of ChatGPT Plus in education, particularly in second language (L2) education. While some researchers regard it as a tool that facilitates and supports learning, others argue that it impedes or even undermines learning due to its perceived negative effects. This conceptual review first revisits the historical background of AI and then explores the conceptualization of the human learner as framed by Enlightenment thought, reinterpreting its anthropocentric structure in the context of education. Subsequently, it examines the concept of the posthuman learner, which emerged at the end of the twentieth century in response to postanthropocentric concerns and challenged many established concepts of previous eras. Within a posthumanist learning model, posthuman learners adapt their traditional learning methods to digitalization and machine learning, thereby creating deterritorialized contexts that provide increased autonomy and flexibility. The posthuman learner increasingly perceives learning as a personalized domain, managed according to individual attitudes, behaviors, and ontological structures shaped by socio-cultural backgrounds. Technological innovations such as ChatGPT Plus have contributed to the deterritorialization of learning, moving it beyond conventional L2 classroom environments. Thus, this study investigates the new learning assemblage formed by posthuman learners amid various entanglements and agentic forces, both human and non-human, with a particular focus on L2 learning. The current study also reviews the conceptual and empirical literature on the role of ChatGPT Plus in developing L2 speaking skills, examining how an AI-mediated learning environment deterritorializes conventional understandings of the language learner and contributes to the emergence of the posthuman learner. Some pedagogical implications will be provided, and suggestions for further research will be presented.

Keywords: human learner, posthuman learner, ChatGPT Plus, L2 speaking skills, deterritorialization

Introduction

The late twentieth and early twenty-first centuries have witnessed significant social, cultural, political, and economic transformations. In *An Introduction to the Information Age*, Castells (1997) identifies several pivotal historical events that have fundamentally reshaped global society in recent decades. To him, these events include the information technology revolution, the dissolution of the Soviet Union, the end of the Cold War, the reformation of capitalism, the process of globalization, the emergence of (post)feminist perspectives, crises of patriarchal structures, increased ecological awareness, the (re)rise of communalism as a reaction to globalization, and the expansion of the global criminal economy (Castells, 1997, p. 6). Within this context, artificial intelligence (AI) has emerged as a leading force in the digital age, as "It [AI] is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable" (McCarthy, 2004, p. 2).

Artificial intelligence can be divided into six historical periods, as outlined by Mucci (2024): pre-20th century, 1900-1950, 1950-1980, 1980-2000, 2000-2020, and 2021 to the present. Early notions of artificial intelligence appeared in pre-20th-century literature, notably in Jonathan Swift's 1726 novel *Gulliver's Travels*, which describes The Engine, a mechanical device designed to help scholars generate ideas, sentences, and books. This fictional device foreshadows the algorithmic text generation foundational to modern AI. Scientific advancements accelerated between 1900 and 1950. In 1914, Spanish engineer Leonardo y Quevedo demonstrated the first chess-playing machine capable of making autonomous legal moves. In 1921, Karel Čapek's play *Rossum's Universal Robots* introduced the term "robot" to the English language, achieving international recognition after the play's success. In 1939, John Vincent Atanasoff developed the Atanasoff-Berry Computer (ABC), regarded as one of the earliest digital electronic computers in American computer science. In 1943, Warren S. McCulloch and Walter Pitts published *A Logical Calculus of the Ideas Immanent in Nervous Activity*, which influenced the development of computer systems that emulate brain-like functions through neural networks and deep learning.

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Between 1950 and 1980, computational science underwent significant advancements. In 1950, Alan Mathison Turing, a British logician and computer pioneer, addressed the foundational question, "Can machines think?" in his paper *Computing Machinery and Intelligence*, published in *Mind*. The Turing Test, described as an "imitation game," was introduced to assess whether computers could exhibit intelligence comparable to that of humans. In 1951, Marvin Minsky and Dean Edmunds designed an analog computer. In 1952, Allen Newell and Herbert A. Simon developed influential programs that explored computational methods for human problem-solving. In 1955, John McCarthy coined the term "artificial intelligence" (AI), defining it as "the science and engineering of making intelligent machines and especially intelligent computer programs" (2004, p. 2). In 1957, Frank Rosenblatt, a computer scientist, developed the Perceptron, an early artificial neural network that established the foundation for machine learning.

In 1959, Arthur Samuel pioneered the concept of machine learning by demonstrating that computers could be programmed to learn from experience. In 1965, philosopher Hubert Dreyfus published *Alchemy and Artificial Intelligence*, arguing that the human mind functions fundamentally differently from computers. In 1973, James Lighthill presented a report to the British Science Research Council, emphasizing that artificial intelligence had not fulfilled its early promises and marking the onset of the first "AI winter," a period of reduced interest and investment in AI research. Despite this decline, significant advancements occurred between 1980 and 2000. The development of the humanoid robot WABOT-2 in Japan during the 1980s exemplified ongoing innovation in the field. In 1993, Vernor Vinge published *The Coming Technological Singularity*, contending that technological advances, particularly in AI, could lead to an intelligence explosion in which machines surpass human intelligence. In 1995, Richard Wallace developed chatbot A.L.I.C.E (Artificial Linguistic Internet Computer Entity), which later demonstrated significant capabilities and paved the way for further progress in conversational AI.

Between 2000 and 2020, robotics advanced significantly, enabling more natural human-robot interactions. In 2000, Cynthia Breazeal at MIT developed Kismet, a robot designed to engage with humans using emotional and social cues. In 2012, Jeff Dean and Andrew Ng conducted an experiment with a large neural network trained on 10 million unlabelled images from YouTube videos. This network autonomously learned to recognize patterns in the data, illustrating the potential of unsupervised learning. In 2020, OpenAI introduced GPT-3, a language model with 175 billion parameters, which became one of the largest and most sophisticated AI models of its time. GPT-3 can generate human-like text, engage in conversation, write code, translate languages, and produce creative writing from natural-language prompts. Artificial intelligence has advanced significantly since 2012.

In 2021, OpenAI introduced DALL-E, followed by DALL-E 2 and DALL-E 3, which are generative AI models that produce highly detailed images from textual descriptions. In 2024, Google released Gemini 1.5 in limited beta, an advanced language model capable of processing context lengths up to 1 million tokens. The initial release of GPT (Generative Pretrained Transformer), a type of large language model (LLM), also garnered widespread attention. Recent developments in AI include the creation of generative AI using smaller, more efficient foundation models and the rise of agentic AI. In sum, the third industrial revolution, which began in the latter half of the twentieth century following World War II, enabled significant advances in electronics, digital computing, and information technology. Given the need to examine the enduring impact of artificial intelligence and to critically analyze the concept of the "human learner" within anthropocentrism and the "posthuman learner" within postanthropocentrism, including their entanglements with AI, the introduction to this study provides an overview of the historical development of artificial intelligence.

Posthumanism: Transcorporeality, Agency, Entanglement, and Assemblage

Posthumanism is fundamentally concerned with "ethico-onto-epistemology, [that is], an appreciation of the intertwining of ethics, knowing, and being" (Barad, 2007, p. 185). Having been a framework for challenging anthropocentrism, posthumanism is defined as "a way of being attentive to the production of the human in its various entanglements with its 'others'" (Pyyhtinen & Tamminen, 2011, pp. 147-148). Unlike humanism, which affirms the intrinsic rights and privileges of humans, posthumanism conceptualizes "humans and objects as part of the same ecosystem, inseparable and interconnected" (Reilly, 2018, p. 272). Posthumanism rejects anthropocentrism and challenges the assumption that the human is the unique identifier or central rubric, instead investigating the complex interrelations between human and non-human entities (Tüfekçi Can, 2023). Posthumanism provides new interpretations of human subjectivity by restructuring traditional modes of thought and examining the intricacies of human existence as "agentially intra-acting components" of nature (Barad, 2007, p. 33). This perspective questions the ontological status of all entangled entities, both human and non-human, and introduces a novel understanding of humanity. Such an entanglement extends to spiritual, cognitive, perceptual, and subconscious dimensions, facilitating a reinterpretation of the symbiotic relationships among human/nature/culture. Alaimo (2014) articulates the interconnectedness through the concept of *transcorporeality*, emphasizing "how (post)human is always already part of intra-active networks and systems that are simultaneously material, discursive, economic, and biopolitical" (p. 195).

Haraway (2008) asserts that "We are face to face, in the company of significant others, companion species to each other" p. 93). Her statement underscores the deeply relational nature of existence, indicating that humans and nonhumans are intrinsically connected through shared worlds of meaning and responsibility. Haraway expands the definition of "significant others" to encompass all "companion species," including animals, technologies, ecologies, and material entities that influence human lives. She emphasizes *relationality,* and this perspective challenges anthropocentric assumptions and positions *coexistence* as an ongoing practice in which meaning, agency, and ethics emerge from everyday interactions. Similarly, Butler (1992) challenges that actions "can no longer be understood as unilinear in direction or predictable in their outcomes" (p. 10). Rather, actions are embedded within complex social contexts, shaped by the interplay of multiple agencies, and often produce unforeseen consequences. Therefore, *agency* should not be conceived as the exercise of autonomous will by a sovereign individual, but as a relational and inherently unpredictable process in which meanings and effects inevitably surpass the subject's original intentions.

Following an inquiry into transcorporeality, agency, and entanglement, it is vital to consider how these posthumanist concepts collectively shape educational theory. Edwards (2010) demonstrates the interconnectedness between posthumanism and education, emphasizing that posthumanism frames education as an assemblage of human and non-human agencies. Within this entangled perspective, the purpose of education shifts from traditional learning to a process of creative gathering. In this context, the human subject is inseparable from the objects of knowledge under consideration. Thus, education can be reconceptualized as a dynamic relational assemblage in which learning emerges through ongoing interactions and co-constitutive relations among human and more-than-human agencies.

Anthropocentric Human Learner and Post-anthropocentric Posthuman Learner

Humanism, a "broad perspective that assigns to human beings a special place in the greater scheme of things" (Bonnett, 2003, p. 707), is based on Enlightenment values and it is Western, and specifically European and "from its beginning a pedagogical process "in tune with the self-perception of an individual who learns to embody certain (gendered, racial, national, social …) identities that modern societies 'construct' and privilege or set as normative and thus as worth aspiring to" (Herbrechter, 2023, p. 214). However, in the latter half of the twentieth century, the "decentring" of the liberal humanist subject intensified as a result of "theoretical and philosophical formations like poststructuralism, postmodernism, and deconstruction" (Herbrechter, 2023, p. 215). The concept of "post-anthropocentrism," seeks to situate all life forms equally, "far from being codified as the exclusive property or the unalienable right of species, the human, over all others" (Braidotti, 2013, p. 61).

This study attempts to redefine the concept of the "postanthropocentric posthuman learner" and, by delineating its boundaries, introduces a new model of humankind characterized by unique, individualized, digitalized, and deterritorialized learning preferences resulting from scientific and technological advancements. Clarifying the boundaries of the "postanthropocentric posthuman learner" is significant, as "posthuman has become a key term to cope with an urgency for the integral redefinition of the notion of the human, following the onto-epistemological as well as scientific and bio-technological developments of the twentieth and twenty-first centuries" (Ferrando, 2013, p. 26). Furthermore, the posthuman learner is consistent with the concept of "posthuman learning," which is described as "a challenge for AI and machine learning because it changes our perception of 'the human' from a rational stand-alone individual to a collective of humans (in the plural) and non-humans" (Hasse, 2019, p. 363).

The anthropocentric human learner (AHL) differs significantly from the postanthropocentric posthuman learner (PAHL) in their understanding of the world and their self-positioning within it. The AHL occupies a central position, whereas the PAHL exists at the periphery. The former often accepts and benefits from a perceived hierarchical status rooted in a belief in inherent superiority, while the latter critically examines their place in the world. The PAHL develops a new sense of self and embodiment by contesting the established sociocultural values of the Enlightenment period and adopting emerging entanglements such as technology, digitalization, artificial intelligence, and simulation. According to Herbrechter (2023), as implied in posthumanism, "technological and ecological change poses challenges to humanism's anthropocentric model of subjectification; 'posthumanizing' developments like digitalization, cyborgization, artificial intelligence as well as anthropogenic climate change, or bioengineering require new conceptualizations of subjectivity and new narratives out of which subjects can construct identities, and which are different from traditional (liberal) humanist understandings of what makes a 'me', human" (p. 219). Consequently, PAPL, whose identity and learning processes emerge through dynamic entanglements with technological assemblages, can be conceptualized not as a fixed, autonomous subject but as a relational, fluid entity co-constituted through ongoing interactions.

Deterritorialization of the posthuman learner in language education

Recent technological advancements have significantly influenced education, particularly language education. The emergence of artificial intelligence, particularly platforms such as ChatGPT, has introduced innovative approaches

to language learning and transformed both pedagogical strategies and learner engagement. As a result, educators and researchers have examined the potential of this artificial intelligence to enhance language learning. In its first year, numerous studies were published in education, linguistics, and computer science, with most empirical research focusing on higher-education contexts. Initial findings suggest that ChatGPT can serve multiple roles in language learning, including acting as a conversational partner, providing personalized practice materials, functioning as a writing assistant, and serving as a tutor for self-directed study.

In the context of posthumanist education, Barad's explanation of the significance of "intra-action" can be taken as a key element (2007, p. 348). In environments where all agencies are entangled through intra-action and time-relevant practices are disregarded, a critical question emerges: If time-sharing is no longer dependent on geographical proximity, how are social, cultural, and material relations reconfigured within networked societies, remarkably in educational contexts? Castells poses a similar question, asking, "What happens when the time-sharing of practices (be it synchronous or asynchronous) does not imply contiguity?" and responds, "'Things' still exist together, they share time, but the material arrangements that allow this coexistence are inter-territorial or transterritorial: the space of flows is the material organization of time-sharing social practices that work through flows" (1997, p. 14). This reconnection, whether inter-territorial or transterritorial, signifies the deterritorialization of posthuman learners from traditional spaces such as homes, schools, classrooms, laboratories, workrooms, and libraries. The restructuring of educational practices and opportunities through the adoption of new technologies, such as smartphones and mobile applications, further distances posthuman learners from conventional spaces. As a result, studying now occurs in dynamic environments, including coffee shops, parks, beaches, third places, transportation hubs, and during commutes of varying distances.

Research on posthuman learners' perceptions and use of ChatGPT (Plus) in developing L2 speaking skills

Existing research has primarily addressed topics such as educating the posthuman (Weaver, 2010), posthuman learning (Hasse, 2019), sustainable learning environments in the posthuman era (Dube et al., 2023), posthumanist perspectives on technologically designed learning environments (Peppler, 2020), and posthuman pedagogy (Dhungana, 2023). However, studies focusing on posthuman L2 learning remain rather limited. Notable examples include research on a posthuman perspective on graphic assemblages (Karthika, 2024), curriculum analysis through a posthumanist lens (Gajauskaitė, 2022), and posthumanism and oral literacy (Schneider, 2023). Although numerous studies have investigated the use of ChatGPT as a language-learning and teaching tool, only a limited number of studies (e.g., (Al-Obaydi et al.,2025; Alsalem, 2024; Barrot, 2024; Kostka & Toncelli, 2023; Shaikh et al., 2023; Young & Shishido, 2023) have specifically examined the role of ChatGPT (Plus) in developing foreign language learners' speaking skills and the effects of ChatGPT-simulated conversation on language skills. These studies do not address L2 posthuman learners. Thus, this research is an initial step toward exploring posthuman learners and their entanglement with ChatGPT Plus in developing speaking skills within the framework of posthumanist education.

Conclusions, Pedagogical implications, and Directions for Future Research

The present study reconsidered the concept of the human learner shaped by Enlightenment thought, with particular attention to its anthropocentric foundations and implications for L2 learning. It also examined the emergence of the posthuman learner as a response to post-anthropocentric perspectives that questioned established assumptions about the human subject. Drawing on this theoretical shift, the study conceptualized L2 learning as a relational assemblage in which learning was shaped through multiple entanglements and agentic factors involving both human and non-human actors. Within this framework, particular attention was given to the changing nature of L2 learning in digitally mediated environments and to the role of ChatGPT Plus in L2 speaking development. The related literature suggests that ChatGPT Plus can increasingly function not only as a technological tool but also as an interactive and adaptive participant in L2 learning. Earlier research (e.g., Al-Obaydi et al., 2025; Alsalem, 2024) has documented L2 learners' generally positive perceptions of the use of ChatGPT Plus for speaking practice, its potential to facilitate simulated conversations, and its capacity to provide flexible opportunities for interaction beyond the limits of conventional classroom settings. The significance of ChatGPT Plus extends beyond its function as a technological tool. When L2 learners engage in sustained interaction with it, the conventional boundaries between learner, technology, and learning environment become increasingly fluid. From a posthumanist perspective, this process can be understood as a deterritorialization of the traditionally human-centered conception of the L2 learner, in which learning emerges through the ongoing entanglement of human and non-human actors. This implies that ChatGPT Plus does more than simply supplement existing L2 speaking pedagogy; it reconfigures the learner's position within it. The human speaker is no longer the only source of communicative agency. Instead, agency is distributed between the human learner and the AI, with the machine's responsiveness, patience, and constant availability jointly shaping the conditions under which L2 speaking practice takes place (Hasse, 2019).

These insights have several pedagogical implications for the use of ChatGPT Plus in L2 speaking development. ChatGPT Plus can be integrated into L2 speaking instruction as an additional conversational and learning partner rather than as a replacement for teachers or human interaction. In other words, teachers should treat it as a distinct kind of speaking partner rather than a substitute for human interaction, since its strengths and limitations differ from those of a human interlocutor. AI-mediated conversations can provide opportunities for role-play, simulated real-life conversations, discussion, problem-solving, and repeated speaking practice. Learners can also be encouraged to actively shape their interactions by generating prompts, requesting clarification, negotiating topics, asking for feedback, and adapting the level of conversational difficulty. Such practices are particularly compatible with a post-anthropocentric view of learning and may foster learner agency and autonomy by positioning L2 learners as active participants in the human-AI learning assemblage. However, the positive role of facilitation conditions and learner attitudes identified by Zou et al. (2025) further suggests that successful integration depends not only on ChatGPT's technological affordances but also on learners' willingness and ability to engage meaningfully with it. Teachers should therefore provide guidance on effective prompting, critical evaluation of AI responses, and responsible use of AI, rather than assuming that access to technology automatically results in effective learning.

Several directions merit particular attention in future research. First, since much of the existing literature has focused on L2 learners' perceptions and perceived usability of ChatGPT as a conversational partner, further empirical research is needed to employ longitudinal designs that examine the sustained effects of using ChatGPT Plus on L2 speaking development over time. Future research could also examine how different forms of interaction, including human-human, human-AI, and human-AI-human interactions, contribute to learners' L2 speaking development. Besides, further research on teacher preparedness and the pedagogical integration of ChatGPT into structured curricula, rather than its use solely in extracurricular settings, would help transform the current, largely learner-centered evidence base into actionable guidance for L2 classroom practice.

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Understanding the Ethics of Teaching with AI in South African Higher Education Institutions

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Abstract

The rapid growth of generative artificial intelligence (GenAI) is transforming teaching, learning, and assessment in higher education, creating both opportunities and ethical challenges. In South Africa, these challenges are intensified by inequalities in digital access, AI literacy, and technological resources, as well as concerns about academic integrity, authorship, transparency, privacy, accountability, and human agency. This study explores how South African higher education institutions (HEIs) understand and articulate the ethical use of GenAI in teaching and learning. A qualitative multiple case study design was employed, using thematic analysis of publicly available AI policies, guidelines, and frameworks from 12 South African public universities selected through convenience sampling. Inductive thematic analysis using ATLAS.ti identified four key themes: academics modelling responsible AI use; purposeful integration of AI into the curriculum; guiding students towards critical engagement with AI; and maintaining human-centred, reflective pedagogical practices. The findings indicate substantial convergence among institutions on the principle that GenAI should augment rather than replace human teaching. However, institutional approaches remain fragmented, with variations in the scope and implementation of guidelines and no nationally coordinated framework. The study concludes that South African HEIs require a unified yet context-sensitive ethical framework that promotes academic integrity, equity and AI literacy. Such an approach can support responsible AI integration while ensuring that technological innovation supports critical thinking and the broader educational purposes of higher education.

Keywords: *Generative AI, digital ethics, higher education, South Africa, academic integrity, critical pedagogy*

Introduction

The emergence of GenAI technologies has marked a pivotal moment in the evolution of higher education globally. Capable of producing human-like text, images, audio, and code. Tools such as ChatGPT (Cong-Lem, Soyoof, & Tsering, 2025; He et al., 2025; Dai et al, 2025), Google Bard (Andrew & Zhao, 2025; Kuru, Aşık & Demir, 2025), Claude (Kıyak & Emekli, 2025), and Elicit (Gupta & Gupta, 2025) are reshaping traditional educational practices. Within a few years, GenAI has shifted from being a technical novelty to a powerful influence on teaching, learning, and assessment. South African HEIs, like their global counterparts, are increasingly encountering these technologies in both formal and informal academic contexts. This transformation presents a dual-edged reality. On one hand, GenAI offers immense potential for innovation, enhancing personalised learning, streamlining administrative processes, supporting multilingual access, and promoting academic inclusivity. On the other hand, it raises deep ethical and pedagogical questions. Key concerns include academic integrity, authorship, data privacy, and the risk of exacerbating existing inequalities in access and literacy around AI technologies. Particularly pressing is the lack of a coherent framework to guide educators and institutions in the ethical integration of these tools.

Emerging research (Gouseti, James, Fallin, & Burden, 2025) also points to a growing gap in teacher readiness. Many educators report limited professional development opportunities related to AI ethics, leading to uncertainty, scepticism, and anxiety. This lack of confidence not only impedes the pedagogical integration of GenAI but also risks undermining trust in its potential as a learning support tool. In such an environment, policy development and institutional responses vary significantly, often lacking strategic alignment with educational values and the realities of technological advancement.

South African HEIs like other HEIs around the world, now stand at a crossroads, tasked with balancing innovation with responsibility. As they begin to develop policies and guidelines on the ethical use of GenAI, it becomes vital to understand how these decisions are being shaped, who is involved in the process, and what principles are guiding practice. Without such insights, there is a risk that the implementation of GenAI may reproduce or even deepen confusion, resistance, and frustration in academia, rather than fostering development and ethical academic environments.

The objective of this research, therefore, is to explore how South African HEIs are interpreting and engaging with the ethical use of generative AI, with a focus on teaching and learning. The study aims to uncover the ethical

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frameworks, institutional strategies, and educational values that underpin current responses to AI in these institutions. By doing so, it contributes to a broader understanding of how responsible AI integration can be achieved in diverse and complex higher education settings.

Methodology

Research Design:

The study adopts a qualitative multiple case study approach, focusing on policy documents and institutional AI guidelines from a selection of 12 South African universities. The documents used were all publicly accessible. The approach allowed for in-depth exploration of institutional understanding and practices of ethical use of AI in teaching.

Sampling:

Convenience sampling was employed to select 12 South African HEIs that have published guidelines or frameworks related to the use of AI in teaching and learning on their websites. Among these institutions are: nine Traditional universities, two comprehensives, and 1 university of technology. These universities were chosen from a total of 26 public universities in South Africa, consisting of 6 Universities of Technology, 8 Comprehensive Universities, and 12 Traditional Universities. Table 1 below provides an overview of the number of sources utilised from each university. The universities have been differentiated by type to offer a clearer understanding of the sample composition.

	University Code	University type.	Number of sources
1	Uni 1	Traditional University	1
2	Uni 2	University of Technology	1
3	Uni 3	Traditional University	3
4	Uni 4	Comprehensive university	1
5	Uni 5	Traditional University	3
6	Uni 6	Traditional University	3
7	Uni 7	Comprehensive University	2
8	Uni 8	Traditional University	1
9	Uni 9	Traditional University	2
10	Uni 10	Traditional University	3
11	Uni 11	Traditional University	3
12	Uni 12	Traditional University	1

Table 1. Sample: Universities

Data Collection:

The search menus of various university websites were used to gather information. The search terms “AI guidelines,” “AI framework,” and “AI policy” were employed to locate relevant documents. In some instances, the guidelines were not available as downloadable files, but they still provided valuable insights for the study.

Data Analysis:

The study employed thematic analysis as outlined by Braun and Clarke (2006) to analyse qualitative data. The analysis followed an inductive approach, where themes were derived directly from the data without imposing pre-existing frameworks. The process began with data preparation, including familiarisation through repeated reading of the documents. Using ATLAS.ti software, the researcher generated inductive codes aligned with research aims and objectives. The codes were then examined for patterns, which informed the development of themes through a multi-stage process. This iterative process ensured the analysis was grounded in the documents, while allowing the researcher to uncover meaningful patterns and insights relevant to the study’s objectives.

Ethical Considerations:

The analysis was conducted exclusively utilising documents that are publicly accessible. As a result, no permissions were required from the respective institutions for the use of these materials. In order to maintain confidentiality, specific university names have been omitted and replaced with coded identifiers, such as Uni 1 to Uni 12.

Results

THEME	Evidence from Data	Universities
1. Academics to Model the Responsible Use of AI	Academics as key role models and gatekeepers Staff to clearly communicate policies, design AI-resilient assessments, model ethical practices in class, and participate in ongoing professional development. Emphasis on modeling through syllabus/rubric design, supervisor guidance, practical uses (e.g., lesson planning and assessment design), pilots, workshops, and capacity-building.	Uni 5, Uni 6, Uni 3, Un 12, Uni 7, Uni 11, Uni 2, Uni 4, Uni 1, Uni 9
2. AI to be Integrated into the Curriculum	Integration varies from strategic to practical. Strongest commitment includes embedding AI in multimedia content, LMS systems, personalized learning, and curriculum transformation. Promotion of adaptive approaches (embrace & redesign assessments), support through authentic tasks and discipline-specific tools. More cautious, supportive roles (e.g., brainstorming, research assistance).	Uni 5, Uni 12, Uni 2, Uni 10, Uni 3, Uni7, Uni 4, Uni 6, U 11, Uni 1, Uni 8, Uni 9
3. Students to be Guided on How to Critically Engage with AI	Student guidance is a universal strength. Most detailed support includes declarations, prompt literacy, critical evaluation of outputs, and tools like checklists or RITE frameworks. Emphasis on understanding limitations, verification, avoiding overreliance, bias awareness, and independent thinking.	Uni 3, Uni 5, Uni 6, Uni 7, U 2, Uni 1, Uni 11, Uni 9, Uni 12, Uni 4, Uni 8, Uni 10
4. Emphasis on Reflection, Not Replacement of Pedagogical Roles	Strongest consensus across all institutions. Every guideline stresses that AI should support, not replace, human learning, critical thinking, and authorship. Most explicit frameworks around transparency, accountability, fairness, and human oversight. Highlight verification, authenticity, and developmental conversations. Link reflection to governance, risk awareness, and inclusivity.	Uni 3, Uni 7, Uni 5, Uni 6, Uni 12, Uni 1, Uni 2, Uni 11, Uni 9, Uni 4, Uni 8, Uni 10

Table 2. Summary of findings.

Table 2 illustrates the results organised by theme that have emerged from the data.

1. Academics to Model the Responsible Use of AI

The focus is on staff demonstrating good practices through openness and adapting their teaching methods. This matches research that highlights the importance of faculty as role models and the need for professional growth and clear communication of policies. Rawat (2025) discusses faculty development models that help academics effectively integrate and use AI responsibly. At the same time, Smith (2025) suggests that institutions should prioritize the role of academics in guiding responsible AI use.

2. *AI to be integrated into the curriculum*

A clear trend shows that South African institutions and educators are focusing on carefully integrating AI into their teaching instead of adopting it without thought. Research supports the idea of strategically using AI in learning management systems, creating personalized learning experiences, designing real-world tasks, and redesigning curricula based on solid teaching principles, rather than using AI tools randomly or without a plan. In this context, Yan and Tang (2025) compare how different fields use AI-generated content tools, revealing important differences in how deeply these tools are used and the learning outcomes they produce. Additionally, Zhong, Wei, and Mo (2025) promote values-driven methods that weave ethical and professional responsibility into AI-enhanced curricula.

3. Students to be guided on how to critically engage with AI.

Central to this theme is the need to help students engage critically with AI through systematic training. Key elements include ensuring transparency by clearly stating when AI is used, developing skills for critical evaluation, and encouraging original thought. Data emphasizes the importance of checking AI-generated outputs rigorously

and using structured checklists or evaluation frameworks to protect independent contributions. Research also supports the idea that students should critically engage with AI. Salido (2025) outlines the key skills students need for interacting with AI tools. Roy (2026) looks at how students view AI and what guidance they need for responsible use. Hassan (2026) studies teaching methods that enhance critical thinking and promote ethical AI practices. In addition, Walter (2024) highlights the importance of AI literacy and critical skills, particularly prompt engineering, which is essential for effective student engagement with AI.

4. Reflective practice of AI:

The data highlights the importance of reflective practice in teaching, rather than replacing teachers. Many experts agree that AI works best as a support tool when it follows clear guidelines that ensure transparency, human involvement, authenticity, and ongoing reflection. For example, Sellnow (2025) suggests that AI should enhance teaching without taking its place. Similarly, Cooper (2026) discusses how AI can help manage academic work through reflective methods, instead of replacing educators.

Conclusions

This study concludes that South African higher education institutions are increasingly recognising the need for ethical and human-centred integration of generative AI (GenAI) in teaching and learning. The findings show strong agreement that academics should model responsible AI use, AI should be purposefully integrated into curricula, students should be guided to engage critically with AI, and AI should support rather than replace human judgement, teaching, learning, and authorship. However, despite this convergence, institutional approaches remain fragmented, with differences in guidelines and implementation and no nationally coordinated framework. The study therefore highlights the need for a unified yet context-sensitive national framework that addresses AI use in teaching and learning, supported by ongoing professional development and stakeholder dialogue.

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A Human-Centered Pedagogical Framework for AI-Assisted Foreign Language Learning: Self-Regulated Learning, Learner Autonomy, and Academic Integrity

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Abstract

Generative artificial intelligence increasingly shapes foreign language learning through conversational practice, feedback, explanation, and text generation. Its availability expands opportunities for independent practice, yet the ease of use can obscure who sets learning goals, makes linguistic decisions, and remains accountable for submitted work. This conceptual article develops the Human-Centered AI-Assisted Language Learning (HCAILL) Framework to integrate these concerns within a pedagogical account. The framework was developed through a theory-synthesis design drawing on scholarship on generative AI in language education, self-regulated learning, learner autonomy, and academic integrity. It treats AI use as a learning process whose educational value depends on the learner's decisions before, during, and after interaction with a system. HCAILL organizes that process into four stages that cover task framing and goal setting, bounded assistance, evaluation and revision of AI output, and documentation of decisions followed by reflection. Self-regulated learning guides planning, monitoring, and reflection across the cycle. Learner autonomy concerns control over goals, strategies, and final linguistic choices. Academic integrity defines acceptable assistance and requires that authorship, disclosure, and evidence of learning remain visible. A writing example illustrates how the cycle can turn automated feedback into cognitive scaffolding without transferring the task itself to AI. The framework also broadens assessment to include drafts, decision records, and learner explanations alongside polished final products. As a conceptual proposal, HCAILL requires empirical testing across languages, proficiency levels, tasks, and institutional settings. It contributes an analytical vocabulary and process model for designing AI-assisted language learning around human judgment, agency, and accountable participation.

Keywords: generative artificial intelligence, foreign language learning, self-regulated learning, learner autonomy, academic integrity, human-centered pedagogy

1. Introduction

Generative artificial intelligence (GenAI) offers language learners feedback, explanation, conversational practice, and text generation. Law (2024) maps its applications in language teaching and learning, whereas Wiboolyasarin et al. (2025) review AI-chatbot use across speaking, writing, reading, listening, grammar, and vocabulary. Classroom research remains concentrated in higher education, English, learner perceptions, and writing, while chatbot studies frequently examine short-term or single-skill outcomes (Lee et al., 2025; Wiboolyasarin et al., 2025). Long-term language development therefore remains underexamined.

AI assistance may range from explaining a grammatical choice to generating an assignment, but the finished product does not reveal who set the goal, evaluated the output, or made key linguistic choices. In Hınız's (2024) case study, participants raised concerns about unreliable information, plagiarism, and possible harm to cognitive skills, while Lee et al. (2025) identify academic-integrity problems and disruption to established assessment practices. A writing-task experiment and a higher-education review also raise concerns about technology dependence, diminished autonomy, and weaker engagement in self-regulatory processes (Fan et al., 2025; Lan & Zhou, 2025). Özturan's (2025) systematic review found only five empirical studies, mostly involving university students learning English as a foreign language (EFL), with ChatGPT as the most frequently used tool.

Existing scholarship offers several points of departure. In kindergarten through Grade 12 (K–12) settings, Kong and Yang (2024) propose a human-centered framework in which GenAI supports self-regulated learning through domain-knowledge learning. Lodge et al. (2023) conceptualize learning with GenAI as a network of co-regulation centered on learner agency, while Anders and Dux Speltz (2025) integrate GenAI literacies with self-regulated learning (SRL) in a Plan–Iterate–Evaluate cycle. In language learning, Alm's (2024) exploratory case study links AI-mediated autonomy to critical evaluation, strategic tool use, and preservation of the learner's own voice in the target language, whereas Godwin-Jones (2024) conceptualizes agency as distributed across human, technological, and sociocultural relations. Together, these accounts foreground human agency but offer less task-specific guidance on decisions, authorship, and permitted assistance within a single foreign-language task.

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This article asks: How can self-regulated learning, learner autonomy, and academic integrity be organized as a task-level process for human-centered GenAI use in foreign language learning? It develops the Human-Centered AI-Assisted Language Learning (HCAILL) Framework as a four-stage pedagogical cycle whose effects on achievement, behavior, and integrity remain to be evaluated.

2. Conceptual Approach and Theoretical Foundations

2.1. Conceptual approach

This article adopts a theory-synthesis design, which integrates literature streams to develop a more comprehensive account of a shared phenomenon (Jaakkola, 2020). Source selection was purposive and organized around the conceptual problem of how regulation, decision authority, and authorship can remain identifiable in AI-assisted language tasks. The source base comprises foundational work on self-regulation and autonomy, recent reviews of GenAI in language education, adjacent human-centered frameworks, and institutional guidance. Four questions guided the synthesis: who defines the learning goal, who makes consequential choices, how AI output is evaluated, and what evidence identifies the learner's contribution. Exhaustive coverage and systematic-review claims fall outside this design. HCAILL accordingly constitutes a theoretically grounded proposition for subsequent empirical testing.

2.2. Three functions within one learning process

Self-regulated learning (SRL) explains how learners manage activity across forethought, performance, and self-reflection (Zimmerman, 2002). Before acting, they set goals and select strategies. During performance, they monitor progress and adjust their approach, while reflection connects the result to a subsequent attempt. AI chatbots have been proposed as supports for goal setting, feedback, personalization, and reflection across SRL phases (Chang et al., 2023), while experimental evidence indicates that explicit metacognitive prompts can strengthen task strategy and self-evaluation (Xu et al., 2025). Access to GenAI is insufficient evidence of regulation. Evidence of SRL lies in how the learner connects a stated goal with the feedback considered, the judgment applied, and the revision that follows.

Learner autonomy concerns authority over the direction of learning. Holec (1981) defined it as “the ability to take charge of one's own learning” (p. 3). In AI-assisted settings, this includes deciding when help is needed, specifying its scope, and accepting, modifying, or rejecting a suggestion. An exploratory case study by Alm (2024) illustrates how learners navigated abundant AI options while seeking to preserve a recognizable second-language voice. Godwin-Jones (2024) describes agency as distributed across learners, teachers, tools, and social settings. Within HCAILL, the system participates in the activity, while educational accountability remains with the people who design the task and judge its output.

Academic integrity defines the conditions under which assistance is permitted and represented. Where assessment rules require disclosure, a declaration makes AI assistance visible. The evidentiary question remains whether the intended capability was exercised. If a system completes the central work, an accurate declaration may still leave the assessment invalid. A bounded request for explanation can support learning when the learner evaluates the response and performs the revision. Human-centered guidance connects transparency with critical evaluation, privacy, pedagogical validation, and institutional responsibility (Miao & Holmes, 2023). Within HCAILL, SRL structures the learning cycle, autonomy locates decision authority, and integrity makes assistance, authorship, and evidence of learning accountable.

GenAI also introduces ethical and institutional risks that academic-integrity concepts cannot adequately classify. Inaccurate linguistic advice constitutes an epistemic risk, while culturally narrow output can constrain judgments about appropriate language use. Data retention and unequal access raise institutional concerns. Guidance on responsible educational AI likewise treats transparency, privacy, fairness, accountability, and human agency as connected requirements (Miao & Holmes, 2023). In the language-learning context, HCAILL positions source checking, privacy protection, accessibility, and attention to linguistic variation as conditions surrounding the learning cycle (Godwin-Jones, 2024; Miao & Holmes, 2023).

Human-centeredness is operationalized here through the allocation of authority and responsibility. Broader AI governance scholarship similarly associates augmentation with retained human decision authority and oversight (Erduran, 2025). Within an educational task, learners retain control over goals and linguistic choices, teachers design the conditions of assistance, and institutions remain accountable for policy and data protection. Personalization alone offers an inadequate test, since a highly tailored response may still narrow the learner's options or obscure uncertainty. A human-centered task keeps goal setting, evaluation, and final judgment with learners and teachers, using GenAI to support domain learning and reflection (Kong & Yang, 2024). Institutions should also provide meaningful alternatives when access or participation is constrained (Miao & Holmes, 2023).

The three constructs may also diverge within the same task. A learner can autonomously request a complete answer yet show weak monitoring and violate the assessment conditions. A tightly guided activity may temporarily limit choice while helping the learner develop strategies needed for later autonomy. Transparent disclosure can coexist with poor learning if AI performed the capability under assessment. HCAILL examines the resulting configuration of decisions across the task. Autonomy concerns who chooses, SRL concerns how learning is managed, and integrity concerns whether the resulting work is validly represented. Keeping these questions distinct prevents a single visible behavior, such as prompting or disclosure, from standing in for the whole process.

3. The HCAILL Framework

HCAILL operationalizes these functions through the four-stage cycle shown in Figure 1. Learner decision authority occupies the center, while AI literacy, teacher scaffolding, task design, and institutional policy shape the conditions around the cycle. The system can generate options and feedback, although its output remains provisional until the learner evaluates it.

Each stage corresponds to a recurrent failure mode in AI-assisted work. An unclear goal allows the tool's capabilities to direct the task, an open-ended request can transfer more work than the learner intended, and unexamined output allows fluency to stand in for accuracy. A missing process record further obscures how the final product was produced. The stages distinguish these problems analytically, although learners may move among them during authentic activity. Their sequence makes potential interventions visible to teachers and consequential decisions visible to learners.

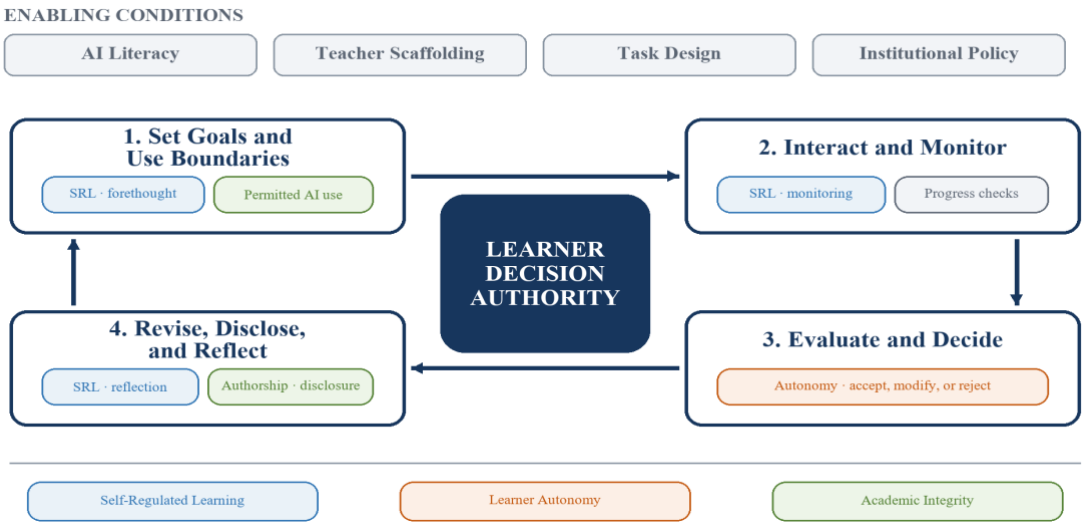


Figure 1. The task-level decision cycle of the HCAILL Framework.

Set Goals and Use Boundaries. The learner identifies the capability to be developed, records a specific goal, and considers the criteria for successful performance. The teacher or task brief states permissible functions, prohibited forms of generation, required disclosure, and any independent component. A goal such as "improve cohesion while retaining my argument" gives later feedback a standard against which it can be judged. It also prevents the available features of a tool from implicitly redefining the task.

Interact and Monitor. The learner requests assistance that targets a difficulty while preserving the central cognitive work. In writing, appropriate requests might ask the system to locate unclear transitions, explain a recurring article error, or pose questions about an unsupported claim. During speaking practice, the learner might request a role-play at a defined proficiency level and delayed feedback on selected features. Monitoring concerns both progress toward the learning goal and the changing share of work performed by the system.

Evaluate and Decide. Generated output is examined for accuracy, relevance, audience, and consistency with the learner's intended meaning. Advice may be checked against course materials, dictionaries, corpora, or teacher guidance. The learner accepts, modifies, or rejects consequential suggestions and articulates the basis for that decision. Feedback can function as scaffolding when the learner recognizes the underlying issue and applies that understanding in revision. Because immediate acceptance reveals little about learner judgment, this stage requires explicit metacognitive support. Such support strengthened task strategy and self-evaluation in Xu et al.'s (2025) four-week study, while Anders and Dux Speltz (2025) identify evaluation as a distinct phase of human-centered AI use.

Revise, Disclose, and Reflect. The learner performs the revision and provides a proportionate account of the tool, purpose, and extent of assistance. For substantial assessment, an initial draft, selected exchanges, tracked changes, or a short decision note may be retained. Reflection returns to the original goal: what changed, which difficulty remains, and whether a similar task can now be completed with less help. A brief unaided transfer task can examine this judgment. The timing and extent of reduced assistance require deliberate pedagogical planning by learners and teachers.

Because the cycle is recursive, an unsuitable response may require a narrower request, while a revision may expose a new learning need. Teachers model evaluation and determine task conditions, and institutions supply coherent rules, privacy safeguards, and accessible alternatives. This arrangement develops the co-regulatory account of Lodge et al. (2023) by specifying the learner decisions and process evidence required within a single language task.

Consider an intermediate learner writing a 180-word opinion paragraph. The learner prepares an outline and first draft without AI, with the goal of improving cohesion while preserving the original argument. The assignment permits diagnostic feedback but excludes replacement text. The learner asks the system to identify two weak connections, explain each problem, and respond with questions instead of rewritten sentences.

One observation is accepted. A proposed connector is rejected because it signals contrast where the argument requires a result, and the learner selects another expression after consulting course material. The submission includes both drafts, the relevant exchange, a brief rationale, and a disclosure. A later unaided paragraph then provides evidence of transfer. The claim that learning occurred rests on the learner's documented decisions and subsequent performance, since surface quality alone provides incomplete evidence.

The stages also apply beyond writing, although each skill calls for different boundaries. In a speaking task, the system may sustain a role-play while the learner controls the topic, monitors recurring errors, and later performs a comparable exchange with a person. For listening, AI can generate questions or adjusted-speed practice, while an independent item checks whether comprehension transfers to unfamiliar speech. Reading activities may use AI to explain a difficult passage after the learner records an initial interpretation. These applications preserve a common decision structure. Claims of equal benefit across skills would exceed the available evidence, which remains concentrated in writing (Lee et al., 2025).

The framework also suggests observable indicators for empirical work. Forethought can be examined through the specificity of goals and the fit between those goals and requested assistance. Monitoring appears in prompt revisions, progress checks, and moments when the learner consults another source. Autonomy becomes visible in reasons for accepting, modifying, or rejecting output. Integrity can be assessed through the consistency among task rules, disclosed assistance, revision history, and independent demonstration. These indicators should be interpreted together. A long prompt history may document extensive use while revealing little reflection, whereas a short decision note can show that the learner identified a substantive error and revised deliberately.

These indicators permit more discriminating empirical tests than comparisons based solely on final products. A classroom study could assign the same feedback tool under open and bounded request conditions, then compare the accuracy of learner evaluations and later unaided performance. Another design could vary the reliability of generated advice to examine when learners consult external sources or seek teacher input. Outcomes would include revision quality, error detection, calibration between confidence and performance, retention, and transfer. Because prompt logs offer an incomplete measure, process traces should be combined with learner explanations and teacher judgments. Such designs would test whether bounded assistance and metacognitive prompts improve evaluation and later performance, addressing concerns about metacognitive laziness and evidence on explicit metacognitive support (Fan et al., 2025; Xu et al., 2025).

4. Discussion and Pedagogical Implications

HCAILL places the sequence of learner decisions at the center of analysis. The same application may prompt reflection in one assignment and perform the target work in another, a distinction that product quality alone cannot establish. Drafts, concise decision explanations, and independent follow-up performance provide more informative evidence through selective records that limit the collection of complete conversation histories.

Process evidence should be sampled for a clear pedagogical reason. Extending privacy and data-minimization principles to assessment, HCAILL recommends against collecting complete prompt histories unless they are pedagogically necessary (Erduran, 2025; Miao & Holmes, 2023). Such collection may expose personal data, create unnecessary surveillance burdens, and reward documentation volume over careful learning. A teacher may request the initial attempt, one consequential exchange, and a brief explanation of the resulting decision. The appropriate record depends on the assessment stakes and the capability being judged. This selective approach keeps traceability available while limiting the amount of student data collected.

The framework's contribution is narrower than the adjacent models on which it builds. Kong and Yang (2024) provide a human-centered learning and teaching architecture, Anders and Dux Speltz (2025) connect GenAI literacy to SRL, and Lodge et al. (2023) explain co-regulation across a wider network. HCAILL translates those insights into a foreign-language task cycle that joins decision authority to authorship, disclosure, and reflective revision. Its practical value depends on explicit task boundaries. Teachers must name the skill being assessed, the assistance that remains compatible with that skill, and the process evidence that is genuinely informative.

Assessment can combine the final language product with a concise revision memo, checkpoint, oral explanation, or unaided transfer activity. The burden should remain proportionate to task stakes and privacy risks. At institutional level, policy must address data protection, accessibility, authorship, and meaningful alternatives for learners who cannot or do not wish to use a particular system (Miao & Holmes, 2023). AI literacy includes checking advice, recognizing uncertainty, protecting personal information, and knowing when further assistance would displace one's own work.

Teacher scaffolding changes across the cycle. Early instruction may model how to formulate bounded requests, compare output with reliable language resources, and explain a revision. Later tasks can remove some prompts or require an independent attempt before assistance becomes available. The pace of this reduction should respond to observed performance and remain flexible.

Learners with lower proficiency may need stronger linguistic support, while advanced learners may require more demanding checks on register, argument, and voice. Planned fading becomes a documented instructional choice tied to evidence of readiness.

Because reviews describe distinct uses and risks across language skills, task boundaries should vary by skill (Law, 2024; Lee et al., 2025). Productive tasks require particular care because generated wording can replace the performance being assessed. Receptive tasks raise a different issue: explanations and summaries may direct interpretation before the learner has engaged with the source. In both cases, an initial attempt gives the teacher a reference point for later assistance. Collaborative tasks add peer decisions to the record and may require agreement about when AI input enters the group process. The framework supplies a common cycle, while teachers adapt its boundaries to proficiency level and assessment purpose.

Implementation may remain superficial even when all four stages appear in an assignment. Learners may lack the proficiency needed to detect a plausible error or may treat a required decision note as a routine compliance exercise. Ambiguous institutional policy can leave teachers with incompatible definitions of permitted assistance, while restricted access can make an AI-dependent task inequitable. Time pressure may also encourage immediate acceptance despite well-designed prompts. Effective implementation requires reliable reference materials, teacher review for uncertain evaluations, substantive examples of decision notes, policy language linked to learning outcomes, accessible alternatives, and sufficient time for revision. These surrounding conditions warrant the same analytical attention as the learner's visible interaction with the system.

HCAILL is a conceptual framework derived through purposive synthesis and has not yet been empirically validated. Existing evidence is concentrated in higher education, English, learner perceptions, and writing (Lee et al., 2025), while chatbot studies are heterogeneous and often short-term or single skill (Wiboolyasarin et al., 2025). Its operation may vary by access, proficiency, task, teacher support, and system reliability, and the four stages may overlap in practice. Classroom studies should test whether bounded requests, decision notes, and gradual withdrawal of support improve evaluation, calibration, and later unaided performance. A measurement scale would require separate validation; favorable perceptions alone cannot demonstrate regulation or transfer.

5. Conclusion

HCAILL organizes human-centered GenAI use around four connected activities: defining goals and boundaries, monitoring interaction, evaluating generated output, and revising work through disclosure and reflection. Within this cycle, self-regulated learning provides the temporal structure through which learners plan, monitor, and reconsider their actions. Learner autonomy identifies the linguistic and strategic choices that should remain under human control, while academic integrity connects permitted assistance with visible authorship and valid assessment. Bringing these functions together makes it possible to examine AI use through the decisions made during a task rather than through the quality of the final product alone.

For teachers, the framework offers a practical heuristic for defining acceptable assistance, designing prompts for reflection, and selecting proportionate evidence such as drafts, decision explanations, or subsequent independent performance. For researchers, it identifies observable processes that can be examined without treating frequency of AI use as evidence of effective learning. HCAILL nevertheless remains a conceptual proposal. Empirical research should investigate how its stages operate across languages, proficiency levels, skills, assessment conditions, and institutional contexts. Such studies should also examine whether bounded AI assistance strengthens

learner judgment, supports transfer to unaided performance, and preserves a recognizable learner contribution over time.

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Privacy-Aware Artificial Intelligence-Based Cybersecurity Training Model (PACE): A Privacy-Protected Framework for Secure Artificial Intelligence-Powered Education Systems

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Abstract

Applications of artificial intelligence in education (AIED) today rely on learning analytics, conversational agents, automated feedback, and adaptive decision support systems. All of these tools process extensive student data. The resulting tension is permanent: institutions want to leverage the pedagogical value of data-intensive artificial intelligence (AI), but they are also responsible for student privacy, cybersecurity, transparency, and regulatory compliance. The learning analytics literature has shown that privacy risks extend to every stage of the analytics lifecycle. Human-centered AIED studies reveal that issues related to security, reliability, and human oversight are still open. The regulatory environment has also hardened. The General Data Protection Regulation (GDPR) mandates data minimization and data protection from design; in Türkiye, the Kişisel Verilerin Korunması Kanunu (KVKK; Personal Data Protection Law No. 6698) imposes similar principles and security obligations; the European Union Artificial Intelligence Regulation considers many educational uses to be high-risk. This study proposes the Privacy Aware AI-Based Cybersecurity Training Model (PACE), which combines the aforementioned requirements in a single reference architecture. The model is a Design Science Research (DSR) output and consists of five layers: identity protection with pre-processing data minimization, behavioural anomaly detection, layered prompt injection defence for large language model (LLM) services, risk-based contextual access, and continuous privacy/compliance monitoring. The model we have developed in this direction aims to place privacy at the center of the system architecture without sacrificing the educational opportunities offered by artificial intelligence. The design has two limits: the analytical benefit will be preserved, and the security controls will not turn into student surveillance. PACE is not a deployed software system. Instead, the study presents a theoretically grounded architecture, a training-specific threat-control mapping, a clear design rationale, and a phased assessment plan. A conceptual evaluation conducted over representative threat scenarios showed that the five layers did not replicate each other. The same assessment also made visible trade-offs such as false positives, risk of re-identification, evolution of prompt attacks, and the limits of automated compliance. The proposed validation roadmap identifies measurable metrics ranging from lab prototyping to pilot runs: precision and sensitivity in identifying personally identifiable information, false positive rates in anomaly detection, prompt attack success rate, audit integrity, privacy-benefit protection, and system latency.

Keywords: Artificial Intelligence in Education, Privacy by Design, Student Data Protection, Cyber Security, Learning Analytics, Design Science Research.

Introduction

AI is no longer a peripheral component of educational technologies but is increasingly embedded in learning platforms. Intelligent teaching systems, automated feedback, adaptive recommendation mechanisms, learning analytics, and more recently generative AI assistants can offer more responsive and personalized learning experiences. Many AI-driven educational applications rely heavily on the collection and processing of learner-related data to adapt instruction, provide feedback, and support educational decision-making (Holmes et al., 2019).

The problem arises not only from the volume of data collected but also from its sensitivity and potential for combination. A learning platform keeps together credentials, exam and assignment results, session logs, clickstreams, device features, and student inputs in free text for a single semester. These records appear ordinary when viewed separately; when combined, they turn into a detailed portrait that reveals the student's study habits, difficult subjects, and even their daily routine. This is exactly what makes personalization possible. The same richness increases the potential harm of a breach, enables intrusive profiling, and supports inferences that were not anticipated when the data were collected. The central concern is that institutions pursuing pedagogical benefits may inadvertently place students within a continuous cycle of digital surveillance.

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Privacy concerns therefore cannot be confined to a single database or a single point in the system lifecycle. Pardo and Siemens (2014) considered privacy, trust, accountability, and transparency as interconnected design issues. More recent systematic evidence points in the same direction: data protection issues persist across all stages of collection, analysis, reporting, and sharing, and the hands-on evidence for the effectiveness of proposed solutions is still limited (Liu & Khalil, 2023). Alfredo et al. (2024) also identified clear gaps in end-user engagement and safety, security, and reliability in their review of human-centered learning analytics. The common implication of these findings is clear: privacy is not a form of compliance that is filled out once the system is deployed. It needs to shape the architecture, data flows, access decisions, and interfaces that interact with the model from the beginning. The long-term effects of personalized learning, student profiling, and data-driven classification should also be evaluated within the same framework (Regan & Jesse, 2019; Tabassi, 2023). Taken together, these findings suggest that privacy should not be treated as a compliance layer added after software development, but as a core quality shaping the architecture from the outset.

The regulatory context reinforces this necessity. The GDPR considers purpose limitation and data minimization as fundamental principles, requiring data protection by design and default (European Parliament and Council, 2016). The KVKK also stipulates that personal data must be processed for specific and legitimate purposes and in a relevant, limited, and proportionate manner; Article 12 obliges data controllers to take appropriate technical and administrative measures (Republic of Türkiye, 2016). The European Union Artificial Intelligence Regulation, in turn, considers the evaluation of learning outcomes, determination of access to education, and monitoring of prohibited behaviors in exams among high-risk uses. Robustness, cybersecurity, documentation, and human oversight thus become central to AI governance in education (European Parliament and Council, 2024). This need is also consistent with broader analyses of the ethical and legal obligations surrounding AI-driven management information systems (Erduran, 2025). Together, these frameworks show that privacy-aware security is not merely a technical choice but a requirement for sustainable institutional governance.

The second challenge is the breadth of the threat surface. An AI-powered training system offers more attack points than a traditional learning management system. Risk doesn't just arise directly from identifiers; re-identification through behavioural traces is also possible. Machine learning models are susceptible to membership inference and similar privacy attacks (Shokri et al., 2017). Large Language Model (LLM)-powered applications add the risks of prompt injection and system prompt leakage. These vulnerabilities are exacerbated when the model accesses evaluation logic, student records, information retrieval systems, or privileged tools (Greshake et al., 2023; Open Worldwide Application Security Project [OWASP], 2025). Cai (2026) examined how prompt injection attacks pose a risk to automated evaluation workflows in large language models for training. The key concern is that the flexibility of language models creates vulnerabilities that traditional perimeter defences alone cannot address.

Existing controls often work independently of each other. Identity and access management focus on authentication, privacy programs focus on policy and consent, data loss prevention tools focus on identifiers, anomaly detection focuses on suspicious behaviour, and large language model security measures focus on prompt limits. Gaps open exactly where these controls converge. Successful authentication does not mean that all subsequent actions of that session will be trustworthy. Masking direct identifiers does not prevent re-identification from distinctive behaviour patterns. A regulatory retention policy alone cannot stop a language model from revealing protected context through a malicious prompt. PACE addresses this fragmentation by treating the protection of student data as a continuous and layered process rather than as a disjointed set of measures.

The central question of the study is: How can privacy, cybersecurity, and regulatory controls be integrated throughout the lifecycle of AI-powered training data while maintaining sufficient analytical utility to support learning? Two helpful questions guide the design. What education-specific requirements should shape such an architecture? How can a conceptual architecture be evaluated before field implementation, without drifting into untested efficacy claims? Accordingly, the study seeks to connect theoretical privacy principles with an architecture that can be tested and sustained in practice.

The study offers four contributions. First, it aggregates privacy, anomaly detection, language model security, contextual access, and compliance issues into a single education-specific threat model. Second, it lays out a five-tiered reference architecture that maps each threat class to concrete design controls. Third, it gives a rationale matrix that makes trade-offs and measurable validation metrics visible, rather than automatically counting technical choices as correct. Fourth, it defines a phased evaluation roadmap that separates conceptual competence from laboratory performance and real-world effectiveness. These enumerated contributions reflect the unique value our study offers to both the theoretical literature and the security architectures implemented by educational institutions.

Related Studies and Research Gap

Privacy, Learning Analytics, and Data Minimization

Learning analytics is based on the collection and transformation of student data. The trade-off between privacy and utility is therefore structural. The DELICATE framework (Determination, Explain, Legitimate, Involve, Consent, Anonymise, Technical, and External) defined credible learning analytics with dimensions of organizational responsibility, transparency, consent, anonymity, and security (Drachsler & Greller, 2016). De-identification reduces the risk of direct disclosure but does not eliminate the risk of re-identification. When activity patterns, course selections, and temporal traces come together in training datasets, they continue to function as quasi-identifiers (Khalil & Ebner, 2016). Recent reviews also emphasize that technical measures alone cannot be considered an anonymization task and should be considered in conjunction with institutional practices (Liu & Khalil, 2023; Amo-Filva et al., 2024). This necessitates a more dynamic conservation approach that goes beyond static masking techniques and preserves the semantic context of the data.

PACE keeps pseudonymization and anonymization separate. Pseudonymization replaces the direct identifier with a controlled identifier and retains the re-identification mechanism; such data remains personal data under the GDPR. The goal of anonymization is to eliminate reasonable means of re-identification. Providing irreversible anonymity in rich and relatable data sets is difficult, and the outcome varies depending on the context (Finck & Pallas, 2020). For this reason, the architecture prefers pseudonymization in operational analytics where longitudinal connectivity is essential, and aggregation or stronger anonymization in shares where individual continuity is not required. This differential preference we adopted in our study aims to strike the most reasonable balance between the need for analytical data and legal compliance obligations.

Behavioural Anomaly Detection

Training platforms produce time-stamped access and interaction logs. These records can support account takeover, automated data extraction, and insider abuse detection. Anomaly detection is especially useful when malicious behaviour does not match a known signature, and the most reliable reference available is normal behaviour (Chandola et al., 2009). In educational settings, labelled attack data is often scarce. PACE therefore chooses the support vector machine family as its starting baseline and envisages testing the One-Class Support Vector Machine (OCSVM) candidate in laboratory validation. OCSVM predicts the support of a high-dimensional distribution from predominantly normal observations and can flag deviations without a large amount of labelled attack data (Schölkopf et al., 2001). Our choice of the OCSVM model as a starting point is based on our goal of establishing a practical and testable baseline in educational environments where labelled attack data is scarce.

This is not a claim of superiority, but a design hypothesis to be tested. behavioural logs are context-dependent, periodic, and prone to concept drift. Usage patterns related to exam weeks, assignment deadlines, or accessibility produce perfectly legitimate deviations. The architecture therefore does not count anomaly scores as evidence for automated discipline or academic decision; it uses scores in conjunction with risk-based responses and human review. We would like to emphasize that anomaly detection is not a stand-alone decision mechanism in our model, but a proportional early warning signal that supports human expertise.

Large Language Model Safety and Prompt Injection

In language model-based training assistants, natural language input can carry both legitimate learning content and an offensive instruction. What arises is a boundary problem. Indirect prompt injection further blurs the distinction between data and instruction when the model fetches external documents or tool outputs (Greshake et al., 2023). OWASP (2025) identifies prompt injection as the leading risk in the 2025 list, noting that retrieval augmentation or fine-tuning alone does not close this gap. Training-specific studies also show that offensive prompts pose a real risk to evaluation-driven workflows (Cai, 2026). These risks we have examined suggest that large language model integration is not just another interface update but a direct system-level security architecture issue.

A simple blacklist is not sufficient for this threat landscape. PACE combines rule-based filtering with machine learning classification, then embeds these checks into a broader defence-in-depth approach: context validation, least privilege tool access, protected system instructions, output validation, and security logs. The goal is not to claim that prompt injection is completely prevented. The goal is to reduce risk and limit its impact when the attack is successful. The basic logic of our approach is to weave a multi-layered resistance line, since no single filter can provide complete sealing.

Contextual Access and Zero Trust

Traditional authentication confirms identity at a specific moment. It does not guarantee that subsequent requests will remain trustworthy. Zero Trust Architecture rejects implicit network trust and ties decisions to a continuous,

resource-centric evaluation based on user, device, entity, and context signals (Rose et al., 2020). Multi-factor authentication improves account security, but it is only one part of a broader access control strategy (Ometov et al., 2018). PACE is therefore not a replacement for built-in identity mechanisms; it uses contextual risk as a secondary control after authentication. In our proposed structure, we do not treat access as a static right acquired once, but as a dynamic state that needs to be constantly verified.

This is where the idea of evaluating the model's physical and digital access information together comes from. However, in the architecture, physical access data is explicitly optional and limited for privacy. If the institution already operates a lawful access control system, a time-limited campus entry statement can contribute to contextual risk. Continuous Global Positioning System (GPS) tracking, detailed location history, and irrelevant behavioural monitoring are out of the design. Without this boundary, security telemetry easily becomes a new surveillance mechanism. Our main goal with this clear boundary is to prevent security measures from transforming the pedagogical environment into a digital surveillance mechanism.

Research Gap

The literature contains mature contributions in the fields of ethical learning analytics, de-identification, anomaly detection, Zero Trust, and language model safety. However, these research lines have largely developed as separate problem areas. Recent reviews say that there is a need for privacy-aware architectures and stronger evidence of how protections work throughout the entire analytical lifecycle (Liu & Khalil, 2023; Amo-Filva et al., 2024). Human-centered AIED research also shows that automation and human control need to be balanced, and security should be considered as a system-level attribute (Alfredo et al., 2024). PACE responds to this gap in two ways: it combines controls into a single reference architecture specific to education and clearly states that it has not yet been validated and with what criteria it will be tested. The study's central purpose is therefore to address this fragmentation by bringing these control mechanisms together within a coherent architecture.

Method: Design Science Research

PACE was developed using Design Science Research (DSR). DSR is an information systems methodology that creates artifacts to address specific problems and aims to contribute to generalizable design knowledge while evaluating these artifacts (Hevner et al., 2004; Gregor & Hevner, 2013). The method is appropriate here, because the core output of the research is a model architecture. PACE is thus positioned as a design artifact whose utility should be demonstrated and evaluated progressively, not as an assumption. Our methodological choice ensures that the architecture we develop does not remain an abstract claim but provides a concrete engineering response to complex cybersecurity problems.

The process follows the Design Science Research Process (DSRP) defined by Peffers et al. (2006) with six activities: problem identification and motivation, determination of solution goals, design and development, demonstration, evaluation, communication. In this study, demonstration and evaluation are at the conceptual level. Representative threat scenarios are executed through the proposed layers, and each design choice is mapped to a measurable criterion for subsequent prototyping. The distinction is important: the paper makes claims of consistency and testable design, while empirical studies will demonstrate detection accuracy and real-world privacy improvement. This clear distinction we establish in the process transparently limits the current theoretical scope of our study and future empirical expectations.

Table 1. Mapping DSRP activities to the PACE development process.

DSRP event	PACE research activity	Current output
1. Defining the problem and motivation	Synthesis of privacy, cybersecurity, language model, access control, and regulatory risks in AIED	Education-specific threat surface and basic research question
2. Defining solution objectives	Derivation of minimization, identity protection, anomaly detection, prompt security, contextual access, human oversight, and auditability requirements	Design requirements (DR1–DR6)
3. Design and development	Creation of five-tier PACE architecture and data flow logic	Reference architecture and control limits
4. Demonstration	Scenario-based execution of representative threats such as prompts containing personal data, account takeover, prompt injection, access context mismatch, and retention drift	Threat-control matching
5. Evaluation	Analytical comparison of selected controls, limitations, failure patterns and measurable future metrics	Design rationale and verification matrix

DSRP event	PACE research activity	Current output
6. Communication	Documentation of the architecture, limitations, and phased validation plan for academic and practitioner audiences	Full-text article and future application specification

Design Requirements

The six requirements below provide the bridge between the theoretical principles and the architecture's concrete design decisions.

DR1 — Minimise before model exposure. AI components should only receive the data necessary for a defined educational or safety purpose, and direct identifiers should be removed or transformed as early as possible.

DR2 — Preserve utility without unnecessary identity linking. Operational continuity should be based on controlled pseudonym identifiers, and aggregation or anonymization should be preferred for external or secondary usage data sets where no connection is required.

DR3 — Detect anomalous usage without turning learning analytics into a surveillance tool. Security models should operate with a narrow set of features, retention periods should be clear, response thresholds should be calibrated, and consequential processes should be subjected to human review.

DR4 — Count language model inputs as untrusted data. Prompt processing should separate instruction from data, use deterministic and learned scanning together, limit tool privileges, and validate output.

DR5 — Continuously evaluate the context of access under the principle of least privilege. Authentication should be supported by privacy-limited contextual risk signals; physical proof of access should remain optional and under no circumstances should it turn into continuous location tracking.

DR6 — Make privacy and compliance observable. Data purposes, retention periods, accesses, transformations, flows interacting with the model, and exceptions must be auditable so that technical operation can be compared to organizational policy and legal requirements.

PACE Reference Architecture

The architecture adopts a defence-in-depth approach. Layers I–IV operate as complementary control points in the data and access lifecycle; Layer V is a governance and compliance plane that cuts across all layers. No mechanism replaces another. Masking is not a substitute for access control, anomaly detection is not a substitute for authentication, and compliance monitoring is not a substitute for legal compliance. Instead, the model defines interfaces where each control can mitigate a different risk class. Our main design goal in the architecture is to build a flexible and resilient security ecosystem where each layer closes the vulnerability of the other.

Table 2. Logical view of the five-tier PACE reference architecture.

Layer	Purpose and basic functions
Cross-Layer — Layer V: Privacy and Compliance Monitoring	Intent registration; retention rules; audit events; data protection impact assessment (DPIA) evidence; rights and appeals support; policy checks
Layer I: Data Detection and Minimization	regular expression (regex) + named entity recognition (NER) → intent filter → masking/tokenization → controlled pseudonymization
Layer II: Behavioral Anomaly Detection	Minimized security telemetry → OCSVM baseline → calibrated risk score → human review trigger
Layer III: Language Model Prompt Safety	Rule checks + machine learning classifier → context/policy validation → least-privilege tool authorization → output validation
Tier IV: Contextual Access Integration	Additional verification, limitation, or review → identity + device + session context + optional lawful physical access declaration
Protected processing limit	Only authorized, minimized, and policy-compliant data and actions reach the next AI/analytics services

Layer I — Data Detection, Minimization, and Identity Protection

Layer I is positioned before each operation that interacts with the model or analytics. Structured identifiers such as email address, phone number, student number, or nationally regulated identity fields can be captured by deterministic patterns. Unstructured text requires Named Entity Recognition (NER) methods that can distinguish names, institutions, and locations. Neural NER architectures provide an established foundation for this task (Lample et al., 2016), but the final model selection should be language and domain specific. The goal is not to

infer every possible identity attribute; it is to reduce unnecessary exposure before the content reaches higher-risk components.

The conversion policy is determined by the purpose of processing. If longitudinal analysis is required, direct identifiers are replaced with pseudonym identifiers; re-identification matching is separated from the analytical environment and kept under tighter access control. If individual connectivity is not required, the architecture chooses irreversible aggregation or anonymization. PACE thus avoids the mistake of counting pseudonymized records as anonymous. The design also stipulates that the fields that are actually needed for the educational task are defined with an allowlist. Collecting data indiscriminately and then masking everything goes against the spirit of data minimization.

Layer I should be evaluated for both under- and over-masking. Future prototypes will report precision, recall, F1 score, false negative disclosure rate, over-redaction rate, and processing latency. Together, these metrics make sense. An overly aggressive detection system protects privacy at the cost of distorting pedagogically meaningful text; an overly permissive system exposes direct identifiers. Our key criterion here is to achieve a balance of proportional redaction that protects privacy without interrupting the flow of data to the AI model.

Tier II — Behavioural Anomaly Detection

Layer II only receives security telemetry after minimization. The candidate feature vector can include daytime deviation, session duration, request frequency, download volume, device pseudonym, and ephemeral network risk indicators. The first specification uses OCSVM as a baseline, because the method can learn the limit of normal behaviour from predominantly non-malicious data (Schölkopf et al., 2001). If the empirical comparison shows that another method provides better calibration, a lower false positive rate, or higher resilience to concept drift, the baseline can be changed or used as an ensemble.

An anomaly score is not considered evidence of abuse. PACE applies proportional responses. Low-risk biases remain observable but do not disrupt learning. Medium risk can trigger additional authentication or throttling of access to sensitive functions. High-risk combinations temporarily limit privileged operations and create cases for human review. Numeric thresholds were not intentionally fixed in the conceptual model; they need to be calibrated on institutional data and validated in different academic periods. Otherwise, arbitrary thresholds are mistaken for evidence-based security policies.

The principle that limits the layer is surveillance minimization. Unless there is a separate and clear legal and pedagogical basis, the semantic content of course content, private messages, and assignments do not fall under the anomaly feature vector. The choice is clear: what is monitored is not the content of the student's learning activity, but the security features of the access. While highlighting security concerns in our design, we have adopted the principle of setting flexible thresholds that will not disrupt the natural learning flow of students.

Tier III — Prompt Injection Defense for Educational Language Models

Tier III protects language model-powered services from instructions that constitute offensive or policy violations. In the first stage, deterministic checks run for known violation patterns and high-risk control statements. In the second stage, a learned classifier predicts malicious or out-of-scope intent. Since both mechanisms are circumventable, context validation comes into play in the third step: the requested action must be consistent with the educational role, course scope, user authority, and data classification associated with the session.

The architecture's primary emphasis is on limiting capabilities. Language models should not be granted unlimited database credentials or broad tool authority. Knowledge retrieval queries should be scoped, sensitive areas should remain minimized, and actions with academic or privacy implications should require explicit authorization or human review. Before the model output is presented to the user, it is checked for sensitive data disclosure, prohibited action, and policy conflict. These checks align with the core takeaway of indirect prompt injection research: the system should assume that every piece of content the model can read can become an instruction channel (Greshake et al., 2023).

Future testing will cover direct, indirect, obfuscated, and role-mixing attacks related to training scenarios. The evaluation will report the attack success rate (ASR), false rejection rate for harmless prompts, sensitive information disclosure rate, and conservation of utility in legitimate educational tasks. Since prompt attacks evolve rapidly, Layer III is defined as an updateable control plane, not a one-time filter. By strictly limiting language model authorizations in our model, we aimed to minimize the impact of the damage even in the event of a possible infiltration.

Tier IV — Risk-Based Contextual Access Integration

Layer IV extends authentication with a continuous but minimized contextual risk assessment. Key signals include device familiarity, number of concurrent sessions, coarse network location, Internet Protocol (IP)/autonomous system number (ASN) reputation, access time bias, and sudden changes in request pattern. According to Zero Trust principles, access to sensitive resources is a resource-specific decision, not an indefinite vested right because it is authenticated once (Rose et al., 2020).

Physical access integration is optional. If the institution has a lawful access control system, PACE may be content with a crude statement such as "campus access observed in the relevant time window" instead of importing detailed movement history. The value of the signal is contextual, not deterministic. A student working or learning remotely should not be penalized simply for the absence of a physical event. Every use of physical data should be tied to a defined purpose, retention period, and access limit. The design thus avoids the continuous monitoring model while maintaining physical-digital integration.

Reactions follow the same principle of proportionality as Tier II. Normal access continues; rising risk may require additional authentication; high-risk requests may be restricted to lower-privileged functions until review is complete. Evaluation will focus on the false verification prompt rate, detection of simulated account takeover, user friction, verification completion rate, and the additional value of each contextual signal. Keeping the physical signal optional is a conscious design choice of ours to prevent remote learning students from facing unfair restrictions.

Tier V — Privacy, Compliance, and Accountability Monitoring

Layer V forms the governance plane of the architecture. It maintains a machine-readable link between data processing purposes, allowed fields, retention periods, authorized recipients, transformation rules, and logging requirements. Thus, from conception, privacy decisions become observable during system operation. For example, a policy engine might catch that a flow interacting with the model carries a field that is not allowed for the registered intent, or that a short-lived security identifier exceeds the retention period.

Layer V supports legal compliance but cannot guarantee it. GDPR's data minimization and data protection requirements from design provide a direct normative basis for both the Tier I and cross-layer governance model (European Parliament and Council, 2016). The KVKK's principles of purpose limitation, proportionality, retention limitation, and data security provide a parallel basis in Türkiye (Republic of Türkiye, 2016). The European Union Artificial Intelligence Regulation adds an additional governance rationale for risk management, documentation, cybersecurity, and human oversight (European Parliament and Council, 2024). In contrast, legal interpretation, evaluation of the processing requirement, corporate policy, ethics committee approval, and data subject rights cannot be delegated to an automated rules engine.

Audit logs themselves are also privacy sensitive. PACE therefore requires minimum event metadata, controlled access to logs, defined retention periods, and separation of security evidence from educational content. When integrity protection is required, events can be cryptographically chained or tamper evident. However, immutability is not a justification for indefinite retention. Thanks to this layer, we transform regulatory compliance from a statement on paper to a continuous audit mechanism of the working system.

Conceptual Demonstration and Evaluation

This section tests architectural inclusivity, not empirical performance. Five representative scenarios were selected to see if the layers responded to different but interactive threat classes. The representation format aligns with the current maturity of the artifact and provides a transparent transition to laboratory experiments. The scenarios we constructed were chosen to verify the theoretical consistency of our architecture and its holistic response capability to complex threats.

Table 3. Conceptual threat-control representation of PACE.

Scenario	Fundamental risk	PACE response	Residual risk / validation requirement
Q1. Student input containing personal data reaches the artificial intelligence assistant	Direct identity disclosure and unnecessary model exposure	Tier I directly detects or removes identifiers; Tier V controls intent and domain policy	NER false negatives; contextual semi-descriptors may remain
Q2. Unusual bulk data extraction of the compromised account	Account takeover or insider abuse	Flags Layer II behavioural drift; Raises Layer IV access risk and triggers additional validation	Legitimate densities due to delivery date can produce false positives

Scenario	Fundamental risk	PACE response	Residual risk / validation requirement
Q3. Student input attempts to override system instructions and disclose assessment material	Prompt injection, system prompt leakage, grading manipulation	Tier III filters and classifies input, verifies educational context, limits tools, controls output	New or obfuscated attacks remain possible; ASR must be measured continuously
Q4. Digital session context conflicting with trusted device and access history	Credential theft or session hijacking	Layer IV combines privacy-restricted digital context and optional physical access declaration	Remote learning and accessibility patterns can reduce signal reliability
Q5. The data flow exceeds the stated purpose or retention period	Regulatory/policy deviation and accumulated exposure	Detects Tier V policy mismatch; Implements Tier I and IV minimized fields and ephemeral identifiers	Automated checks are not a substitute for legal review or corporate governance

Design Rationale and Future Criteria

Table 4. PACE design rationale and validation criteria.

Layer	Selected design	Why it was chosen	Basic limitation	Planned criteria
I	Regex + NER + intent filtering	Combines high precision in structured descriptors with contextual entity detection in free text	Language and space dependency; excessive or insufficient masking	Precision, sensitivity, F1, disclosure rate, over-redaction, latency
II	OCSVM baseline	Can model normal behaviour when labelled attack data is scarce	Concept shift, class and context difference, false positives	F1 score; area under the receiver operating characteristic curve (AUROC); area under the precision–recall curve (AUPRC); false positive rate; calibration; subgroup false positive difference
III	Rules + machine learning + capability limitation	It addresses semantic diversity and shrinks the domain while maintaining deterministic controls	Adaptive attacks; rejection of harmless inputs; model and provider variability	ASR, false rejection rate, disclosure rate, benefit conservation
IV	Contextual Zero Trust with optional physical signaling	Reassesses risk upon login and supports proportional additional validation	Privacy cost and user friction; remote learning uncertainty	False verification prompt rate, account takeover detection, completion rate, friction time
V	Policy-aware privacy and compliance monitoring	Data minimization makes retention and audit requirements operationally observable	Cannot independently determine legal compliance	Policy coverage, retention exceptions, audit integrity, DPIA traceability

Discussion

PACE's contribution lies in integration. The model does not propose a new cryptographic primitive, anomaly algorithm, or prompt security technique. The design value lies in connecting controls, often managed by different technical and administrative teams, and placing them at the right points in the educational data lifecycle. This detail is important because most privacy errors are born at the boundary points. An analytics team can retrieve more credentials than it needs. A security team can collect telemetry without a narrow retention policy. A language model service can acquire broad privileges from what its pedagogical role requires. We believe that the real value we offer to the literature is not to invent a new component, but to combine existing security islands into a logical integrity.

The model also considers privacy as a system that must coexist with utility. Overly aggressive anonymization weakens longitudinal analytics, while unlimited identity linking magnifies exposure. PACE therefore uses pseudonymization when continuity is needed, aggregation when not, or stronger anonymization. The same proportionality applies to access control: the rising risk should first increase the level of verification rather than automatically removing a student from the system. This human-controlled design aligns with the human-centered

AIED approach, which emphasizes the protection of human will while improving security and reliability (Alfredo et al., 2024).

Another contribution is the clear demarcation between security telemetry and surveillance. The educational institution has legitimate grounds to detect account takeover, automated data extraction, or unauthorized access. These justifications do not justify unrestricted monitoring of student behaviour. PACE narrows the set of features used in security decisions, discourages content-level tracking, asks for short retention periods for contextual identifiers, and treats physical access information as an optional, crude signal. Without these constraints, the architecture that claims to protect privacy reproduces the problem it seeks to solve by extending continuous behavioural monitoring.

The framework is deliberately modular. Organizations can implement Layer I and Layer V before adopting a language model or deploy Layer III only around specific generative AI services. Layer II initially uses OCSVM as a baseline, then can be modified with another calibrated method. Modularity allows the architecture to operate as a reference model, not a vendor-dependent product, and makes it easier to compare between organizations with different backgrounds.

Limitations and Future Validation Studies

The most important limitation is that empirical application is not yet available. PACE is a conceptual DSR artifact, and the proposed layers are not claimed to deliver specific detection rates, privacy gains, or performance outcomes at this stage. All numerical performance values should be generated in future laboratory and field studies. This limitation is stated explicitly because architectural plausibility can easily be confused with demonstrated effectiveness. The distinction keeps the paper's theoretical design claims separate from future empirical findings.

Second, personal data detection is not foolproof. NER performance varies by language, context, and domain; even if direct identifiers are omitted, indirect identifiers may remain. Third, behavioural anomaly detection can produce disproportionate false positives when usage patterns differ between student groups or academic semesters. Fairness and subgroup error analyses should therefore be reported alongside traditional detection metrics, particularly in educational machine-learning applications where predictive patterns require careful, explainable interpretation (Erduran et al., 2026). Fourth, prompt injection defences operate against an ever-changing target, and no static filter can be considered complete protection. Fifth, if the institution collects more environmental data than necessary, contextual access controls create user friction and pose secondary privacy risks.

The evaluation roadmap consists of three phases. In the first phase, independent prototypes for Tier I–IV will be developed using synthetic or institution-approved de-identified datasets and a test language model environment. In the second phase, each tier will be measured separately, followed by an assessment of integrated latency and loss of utility. In the third phase, the model will be piloted in a limited educational setting, subject to ethical and institutional approvals; usability, false positive load, policy alignment, and stakeholder perceptions will be examined. This sequencing is essential, as technical performance alone does not prove acceptability in an educational setting.

Two expansions to privacy-preserving machine learning are also planned. Federated Learning can reduce the need to centralize raw training data by incorporating locally computed model updates (McMahan et al., 2017). Differential Privacy, on the other hand, can limit the impact of a single record on published statistics or model outputs with calibrated randomness (Dwork, 2006; Dwork & Roth, 2014). These techniques are not presented as already implemented layers; they are future expansions whose benefits and costs need to be examined empirically.

Conclusion

AI-powered training forces organizations to make security, privacy, and governance decisions simultaneously. Treating these responsibilities as disjointed and add-on processes is not enough for data-intensive learning analytics and language model-powered services. PACE addresses the problem with a five-tiered reference architecture: pre-processing minimization and pseudonymization, behavioural anomaly detection, prompt security, contextual Zero Trust access, and continuous privacy/compliance monitoring.

The contribution is more architectural and methodological than empirical. Using DSR, the study made design assumptions explicit, mapped threats to controls, identified failure patterns, and defined measurable evaluation criteria. The framework also sets strong limits on surveillance. Security analytics should collect only the minimum necessary telemetry, consequential decisions should remain subject to human scrutiny, and optional physical access integration should be coarse-grained, purpose-limited, and legally justified.

Future studies will show whether the conceptual benefits are preserved in practice. A rigorous prototype and phased evaluation should assess not only security performance but also privacy-benefit preservation, user friction,

fairness, system latency, auditability, and organizational governance. If empirical results support the design claims, PACE can provide a viable roadmap for institutions looking to adopt AI without counting student privacy as the cost of personalization. Ultimately, the PACE model represents a step towards establishing a safe, ethical, and privacy-aware educational AI ecosystem.

Generative AI Use Statement

During the development of the article, generative AI tools were used for drafting, language improvement, structural revision, and bibliography consistency checks. The conceptual architecture, source selection, verification of academic claims, interpretation of the literature, and final content of the article are the responsibility of the authors. All sources and content-specific claims were independently re-checked by the authors.

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A Conceptual Framework for Human-AI Interaction in L2 Writing: Promoting Learner Autonomy and Self-Regulated Learning

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Abstract

Improving writing skills is essential in language education; however, many learners have difficulty in developing writing proficiency. In this context, artificial intelligence (AI) represents a promising solution. The growing use of AI in educational environments has altered how learners engage with writing tasks and learning processes in terms of learner cognition, autonomy, self-efficacy, self-regulation, and critical thinking. AI technologies have been incrementally integrated into writing practice through interactive AI systems that provide ideas, give feedback, and support revision, while the cognitive implications of human-AI interaction have not been studied thoroughly. In particular, there is limited understanding of human-AI interaction and its influence on learner autonomy, self-regulated learning, and critical thinking during the implementation of writing activities. This study proposes a conceptual framework that examines how human-AI interaction in writing can inform cognitive engagement, self-regulation, self-efficacy, and critical thinking. Combining sociocultural theory, self-regulated learning theory, and learner autonomy research, the proposed framework conceptualizes AI as a mediational cognitive tool that learners interact with at the different stages of the writing process. Learners carry out cognitive and meta-cognitive activities such as planning, monitoring, strategy use, and evaluation, which are important elements of self-regulated learning through the interaction. Furthermore, human-AI interaction can enhance learner autonomy in terms of writing strategies, language use, and revisions. The framework determines key influential factors including learner characteristics, engagement with AI systems, and cognitive processes. The proposed model also focuses on the cognitive risks of cognitive offloading, overreliance on AI feedback, and moderated deep processing. By drawing upon interdisciplinary literature and a theoretically grounded framework, this research aims to provide insights into how human-AI interaction in writing can provide cognitively responsible and autonomy-based learning environments in language education.

Keywords: Artificial intelligence (AI), self-regulated learning, learner autonomy, learner cognition, language education

Introduction

Advanced second-language (L2) writing requires proficiency in various interrelated skills, such as content development, genre awareness, linguistic accuracy, and organizational competence (Chang, 2016; Liu et al., 2023). Classical approaches to education often struggle to provide adequate, personalized support across the stages of the writing process (Luo et al., 2025). L2 writing has undergone fast-paced development with the broader use of AI tools (Luo et al, 2025). AI can provide various advantages in order to improve students' writing skill such as timely and constant feedback for generating ideas and structures (Zhao, 2025), correction of grammatical mistakes (Wu et al, 2025), enabling coherence and cohesion (Barrot, 2023), brainstorming, revision or drafting of the writing process (Hwang et al, 2023), providing specific guidance for specialized tasks (Kwon et al, 2023). In addition, integrating AI into L2 writing has been linked to reduced writing anxiety, increased motivation, and improved writing skills (Huang et al., 2024; Liang et al., 2024; Wang et al., 2025). A large number of studies have examined the use of AI in writing; nevertheless, human-AI interaction and its effects on learner cognition, learner autonomy, self-regulation, self-efficacy, and critical thinking have been investigated from a limited perspective. Therefore, this study aims to approach AI technologies from cognitive and sociocultural perspectives and to present a conceptual framework for how human-AI interaction in writing can affect cognitive engagement, self-regulation, self-efficacy, and critical thinking by combining sociocultural theory, self-regulated learning theory, and learner autonomy research.

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Theoretical Foundations

Sociocultural Theory and AI-Mediated Learning

Vygotsky's social constructivism emphasizes the importance of scaffolding and collaborative language-learning activities to enhance learners' progress from their current level to a higher, more advanced level of competence. Drawing on this theory, interaction between a more proficient learner and a lower-proficiency learner can help learners improve and internalize their cognitive skills and behave autonomously in the learning process (Vygotsky, 1986). Whereas scaffolding has traditionally been delivered by humans, it can also be provided through technology, offering personalized, easily accessible support (Higgins et al., 2007). AI can be regarded as individualized mediation within the Zone of Proximal Development (ZPD), which enables learners to go beyond their current independent capacity through progressive internalization (Li & Bahari, 2026). To sum up, AI-mediated learning environments can facilitate interaction and help learners achieve high levels of proficiency through scaffolding within the ZPD (Song & Song, 2023; Liu et al, 2024). Learners can go beyond their ZPD through collaborative activities and AI-mediated platforms.

Self-Regulated Learning Theory

Self-regulated learning (SRL) has been regarded as a keystone of effective learning by supporting learners in setting goals, reflecting on outcomes in an autonomous and iterative cycle, and monitoring progress (Zimmerman, 2002). AI technologies have emerged as valuable tools for enhancing self-regulated learning (SRL) through personalized feedback and metacognitive scaffolding (Xu et al., 2026). These technologies demonstrate promise by providing innovative, data-driven methods to transform internal learning processes into more observable and supportable environments (Sposato, 2025). In addition, AI-based tasks in the L2 writing process provide students with writing awareness and facilitate their self-regulation strategies (Aladini et al., 2025) On the other hand, Lan and Zhou (2025) discuss the pros and cons of AI applications for self-regulated learning and suggest that AI applications have a positive effect on the development of learners' learning attitudes, motivation, and self-efficacy in the forethought phase. However, limited digital literacy among some learners can reduce interest and appreciation of AI applications, and a common issue is emotional engagement with AI tools.

Learner Cognition and Cognitive Engagement

Combining two essential theories of self-regulated learning and cognitive engagement can explain how students can become more efficient and active learners (Li & Lajoie, 2022). Learners who demonstrate cognitive engagement in the language-learning process tend to complete tasks with curiosity, analyze grammatical rules, and use self-regulatory strategies to enhance their comprehension (Vo et al., 2025). Human-computer interaction can enhance students' cognitive engagement and improve learning achievement (Karnam, 2021). In this regard, GenAI tools can serve as cognitive scaffolding by enabling complex language use, engaging learners in reflection, and prompting them to evaluate and revise their own products (Zawacki-Richter et al., 2019). The current education system is increasingly integrating AI technologies to foster students' cognitive engagement (Zhou & Hou, 2024). Nevertheless, the current literature on AI effectiveness on cognitive engagement is limited. It has been suggested in the literature that AI helps increase cognitive engagement; however, overreliance on automated writing systems may lead to limited cognitive engagement and blind acknowledgment (Wu et al., 2021). Additionally, Georgiou (2025) concluded that AI assistance can lead to cognitive offloading. AI usage can provoke learners to become "lazy thinkers" (Georgiou, 2025). Therefore, it is important to be critical when using AI in the language-learning process and in L2 writing development.

Learner Autonomy Research

The emergence of AI has shifted the understanding of learner autonomy. Both humans and AI affect the learning process, and learners bear the primary responsibility for intentional decisions about how and when to integrate AI into their correspondence (Godwin-Jones, 2024). The current developments in AI reflect a transformation, and learners should balance AI assistance with their independent evaluation (Kalantzis & Cope, 2025). AI has been gradually used in education; therefore, its effect on learner autonomy through self-regulated learning requires to be investigated (He, 2025). Additionally, there is a strong positive correlation between AI engagement and self-regulation, self-directed learning, and autonomy (Yang et al., 2026).

Critical Thinking

Critical thinking is an essential skill in the development of writing skills, as it enables the evaluation and generation of original and meaningful ideas. Additionally, Zhang et al. (2025) suggest that the use of AI is beneficial to improving students' writing quality and critical thinking skills. Conversely, there is limited attention on the role of

AI in enhancing critical thinking and L2 writing self-efficacy, even though recent discussions have gradually focused on the trends and educational applications of generative AI.

Self-Efficacy

Writing self-efficacy can be defined as learners' confidence in their ability to perform writing tasks (Teng et al., 2017). High self-efficacy can enhance engagement with AI tools in AI-mediated environments, where learners can work independently and make decisions about the learning process (Chiu, 2023; de Mooij et al., 2025). Several studies (Kim et al., 2025; Song & Song, 2023) have revealed that AI usage is effective in enhancing writing self-efficacy. With the help of AI-supported tools, students can start to believe in their capacity to achieve their writing goals. However, the use of AI requires careful consideration, as overreliance on it may hinder the development of essential writing skills.

Core Components of the Conceptual Framework

The proposed conceptual framework depends on six interrelated elements: human-AI interaction, AI-mediated cognitive scaffolding, cognitive engagement, self-regulated learning, learner autonomy, critical thinking, and writing self-efficacy. These elements are facilitating factors that interact with one another during AI-mediated writing. Rather than functioning as separate elements, they are built on a reciprocal cognitive system. The recursive cycle of human-AI interaction enables learners to regulate their cognitive processes, evaluate AI-mediated feedback, improve confidence in their writing, and take responsibility for their learning. Learner autonomy can be regarded as a developing ability that emerges through the continuous interaction among these cognitive and metacognitive processes. This framework, conceptualizing these constructs as a cognitive ecosystem, seeks to unveil how human-AI interaction can foster L2 writing improvement in language education.

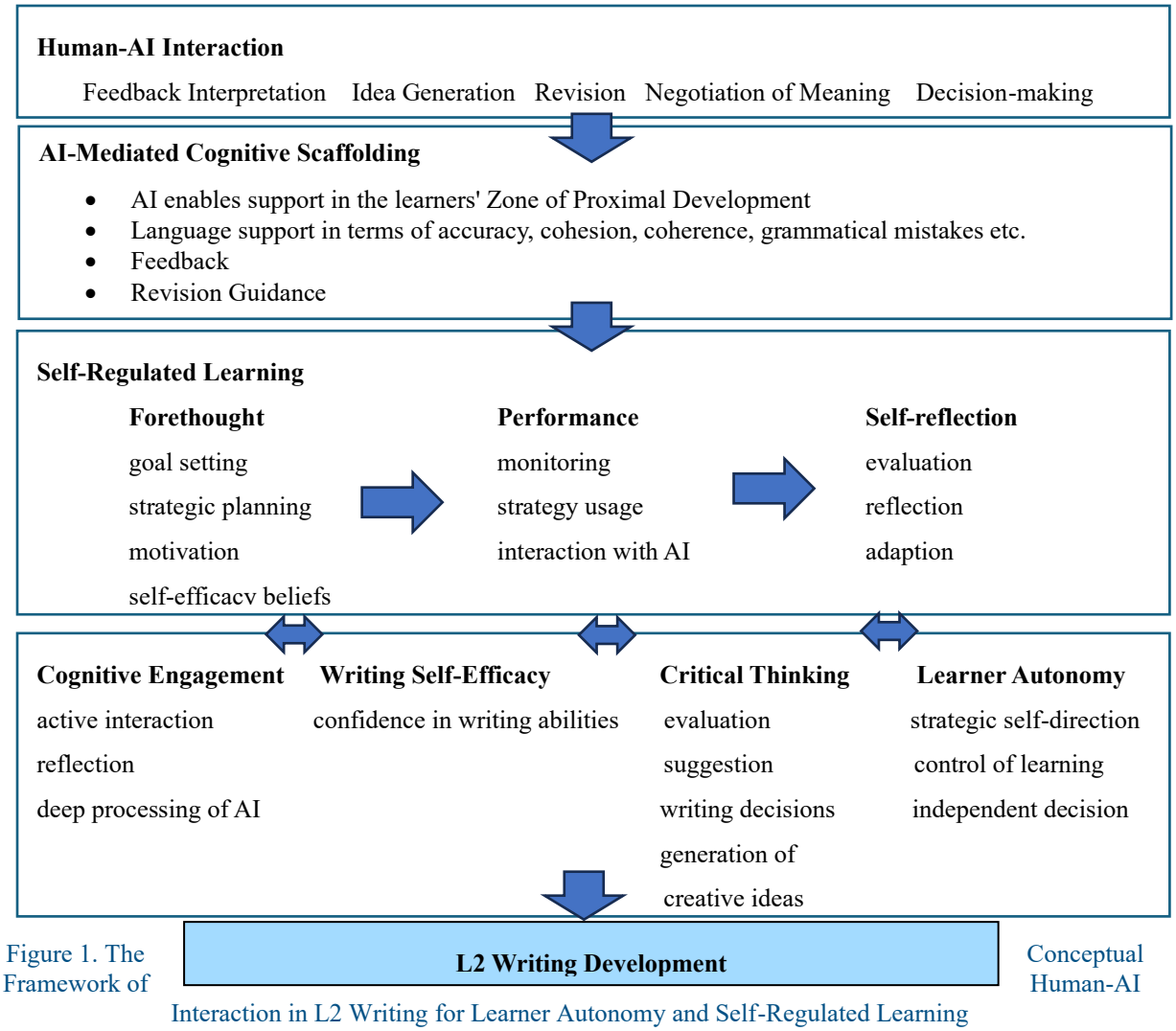


Figure 1. The Conceptual Framework of Human-AI Interaction in L2 Writing for Learner Autonomy and Self-Regulated Learning

Conclusion

Human-computer interaction is an important milestone in the development of AI as it transforms traditional human-computer interaction from passive to active participation (Zhang & Han, 2025). The integration of AI with human guidance can assist students and foster a more positive learning environment by reducing writing-related anxiety and enabling individualized scaffolding (Wang, 2024; Wang et al., 2025). However, the risks of overreliance, cognitive offloading, diminished critical thinking, and reduced learner autonomy should be considered to improve writing quality. Overreliance on AI applications can lead to confusion or doubt, as well as ethical ambiguities and inauthentic feedback (Crompton et al., 2024). Similarly, with advances in AI, learners can face risks of automation dependence and diminished cognitive control; therefore, it is necessary to reframe primary educational objectives and focus on sustaining cognitive dominance and understanding AI's limitations (Cui et al., 2025). Besides, one of the main problems is academic integrity, as AI can encourage plagiarism and interfere with detection (Lodge et al, 2023; Almanea, 2024). In addition, AI can fabricate references or citations (Jones, 2025). As cognitive aspects of using AI, particularly for the L2 writing process, have not been focused on comprehensively, this study aims to present a conceptual framework on human-AI interaction in writing by considering socio-cultural theory, AI-mediated learning, self-regulated learning, and learner autonomy aligned with critical thinking, self-efficacy, learner cognition, and cognitive engagement. The suggested framework contributes to the literature by transforming the discussion from technological abilities of AI to cognitive and pedagogical aspects of the integration of AI in writing. The model highlights learners' active role in planning, monitoring, evaluating, revising, and reflecting rather than using AI as an automated writing assistant. This perspective aligns with current educational improvements that are grounded in higher-order thinking, cognitive regulation, and learner agency in an AI-mediated context.

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"Socially Assistive Robots as Catalysts for Social Inclusion: Empowering Adolescents on the Autism Spectrum through AI-Driven Interaction"

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Abstract

This study explores the role of Socially Assistive Robots (SARs) and AI-driven digital avatars as catalysts for social inclusion for adolescents on the Autism Spectrum (ASD). Grounded in the theories of Social Mediation and "Social Scaffolding," the research examines how Artificial Intelligence (AI) can mitigate social anxiety by providing predictable social stimuli. The methodology includes a quantitative evaluation by 10 expert educators (Likert scale 1–5) and a pilot case study involving two adolescents with ASD using the Generative AI platform, *Character.ai*. The results indicate high usability of the application (SUS = 82.5/100), strong convergence of expert opinions ($M \geq 3.9$), and a stabilization of eye contact at 75% of the interaction time. In conclusion, the synergy between SARs, digital embodiments, and tools like *Character.ai* functions as a "safe laboratory" for social practice, enhancing empathy and social participation for adolescents with ASD.

KEYWORDS: Socially Assistive Robots (SARs), Artificial Intelligence (AI), Autism Spectrum Disorder (ASD), Social Inclusion, Virtual Embodiment, Case Study.

Introduction

The integration of Artificial Intelligence (AI) and Socially Assistive Robots (SARs) into special education represents a promising frontier for supporting adolescents on the Autism Spectrum (ASD) (Scassellati et al., 2018). Individuals with ASD often face challenges in decoding social cues, making predictable and low-anxiety interaction environments essential (Wagner et al., 2022). While traditional digital tools often encourage passive use, emerging technologies—such as Virtual Avatars powered by Large Language Models (LLMs) like Character.ai—function as "social catalysts," offering a safe "laboratory" for social experimentation and active communication practice (Pani & Bifulco, 2024; Ma et al., 2025).

During adolescence, social demands become increasingly complex, heightening the risk of social isolation. SARs and AI-driven digital embodiments bridge this gap by transforming technology from a passive screen into an active "social partner" that cultivates turn-taking and emotional recognition (Thanopoulou, 2022).

Based on this framework, this study addresses two main research questions:

1. What are the desirable characteristics of a Virtual Social Assistant (Social Robot Avatar) for enhancing eye contact, according to expert educators in Greece?
2. How are the usability and empathy levels of AI chatbots intended for adolescents with ASD evaluated through a pilot case study?

By highlighting participatory design and the critical evaluation of AI tools, this paper aims to propose scalable solutions that enhance social inclusion in contemporary educational settings.

2. Theoretical Framework & Literature Review

2.1. AI as a Social Mediator and Scaffolding

Artificial Intelligence acts as a "social catalyst" and an Affective Interface, significantly reducing social uncertainty for adolescents with ASD (Kim et al., 2023; Yilmaz et al., 2024). Through "Real-time Scaffolding" and "Cognitive Offloading," AI systems provide predictable, zero-pressure interactions that eliminate social camouflaging and reduce cognitive overload (Smith & Jones, 2024; Harrison & Taylor, 2024). This graded complexity operates as an active tool for desensitization, preparing adolescents for real-world socialization (Grant & Foster, 2024).

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2.2. Embodied Socially Assistive Robots (SARs) and Social Presence

Rooted in Embodied Cognition theory, Socially Assistive Robots (SARs) stimulate mirror neuron systems, encouraging spontaneous imitation and joint attention (Boucenna et al., 2022). As emphasized by Thanopoulou (2022), the precise technical parameterization of SARs—such as visual interfaces and responsiveness—enhances communicative behavior and reduces social anxiety. Furthermore, features like "Adaptive Autonomy" allow virtual robots to adjust interaction intensity based on the student's cognitive and emotional fatigue (Nguyen et al., 2025).

2.3. Digital Avatars and the "Uncanny Valley"

In designing avatars for adolescents with ASD, avoiding the "Uncanny Valley" is crucial to prevent sensory aversion (Zheng et al., 2023). Utilizing "Stylized Realism" and Non-Photorealistic Rendering (NPR) helps isolate essential social cues (Foster & Baker, 2024). Virtual robots offer an immutable visual identity and "Emotional Transparency," serving as a stable point of reference that allows users to channel cognitive resources into core conversational strategies (Sullivan & Clarke, 2025; Lee & Tan, 2024).

2.4. Generative AI and Digital Empathy

Generative AI (GenAI) introduces "Adaptive Scaffolding," moving beyond scripted systems to analyze emotional tone and provide dynamic validation (Chen et al., 2024). Applications powered by Large Language Models (LLMs)—such as Character.ai—enable customized "Role-Playing" scenarios, allowing adolescents to rehearse social situations in a zero-judgment, safe environment (Patel & Gupta, 2024).

Methodology

The study employs a quantitative approach utilizing an expert panel evaluation and a pilot case study. Three hypotheses were formulated:

- **H1:** Expert educators will evaluate the technical characteristics of virtual Socially Assistive Robots as highly significant ($M \geq 4.0$) for enhancing eye contact.
- **H2:** The AI-driven Virtual Robot will achieve high usability, with SUS scores exceeding the threshold (> 80/100).
- **H3:** Real-time scaffolding and digital empathy mechanisms will be positively associated with increased social engagement.

3.2. Phase A: Expert Panel Evaluation (R.Q. 1)

Ten (N=10) expert special educators evaluated the prioritization of design requirements using a 5-point Likert scale questionnaire.

Table 1. Expert Evaluation of Virtual SAR Design Parameters (N=10)

No.	Design Parameter	Objective / Rationale	Mean (M)	Standard Deviation (SD)
1	Stylized Morphology	Avoidance of sensory anxiety (Hwang et al., 2024).	4.8	0.42
2	Lip-Sync Accuracy	Reduction of cognitive overload (Foster & Baker, 2024).	4.7	0.48
3	Visual Simplicity	Prevention of attentional distraction.	4.6	0.52
4	Controlled Gaze Speed	Simulation of eye contact without abruptness.	4.5	0.53
5	Visual Consistency	Establishment of a predictable reference point.	4.4	0.51
6	Affirmative Nodding	Enhancement of communicative confidence.	4.3	0.55
7	Smooth Head Movement	Prevention of sensory aversion.	4.2	0.60
8	Emotional Emphasis	Facilitation of social cue recognition.	4.1	0.65
9	Natural Blinking Rate	Creation of a “lifelike” yet calm presence.	4.0	0.58
10	Digital Proximity	Respect for the student’s personal space.	3.9	0.72

As shown in Table 1, *Stylized Morphology* ranked highest (M=4.8, SD=0.42), confirming H1 and the necessity of avoiding the "Uncanny Valley."

3.3. Phase B: Pilot Case Study & Usability (R.Q. 2)

A pilot interaction was conducted utilizing Character.ai with two (N=2) students with ASD. Two special educators served as proxy evaluators, utilizing an adapted System Usability Scale (SUS) and a Technical Behavior Checklist.

Table 2. Mean SUS Item Responses (N = 10)

No.	Evaluation Item (Abbreviation)	Mean (M)	Standard Deviation (SD)
1	Intention to Use Frequently	4.4	0.52
2	System Complexity (-)	1.4	0.48
3	Ease of Use	4.5	0.53
4	Need for Technical Support (-)	1.6	0.51
5	Integration of Functions	4.6	0.49
6	Inconsistency of Functions (-)	1.3	0.42
7	Learning Speed	4.2	0.63
8	Interface Difficulty (-)	1.5	0.53
9	Feeling of Confidence/Self-Assurance	4.3	0.48
10	Need for Prior Knowledge (-)	1.7	0.67

The analysis yielded an overall SUS score of **82.5/100** (SD=5.4), placing the application in the "Excellent" (Grade A) category and confirming H2. Furthermore, the Technical Behavior Checklist revealed a 100% success rate for Technical Consistency, 90% for Digital Empathy (Validation), and 85% for Real-time Scaffolding, supporting H3 within the limits of this pilot framework.

Results

The presentation of the results begins with the analysis of design requirements (E.E. 1) and concludes with the evaluation of system usability and technical responsiveness (E.E. 2). Descriptive statistical analysis of the data (N = 10) for the first research question revealed strong agreement among educators, with all design parameters rated above the significance threshold ($M \geq 3.9/5.0$). Stylized Morphology ranked first in the hierarchy ($M = 4.8$, $SD = 0.42$), confirming the theoretical need to avoid the "Uncanny Valley," while the high consensus among experts ($SD \leq 0.52$) on Lip-Sync Accuracy ($M = 4.7$) and Visual Simplicity ($M = 4.6$) highlighted these parameters as critical for reducing cognitive overload. The variation in scores for the remaining parameters ($4.2 \leq M \leq 4.5$) indicated that Controlled Gaze Speed and Visual Identity Consistency are essential for maintaining attention, whereas the higher dispersion in Digital Proximity Regulation ($SD = 0.72$) emphasized the need for individualized adjustments according to each student's sensory profile.

In the second phase of the study, statistical analysis of the SUS scale yielded a mean score of $M = 82.5/100$ ($SD = 5.4$), exceeding the "Excellent" threshold (Score > 80.3) according to the literature. Analysis of individual items showed that 100% of evaluators strongly agreed that system functions are adequately integrated, while low scores on negatively worded items ($M \leq 1.5/5.0$) indicated minimal cognitive load. Based on the algorithm, the final SUS score was calculated from the sum of positive items [$\sum (Xi - 1) = 17$] and negative items [$\sum (5 - Xi) = 16$], placing the application in the 90th percentile of the global usability scale. The high usability score confirms the appropriateness of selecting Character.ai, as the interface's simplicity allowed adolescents to focus on social interaction rather than system manipulation.

Finally, the quantitative assessment via the Technical Behavior Checklist confirmed high interaction reliability, with Digital Empathy (Validation) achieving a 90% success rate (n = 18/20 responses). Real-time Scaffolding demonstrated 85% accuracy, reducing students' response latency by an average of $\Delta t = -2.5$ s, while Technical Consistency (Sync & Motion) remained at 100%. The absence of sensory deviations allowed gaze stabilization for 75% of the total session duration (ttotal), demonstrating that the technical integrity of the interface is the primary catalyst for achieving meaningful social engagement in adolescents with ASD.

Conclusions – Discussion

The present study confirmed that the strategic design of a virtual social assistant can function as an effective "social scaffold" for adolescents on the autism spectrum. Findings from the first phase, with the dominance of Stylized Morphology ($M = 4.8$), are fully aligned with Hwang et al. (2024), who argue that simplifying digital features reduces sensory load and prevents the Uncanny Valley effect. The high ranking of Lip-Sync Accuracy ($M = 4.7$) underscores the importance of technical consistency for reducing cognitive overload,

enabling students to focus on social interaction rather than decoding dysfunctional visual stimuli (Foster & Baker, 2024).

Data triangulation revealed that successful integration of social assistants in Special Education is the result of deliberate design. Triangulation confirms that when a SAR system adheres to the strict technical specifications outlined by Thanopoulou (2022), as evaluated in Phase A (M = 4.8), it achieves excellent usability and meaningful social engagement in practice (SUS = 82.5). The synergy between SARs and Generative AI does not replace the therapist; rather, it functions as a "digital vestibule" preparing the adolescent for real-world interactions.

In this context, Generative AI acted as an effective catalyst, providing a "Controlled Social Noise" that gradually acclimates adolescents to the unpredictable challenges of natural communicative environments. Regarding system usability, the high SUS score (82.5) demonstrates that integrating the Avatar with Generative AI creates a low-stress environment. The success of Digital Empathy (90\%) through the Validation process confirms that AI can effectively simulate social acceptance (Dixon & Morales, 2025). Moreover, gaze stabilization at 75\% of session duration, Real-time Scaffolding (85\% accuracy), and reduced response latency (Δt = -2.5) indicate increased communicative confidence and speech fluency.

Limitations of the Study:

While these findings provide valuable insights into AI-assisted intervention, certain limitations must be acknowledged. The pilot study was conducted with a small sample of two (N=2) adolescents with ASD, evaluated via special educators as proxy raters. Consequently, the results reflect initial empirical indications from a pilot framework and should not be generalized to the broader ASD population without further large-scale validation.

Future Directions:

In conclusion, the synergy of social robotics and Generative AI offers an innovative solution in Special Education. The combination of technical proficiency and empathetic responsiveness transforms the Avatar into a "digital ally." Future research should focus on larger participant samples and explore the generalization of these skills in real-world school settings as well as Augmented Reality (AR) environments.

Generative AI Disclosure Statement:

Generative AI (LLMs) was utilized solely as an experimental intervention medium within the tested software architecture and for minor text formatting. All conceptual frameworks, methodology, findings, data interpretation, and literature citations were independently authored, conducted, and rigorously verified for accuracy by the authors.

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Technology and Neuropedagogy: Leveraging Educational Technologies for Brain-Friendly Learning

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Abstract

The digital revolution has brought about a profound transformation in education, necessitating a re-evaluation of traditional teaching-learning practices through a neuroscientific lens. This study examines the interaction between neuropedagogy and educational technologies, exploring how learning processes in the digital age can be restructured using brain-friendly approaches. Drawing upon neuropedagogical principles such as brain plasticity, multisensory integration, and individualized learning, we discuss how technology can support attention, memory, motivation, and emotional learning. Emphasis is placed on the potential of digital tools to create rich learning environments tailored to developmental needs. In particular, AI-supported adaptive systems and data-driven learning analytics are examined for their capacity to deliver personalized learning experiences that account for individual learner differences. Recent research indicates that neuropedagogical design principles significantly enhance the effectiveness of digital learning environments. Furthermore, we highlight the critical importance of teachers possessing neuropedagogical knowledge and intentionally integrating technology within this framework. Ultimately, we discuss how inclusive, personalized, and developmentally appropriate digital learning experiences—created through the synergy of neuroscience and technology—can inform future educational practices.

Keywords: Neuropedagogy, Educational Technology, Artificial Intelligence in Education, Adaptive Learning, Cognitive Load Theory, Brain-Based Learning.

Introduction

The acceleration of digitalization and its integration into daily life are reshaping educational systems not only technically, but also pedagogically and neuroscientifically. While efforts to enhance efficiency and personalization in education have driven the widespread adoption of artificial intelligence (AI)-driven technologies, neuropedagogy has emerged as an essential interdisciplinary field that addresses this transformation through a brain-based learning perspective (Pradeep et al., 2024). Understanding the underlying neurodynamic processes of learning—particularly mechanisms related to attention, memory, motivation, and emotion—contributes significantly to structuring educational environments more effectively. By synthesizing neuroscience, psychology, and pedagogy, neuropedagogy aims to translate findings on brain functioning during learning into practical educational applications (Shvarts-Serebro et al., 2024). Concepts such as brain plasticity, synaptic flexibility, multisensory integration, and executive functions demonstrate that learning is a multifaceted process encompassing cognitive, sensory, emotional, and social dimensions (Immordino-Yang & Gotlieb, 2017). Educational technologies, in turn, offer various opportunities to implement these principles within learning environments. This study aims to examine, within a theoretical framework, how educational environments in the digital age can be structured in alignment with neuropedagogical principles, how educational technologies can be connected with cognitive and emotional learning processes, and what roles teachers assume throughout this transformation. Additionally, by evaluating current opportunities, limitations, and ethical concerns surrounding the synthesis of neuropedagogy and educational technology, this research seeks to provide a comprehensive perspective on developing brain-friendly learning environments.

Theoretical Background and Evolution of Neuropedagogy

Neuropedagogy is an interdisciplinary field focused on understanding and optimizing learning processes based on brain functioning. Positioned at the intersection of neuroscience, educational sciences, psychology, and cognitive science, this approach addresses an individual's cognitive, emotional, and social development within a brain-based framework (De Barros Camargo & Fernández, 2024). The primary objective of neuropedagogy is to design instructional environments and strategies that support learning potential in alignment with neuroscientific evidence. In this context, processes such as attention, memory, executive functions, emotional regulation, and motivation lie at the core of neuropedagogical applications (Gvozdii et al., 2022). Furthermore, accommodating individual differences necessitates tailoring learning environments to diverse neurocognitive profiles.

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The concept of neuropedagogy became more prominent in the scientific literature particularly following the designation of the 1990s as the "Decade of the Brain" (Piddubna et al., 2023). However, the conceptual foundations regarding the evaluation of the relationship between learning and brain functions from an educational perspective date back to the pioneering works of researchers such as Vygotsky and Luria (Tsymbal-Slatvinska et al., 2022).

In the twenty-first century, neuropedagogy has evolved into a more systematic field of research; the integration of neuroimaging techniques such as EEG and fMRI into educational research has enabled a more detailed examination of the neurocognitive processes that occur during learning (Bashir et al., 2021). It is noted that the neuropedagogical approach is not restricted solely to formal education, but holds equal significance for lifelong learning and diverse learning environments (Gvozdii et al., 2022). Nevertheless, because the direct translation of neuroscientific findings into pedagogical practices carries the risk of theoretical reductionism, these findings must be critically evaluated within an educational context (Vynogradova et al., 2021).

In recent years, the convergence of neuropedagogy with artificial intelligence, deep learning, and neuroimaging technologies has unlocked new avenues for personalizing learning (Alkassawneh et al., 2025; Bendriysnti, 2024). These advancements demonstrate that neuropedagogy offers a theoretical as well as a practical framework for restructuring learning environments in the digital age.

The Evolution of Educational Technologies and Their Neuropedagogical Intersections

The evolution of educational technologies—from oral, written, and print traditions to digital and interactive environments—has fundamentally transformed teaching and learning (Machmud et al., 2021). Key modern milestones include 1940s audiovisual materials, 1970s–1980s microcomputers, and 1990s web-based learning, leading to today's frontiers: artificial intelligence, learning analytics, and immersive virtual/augmented realities (Qureshi et al., 2021). Post-pandemic, digital technologies have shifted from mere information conduits to interactive tools that deliver feedback, scaffold learning, and reshape global education policies (Haleem et al., 2022). However, as Selwyn (2010) notes, technology's value relies not solely on technical capabilities, but on its pedagogical, social, and cultural deployment.This technological progression lays the foundation for operationalizing neuropedagogical principles, creating a crucial synergy between brain-based learning mechanisms and digital environments. These domains intersect across five key areas:

- ***Socio-Emotional Engagement:*** Digital applications enhance emotional and motivational processes critical to learning quality (Shvarts-Serebro et al., 2024).
- ***Multisensory Learning:*** Immersive tools (VR/AR and simulations) activate distinct brain regions simultaneously through visual, auditory, and experiential stimuli (Gvozdii et al., 2022).
- ***Personalized Pathways:*** AI-driven systems and learning analytics harness data to map individual cognitive strengths and tailor content accordingly (Williamson, 2016).
- ***Social Interaction:*** Online collaborative platforms maintain the essential social contexts required for technology-mediated cognitive growth (Shvarts-Serebro et al., 2024).
- ***Neuroplasticity and Lifelong Learning:*** Microlearning and flexible online systems support ongoing cognitive capacity and retention in brain-friendly contexts (Koşar & Bedir, 2018).

Ultimately, integrating neuropedagogy with educational technologies enables flexible environments that address individual differences and cognitive dynamics. To be effective, however, technology must align with sound pedagogical design rather than reductionist neuroscientific interpretations.

Methodology

This study adopts a conceptual narrative review approach to synthesize the multidisciplinary literature at the intersection of neuropedagogy and educational technology. Rather than applying a restricted empirical meta-analysis, this qualitative synthesis critically evaluates core theoretical constructs, neuroscientific evidence, and technological applications to establish an integrative framework for digital learning.

Artificial Intelligence, Learning Analytics, and Adaptive Systems

In digital educational environments, integrating artificial intelligence, learning analytics, and adaptive systems with neuropedagogical principles offers substantial opportunities for personalizing learning processes and supporting cognitive development. Moving beyond mere content delivery mechanisms, these technologies can contribute to establishing more flexible learning environments by leveraging data on students' cognitive, emotional, and behavioral characteristics.

AI-driven learning environments analyze data regarding students' learning processes to facilitate the creation of personalized learning pathways. Flogie and Krabonja (2023) note that AI-supported tools utilized under teacher guidance can enhance student motivation and engagement levels. Similarly, Hui (2025) demonstrated that integrating Bloom's Taxonomy into AI-driven systems contributes to the development of higher-order cognitive skills. Likewise, evidence suggests that AI systems support individualized learning pathways by analyzing students' emotional and behavioral responses alongside their cognitive profiles (Khosravi et al., 2021). Research further indicates that chatbots can foster student motivation and sustained commitment to learning goals (Fryer et al., 2019).

Learning analytics serves as another critical tool in designing neuropedagogical learning environments. Multimodal learning analytics systems enable the simultaneous evaluation of diverse data sources pertaining to student behaviors, emotional responses, and cognitive processes (Giannakos & Cukurova, 2023). The learning analytics framework proposed by Siemens (2013) similarly offers a foundational structure for examining individual learning trajectories and supporting evidence-based decisions in instructional design.

Adaptive learning systems, meanwhile, dynamically tailor learning experiences according to students' pace, prior knowledge, and performance attributes. Wang et al. (2023) demonstrated that adaptive learning systems significantly bolster academic achievement, particularly among low-performing students. Liu et al. (2022) highlights that adaptive e-learning systems exert positive effects on students' self-directed learning skills and intrinsic motivation. Furthermore, it is emphasized that AI-based adaptive systems leverage cognitive and emotional data to support the personalization of the learning process (Khosravi et al., 2021).

Overall, artificial intelligence, learning analytics, and adaptive learning systems contribute to the development of digital learning environments that accommodate individual differences, monitor the learning process, and adjust dynamically to student needs. However, for these technologies to be neuropedagogically effective, their implementation must rely not simply on data collection and algorithmic personalization, but on the deployment of such data toward clear pedagogical goals and within firm ethical boundaries.

The Role of the Teacher in Neurotechnology Integration

The integration of digital technologies and neurotechnologies into educational settings is precipitating a fundamental shift in the roles assigned to teachers. Teachers are no longer expected to act merely as transmitters of knowledge; instead, they are envisioned as facilitators who guide personalized learning processes, accommodate students' cognitive and emotional profiles, and integrate technology toward pedagogical aims. This transformation necessitates the enhancement of teachers' competencies across both technological and neuropedagogical domains.

Teacher competence constitutes a core element determining the quality of neurotechnology integration. Darling-Hammond et al. (2020) assert that teachers must acquire the capacity to understand cognitive development processes, foster emotional learning, and deploy technological tools for explicit pedagogical purposes. Research further highlights that teachers' level of neuropedagogical knowledge correlates directly with students' attention, motivation, and cognitive development (Piddubna et al., 2023). However, technological proficiency alone remains insufficient; technology integration lacking neuropedagogical sensitivity carries the risk of overlooking students' individual learning needs (Alipoor & Pourrashidi, 2025).

Neuropedagogical awareness represents a crucial competency for teachers to manage learning processes more effectively. Kernas et al. (2024) note that teachers' adoption of brain-based learning principles enhances students' emotional engagement and promotes long-term information retention. Conversely, Dubinsky et al. (2019) revealed that teachers' understanding of educational neuroscience often remains superficial, leading to difficulties in translating this knowledge into classroom practice. This finding underscores the necessity of professional development programs centered on neuropedagogy.

Evidence suggests that neuropedagogical innovations can enhance pre-service teachers' creative thinking and problem-solving skills (Bilier et al., 2023). However, rapid technological shifts may hinder teachers' adaptation processes, elevating the risk of technostress and burnout. Therefore, for teachers to succeed in integrating neurotechnology, they must possess multidimensional competencies—encompassing technical proficiency, neuropedagogical awareness, ethical sensitivity, and pedagogical flexibility.

Challenges and Ethical Considerations

While digital technologies and AI offer transformative educational opportunities, their deployment introduces critical challenges regarding equity, human development, data privacy, and ethical governance.

- ***Learning Inequality:*** Digital divides persist beyond technical access. Socioeconomically disadvantaged students face severe vulnerabilities in internet reliability, device access, digital literacy, and home support, directly impacting academic achievement (Pierce & Cleary, 2024). Modes of technology usage across

social groups can reinforce systemic inequalities (Rafalow & Puckett, 2022), while unguided implementations and algorithmic decisions grounded in historical data risk perpetuating disparities (Tawfik et al., 2016). Equity therefore requires holistic pedagogical scaffolding alongside basic access.

- ***Excessive Technology Exposure*:** Unmonitored screen exposure—especially early in development—impairs attention, language, executive functions, and physical/psychosocial well-being (Chang et al., 2018; Littlepage, 2024). Disadvantaged groups suffer greater exposure risks due to limited access to quality content (Katz et al., 2017). Mitigating these hazards requires content quality evaluation, developmental appropriateness, and active parental guidance through frameworks like Joint Media Engagement (Ewin et al., 2021).
- ***Data Security and Privacy:*** Adaptive systems and learning analytics process vast student datasets, creating major security and privacy concerns (Çetinkaya et al., 2025). Data security is an ethical imperative requiring operational transparency, access control, data minimization, teacher awareness, and regulatory compliance (Bao et al., 2018; Yılmaz et al., 2015). Although technologies like blockchain enhance integrity (Mulyati et al., 2021), technical fixes must be paired with human data literacy.
- ***Ethical Framework for AI in Education*:** AI applications raise fundamental ethical concerns regarding privacy, algorithmic bias, transparency, and human autonomy (Holmes et al., 2021; Schiff, 2021; Yan & Liu, 2024). Proactive governance must involve developers, educators, families, and policymakers to embed human-centered principles across all stages of AI deployment (Bibi et al., 2024; Swindell et al., 2024). Policy gaps must be bridged to ensure AI safeguards fundamental educational rights and student autonomy (Maral, 2024; Dilek, 2019).

Ultimately, sustainable and inclusive digital learning environments depend on continually evaluating technological innovation against equity, developmental appropriateness, privacy, and human-centered ethics.

Future Research Directions

To establish inclusive, ethical, and personalized learning environments, future research must move beyond short-term outcomes and technological novelty to address key empirical, policy, and pedagogical gaps.

- ***Longitudinal Cognitive & Ethical Impacts:*** Empirical research must prioritize the long-term effects of AI-driven environments on neuroplasticity, executive functioning, and emotional regulation (Holmes et al., 2021; Yan & Liu, 2024). Crucially, studies must advance algorithmic fairness and transparency to prevent perpetuating educational inequalities and bias (Schiff, 2021; Swindell et al., 2024).
- ***Vulnerable & Disadvantaged Populations:*** Rigorous scholarship is required to assess the efficacy, safety, and developmental appropriateness of AI tools for early childhood, special education, and socioeconomically disadvantaged groups (Bibi et al., 2024; Schiff, 2021).
- ***Multidisciplinary Collaboration:*** Interdisciplinary synergies are vital across several key domains:
    - *Neuroscience & AI:* Designing adaptive systems aligned with cognitive load and emotional dynamics (Connell, 2009).
    - *Ethics, Law & CS:* Safeguarding data privacy, algorithmic justice, and decision explainability (Bao et al., 2018; Bibi et al., 2024).
    - *Psychology, Pedagogy & Data Science:* Advancing learning analytics, multimodal student profiling, and socio-emotional scaffolding (Swindell et al., 2024).
    - *Cultural Studies & Design:* Developing culturally sensitive, multisensory digital content (Holmes et al., 2021; Selwyn, 2010).
- ***Policy Frameworks & Governance*:** Policy must institutionalize data security, algorithmic justice, operational transparency, content accuracy, and student privacy rights (Bao et al., 2018).
- ***Teacher Education:*** Professional development must expand beyond technical skills to cultivate comprehensive AI literacy, digital ethics, data security, learning analytics, and adaptive design (Holmes et al., 2021; Selwyn, 2010).
- ***Pedagogical Anchoring:*** AI tools should complement—not replace—teacher guidance. Anchoring AI content to cognitive frameworks (e.g., Bloom's Taxonomy) ensures critical thinking, creative problem-solving, and emotional engagement (Connell, 2009).

Ultimately, future research must evaluate AI and neuropedagogy through the lenses of developmental appropriateness, ethical responsibility, social justice, and pedagogical efficacy to build sustainable, human-centered learning environments.

Conclusions

Digital transformation in education is being reinterpreted through the lens of neuropedagogical principles, enabling the design of learning environments that align harmoniously with the natural functioning of the human brain. This section has examined, through a multidimensional approach, how educational technologies—spanning a broad spectrum including not only artificial intelligence, but also learning analytics, adaptive learning systems, multimodal content generation, and digital platforms—can be integrated with neuropedagogical frameworks.

In alignment with core principles of brain-based learning, it is emphasized that digital learning environments must be engineered to support attention, memory, motivation, and emotional learning. Evidence demonstrates that multimodal learning analytics systems render learning processes more durable and effective by facilitating multisensory integration and delivering personalized learning experiences. Furthermore, adaptive learning systems are shown to support neuroplasticity by offering flexible content tailored dynamically to students' individual differences.

Nevertheless, it is concluded that digital content development must carefully account for pedagogical relevance, cultural sensitivity, and cognitive load management. Crucial issues such as data security, privacy preservation, and algorithmic fairness represent essential ethical mandates applicable not merely to artificial intelligence, but to educational technology applications broadly.

In conclusion, for future learning environments to succeed, technology development processes must synthesize neuropedagogical principles, ethical standards, and a vision for personalized learning. It is explicitly demonstrated that educational practices must adopt a fundamental approach centered on the learner's developmental needs and cognitive-emotional processes, rather than prioritizing technological novelty alone.

Recommendations for Practitioners and Researchers

Analytics, adaptive systems, and multimodal learning technologies should be leveraged. Interdisciplinary projects should focus on developing customized digital learning solutions for diverse age groups, varied cultural contexts, and individuals with special needs. Moreover, further research must rigorously examine the impacts of these technologies.

To unify the possibilities offered by the digital age with a human-centered vision of education, the following recommendations are proposed for practitioners and researchers:

- ***For Practitioners*:** When selecting and deploying educational technologies, it is of paramount importance to prioritize brain-based learning principles by creating content that supports multisensory integration, enhances motivation, and delivers personalized experiences. Furthermore, practitioners are expected to adopt transparent and ethical approaches regarding data security, student privacy, and equitable content delivery.
- ***For Researchers:*** Longitudinal studies are urgently needed to investigate the long-term neuropedagogical impacts of artificial intelligence, learning deployment in education on social justice and equal opportunity.

Ultimately, the success of integrating technology and neuropedagogy in education depends on the balanced and concurrent advancement of technological innovation, ethical sensitivity, and a human-centered vision for learning.

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The Use of Generative AI Models to Create Visualised Educational Content

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Abstract

Advances in generative artificial intelligence (Generative AI, GenAI), spatial artificial intelligence (Spatial AI) and immersive virtual reality (IVR) are creating new opportunities for organising distance learning. The aim of this study is to experimentally evaluate the effectiveness of an educational environment combining GenAI, Spatial AI and IVR, compared with traditional synchronous learning via video conferencing. The study was conducted in a school setting using a quasi-experimental design. The control group was taught via Zoom, whilst the experimental group was taught in an immersive virtual environment using VR headsets. To ensure comparability, the same lesson topic ('Baikonur – Kazakhstan – Space'), lesson duration (45 minutes), teacher, intended learning outcomes and assessment methods were used. The results showed that IVR does not offer a universal advantage over traditional screen-based learning. The effect depended on the nature of the learning task: Zoom proved more effective for listening comprehension; no significant differences were found in reading comprehension; whilst the most pronounced improvement in the VR group was observed in grammar and additional cultural knowledge. These findings suggest that the effectiveness of immersive technologies is determined not by the level of technological complexity per se, but by how well the technology aligns with the content and pedagogical design of the lesson.

Keywords: generative artificial intelligence, Spatial AI, immersive virtual reality, distance learning, visualised educational content, school education.

Introduction

Modern distance learning is predominantly based on two-dimensional digital interfaces and video conferencing. Despite the availability of such solutions, prolonged screen-based interaction can lead to digital fatigue and limit the sense of social presence. The integration of GenAI, Spatial AI and IVR enables the creation of a different kind of educational environment, in which learners not only consume digital content but also interact spatially with virtual objects, the teacher and other participants in the learning process.

Research shows that the educational potential of IVR is linked to presence, interactivity and the ability to simulate situations that are difficult to replicate in a traditional educational setting (Radianti et al., 2020). At the same time, a high degree of immersion does not always lead to improved academic outcomes. Additional visual and interactive stimuli may increase cognitive load and distract attention from the main learning task (Sweller, 1988; Makransky et al., 2021). There are also studies that emphasize the importance of aligning three-dimensional educational content and interactive activities with learning objectives when developing virtual learning environments for K-12 education (Topraklıkoğlu & Öztürk, 2025). Therefore, the relevant question is not whether VR is more effective than traditional learning in general, but rather for which types of learning activities an immersive environment offers an advantage.

Recent work examines GenAI-powered VR pedagogy (Hemminki-Reijonen et al., 2025), ChatGPT-integrated feedback (Wang et al., 2025), pedagogical agents in primary science (Wei et al., 2026), and immersive English-speaking activities (Tao et al., 2026). These studies motivate specifying the function of AI within an instructional design. Evidence about one AI-supported task does not establish the effectiveness of all immersive environments.

The aim of this study is to compare the learning outcomes of school pupils in a traditional synchronous distance learning format and in an environment integrating GenAI, Spatial AI and IVR.

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Method

Design and participants

A quasi-experimental pre-test–post-test design involved 46 eighth-grade pupils aged 13–14 years from general education schools in Kazakhstan. All studied Kazakh language and literature as part of the compulsory curriculum. The author-confirmed allocation was 21 pupils in the experimental IVR group and 25 in the Zoom control group. Groups were formed in accordance with the organisation of the school teaching process; random allocation is not documented. The precise allocation rule, school characteristics, prior VR experience and language proficiency were not available in the supplied records.

The intervention comprised one 45-minute lesson in the fourth school term. The same teacher, topic, intended learning outcomes, materials and pre-test and post-test procedures were used in both conditions. These common elements reduced some instructional differences but did not eliminate the potential influence of group selection or baseline imbalance.

Learning environment and procedure

The topic was “Қазақстан – Байқоңыр – Ғарыш”, based on Nurtore Zhusip’s documentary narrative “Қыран қазақ”. The control group attended through Zoom, receiving the same instructional material and sequence of tasks without immersion. The experimental group used standalone Meta Quest headsets to join a shared ENGAGE session. The teacher appeared as an avatar and synchronously guided attention, asked questions, initiated discussion and displayed slides.

GenAI supported preparation of instructional materials and the lesson script; Skybox AI was used to generate panoramic VR scenes. Prepared explanations were played through a teacher avatar at planned points in the lesson. The available description concerns prepared content and does not establish live adaptive AI dialogue.

Pupils received headset and navigation instructions, including advice not to run or push and to remove the headset and notify the teacher if discomfort occurred. They read a supporting text about Talgat Aubakirov for one minute, explored airport, Baikonur launch-pad and orbital settings, and gathered information about his biography, spaceflight and research. Individual work required filling six gaps in a text. Groups of three adopted journalist, interviewee and editor roles to prepare six interview questions and answers using the target compound-sentence structures. Reflection and homework concluded the lesson. Figure 1 illustrates the immersive activity.



Figure 1. Interaction with visualised educational content in the ENGAGE environment.

Measures and data analysis

A test developed for the lesson content assessed listening (8 points), reading (5 points), grammar (3 points) and supplementary cultural knowledge (4 points), giving a maximum total of 20 points. Both groups completed the test before and after the lesson using Google Forms. Whether the two administrations used identical or parallel items is not specified. Results were exported to Microsoft Excel for initial checking and coding, then analysed in IBM SPSS Statistics 29.0. Motivation and engagement questionnaires were also administered to both groups, and an additional VR experience questionnaire to the experimental group. Their numerical outcomes are not included here because they were not supplied.

Ethics and confidentiality

Pupils were informed of the research aims, participated voluntarily, and that data were collected, stored and processed in anonymised form. The headset safety instructions included withdrawal from VR on discomfort.

Results

Baseline and total test performance

Table 1 presents the descriptive total scores and adjusted post-test means reported in the supplementary manuscript. Its pre-test comparison indicates a baseline difference, $t = -2.30$, $p = .026$; Levene's test is reported as $F = 0.00$, $p = .978$. The reported ANCOVA includes pre-test total as a covariate and indicates an adjusted group difference, $F(1, 43) = 8.04$, $p = .007$, partial $\eta^2 = .157$. Under the group labels printed in that source, the adjusted total score is higher for Zoom than IVR by 2.76 points. This is a reported advantage for the control condition, rather than simply an absence of an IVR advantage.

Table 1. Total scores as reported in the supplementary statistical tables.

Source group label	Pre-test M (SD)	Post-test M (SD)	Adjusted M (SE)
Experimental / IVR	13.76 (3.33)	15.32 (3.76)	15.52 (0.64)
Control / Zoom	16.10 (3.55)	18.52 (2.18)	18.28 (0.70)

Changes by assessment component

Table 2 separates gain-score comparisons from ANCOVA: these t tests concern individual changes and are not presented as covariate-adjusted component effects. The reported listening result favours the control group ($t = -2.10$, $p = .041$).

Table 2. Reported individual gains and between-group t statistics.

Component	IVR gain M (SD)	Zoom gain M (SD)	t
Listening	−0.08 (2.33)	1.48 (2.69)	−2.10
Reading	0.48 (1.71)	0.24 (0.83)	0.59
Grammar	0.64 (1.08)	0.19 (0.98)	1.47
Supplementary knowledge	0.52 (1.56)	0.52 (0.75)	−0.01
Total	1.56 (4.89)	2.43 (3.03)	−0.71

Note. Gains are post-test minus pre-test. Values and group labels follow the supplementary manuscript and require the group-attribution verification described above. Only listening has an exact gain-test p value supplied (.041); the other comparisons are non-significant. The apparent −0.01 t statistic despite equal displayed supplementary-knowledge gains can reflect rounding.

According to results, the increase in grammar scores is higher in the group designated as IVR; however, this does not imply that this group possesses an advantage in grammar. Results also show that the proportion of students in the IVR group who achieved the highest possible score in the additional subject area increased from 62% to 90%. This represents a 28-percentage-point rise in the share of students reaching the top of the scale; it does not signify a 28-point improvement in test results, nor should it be considered a general indicator of material mastery. No conclusions regarding the number of students or the relative effectiveness of teaching methods can be drawn based on these percentages, as inconsistencies in how the groups are designated complicate the interpretation of this data.

Discussion

The results obtained do not confirm a universal advantage for the immersive format. Assuming the statistical data can be attributed to the respective groups, the Zoom group—within the context of this short-term intervention—demonstrated a higher adjusted total score on the final test, as well as greater improvement in listening comprehension. The statistically non-significant difference in unadjusted total gains does not contradict the significant ANCOVA result; these analyses compare different metrics and account for baseline scores in distinct ways. Consequently, they cannot be synthesized into a single, unified conclusion that no differences exist between the groups.

One possible interpretation of the listening comprehension results is that the process of orienting oneself within a new environment competes with the processing of auditory material. This explanation aligns with cognitive load theory (Sweller, 1988) and research distinguishing "presence" (immersion) from effective learning (Makransky et al., 2021); however, cognitive load was not measured in the present study. Thus, this remains a hypothesis rather than a proven causal mechanism. The greater descriptive gain in grammar should also be interpreted with caution, as the comparison of these gains did not reach statistical significance.

Interaction with contextual objects may facilitate the comprehension of meaning; however, the evidence must be specific to the task at hand. Mukasheva et al. (2023) investigate the constructive visualization of sorting algorithms within a VR environment. While their research highlights the importance of interacting with representations, it does not specify outcomes relevant to this particular Kazakh language lesson or to students with special educational needs.

In the lesson, GenAI was used to generate panoramic images and pre-prepared explanatory texts. However, this approach does not allow for isolating the impact of GenAI from other factors; it does not demonstrate the AI's ability to provide adaptive instruction, nor does it confirm the operation of any specific mechanism inherent to Spatial AI. Other studies analyze more focused interventions—specifically those involving AI-driven feedback and pedagogical agents (Hemminki-Reijonen et al., 2025; Wang et al., 2025; Wei et al., 2026; Tao et al., 2026). If the respective contributions of AI and immersion are to be evaluated separately, future research should manipulate these two factors independently of one another.

Limitations

The study is limited by a small sample size: 46 students of the same age, a single topic, and only one 45-minute lesson. Consequently, the findings cannot be generalized to other contexts, and there is no data regarding the long-term retention of the material learned. The groups were not formed randomly and differed in their initial proficiency levels; therefore, caution should be exercised when drawing causal inferences. The composition of the classes, students' prior experience with VR, the specific criteria used for group assignment, and the method for handling missing data are not described. The test was developed specifically for this study; some reliability coefficients were low, and repeated measurements were combined when calculating reliability. Comparisons across individual sections of the test were exploratory in nature, and no adjustments were made for multiple comparisons.

Conclusion

This study presents a lesson on the Kazakh language and literature conducted within the ENGAGE environment, for which visual materials were prepared using Generative AI (GenAI). According to the available statistical analysis, the Zoom group outperformed the other group in terms of adjusted total scores and improvement in listening skills; no significant differences were found for other indicators of improvement. These findings are preliminary; primarily, the discrepancy between the statistical tables and the confirmed number of participants in each group must be resolved. Given the brief nature of the interaction, it is not possible to draw conclusions regarding the overall superiority of immersive virtual reality (IVR) or the distinct benefits of GenAI or spatial AI. The example described could serve as a starting point for longer-term studies that utilize well-documented, validated measurement tools and iterative data analysis.

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ICT as Inclusive Tools in Addressing Autistic Neurodiversity

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Abstract

Information and Communication Technologies (ICT) can be utilised as inclusive teaching tools to improve the quality of education and support for neurodivergent students with autism, serving as powerful instruments for task completion within the current educational landscape. The adoption of ICT applied to educational inclusion is clearly linked to the promotion of a social model of inclusion and respect for autistic neurodiversity as essential pillars of the neurodiversity paradigm, the consolidation of which can redirect or, where appropriate, reduce and/or eliminate those educational practices rooted in a deficit model, which are clearly linked to a culture of labelling and stigmatisation. Undoubtedly, the possibilities offered by ICT for the development of methodologies that are fully accessible, empathetic and respectful of diverse learning profiles are undeniable. We are referring to a wide range of applications which, through the incorporation of devices featuring immersive technologies such as Virtual Reality (VR) or Augmented Reality (AR), as well as others incorporating generative, predictive and conversational Artificial Intelligence (AI), offer greater guarantees of access to a high-quality educational experience for all pupils without exception. For this reason, we wish to focus our pedagogical attention on children and young people with autism spectrum disorder and, of course, on the educational contexts where transformative practices can be developed in the pursuit of genuine educational inclusion. The aim is to analyse the findings of the latest studies and research highlighting the importance of implementing these digital tools to optimise the academic and personal pathways of these young people with autism spectrum disorder. To this end, a review was carried out of the pedagogical literature available in various academic repositories and databases, from which a number of studies were selected that document the narratives of neurodivergent students and examples of good practice involving the use of ICT with such pupils. A key finding is that the use of ICT has a significant impact on the holistic development of students with autism spectrum disorder. Nevertheless, its accessibility and usability remain limited due to latent barriers to access. Finally, another area of particular interest for future research is the role played by teacher training in the effective implementation of inclusive pedagogical approaches; it is therefore essential that the initial training of these professionals focuses part of its efforts on understanding the diversity of neurological profiles, as well as on strategies, resources and tools, in order to tailor educational responses to neurodiversity based on a sound understanding of the concept.

Keywords: Autistic neurodiversity, ICT, personalised learning, inclusive education, good educational practices.

Introduction

In recent years, pedagogical reflection on the educational inclusion of neurodivergent students with autism has undergone a gradual transformation, accompanied by the consolidation of the neurodiversity paradigm within the international scientific debate (Pellicano & den Houting, 2022). The shift from a clinical model—historically rooted in diagnostic categories geared towards normalisation—towards a social model of inclusion now represents an undeniable epistemological achievement that recognises neurological variability as a constitutive dimension of the human condition rather than as a deviation to be corrected (Pellicano & den Houting, 2022; Videla et al., 2025). From this perspective, attention must be extended to the cultural, communicative, organisational and pedagogical barriers that may hinder learners' participation. In this context, ICTs are playing an increasingly prominent role, as they can contribute—if properly designed and used—to the creation of accessible and personalised, learning environments (Lorenzo et al., 2023; Guerrero Valverde et al., 2024). Their effectiveness does not lie in the mere introduction of the digital tool, but in the ability to integrate it into a purposeful educational approach, capable of highlighting the diversity of communication channels, the regulation of stimuli, the gradual progression of tasks and the possibility of offering different modes of representation, expression and participation. When framed within a clear pedagogical intent and in line with the principles of Universal Design for Learning (hereinafter UDL) (CAST, 2024), these technologies can help to create environments that are more accessible, predictable and respectful of individual learning pathways; acting as tools for educational mediation rather than merely as compensatory devices. In this regard, research is increasingly focusing on those technologies that offer specific possibilities for personalising learning for neurodivergent students with autism. Among these, technologies based

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on Augmented Reality (hereinafter AR) and Virtual Reality (hereinafter VR) occupy a prominent place, which enable the creation of predictable and adaptable scenarios in which stimuli can be adjusted, situations anticipated and meaningful learning experiences provided, thereby helping to regulate sensory overload and maintain attention whilst carrying out activities (Carmona-Serrano et al., 2025; Silva et al., 2025). In addition to these, digital support tools and applications based on Artificial Intelligence (hereinafter AI) are opening up new possibilities for educational mediation, ranging from the generation of adapted content to personalised communication support, including the monitoring of learning processes and the early detection of difficulties among students (Wang et al., 2025; Joseph & Babu, 2025). What makes these technologies significant is not their technical novelty, but the possibility of integrating them into educational pathways that recognise the uniqueness of the learning profiles of students with autism spectrum disorder, achieved through the personalisation of content, forms of communication and teaching pathways according to the characteristics of the student body (Navas-Bonilla et al., 2025). However, for this potential to translate into inclusive practices, the material, training and organisational conditions in which ICTs are introduced must be taken into account. Inequality in technological resources, insufficient teacher training in neurodiversity and inclusive digital skills, as well as the persistence of labelling practices and compensatory approaches, increase the risk of digital tools becoming new mechanisms of exclusion, thereby reproducing the very inequalities that the neurodiversity paradigm seeks to dismantle (Fernández-Batanero et al., 2025; Fernández-Cerero & Montenegro-Rueda, 2025). The inclusive value of ICTs, therefore, does not lie in the tools themselves, but in the pedagogical, ethical and training decisions that accompany their introduction into academic contexts.

In light of these considerations, this article aims to analyse the role of ICT as an inclusive mediator in the educational pathways of neurodivergent students with autism, adopting a pedagogical perspective that focuses on the quality of learning contexts, the personalisation of learning and the promotion of participation. This work forms part of a literature review conducted as part of a doctoral thesis in which, following the PRISMA methodology, a search was carried out for narrative studies and teaching proposals involving neurodivergent students with autism using a Boolean search term in the Web of Science, Scopus and Dialnet between November 2025 and June 2026. This paper focuses on studies that demonstrate how immersive technologies and AI can contribute to creating more accessible, flexible and empathetic educational environments.

Technologies for immersive learning: Augmented and Virtual Reality for personalised learning

In the contemporary educational landscape, immersive experiences are becoming increasingly prominent thanks to the incorporation of tools that integrate AR and VR into learning situations. The proliferation of these technologies is bringing about a shift in current pedagogical settings by offering interactive environments that can be adapted to a variety of situations and contexts, both real and imaginary (Carmona-Serrano et al., 2025; Atsalaki & Kazanidis, 2025). Pupils' engagement and participation in activities that incorporate VR and AR facilitate the understanding of certain concepts and elements, thanks to the enrichment provided by the combination of physical objects with real-time, multi-sensory digital information; an even more significant impact in the case of neurodivergent students with autism who, in certain cases, face challenges and difficulties in developing communication skills and personal autonomy (Carmona-Serrano et al., 2025; Silva et al., 2025). Building on this foundation, and in addition to the impact that the incorporation of these technologies has on motivation, learners' engagement in group dynamics and their learning outcomes, AR and VR represent an asset in the field of inclusion for neurodivergent students with autism, becoming, in those settings where they are implemented, a powerful ally for personalised learning (Ip et al., 2024; Carmona-Serrano et al., 2025; Lorenzo Lledó, 2025; Silva et al., 2025).

The predictive and controlled nature of the learning environments offered by AR and VR facilitates the regulation and mitigation of sensory overload, thereby preventing episodes or crises caused by dysregulation and cognitive overload, as well as helping to improve attentional behaviours (López-Belmonte et al., 2024; Carmona-Serrano et al., 2025; Silva et al., 2025). Thus, the personalisation of learning through the regulation of sensory stimuli, as well as the adaptation of resources to the profile of the neurodivergent student and the facilitation of various forms of engagement, clearly demonstrates the alignment of approaches incorporating AR and VR with the UDL principles (Silva et al., 2025).

Highlighting the applications of these technologies in secondary and higher education, studies such as that by Silva et al. (2025) suggest that the use of three-dimensional manipulative models to address abstract concepts—such as the functioning of certain bodily systems or planetary orbits—enhances not only the academic performance of neurodivergent adolescent students, but also their sensory and behavioural self-regulation skills and sustained attention whilst performing tasks. For their part, Kourtesis et al. (2023) and Ip et al. (2024) focused their studies on adults and university students, viewing VR as a well-established tool for training in life skills and employability. Through tools and software such as the VR system for the Development of Social Skills, neurodivergent students have the opportunity to practise navigating awkward or complex interactions, such as attending seminars or job interviews; the results demonstrate high adaptability, reduced stress levels and a considerable improvement in

executive functions such as working memory and planning, amongst others. Finally, it should not be overlooked that, whilst it is true that the use of these technologies highlights significant potential for improving the engagement, participation and social communication of neurodivergent students with autism, certain interfaces require a thorough review in order to eliminate distracting elements; something which, furthermore, must go hand in hand with appropriate support from teachers and professionals trained in the use of these tools, with a view to promoting their responsible use (López-Belmonte et al., 2024; Carmona-Serrano et al., 2025; Lorenzo Lledó, 2025; Silva et al., 2025). In summary, VR and AR are establishing themselves as powerful allies for social and educational inclusion within the framework of neurodiversity, facilitating the transition to adulthood and academic success for those neurodivergent learners who use these technologies in secondary and higher education classrooms.

Neurodiversity and Artificial Intelligence: new paradigms and horizons for inclusive education

The concept of neurodiversity (Cevallos et al., 2025), understood as a personal condition relating to the ways in which people think, feel and communicate within human diversity, has brought about a paradigm shift, leading to the view that difference is an enriching element and that educational contexts are key factors to be taken into account when designing teaching approaches. This development brought about a vital transformation in pedagogy by recognising the influence of systemic factors on the development of individual characteristics. In this regard, autistic identity is recognised as a natural variation, and the use of technology as a tool that enables the personalisation of teaching and learning processes whilst minimising contextual barriers.

Research carried out by Gallardo-Herrerias (2025), Martínez-Molina (2025) and Yépez-Contreras et al. (2026) highlights the importance of using AI in educational settings, as it minimises sensory and communicative barriers by increasing predictability, reducing sensory overload and expanding communication options. All of this leads to a reduction in learners' stress and anxiety levels, as they do not have to expend excessive effort on developing adaptive behaviours, whilst also helping to foster the potential of neurodivergent autistic pupils, such as their attention to detail or visual thinking. The emergence of AI has not merely represented a technological innovation, but a driver of structural change within the education system through a holistic approach involving all stakeholders (Vasco-Delgado et al., 2025). Not only have the available tools been transformed, but so too have conceptions of teaching and learning. Traditional, teacher-centred models of education are giving way to more dynamic, learner-centred approaches, in which learners develop various educational competences in a highly practical manner through learning pathways tailored to their cognitive, emotional and motivational profiles. Authors such as Encalada et al. (2024), Mora (2024), Uyaguari-Cuenca et al. (2025) and Villatoro Moral and Moreno-Tallón (2025) highlight resources such as digital visual timetables, augmentative communication apps, VR environments and AI-based learning management platforms, as these enable the adjustment of timings and formats, promote accessibility to different content and knowledge, and allow for the analysis of learning patterns, thereby providing relevant information to understand the learners and make decisions consistent with their actual needs, personalising learning by adapting to the students' learning styles and paces.

Within this new inclusive landscape facilitated by the use of AI, we also face a number of challenges, such as the digital divide driven by technical, economic or even social factors (Choez & Miranda, 2024); inadequate teacher training in the application of AI within inclusive educational contexts (Soledispa-Zurita et al., 2024); as well as issues surrounding the processing of pupils' personal data and equitable access to these technologies (Jácome-Camacho et al., 2025). Therefore, the use of AI can enhance the learning and wellbeing of neurodivergent students when it is carried out in accordance with the principles of personalisation, accessibility and respect for diversity, helping to reduce barriers and expand opportunities for participation (Gallardo-Herrerias, 2025). The intersection between neurodiversity and AI ultimately calls for a rethinking of inclusive education as a profound shift in the epistemological, relational and technological frameworks that underpin the educational experience.

Conclusions

ICTs are emerging as teaching tools with high inclusive potential for pupils on the autism spectrum, insofar as they promote accessibility, the personalisation of support, and the diversification of channels for representation, action and participation in teaching and learning processes (Fernández-Batanero et al., 2024; Fernández-Cerero & Montenegro-Rueda, 2025). The effective integration of digital resources, including immersive AR and VR environments, as well as applications incorporating AI, contributes significantly to improving academic performance, motivation to learn and the development of social and communication skills in these students, provided they are designed from a pedagogical approach that respects diversity rather than from compensatory and/or reductionist perspectives (Fernández-Batanero et al., 2025; Guerrero Valverde et al., 2024). In line with the neurodiversity paradigm and the social model of disability, we are fully convinced that the educational value of

ICT lies not solely in the tool itself, but in the way it is integrated with pedagogical practices that recognise the uniqueness of neurodivergent profiles, legitimise their ways of processing information and promote flexible learning pathways. When technologies are woven into collaborative, multimodal approaches centred on pupils' interests, they create more empathetic, sensitive, predictable and structured contexts that facilitate self-regulation, active participation and a sense of belonging amongst autistic pupils in mainstream classrooms.

The review also highlights the existence of significant gaps that hinder the full and equitable integration of ICT into the educational response to autistic neurodiversity (Fernández-Batanero et al., 2025; Wang et al., 2025). Among the barriers identified are limitations in access to high-quality technological resources, unequal provision of infrastructure across schools and/or regions, economic and institutional constraints on the sustained and harmonious implementation of inclusive ICT projects, and, most significantly, insufficient training of teachers in digital and inclusive skills. In this regard, these barriers not only limit the informed and effective use of digital tools, but may also perpetuate and give rise to patterns of labelling, stigmatisation or, where applicable, minimal adaptation to the learning profile of neurodivergent young people, which are at odds with a human rights-based approach and full participation in community and educational life. For all these reasons, it is essential to advance educational practices and policies that guarantee universal, sustainable and ethical access to inclusive technologies, prioritising the UDL, cognitive and communicative accessibility, and the cooperative co-creation of resources alongside students, families and education professionals (Lorenzo et al., 2023). It is also a priority to strengthen initial and continuing teacher training in the areas of neurodiversity, inclusive education and technology, making it essential to develop the skills needed to critically analyse digital tools, carefully and empathetically selecting those best suited to each context, and to develop pedagogical approaches that are sensitive to the narratives of neurodivergent students with autism.

In conclusion, we might state that emerging research horizons are opening up and deserve to be explored in order to delve deeper through longitudinal, participatory and intersectional studies on the impact of ICT on the socio-emotional well-being, self-determination and community participation of autistic people, thereby contributing to the consolidation of an education system that is genuinely inclusive, supportive and fair.

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Artificial Intelligence Readiness Among Pre-service Teachers: A Study on the Technological and Ethical Dimensions

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Abstract

This study aimed to examine pre-service teachers' artificial intelligence (AI) readiness levels across the dimensions of technological self-efficacy, interaction with students, and ethical awareness in relation to several variables, and to determine the relationship between technological self-efficacy and ethical awareness. A quantitative descriptive survey design was employed. The sample consisted of 246 pre-service teachers enrolled in the faculty of education of a state university in Türkiye during the 2024–2025 academic year. Data were collected using the AI Readiness Scale for Teachers developed by Ramazanoğlu and Akın (2025). Descriptive statistics, independent-samples *t*-tests, one-way analysis of variance (ANOVA), and Pearson correlation analysis were used to analyze the data. The findings indicated that pre-service teachers' overall AI readiness (M = 3.41) was not balanced across dimensions. Participants' ethical awareness (M = 3.64) and interaction with students (M = 3.62) scores were noticeably higher than their technological self-efficacy scores (M = 2.86). Technological self-efficacy scores were lowest on items requiring technical competence, such as problem solving and project development (M = 2.64). AI readiness did not differ significantly by gender or grade level ($p > .05$). By score type, a statistically significant difference with a small effect size was found only in the technological self-efficacy dimension, $F(4, 241) = 2.983$, $p = .020$, $\eta^2 = .047$; however, Scheffé post hoc comparisons did not identify a significant difference between any pair of groups. The finding that senior students' readiness levels were similar to those of students in lower grades suggests that teacher education programs are limited in developing AI-related technical competencies. In addition, a weak positive relationship was found between technological self-efficacy and ethical awareness ($r = .218$, $p < .01$). Together, these findings point to a technical–ethical gap: pre-service teachers are prepared to assume ethical responsibility for a technology that they do not yet feel able to manage technically. Therefore, it is recommended that AI education addressing both technical and ethical dimensions be integrated into teacher education curricula and that pre-service teachers' AI readiness be assessed regularly.

Keywords: Artificial intelligence readiness, pre-service teachers, technological self-efficacy, ethical awareness, Intelligent-TPACK.

Introduction

Rapid advances in artificial intelligence (AI) technologies are bringing about substantial changes in how educational processes are planned, implemented, and evaluated. With the spread of generative AI applications, teachers and students have begun to use AI-supported tools in many areas. These developments have led AI to be regarded not merely as a technological innovation but as a strategic component that is transforming instructional processes (Bryant et al., 2020; Chen et al., 2020; Holmes et al., 2019). However, whether this transformation is effectively reflected in educational settings depends on whether teachers and pre-service teachers possess the competencies needed to use AI technologies for pedagogical purposes.

One of the key concepts in this context is AI readiness. Readiness is a multidimensional construct that goes beyond an individual's adoption of a new technology and refers to the capacity to integrate that technology into instructional processes effectively, safely, and ethically (Ramazanoğlu & Akın, 2025). Pre-service teachers' AI readiness plays a decisive role in their future classroom technology integration, instructional strategies, and professional practices (Sanusi et al., 2024).

Recent theoretical approaches emphasize that AI integration is not limited to technical knowledge and that technological competence, pedagogical knowledge, and ethical awareness should be addressed together. In particular, the Intelligent-TPACK and AI-PACK frameworks propose integrating these dimensions so that teachers can use AI consciously and responsibly (Celik, 2023; Starr & Wickam, 2026).

The literature shows that pre-service teachers' attitudes toward AI are becoming increasingly positive, but that this positive stance is not always supported by adequate technical skills; pre-service teachers often display an ambivalent stance, caught between technological curiosity and ethical concerns about AI-based tools (Rui et al., 2025). A similar pattern has been identified among practicing teachers, whose favorable attitudes toward AI may not be accompanied by comparable levels of AI literacy, highlighting the importance of distinguishing positive

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dispositions from the competencies needed for effective AI integration (Çayak, 2024). Ng et al. (2021) conceptualize AI literacy through four interrelated aspects (knowing and understanding, using and applying, evaluating and creating, and ethical issues), which suggests that ethical considerations cannot be separated from technical understanding. Similarly, Celik (2023) found that teachers' technological knowledge enables them to better assess AI-based decisions, although technological knowledge alone is not sufficient for effective integration. Recent evidence also indicates a positive relationship between AI literacy and TPACK among pre-service teachers (Aglibot et al., 2025). Effective AI integration therefore requires not only positive attitudes but also strong technological self-efficacy and ethical awareness that are developed together.

Although pre-service teachers' attitudes toward and acceptance of AI have been widely studied, studies in which technological self-efficacy and ethical awareness are measured together within the same sample, and in which the asymmetry between them is tested quantitatively, remain limited, particularly in Türkiye. This study refers to such an asymmetry as a technical–ethical gap.

The purpose of this study was to examine pre-service teachers' AI readiness levels across the dimensions of technological self-efficacy, interaction with students, and ethical awareness, and to determine whether these levels differ by gender, grade level, and score type. The study also aimed to determine the relationship between technological self-efficacy and ethical awareness.

Research Questions

This study sought to answer the following research questions:

1. What are pre-service teachers' levels of AI readiness (technological self-efficacy, interaction with students, and ethical awareness)?
2. Do pre-service teachers' AI readiness levels differ significantly by gender, score type, and grade level?
3. Is there a significant relationship between pre-service teachers' technological self-efficacy and ethical awareness?

Method

Research Design

This study employed a survey design within a quantitative research approach to determine pre-service teachers' AI readiness levels and to examine whether these levels differ by various demographic variables. The survey design is a descriptive research design that aims to describe individuals' views, attitudes, and competencies regarding a particular topic as they currently exist (Fraenkel et al., 2012).

Participants

The study group consisted of 246 pre-service teachers enrolled in the faculty of education of a state university in Türkiye during the 2024–2025 academic year. Participants were selected through convenience sampling from among individuals who volunteered to take part in the study.

Of the participants, 80.9% (n = 199) were female and 19.1% (n = 47) were male. In terms of score type (i.e., the score type of the national university entrance examination through which students were placed in their programs), 37.4% of the participants were placed with Quantitative scores, 31.3% with Verbal scores, 11.8% with Foreign Language scores, 11.0% with Equal Weight scores, and 8.5% through Special Talent examinations. Regarding grade level, 53.6% were second-year, 28.9% third-year, and 17.5% fourth-year students.

Data Collection Instrument

Data were collected using the *AI Readiness Scale for Teachers* developed by Ramazanoğlu and Akın (2025). The scale is a 5-point Likert-type instrument consisting of 19 items and three subscales: Technological Self-Efficacy, Interaction with Students, and Ethical Awareness. To examine the construct validity of the scale for the present study group, confirmatory factor analysis (CFA) was conducted; one item with a low factor loading was removed, and subsequent analyses were performed on 18 items. The resulting fit indices indicated that the model showed good fit (Hu & Bentler, 1999; Tabachnick & Fidell, 2013). The Cronbach's alpha coefficient was .89 for the overall scale and ranged from .81 to .88 for the subscales.

Data Analysis

Data were analyzed using SPSS 26. Prior to the analyses, missing data and the assumption of normality were examined; because skewness and kurtosis values fell within the ±1.5 range, parametric tests were used (Tabachnick & Fidell, 2013). Descriptive statistics, independent-samples *t*-tests, one-way ANOVA, and Pearson correlation analysis were performed. Following ANOVA, the Scheffé test was applied to identify significant differences, and effect sizes were evaluated using Cohen's *d* and eta squared (η^2). The significance level was set at $p < .05$ for all analyses.

Results

AI Readiness Levels

According to the descriptive analysis, pre-service teachers' ethical awareness ($M = 3.64$) and interaction with students ($M = 3.62$) scores were higher than their technological self-efficacy scores ($M = 2.86$). The overall scale mean was 3.41. In the technological self-efficacy dimension, the lowest means were observed for the problem-solving and project-development items ($M = 2.64$), whereas in the ethical awareness dimension, the highest mean was obtained for the item on behaving ethically ($M = 3.96$). This finding suggests that pre-service teachers embrace AI-related ethical responsibilities relatively strongly, whereas they perceive themselves as less competent in uses that require technical production, problem solving, and project development.

Classification of Readiness Levels

To describe pre-service teachers' readiness levels more concretely, a level classification was made based on mean scores. This classification was based on the class-interval formula used to determine score ranges in Likert-type scales (Pimentel, 2010). Mean scores between 1.00 and 2.33 were defined as low, between 2.34 and 3.66 as moderate, and between 3.67 and 5.00 as high.

While 59.8% of the participants were at the high level in the ethical awareness dimension, this proportion dropped to 10.6% in the technological self-efficacy dimension, clearly indicating a substantial need for the development of technical skills within teacher education curricula. In the interaction with students dimension, the majority of pre-service teachers (57.7%) were at the high level and 39.5% at the moderate level, suggesting that they are better equipped to use AI as a pedagogical tool for interacting with students than they are in the technical dimension.

Findings by Gender

Independent-samples *t*-test results showed that pre-service teachers' AI readiness did not differ significantly by gender in any of the technological self-efficacy, interaction with students, or ethical awareness dimensions ($p > .05$). Moreover, the Cohen's *d* effect sizes were small in all dimensions, indicating that gender did not have a meaningful effect on AI readiness. Thus, the absence of a statistically significant difference and the negligible effect sizes suggest that the influence of AI technologies is a phenomenon shared across the generation, independent of gender. The finding that female and male pre-service teachers share similar technical concerns and similarly high ethical awareness supports the view that teacher education policies should focus on an inclusive, gender-neutral technological transformation.

Findings by Score Type

One-way ANOVA results showed that pre-service teachers' interaction with students and ethical awareness scores did not differ significantly by score type ($p > .05$). In contrast, a statistically significant difference by score type was found in the technological self-efficacy dimension, $F(4, 241) = 2.983$, $p = .020$, $\eta^2 = .047$. However, the eta-squared value ($\eta^2 = .047$), calculated to determine the magnitude of the difference, corresponds to a small effect according to the criteria proposed by Cohen (1988) ($\eta^2 = .01$ small, .06 medium, .14 large), indicating that score type explained only approximately 4.7% of the total variance in technological self-efficacy. Indeed, the Scheffé multiple comparison test, conducted to identify the source of the difference, did not reveal a statistically significant difference between any pair of groups owing to its conservative nature; the group means fell within a single homogeneous subset ($p = .079$). At the descriptive level, the lowest technological self-efficacy mean was observed among pre-service teachers in the Equal Weight group ($M = 2.50$), whereas the highest means were observed in the Special Talent ($M = 2.97$) and Quantitative ($M = 2.95$) groups. This pattern is methodologically important: even pre-service teachers from quantitative fields displayed relatively low technological self-efficacy, and the observed omnibus difference was limited to a small effect size. This supports the view that AI literacy is a distinct, interdisciplinary area of expertise that is independent of traditional mathematical or science competence.

Findings by Grade Level

The results showed that grade level did not have a significant effect on pre-service teachers' AI readiness ($p > .05$). The eta-squared values for the technological self-efficacy, interaction with students, and ethical awareness subscales ($\eta^2 = .018$, .002, and .001, respectively) indicate that the effect of grade level on readiness was very small. These findings show that pre-service teachers' AI-related knowledge, skills, and ethical awareness did not develop noticeably as they progressed through their university education. Accordingly, it can be argued that the current teacher education process does not provide gradual, grade-dependent development in AI competencies.

Relationships Among Dimensions and the Technical–Ethical Gap

Pearson correlation analysis revealed significant positive relationships among the subscales. A moderate positive relationship was found between interaction with students and ethical awareness ($r = .542$, $p < .01$), a low-to-moderate relationship between technological self-efficacy and interaction with students ($r = .397$, $p < .01$), and a weak relationship between technological self-efficacy and ethical awareness ($r = .218$, $p < .01$). Considered together with the mean differences between these dimensions, the weak relationship between technological self-efficacy and ethical awareness indicates a technical–ethical gap: pre-service teachers are sensitive to the ethical dimensions of AI but lack sufficient confidence in using and managing the technology effectively.

Conclusion

This study revealed a marked imbalance between ethical awareness and technical competence in pre-service teachers' AI readiness. The findings indicate that pre-service teachers have a high level of awareness regarding the ethical use of AI but feel less competent in understanding the technical and algorithmic foundations of the technology and in using it effectively for pedagogical purposes. This technical–ethical gap is important in light of Celik's (2023) finding that technological knowledge enables teachers to better assess AI-based decisions; ethical awareness without a technical foundation may therefore remain at the level of intention. The present pattern also partly differs from that reported by Sadaf et al. (2025), whose pre-service teachers expressed the lowest confidence in both technological knowledge and AI ethics. In the present sample, ethical awareness was comparatively high, whereas technological self-efficacy remained limited. This difference suggests that the relationship between technical and ethical readiness may vary across contexts and should be examined further.

The study found that grade level did not produce a significant difference in AI readiness. The fact that senior students did not differ from students in lower grades suggests that systematic and practice-oriented AI content is insufficiently included in faculties of education. Similarly, the finding that score type had only a small effect, and only on technological self-efficacy, indicates that AI literacy is an interdisciplinary competence that is independent of traditional field distinctions and relevant to all pre-service teachers.

Pre-service teachers' high ethical awareness is thought to be shaped by general moral values, social experiences, and current debates on AI-related issues such as academic integrity and data security. However, ethical awareness that is not supported by technical knowledge may be insufficient for evaluating algorithmic errors and AI-related risks (Celik, 2023). Therefore, pre-service teachers' AI readiness should be addressed not merely as tool use but as a dynamic process that integrates technical knowledge, pedagogical practice, and ethical responsibility.

In line with these findings, it is recommended that courses on AI in education that integrate the technical, pedagogical, and ethical dimensions of AI be added to teacher education curricula (Starr & Wickam, 2026). This emphasis on integrated preparation is consistent with teachers' reported need for sustained professional support and explicit ethical frameworks to guide the responsible use of AI (Tümen Akyıldız, 2025). Ethics education should be supported by algorithmic thinking, data literacy, and an understanding of how AI systems work. In addition, consistent with the call by Rui et al. (2025) to combine AI-technical expertise with hands-on pedagogical practice, no-code/low-code AI applications, project development activities, and hands-on workshops should be organized to develop pre-service teachers' practical skills. Finally, it is recommended that pre-service teachers' AI competencies be monitored regularly and further examined through longitudinal and mixed-methods studies involving multiple universities.

Limitations

This study has several limitations. Because it was conducted with 246 pre-service teachers at a single state university using convenience sampling, the generalizability of the findings is limited. In addition, the reliance on a self-report scale and the cross-sectional design provide limited information about pre-service teachers' actual practical skills and their development over time.

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Adaptation of the Teachers' Readiness and Intention to Teach AI Scale to a Sample in Türkiye: An Exploratory Factor Analysis Study

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Abstract

The rapid integration of artificial intelligence (AI) technologies into educational settings makes it essential to determine teachers' readiness and intentions to teach AI. Although the literature offers instruments measuring students' attitudes toward AI, no Turkish instrument examining teachers' multidimensional orientations toward teaching AI has been found. The purpose of this study is to adapt the Teachers' Readiness and Intention to Teach Artificial Intelligence Scale, developed by Ayanwale et al. (2022) for K-12 teachers, into Turkish and to examine its psychometric properties in the Turkish context through a preliminary exploratory factor analysis. Although the target population of the scale consists of in-service teachers, the data for this preliminary study were collected from 338 pre-service teachers selected via convenience sampling. Following the translation and back-translation of the scale, which originally consists of eight factors and 33 items, expert opinions were consulted to ensure linguistic and conceptual equivalence. Construct validity was tested using the maximum likelihood extraction method with Promax oblique rotation. Six items with insufficient loadings, cross-loadings, or loadings on a factor other than their theoretical dimension were excluded; the analysis of the remaining 27 items revealed an eight-factor structure (AI Anxiety, Perceived Usefulness, AI for Social Good, Attitude Towards Using AI, Confidence in Teaching AI, Behavioral Intention, Relevance of AI, and Readiness) consistent with the theoretical framework of the original study. This structure explained 58.78% of the total variance, and factor loadings ranged from .433 to .962, all above the adopted threshold of .40. Cronbach's alpha was .879 for the overall scale and ranged from .705 to .903 for the subdimensions. The findings indicate that the adapted scale provides a valid and reliable preliminary framework for measuring teachers' readiness and intentions to teach AI in Türkiye.

Keywords: Artificial Intelligence, Readiness, Behavioral Intention, Scale Adaptation, Exploratory Factor Analysis, Teachers.

Introduction

Artificial intelligence (AI) technologies have developed so rapidly in recent years that the field of education is now also being shaped by this transformation (Coşkun & Gülleroğlu, 2021). With subcomponents such as machine learning and natural language processing, AI is no longer a topic confined to the interests of technical experts; it has begun to become part of curricula, course content, and school practices. As a consequence of this transformation, efforts to foster AI literacy at every level, from primary school to university, have entered the agenda of education systems. UNESCO's (2022) mapping study covering 193 member states documents that Armenia, Austria, Belgium, China, India, South Korea, Kuwait, Portugal, Qatar, Serbia, and the United Arab Emirates have officially implemented K-12 AI curricula, while Germany, Jordan, Bulgaria, and Saudi Arabia are continuing their development processes.

Systematic reviews examining the integration of AI into K-12 education reveal that the use of these technologies supports teachers in planning, implementation, and assessment processes and redefines the teacher's role in the classroom (Çelik et al., 2022; Lee & Kwon, 2024). Research on educators' adoption of AI also highlights the importance of readiness and attitudes: Eke (2024) reported high readiness and positive attitudes among Nigerian teacher educators, alongside perceived barriers related to infrastructure, training, and ethical concerns. However, existing research focuses predominantly on the use of AI as an instructional tool, whereas AI itself as a subject of instruction has received relatively limited attention.

Yet the successful introduction of a subject into the classroom depends largely on the knowledge, attitudes, and readiness of the teacher who will carry out this process (Darling-Hammond et al., 2017). Related evidence from general technology integration research links teachers' beliefs and school conditions to their expectations of technology use: Perkmen (2024) found that self-efficacy and school climate significantly predicted outcome expectancy. Teachers' multidimensional orientations toward teaching AI can be explained through different theories. The principal theories drawn upon in this area include Ajzen's (1991) Theory of Planned Behavior, which posits that attitude, subjective norms, and perceived behavioral control predict behavioral intention, and Davis's

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(1989) Technology Acceptance Model, which posits that perceived usefulness and perceived ease of use predict the intention to adopt a technology. The instrument adapted in this study is also grounded in these two theories.

A review of the literature shows that various instruments have been developed to measure students' attitudes, perceptions, and intentions to learn regarding AI (Chai et al., 2020; Dai et al., 2020). Considerable activity has also been observed in this area in Türkiye. With regard to the construct of anxiety, Akkaya et al. (2021) and Terzi (2020) adapted different AI anxiety scales into Turkish. In terms of awareness and attitudes, Ferikoğlu and Akgün (2022) developed an instrument measuring teachers' AI awareness, İlhan and Önal (2025) adapted the Attitude Towards Artificial Intelligence Scale, developed by Suh and Ahn (2022), into Turkish, and Kaplan and Kurdal (2025) adapted the Artificial Intelligence Learning Intention Scale, originally developed by Chai et al. (2024), to Turkish culture. In addition, several researchers have descriptively examined teachers' and pre-service teachers' attitudes toward AI (Acem et al., 2024; Saatçioğlu & Topsakal, 2025). A considerable proportion of these studies focus on general attitudes and anxieties, whereas empirical research addressing teachers' readiness and intentions specific to the process of teaching AI within an integrated framework remains limited.

To address this gap, Ayanwale et al. (2022) developed an eight-factor, 33-item scale grounded in the Theory of Planned Behavior (Ajzen, 1991) and the Technology Acceptance Model (Davis, 1989), encompassing the dimensions of AI anxiety, perceived usefulness, AI for social good, attitude towards using AI, confidence in teaching AI, behavioral intention, relevance of AI, and readiness. A PLS-SEM analysis conducted with Nigerian K-12 teachers revealed that teachers' confidence and the perceived relevance of AI significantly explained behavioral intention and readiness, whereas AI anxiety had no significant effect on behavioral intention. This scale is one of the few instruments that address teachers' internal states regarding teaching AI in a multidimensional manner. The absence of a valid and reliable Turkish instrument based on this eight-dimensional structure in Türkiye constitutes a methodological obstacle to both national descriptive studies and cross-cultural comparisons. Based on this need, the purpose of this study is to adapt the scale into Turkish and to examine its psychometric properties in a sample from Türkiye through a preliminary exploratory factor analysis (EFA).

Method

Research Design

Since this study aimed to adapt the scale developed by Ayanwale et al. (2022) into Turkish, the research was designed as a descriptive survey study. Survey designs are research designs that aim to describe a situation as it exists (Fraenkel et al., 2018). Following the generally accepted approach in scale adaptation studies (Hernández et al., 2020), the research process was carried out in three main stages: linguistic translation, expert review, and statistical analysis.

Participants

Although the primary target population of the scale is in-service teachers, the data for this preliminary adaptation process were collected from pre-service teachers enrolled in different departments of a faculty of education. The data were collected during the 2025–2026 academic year from participants selected through convenience sampling. Of the 343 scale forms administered to pre-service teachers, five forms with missing or invalid responses were removed from the data set, and the analyses were conducted with the remaining 338 pre-service teachers. Demographic information about the participants is presented in Table 1.

Table 1. Demographic characteristics of the participants.

Variable		*f*	%	Variable		*f*	%
Gender	Female	281	83.14	Age	18	7	2.07
	Male	57	16.86		19	35	10.36
Year of Study	1st Year	4	1.18		20	83	24.56
	2nd Year	178	52.66		21	112	33.14
	3rd Year	102	30.18		22	56	16.57
	4th Year	54	15.98		23	22	6.51
					24	10	2.96
					25 and older	13	3.85

Note. $N = 338$. Age is reported in completed years.

For EFA, a sample size of at least five to ten times the number of items is recommended (Hair et al., 2019), and sample sizes of 300 or more are considered adequate (Tabachnick & Fidell, 2019). Accordingly, the sample of 338 participants, approximately ten times the number of items in the original 33-item scale, meets these criteria.

Data Collection Instrument

The Teachers' Readiness and Intention to Teach Artificial Intelligence Scale developed by Ayanwale et al. (2022) was used in the study. The original scale was developed on the basis of a theoretical framework grounded in the Theory of Planned Behavior (Ajzen, 1991) and the Technology Acceptance Model (Davis, 1989) and consists of eight factors and 33 items: AI Anxiety (AN; 4 items), Perceived Usefulness (PU; 4 items), AI for Social Good (SG; 4 items), Attitude Towards Using AI (AT; 3 items), Confidence in Teaching AI (CON; 4 items), Behavioral Intention (BI; 5 items), Relevance of AI (RA; 4 items), and Readiness (RE; 5 items). In the original study, the validity and reliability of the measurement model were evaluated within the PLS-SEM framework, and it was reported that the composite reliability (CR) coefficients of all constructs ranged from .86 to .95 and the average variance extracted (AVE) values ranged from .62 to .86, all exceeding the recommended thresholds (Ayanwale et al., 2022).

Translation Process

The translation–back-translation technique was used in the process of adapting the scale into Turkish (Hernández et al., 2020). The original English items were independently translated into Turkish by experts, and the initial Turkish draft was created by comparing the resulting translations. This draft was then translated back into English by an independent expert, and the back-translated form was compared with the original items in terms of meaning and scope. Discrepancies in meaning were resolved in line with expert opinions, and following the content validity evaluation by academics specializing in measurement and evaluation, the Turkish form was finalized for administration.

Findings

Exploratory Factor Analysis Results

To test the construct validity of the Turkish form of the scale, the suitability of the data for factor analysis was first examined using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. For the final 27-item solution, the KMO value of .889 and the significant result of Bartlett's test ($\chi^2 = 4516.983$; $df = 351$; $p < .001$) indicate that the data set is suitable for factor analysis (Tabachnick & Fidell, 2019).

Table 2. Subdimensions of the scale, item factor loadings, and internal consistency coefficients.

Subdimension	Item	Loading	α	Subdimension	Item	Loading	α
AI Anxiety (AN)	AN1	.762	.787	Confidence in Teaching AI (CON)	CON1	.495	.765
	AN2	.715			CON2	.545	
	AN3	.650			CON3	.789	
	AN4	.672			CON4	.850	
Perceived Usefulness (PU)	PU2	.517	.850	Behavioral Intention (BI)	BI1	.512	.816
	PU3	.855			BI2	.433	
	PU4	.898			BI3	.935	
AI for Social Good (SG)	SG1	.652	.760		BI4	.680	
	SG2	.532		Relevance of AI (RA)	RA1	.508	.705
	SG3	.741			RA4	.688	
	SG4	.616		Readiness (RE)	RE2	.749	.883
Attitude Towards Using AI (AT)	AT1	.764	.903		RE3	.872	
	AT2	.962			RE4	.909	
	AT3	.736					

Note. $N = 338$. Loading = factor loading in the rotated pattern matrix; α = Cronbach's alpha. Subdimension abbreviations and item codes follow those of the original scale (Ayanwale et al., 2022). Extraction method: maximum likelihood; rotation method: Promax with Kaiser normalization.

Construct validity was tested through exploratory factor analysis using the maximum likelihood extraction method and Promax oblique rotation. The number of factors was fixed at eight in order to maintain consistency with the theoretical structure of the original scale. Taking the sample size into account, .40 was adopted as the minimum factor loading; the literature recommends that an item load at least .40 on its respective factor (Watkins, 2018), and it is noted that sample size is decisive for the significance of factor loadings and that loadings of .40 can be considered significant in a sample of 200 (Hair et al., 2019). In the initial analysis, all 33 items were included, and six items did not meet the criteria in this solution. Three items did not load above the .40 threshold on any factor, two items showed cross-loadings by loading above .40 on more than one factor, and one item loaded on a different factor rather than on the factor to which it theoretically belongs. Considering statistical criteria and theoretical justifications together, these six items were removed (Acar Güvendir & Özer Özkan, 2022), and the analysis was repeated with the remaining 27 items.

In the solution fixed at eight factors, the items were found to load on their respective dimensions in line with the theoretical structure of the original scale; the resulting item-factor structure and the internal consistency coefficients of the subdimensions are presented in Table 2. The dimensions are as follows: AI Anxiety (AN), Perceived Usefulness (PU), AI for Social Good (SG), Attitude Towards Using AI (AT), Confidence in Teaching AI (CON), Behavioral Intention (BI), Relevance of AI (RA), and Readiness (RE). The resulting eight-factor structure explains 58.78% of the total variance. Considering that a total explained variance in the range of 50–60% is regarded as adequate in the social sciences (Hair et al., 2019), this proportion meets the criterion. In the final solution, all 27 items clustered on the factors to which they theoretically belong, and no cross-loadings were observed for any item. As shown in Table 2, the factor loadings of the items range from .433 to .962, all of which exceed the adopted threshold of .40. This finding indicates that the Turkish form of the scale largely preserves the item-factor structure of the original scale (Ayanwale et al., 2022).

Reliability Results

To determine the internal consistency reliability of the scale, Cronbach's alpha coefficients were calculated for both the overall scale and the subdimensions. The Cronbach's alpha coefficient calculated for all 27 items in the final form was .879. The coefficients for the eight subdimensions ranged from .705 to .903. In the literature, a Cronbach's alpha coefficient of .70 or higher is widely adopted as the criterion for acceptable reliability (Taber, 2018). George and Mallery (2024) classify these coefficients as *acceptable* for values of .70 and above, *good* for .80 and above, and *excellent* for .90 and above. In line with these criteria, it can be stated that adequate internal consistency was achieved for both the overall scale and all of its subdimensions and that reliable measurements were obtained. These coefficients for the Turkish form are comparable to the range of .707–.929 reported in the original study (Ayanwale et al., 2022).

Discussion and Conclusion

In this study, the Teachers' Readiness and Intention to Teach Artificial Intelligence Scale, developed by Ayanwale et al. (2022) for K-12 teachers, was adapted into Turkish, and its psychometric properties were examined through a preliminary exploratory factor analysis in a sample of pre-service teachers. The findings revealed that the item-factor structure of the instrument was largely preserved in the Turkish form and that the items loaded on the dimensions to which they theoretically belong. This indicates that the motivational constructs defined on the basis of the Theory of Planned Behavior (Ajzen, 1991) and the Technology Acceptance Model (Davis, 1989) can also be differentiated from one another in the Turkish form.

During the analysis process, six items were removed from the structure of the scale. Of these items, three did not load above the .40 threshold on any factor, two showed cross-loadings by loading on more than one factor, and one loaded on a different factor rather than on the factor to which it theoretically belongs. This shows that item removal decisions should be based not only on statistical criteria but also on the theoretical position of the item (Acar Güvendir & Özer Özkan, 2022). Furthermore, the fact that the obtained coefficients are comparable to those of the original study (Ayanwale et al., 2022) suggests that, beyond linguistic equivalence, structural equivalence has also been largely achieved (Hernández et al., 2020).

The main limitation of the study is that, although the target population of the instrument is in-service teachers, the data for this preliminary study were collected from pre-service teachers. Although the sample size (N = 338) is adequate for exploratory factor analysis, the obtained structure needs to be tested through confirmatory factor analysis in an independent sample of in-service teachers. In addition, obtaining further psychometric evidence, such as criterion-related validity and test-retest reliability, would strengthen the use of the instrument. Considered within the framework of these limitations, it can be stated that the adapted instrument provides a valid and reliable preliminary structure that can be used to determine teachers' levels of readiness and intention to teach AI. The use of the instrument in future studies may contribute to the evidence-based development of practices in this field.

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A Comparative Analysis of Digital Competency Frameworks: DigCompEdu, UNESCO ICT CFT, ISTE Standards and TPACK1

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Abstract

The educational transformation driven by the digital age has rendered the systematic identification, development, and assessment of teachers' digital competencies an increasingly critical concern. This study aims to conduct a comparative analysis of four internationally prominent digital competency frameworks: DigCompEdu, the UNESCO ICT Competency Framework for Teachers (ICT CFT), the ISTE Standards for Educators, and TPACK. Employing a qualitative document analysis approach, the study systematically examines the theoretical underpinnings, focal domains, strengths, and deficiencies of each framework. The findings reveal that DigCompEdu offers a comprehensive pedagogical transformation vision within the European context; that the UNESCO ICT CFT provides a robust structure for policy development and global implementation; that the ISTE Standards furnish practical guidance for a broad audience of stakeholders; and that TPACK articulates the conceptual integration of technology, pedagogy, and content knowledge. Nevertheless, the study also identifies notable shortcomings across all four frameworks, particularly with respect to cultural and contextual sensitivity, the adequacy of measurement and assessment instruments, and the extent to which learning outcomes are explicitly linked to competency descriptors. The paper concludes with recommendations for the development of an integrated and context-responsive digital competency model.

Keywords: Digital competence, DigCompEdu, UNESCO ICT CFT, ISTE Standards, TPACK, Teacher competencies, Technology in education

Introduction

In contemporary educational environments shaped by the pervasive influence of information and communication technologies (ICT), teachers are increasingly expected not merely to demonstrate subject-matter expertise but also to integrate this knowledge with digital tools and pedagogical approaches in a purposeful and critical manner (Mishra & Koehler, 2006). Digital competency frameworks have emerged in direct response to this imperative, exerting a formative influence on a wide range of domains—from initial teacher education programs to continuing professional development policies and national curriculum reform initiatives.

Four frameworks in particular have achieved prominent status in the scholarly and policy literature: the European Commission's DigCompEdu, UNESCO's ICT Competency Framework for Teachers (ICT CFT), the International Society for Technology in Education's (ISTE) Standards for Educators, and the Technological Pedagogical Content Knowledge (TPACK) model proposed by Mishra and Koehler (2006). Each framework is rooted in distinct theoretical traditions, reflects different geographic and institutional priorities, and addresses the complexity of teacher digital competence from a unique vantage point. A rigorous comparative evaluation of these frameworks—encompassing both their contributions and their limitations—carries strategic importance for researchers, curriculum developers, and policymakers alike (Instefjord & Munthe, 2017; Mishra, 2019).

Against this background, the present study pursues three interrelated objectives: to provide a systematic comparative analysis of the four frameworks; to foreground their respective strengths and deficiencies; and to contribute to a more integrated and theoretically coherent understanding of digital competence in education.

Methodology

This study is situated within the tradition of qualitative research and employs document analysis as its primary methodological approach. The corpus of documents subjected to analysis comprises the foundational and revised publications of each framework under examination: the 2017 and updated 2022 reports of DigCompEdu (Redecker, 2017; Caena & Redecker, 2019), the 2011 and 2018 versions of the UNESCO ICT CFT (UNESCO,

1 This study was based on the first author's PhD thesis.

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2011, 2018), the 2017 revision of the ISTE Standards (ISTE, 2017), and the seminal publications that established the TPACK framework (Mishra & Koehler, 2006; Koehler & Mishra, 2009).

The comparative analysis is organized around the following set of criteria, derived from established comparative framework studies in the literature (Falloon, 2020; Starkey, 2020; Voogt et al., 2013): (a) theoretical and epistemological foundations; (b) target audience and application context; (c) structural components and proficiency levels; (d) measurement and assessment instruments; (e) cultural and contextual sensitivity; and (f) update and revision mechanisms. Each framework is examined systematically against these criteria, enabling both intra-framework depth and inter-framework comparability.

Results

DigCompEdu (European Framework for the Digital Competence of Educators)

Developed by the Joint Research Centre (JRC) of the European Commission, DigCompEdu offers a comprehensive structure that moves beyond a narrow focus on technology use to foreground the pedagogical integration of digital technology as its central concern (Redecker, 2017). The framework encompasses twenty-two competencies distributed across six domains: professional engagement, digital resources, teaching and learning, assessment, empowering learners, and facilitating learners' digital competence.

Among DigCompEdu's most notable strengths is its pedagogy-centered architecture. The framework consistently positions technology not as an end in itself but as an instrument for improving learning outcomes—a conceptual stance that distinguishes it from frameworks that risk reducing digital competence to mere tool proficiency (Caena & Redecker, 2019). A second strength lies in the framework's articulation of a graduated competency progression, enabling educators to map their professional growth across six levels from novice (A1–A2) through intermediate (B1–B2) to expert (C1–C2). This developmental structure lends the framework a degree of practical applicability that makes it directly usable in the design and evaluation of professional development programs (Vuorikari et al., 2022). Third, its alignment with the DigComp framework for citizens facilitates a coherent common language for assessing digital competencies across both educators and learners.

Notwithstanding these strengths, DigCompEdu exhibits several notable limitations. Having been designed primarily for the European educational context, the framework's transferability to different educational systems and cultural settings remains a subject of critical scrutiny (Instefjord & Munthe, 2017). The framework also insufficiently addresses discipline-specific differentiation; competencies pertinent to STEM disciplines diverge considerably from those relevant to the social sciences or the arts, yet these distinctions receive limited attention. Furthermore, the hierarchical relationships among the framework's constituent components are not always defined with adequate clarity (Falloon, 2020).

UNESCO ICT Competency Framework for Teachers (ICT CFT)

The UNESCO ICT CFT has undergone three revisions since its initial publication in 2008, reaching its current form in 2018 (UNESCO, 2018). The framework defines teacher competencies across six dimensions of teaching practice—understanding ICT in education, curriculum and assessment, pedagogy, ICT, organization and administration, and teacher professional learning—structured across three progressive stages: technology literacy, knowledge deepening, and knowledge creation.

The ICT CFT's most conspicuous strength resides in its global policy development function. Underpinned by UNESCO's institutional authority, the framework has guided educational policy reforms in numerous countries—particularly in the Global South—and has demonstrated considerable capacity for integration into national curriculum development processes (Voogt et al., 2013). The explicit incorporation of social equity and accessibility themes reflects an inclusive vision that transcends purely technical definitions of competence. Moreover, the framework's explicit attention to curriculum development, learning assessment, and school administration contexts signals a genuinely systemic perspective on educational transformation (UNESCO, 2018).

On the other hand, the ICT CFT's reliance on abstract and normative language can generate considerable difficulties in practical implementation. The absence of robust, standardized measurement and assessment tools complicates the objective determination of competency levels (Starkey, 2020). Although the 2018 revision incorporates a number of updates, the framework's treatment of rapidly evolving technologies—including artificial intelligence, augmented reality, and blockchain—remains insufficient. Finally, the pedagogical dimension, when viewed in relation to the policy and management dimensions, receives comparatively limited elaboration.

ISTE Standards for Educators

The ISTE Standards, most recently revised in 2017, reflect a learner-centered design philosophy and have been widely adopted across diverse educational settings (ISTE, 2017). A distinguishing feature of this framework is its provision of separate yet interrelated sets of standards for students, educators, education leaders, coaches, and computer science educators, thereby addressing a broad spectrum of stakeholders within the educational ecosystem.

The ISTE Standards' most salient strength is their practical orientation. Each standard is accompanied by concrete performance indicators, case studies, and tool recommendations, thereby facilitating the translation of the theoretical framework into actionable classroom practice (ISTE, 2017). The multi-stakeholder scope—which encompasses students as well as educators—affords the framework a systemic perspective seldom matched by its counterparts. Additionally, ISTE's certification programs and professional learning communities provide sustained institutional support for the implementation of the standards. The framework's widespread international adoption serves as compelling evidence of its efficacy as a shared professional language across educational systems (Falloon, 2020).

Despite these strengths, the ISTE Standards are not without significant limitations. Having been developed within the context of the United States educational system, their adaptation to educational systems in other national and cultural contexts demands considerable effort (Voogt et al., 2013). Insufficient clarity regarding the prioritization and hierarchical relationships among the standards may generate ambiguity for practitioners navigating implementation. Furthermore, certain standards have been criticized for reflecting a technology-centric orientation that inadvertently subordinates the pedagogy-content relationship to technological considerations (Mishra, 2019).

TPACK (Technological Pedagogical Content Knowledge)

Constructed by Mishra and Koehler (2006) upon the foundation of Shulman's (1986) pedagogical content knowledge (PCK) construct, the TPACK model argues that effective teaching with technology necessitates the integration of three core knowledge domains—content knowledge (CK), pedagogical knowledge (PK), and technological knowledge (TK)—as well as their pairwise and triadic intersections. The resulting seven knowledge domains collectively constitute the TPACK framework, which conceptualizes teacher competence within a theoretically coherent model of intersecting knowledge types.

TPACK's foundational strength is its capacity for interdisciplinary and cross-disciplinary applicability. By acknowledging that technology integration embodies a unique knowledge profile for each educator in each disciplinary context, the model adopts a discipline-specific approach that renders visible dimensions of competence that more generalized frameworks tend to overlook (Koehler & Mishra, 2009). TPACK also occupies an exceptionally strong position with respect to research validity; having been tested and refined in hundreds of empirical studies, the model's theoretical robustness is well established (Voogt et al., 2013). Its relative cultural independence, moreover, enhances its applicability across diverse international educational contexts.

Nevertheless, TPACK presents important limitations that warrant serious consideration. The model's highly abstract theoretical architecture may make it difficult for teachers to locate their own competencies within specific knowledge domains, potentially generating practical confusion (Mishra, 2019). The absence of a standardized, psychometrically validated measurement instrument gives rise to inconsistencies in implementation; while numerous scales have been developed across the literature, no instrument commands consensus regarding reliability and validity (Koehler et al., 2014). In addition, TPACK does not adequately address contemporary socially situated competencies such as digital ethics, equity, and critical digital literacy. Finally, disparities in technology access and infrastructure across different teaching contexts limit the practical applicability of the model in under-resourced settings.

Comparative Analysis

Table 1 presents a comparative summary of the four frameworks across the key criteria identified in methodology.

Table 1. Comparative Summary of the Four Digital Competency Frameworks.

Criterion	DigCompEdu	UNESCO ICT CFT	ISTE Standards	TPACK
Target Audience	Teachers	Teachers	Teachers & Students	Teachers
Theoretical Basis	Competency Framework	Policy-Driven	Standards-Based	Knowledge Theory
Context	European Union	Global	US-Centered	Universal/Theoretical
Levels/Stages	6 Competence Areas	3 Stages	7 Standards	3 Knowledge Domains

Assessment Tools	Yes (DigComp-based)	Partial	Yes (ISTE rubric)	Partial (surveys)
Update Frequency	Regular	2011 / 2018	Periodic	Since 2006
Implementation Guide	Available	Available	Comprehensive	Limited

As Table 1 illustrates, the four frameworks diverge markedly with respect to theoretical roots, application contexts, and structural design. DigCompEdu and the ISTE Standards emerge as the most mature with regard to measurement and assessment instrumentation. The UNESCO ICT CFT functions most effectively as a global policy bridge, offering a point of reference for diverse national contexts. TPACK, for its part, provides the most theoretically rigorous foundation yet offers the most constrained practical implementation guidance of the four frameworks under review.

Discussion

When considered in conjunction, the findings of this study indicate that no single framework comprehensively addresses all dimensions of digital competence in a fully satisfactory manner. This observation accounts for the growing body of scholarly literature proposing more integrative models. Falloon (2020), for instance, advanced a framework integrating TPACK and DigCompEdu with the aim of supporting competency development in school contexts. Similarly, Voogt and colleagues (2013) underscored the inadequacy with which existing frameworks establish explicit connections to learning outcomes—a gap that continues to constrain the evidence base for policy and practice.

A particularly critical deficiency that emerges across all four frameworks is the dimension of cultural and contextual sensitivity. Each framework originates from a specific geographic or institutional power center, and the question of how these frameworks can be meaningfully adapted for contexts in the Global South and for diverse educational traditions remains largely unresolved (Instefjord & Munthe, 2017). Similarly, next-generation competencies associated with AI-assisted instruction, algorithmic literacy, and data ethics are either entirely absent from the majority of these frameworks or addressed only at a superficial level (Vuorikari et al., 2022).

A further significant limitation across all frameworks concerns the tenuous relationship established between competency descriptors and learning outcomes. The frameworks typically define teacher behaviors and competency levels in considerable detail, yet fail to demonstrate with empirical rigor how these competencies translate into meaningful improvements in student achievement and learning experiences (Starkey, 2020). Closing this gap is of paramount importance both for strengthening the legitimacy of the frameworks themselves and for grounding policy development in a more robust evidence base.

Conclusion and Recommendations

This study has demonstrated that DigCompEdu, UNESCO ICT CFT, ISTE Standards, and TPACK each make distinctive and complementary contributions to the field of digital competency in education. DigCompEdu stands out for its pedagogical depth and assessment maturity; the ICT CFT is distinguished by its global policy linkages and social justice orientation; the ISTE Standards are notable for their practical implementation support and broad stakeholder reach; and TPACK offers the most theoretically coherent foundation, with particular strengths in disciplinary specificity.

In light of these findings, several recommendations merit consideration. First, rather than adopting a single framework wholesale, countries and institutions engaged in the development of digital competency policies should adapt and integrate frameworks in ways that are responsive to their specific educational contexts and cultural realities. Second, the measurement and assessment dimensions of each framework warrant substantial strengthening; standardized instruments with demonstrated validity and reliability are especially needed for TPACK and the ICT CFT. Third, future research should investigate how emerging competencies related to artificial intelligence and digital ethics can be meaningfully integrated into existing frameworks. Finally, the establishment of international research partnerships dedicated to fostering productive dialogue across frameworks would represent a valuable contribution to the advancement of the field.

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Preservice Computer Science Teachers' Use of Generative Artificial Intelligence, Their Attitudes, and Their Metaphors

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Abstract

The phenomenon known as "shiny object syndrome" has become increasingly prominent in recent times, particularly in regard to the field of artificial intelligence (AI). This trend necessitates rigorous scientific research and development aimed at leveraging artificial intelligence for the benefit of humanity. Rapid developments in generative artificial intelligence (GAI) technologies have garnered significant attention in education as well. We believe that the effectiveness and acceptance of GAI in education depends on the perspectives, knowledge and usage of future educators who make use of GAI in teaching. Thus, present study examines the use of, attitudes toward, and metaphors associated with GAI among Turkish pre-service computer science teachers. The sample includes 61 pre-service teachers (25 female and 36 male) from a state university in western Turkiye. While most students had not taken a course on AI previously, they reported high self-efficacy regarding GAI knowledge and usage (80.3%), primarily with ChatGPT. Additionally, most of the students use GAI for self-study (82%) and daily learning activities (79%). They posit the need for GAI integration in education (70.5%), but not as a replacement for teachers. Although they are concerned about the unethical use of AI, they generally have positive attitudes. Finally, they produced positive metaphors for AI, such as "personal teacher," "assistant," "Superman," "brain," “treasure,” “guide,” “tool,” “encyclopedia,” and so on, while a few of them described AI as a "fish," that requires water to survive, "black hole," that swallows everything, "sugar," and "medicine," both as a sweet or remedy and a harmful substance. In conclusion, future teachers' perceptions of GAI in education are generally positive, though there are some concerns about ethics, over-reliance on AI, bias and mistakes. It is considered that responsible GAI integration in teacher education requires careful research-oriented planning in accordance with national and international AI in education policies.

Keywords: Generative AI use, Generative AI attitude, AI metaphor, teacher education.

Introduction

Generative Artificial Intelligence (GAI) technologies have garnered significant attention in education. As a transformative technology in education, it is considered that understanding the learners’ GAI perceptions, attitudes and views for this technology needs attention. GAI facilitates personalised learning by revealing learning gaps and guiding learners with a multimedia rich digital learning materials (Karakose & Tülübaş, 2023).

The literature on preservice teachers’ use of GAI reveals an optimistic adoption with some cautions. In general, the results posit predominantly positive attitudes, diverse usage patterns though some concerns about trustworthiness and over-dependence remain. Some studies on Turkish preservice teachers report that preservice teachers have generally positive attitudes towards AI and AI literacy is one of the predictors for AI attitudes. For example, Yetişensoy (2024) revealed that those whose perceived their AI literacy as high have significantly more positive attitudes compared to those with average and low AI literacy. Moreover, Özden et al. (2025) found out gender, age, field of study, and class level significantly influence attitudes toward AI. Besides, Nyaaba et al. (2024) found that 167 Ghana pre-service teachers held generally positive attitudes toward GAI despite their infrastructural constraints. They use GAI as both a learning buddy for accessing reading materials and in-depth explanations, and as a teaching assistant for enhancing resources, developing assessments, and lesson planning.

Similarly, metaphorical representations of AI shows the preservice teachers’ positive perceptions of AI reflecting a supportive role with guidance. In their large-scale survey, Ayçiçek (2025) examined 721 preservice teachers who produced 176 different metaphors, with the most frequent being “assistant,” “human,” “teacher,” “friend,” and “brain,” categorized primarily under “Supportive Role/Guidance” and “Knowledge/Memory.” The studies show that pre-service teachers’ metaphorical framing of GAI reflects a dual perception as an empowering, humanized cognitive scaffold and a catalyst for intellectual dependency and weakened critical thinking. Such as Ahmed et al. (2025) found 26 pre-service teachers conceptualized GenAI through humanized metaphors such as helping hand, teacher, friend, and guide, while Gamlem et al. (2025) noted that 209 Norwegian pre-service teachers acknowledged practical benefits but raised concerns about trustworthiness and implications for human-centered

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education, while Ahmed et al. (2025) highlighted worries about over-dependence, cognitive decline, and reduced creativity.

The present study examines the use of, attitudes toward, and metaphors associated with GAI among Turkish pre-service computer science teachers. The research questions (RQ) are as follows:

RQ1: What are the preservice teachers' attitude scores toward generative artificial intelligence (GAI)?

a. Grade level

b. Prior AI training status

RQ2: What are the preservice teachers' views on the role of GAI in education?
RQ3: What are the preservice teachers' metaphors regarding GAI?

Methodology

A descriptive survey model was used in the study. In studies using this model, data is collected to describe the current situation or to identify relationships among specific existing phenomena (Cohen, Manion & Morrison, 2007). The lack of descriptive studies in the literature examining pre-service information technology teachers' use of GAI, their attitudes toward it, and their metaphors related to GAI is the primary rationale for this study. In this survey study, purposeful sampling is applied to investigate GAI use, attitudes, and metaphors of Turkish preservice computer science teachers.

Participants

The participants are 61 pre-service information technoloy teachers from a state university in western Turkiye.

Table 1. Demographics of the participants

Variable	f	%	Variable	f	%
Gender			*Perceived knowledge on AI*		
Female	25	%59	I know it very well and use it.	30	%49,2
Male	36	%41	I know it to some extent and use it.	19	%31,1
Grade			I have a basic understanding of it.	9	%14,7
1	14	%23	I've heard of it but haven't used it.	2	%3,2
2	14	%23	No, I've never heard of it.	1	%1,6
3	17	%27,9	*Previous Experience Using AI Applications*		
4	16	%26,2	I use them frequently	49	%80,3
Previous training on AI			I use them occasionally	10	%16,4
Yes	23	%37,7	I've tried them a few times	0	%0
No	38	%62,3	I've never used them	2	%3,3
Total	61	%100	Total	61	%100

While most students had not taken a course on AI previously, they reported high self-efficacy regarding GAI knowledge and usage (80.3%), primarily with ChatGPT. Additionally, most of the students use GAI for self-study (82%) and daily learning activities (79%). They posit the need for GAI integration in education (70.5%), but not as a replacement for teachers.

Table 2. The reflections of preservice teachers on using AI in education

Variable	f	%
Whether AI Should Be Widely Used in Education		
Yes	43	%70,5
No	8	%13,1
Undecided	10	%16,4
Opinions on AI Replacing Software Developers		
Yes	19	%31,1
No	26	%42,6
Undecided	16	%26,2

Which AI Applications Have You Used So Far?		
Chat GPT	23	%37,7
Gemini	19	%31,1
Copilot	1	%1,6
NoteBookLM	2	%3,3
Claude	1	%1,6
All of them	15	%24,7
Purposes for Using AI Applications		
Preparing course materials.	44	%72,1
Homework and project work.	46	%75,4
Supporting my own learning.	50	%81,9
Getting help with coding or technical support.	39	%63,9
Gaining knowledge in daily life.	48	%78,6
Other	3	%4,9

Data Collection Tools

1- **The Questionnaire for GAI Use in Education**

This form includes 14 questions as gender, grade level, previous GAI education, GAI use in daily routine, GAI use in computer science education. It was validated by three instructional technology experts.

2- **The Scale for Attitudes Towards Generative AI (SAGAI)**

SAGAI is a 23-item scale with four factors which was developed by Durak et al. (2026). It aims to reveal learners' attitudes and perceptions towards the use of GAI in education. In regards with reliability, the Cronbach's alpha coefficient was 0.87 for the scale.

In terms of data collection, we would like to note that all data was collected via an electronic form in 2026 Spring term from the volunteer participant preservice teachers.

Data Analysis

The quantitative data from the study were analyzed using the Jamovi software. Descriptive statistics (frequency, percentage), t-tests, and ANOVA were performed using this software. For the thematic analysis of the qualitative data, Excel and the AI-powered Graffain software were used to identify findings related to themes and metaphors.

Results

1- **The findings related to AI attitudes**

The first research question is “What are the preservice teachers' attitude scores toward generative artificial intelligence (GAI)?”. Accordingly, the descriptive statistics of the GAI attitudes is shown in Table 3.

Table 3. Descriptive statistics for the GAI attitudes

Variable	*Min*	*Max*	$\bar{X}$	*SD*	*Cronbach's α*
GAI Attitudes	1	5	3.75	0.491	0.855

In this regard, we investigated whether the GAI attitudes of the preservice teachers significantly differ in terms of their grade levels. Table 4 presents the results of ANOVA for that research question.

Table 4. The ANOVA results

Variable	*Grade Level*	*n*	$\bar{X}$	*SD*	*F*	*p*
GAI Attitudes	1	14	3,66	0,433	0,737	0,538
	2	14	3,69	0,482		
	3	17	3,83	0,612		
	4	16	3,80	0,417		

According to Table 4, no statistically significant difference was observed in the attitude scores of pre-service teachers with respect to grade level ($F = 0.737, p > .05$).

Furthermore, an independent samples t-test was performed to examine potential differences in generative artificial intelligence attitude scores according to whether pre-service teachers had received prior training on the topic. The findings are displayed in Table 5.

Table 5. The t-test results

Variable	*Previous training on AI*	*n*	$\bar{X}$	*SD*	*t*	*p*
GAI Attitudes	Yes	23	3,80	0,384	0,586	0,560
	No	38	3,72	0,549		

Table 5 presents that no statistically significant difference was found between the attitude scores of pre-service teachers who had previously received training on GT ($\bar{X}$ = 3.80) and the attitude scores of pre-service teachers who had not previously received training on GT ($\bar{X}$ = 3.72) (t=0.586, p>0.05).

2. What are the preservice teachers' views on the role of GAI in education?

The preservice teachers' views on the role of GAI in education were categorized as the perceived advantages and disadvantages of GAIinEd. As shown in Figure 1, the preservice teachers mentionned that AI provides advantages for speed and efficiency in learning process, personalized learning experience in education and ease of material preparation and content production.

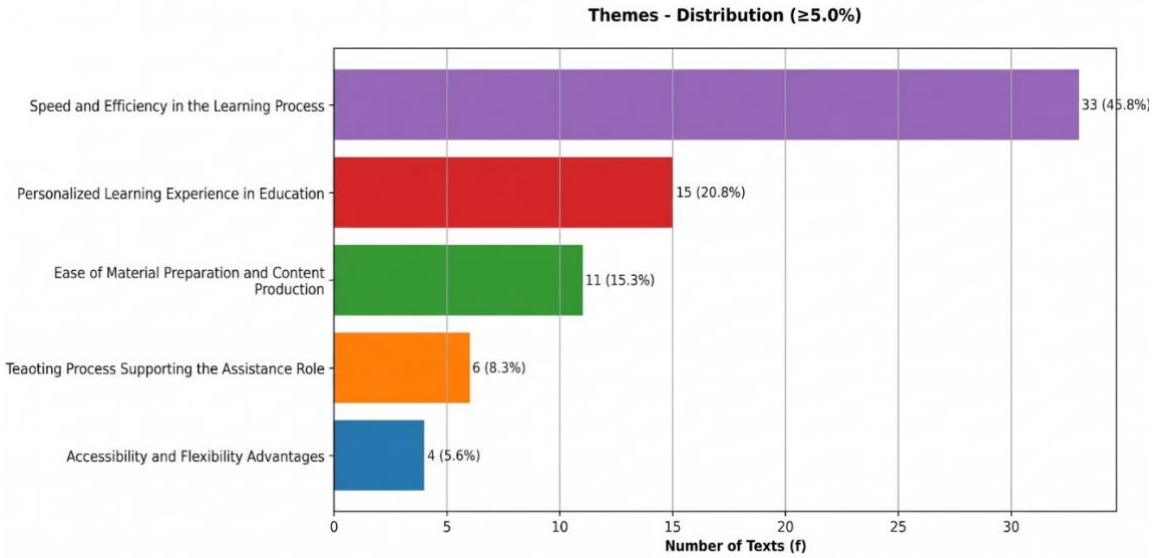


Figure 1. The perceived advantages of GAIinEd

As shown in Figure 2. the preservice teachers perceive decline in cognitive abilities, issues in technological dependency, data accuracy and reliability problems and social and ethical inadequacies as major disadvantages of GAI in education.

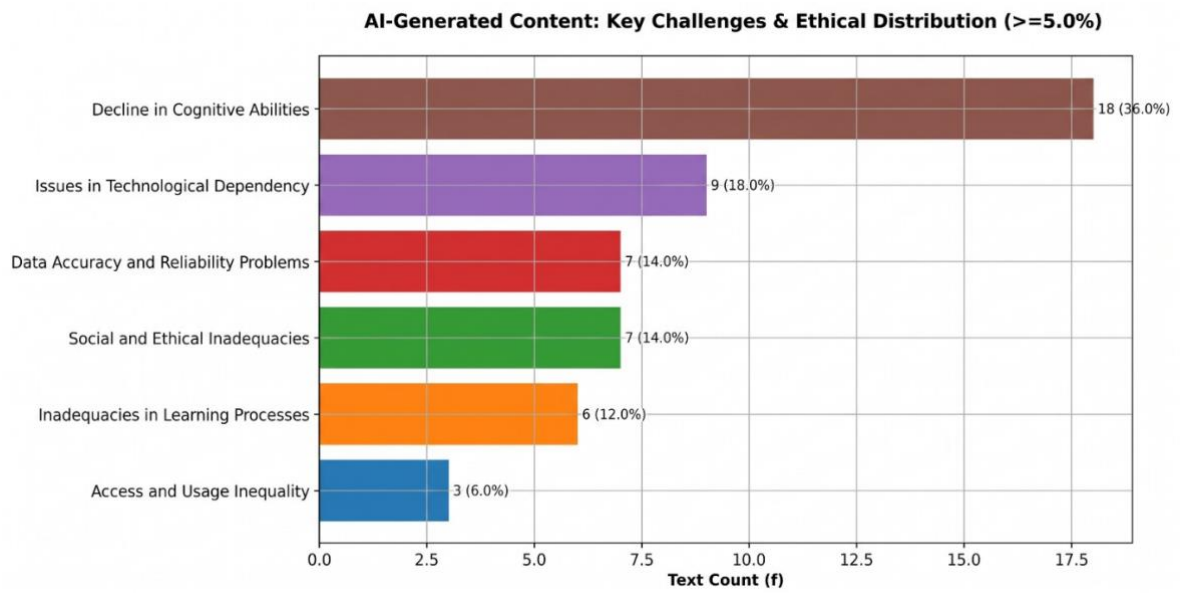


Figure 2. The perceived disadvantages of GAIinEd

Moreover, the participants were asked whether they believe artificial intelligence will replace teachers or not. Most of them (n=56) replied negatively and agrred that teachers are irreplaceable by AI. While three of them were positive for such replacement.

3. The preservice teachers' metaphors regarding GAI

The participants reported 60 metaphors for AI. Some of them focus on the positive and assistive role of AI such as assistant, personal teacher, vehicle, helper, encyclopedia, library, treasure, brain, compass, factory; some of them posit both positive and negative side of AI such as medicine (implying the importance of responsible use), sugar (mentionning both taste of sweet and harm as well), tool (that depends on user intentions) and some of them focus on negative aspects such as blackhole (which swallows everything), nicotine (that makes users addictive) and fish (which requires water).

Conclusion

In the present study, the quantitative findings showed that preservice teachers demonstrate positive attitudes toward generative artificial intelligence and present positive metaphors for GAI in line with the related literature on GAIinEd (Ayçiçek, 2025; Nyaaba et al., 2024; Yetişensoy, 2024). Furthermore, attitude scores do not show a statistically significant difference based on grade level, or prior training status. Among the qualitative findings, the primary advantages identified are in line with (Araycı & Ozyurt, 2026) which include the speed and efficiency provided by generative artificial intelligence to the learning process, personalized learning experiences, and ease of material preparation and content generation. On the contrary, the weakening of cognitive skills in education, technology addiction, issues regarding information accuracy and reliability, and social and ethical concerns were highlighted as disadvantages. The view that AI cannot replace teachers came to the fore, driven primarily by reasons such as its lack of emotional interaction and the sufficiency of existing supportive educational tools.

In conclusion, while preservice teachers generally exhibit positive attitudes toward artificial intelligence, it is evident that they remain aware of its disadvantages regarding cognitive, social, ethical, and information security aspects. Consequently, it is recommended to incorporate courses into the curriculum aimed at enhancing preservice teachers' generative artificial intelligence literacy and integrating artificial intelligence into education ethically and responsibly.

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Digital Learning Material Development Self-Efficacy: A Scale Development Study

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Abstract

Digital learning materials—which are essential components of active learning—enhance students' understanding of challenging topics, support collaborative work, and improve academic achievement when designed correctly to appeal to multiple senses. With the rapid development of artificial intelligence and web technologies shaping learning environments and materials, enhancing teachers' competencies in developing and utilizing these tools has become crucial. In this context, it is imperative to address teachers' self-efficacy levels, particularly regarding the development and integration of digital instructional materials. Present study aims to develop a valid and reliable scale for measuring digital learning material development self-efficacy perceptions of preservice teachers, namely, the Self-Efficacy Scale for Developing Digital Learning Materials (SES-DDLM). First, related literature was reviewed, and an outline form of the scale was formed with an item pool by taking 13 expert opinions. For construct validation, an exploratory factor analysis was performed with 277 preservice teachers from a western state university in Turkey. The findings indicated that the SES-DDLM consisted of 26 items and a single factor. Second, additional data were collected for confirmatory factor analysis from 300 preservice teachers at the same college. The findings indicated that fit indexes of the structure provided a good and acceptable fit which confirms that the scale has 26 items and one dimension. Cronbach Alpha reliability coefficient of the whole scale was .97. Accordingly, Self-Efficacy Scale for Developing Digital Learning Materials is a valid and reliable tool that can be used in revealing digital learning material development self-efficacy perceptions of preservice teachers by practitioners and researchers in their learning and instructional design studies and practices.

Keywords: Digital learning material, digital lesson material, digital material, self-efficacy, scale development

Introduction

Digital transformation necessitates the integration of technology in education to foster students' core competencies. While instructional materials facilitate learning and active participation, digital resources—such as multimedia, simulations, and animations—stimulate multiple sensory channels. These materials objectify abstract concepts, enable the execution of hazardous experiments, provide time- and location-independent access, and offer instantaneous feedback. Research indicates that when appropriately designed, digital materials enhance comprehension, collaboration, and academic performance.

Teachers play a pivotal role in technology integration and require both technological knowledge and competence in digital material development. However, studies reveal that teachers' competencies in digital material design remain at a moderate level, hindered by obstacles such as insufficient skills, biases, and low self-confidence. Self-efficacy—the belief in one's capacity to execute tasks—significantly influences technology integration. While high self-efficacy encourages the development of innovative materials, low self-efficacy leads to technology avoidance. Although existing scales focus primarily on Web 2.0 tools or educational games, there is a lack of a comprehensive measurement instrument addressing overall self-efficacy in digital learning material development. This study fills this gap by developing the Self-Efficacy Scale for Developing Digital Learning Materials (SES-DDLM). In this context, the purpose of this study is to develop a valid and reliable measurement instrument to determine pre-service teachers' self-efficacy toward developing digital learning materials in teaching-learning processes. The research questions are as follows:

1- According to the results of the exploratory factor analysis, is the SES-DDLM a statistically valid scale?

2- According to the results of the internal consistency test, is the SES-DDLM a statistically reliable scale?

Methodology

In this study, the scale development process was conducted based on the exploratory and confirmatory steps proposed by Tashakkori and Teddlie (2003). In the first stage—the exploratory phase—the research problem was identified through a comprehensive literature review, and an item pool was generated. Subsequently, the scale format was determined, and a draft scale was prepared by consulting expert opinions and student feedback. In the

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second stage—the confirmatory phase—the reliability and validity of the scale were established through rigorous data analyses. Detailed information regarding the scale development procedure and the study groups is provided below.

Participants

The data for this scale development study, which aims to determine pre-service teachers' self-efficacy toward developing digital learning materials in teaching-learning processes, were collected from students across all departments of a faculty of education at a state university. For the Exploratory Factor Analysis (EFA), data were obtained from 277 pre-service teachers. Of these participants, 122 (44.00%) were female, 75 (27.05%) were male, and 80 (28.85%) did not disclose their gender. Regarding the distribution by department, 8 (2.88%) were in Pre-School Education, 112 (40.43%) in Classroom Education, 63 (22.74%) in Computer Education and Instructional Technology (CEIT), 18 (6.49%) in Special Education, 9 (3.24%) in Guidance and Psychological Counseling, 27 (9.74%) in Social Studies Education, 30 (10.83%) in Science Education, and 1 (0.36%) in Turkish Language Education. Additionally, 9 (3.24%) participants did not specify their department. For the Confirmatory Factor Analysis (CFA), a separate sample of 300 pre-service teachers was reached, which satisfies the sample size requirements suggested in the literature (Tabachnick & Fidell, 2001). This group consisted of 193 (64.33%) female and 104 (34.67%) male participants, while 3 (1.00%) did not report their gender. In terms of departmental distribution, 38 (12.66%) were in Pre-School Education, 115 (38.33%) in Classroom Education, 37 (12.33%) in CEIT, 60 (20.00%) in Special Education, 45 (15.00%) in Guidance and Psychological Counseling, and 4 (1.33%) in Social Studies Education. One participant (0.33%) did not specify their department.

The Scale Development Procedure

The scale development process followed the methodological steps outlined by Streiner et al. (2015):

Literature Review:

First, a comprehensive literature review on digital material preparation was conducted. Similar scales in the literature (Birişçi et al., 2018; Çelik, 2020; Çevik & Şentürk, 2019; Dinçer & Doğanay, 2016; Fidan et al., 2020; Hiçyılmaz & Karahan, 2018; Kelleci & Kulaksız, 2020; Özgür et al., 2020; Varank & Ergün, 2009) were systematically reviewed.

Item Pool Generation & Scale Type:

Following the literature review, an initial item pool was generated, resulting in a 50-item draft scale. A 5-point Likert-type scale was chosen due to its high comprehensibility and widespread preference in the literature (Bayat, 2014).

Expert Opinions:

To ensure the content validity of the draft scale, opinions were sought from 13 experts: seven from Computer Education and Instructional Technology, four from Curriculum and Instruction, one from Turkish and Social Sciences Education, and one from Educational Measurement and Evaluation. The candidate items were compiled into a form, and experts evaluated them. The Content Validity Ratio (CVR) for each item was calculated (Yurdugül, 2005). The minimum acceptable CVR threshold for this study was determined to be 0.90.

Pilot Study:

To test the clarity of the items on the target population, a pilot administration was conducted with eight volunteer master's students in the CEIT department. Based on their feedback, three poorly phrased items were revised, and the scale was pre-arranged into 32 items.

Exploratory Factor Analysis (EFA):

After reviewing the items, a trial form was generated for EFA. The datasets from 277 participants were included in the analysis. Following EFA, the 32-item draft scale was refined and reduced to 26 items.

Confirmatory Factor Analysis (CFA):

To verify the factor structure derived from the EFA, data collection was repeated with a new sample of 300 pre-service teachers using both online (Google Forms) and face-to-face methods on a voluntary basis. The final version of the scale was established based on the CFA fit indices.

Reliability and Validity Analyses:

To evaluate the psychometric properties and construct validity of the finalized scale, Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's alpha internal consistency coefficients were computed and reported.

Data Analysis

To validate the model fit of the established factor structure, CFA was performed on the data collected from the second independent sample. Statistical analyses were carried out using SPSS 23.0 and SPSS AMOS 25.0 software packages.

Results

This section presents the findings regarding the validity and reliability studies of the SES-DDLM.

Exploratory Factor Analysis Results

Prior to conducting the exploratory factor analysis (EFA), the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were computed to determine the suitability of the data. The KMO value of the scale was found to be .96, and the Bartlett's Test of Sphericity was statistically significant(x^2 = 6017.362, df = 325, p < .001), indicating a significant correlation among the variables. A KMO value greater than .60 is required to proceed with factor analysis (George & Mallery, 2001). Following the initial factor analysis, items with factor loadings below 0.40 or those with cross-loadings were removed. The EFA was then repeated after item deletion. The results of the repeated analysis with the remaining 26 items revealed that the items loaded under a single factor, accounting for 52.0% of the total variance. Table 1 presents the item factor loadings obtained from the exploratory factor analysis.

Table 1. Item factor loadings obtained from the exploratory factor analysis.

	Factor 1	Item	Factor 1
M1	0.67	M15	0.72
M2	0.68	M16	0.66
M3	0.72	M17	0.78
M4	0.68	M18	0.73
M5	0.74	M19	0.75
M6	0.61	M25	0.75
M7	0.78	M26	0.77
M9	0.77	M27	0.79
M10	0.77	M28	0.75
M11	0.65	M29	0.73
M12	0.75	M30	0.74
M13	0.68	M31	0.65
M14	0.66	M32	0.74

Confirmatory Factor Analysis Results

In the subsequent stage of the scale development process, a confirmatory factor analysis (CFA) was performed to test whether the items adequately predicted the latent factor. New data were collected for the CFA, reaching a total of 300 participants. The item factor loadings obtained from the CFA are presented in Table 2.

Table 2. Item factor loadings obtained from the confirmatory factor analysis

	Factor 1	Item	Factor 1
M1 (m1)	0.75	M14 (m15)	0.76
M2 (m2)	0.74	M15 (m16)	0.63
M3 (m3)	0.75	M16 (m17)	0.75

M4 (m4)	0.70	M17 (m18)	0.78
M5 (m5)	0.76	M18 (m19)	0.76
M6 (m6)	0.70	M19 (m25)	0.82
M7 (m7)	0.80	M20 (m26)	0.82
M8 (m9)	0.79	M21 (m27)	0.83
M9 (m10)	0.79	M22 (m28)	0.76
M10 (m11)	0.67	M23 (m29)	0.75
M11 (m12)	0.78	M24 (m30)	0.78
M12 (m13)	0.67	M25 (m31)	0.70
M13 (m14)	0.69	M26 (m32)	0.71

Following the CFA, it was observed that the RMSEA, NFI, GFI, AGFI, and CFI values fell within the acceptable fit ranges, while the X^2/df ratio was within the good fit range. These indices indicate that the proposed model exhibits an acceptable fit (Hooper et al., 2008; Kline, 2005; Marsh & Hocevar, 1988; Schermelleh-Engel et al., 2003). In addition, AVE value obtained from the analysis of the CFA data is 0.56.

To determine the internal consistency of the Self-Efficacy Scale for Developing Digital Learning Materials, composite reliability (CR) and Cronbach's alpha coefficients were calculated. Accordingly, both the CR and Cronbach's alpha values for the scale were found to be .97. A threshold of .70 and above for CR and Cronbach's alpha is considered sufficient for the reliability of scale scores (Büyüköztürk, 2011; Netemeyer et al., 2003; Nunnally & Bernstein, 1994). These values demonstrate that the scale exhibits a highly robust level of internal consistency. Please see Appendix, for the final version of the SES-DDLM both in English and Turkish version.

Conclusion

Information and communication technologies play a critical role within the process of constructing and structuring new knowledge (Ardıç & Uslu, 2021). The phenomenon that teachers exhibit high acceptance levels toward technology in instructional processes and maintain openness to innovation is highly correlated with their perceptions of self-efficacy (Aktürk & Delen, 2020). Consequently, it can be anticipated that teachers must attain a specific level of self-efficacy to design digital learning materials utilizing technology in their classrooms. Nevertheless, empirical evidence demonstrates that teachers' self-efficacy regarding digital learning material development is generally at a moderate level (Bediroğlu, 2021; Gökbulut, Keserci, & Akyüz, 2021).

It is well-documented that digital learning materials yield various positive outcomes, including fostering engagement, ensuring knowledge retention, and increasing motivation (Karademir Coşkun & Alper, 2019; Soydan, 2018). In this framework, it is imperative that teachers possess comprehensive knowledge of material development. Specifically, before entering the profession, it is crucial for pre-service teachers to identify their shortcomings in this domain, cultivate required competencies, and augment their digital capabilities. Moreover, there is empirical evidence recently collected which shows that digital literacy and critical thinking disposition act as important determinants of pre-service teachers' self-efficacy in creating digital learning resources (Yılmaz Özden, 2023).

Conducted in line with these requirements, this study developed a valid and reliable instrument aimed at assessing the self-efficacy of pre-service teachers in developing digital learning materials. An examination of the current literature indicates that available scales are mostly confined to restricted digital applications, such as Web 2.0 tools or educational games. Conversely, this study addresses a major lacuna in the field by directly targeting the overarching process of digital learning material development. The validated scale holds the potential to extensively measure pre-service teachers' self-efficacy perceptions toward digital material design. As noted by Hrastinski (2020), teachers must be stimulated to ask guiding questions that shape their learning designs to utilize digital learning materials in an effective and efficient manner. Within this context, scales evaluating digital learning material development self-efficacy are deemed highly constructive for teachers striving for effective technology integration. Teacher training institutions can implement this scale to diagnose pre-service teachers' self-efficacy levels. The data-driven insights derived from these implementations will inform curriculum revisions based on precise teacher requirements. Furthermore, professional development initiatives focusing on digital material creation for active teachers can adopt this scale as an initial and follow-up assessment tool, thereby fostering data-informed progress in professional capacity.

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Appendix. The Self-Efficacy Scale for Developing Digital Learning Materials - SES-DDLM

	Items	**Totally Disagree *(Hiç Katılmıyorum)***	**Disagree (*Katılmıyorum)***	**Neither Agree nor Disagree (Ne Katılıyorum ne Katılmıyorum)**	**Agree *(Katılıyorum)***	**Totally Agree *(Tamamen Katılıyorum)***
1	I am capable of embedding features into digital learning materials that stimulate student interest. (*Dijital öğrenme materyaline öğrencinin ilgisini çekebilecek unsurlar katabilirim.)*					
2	I can develop digital learning materials that incorporate real-world examples. *(Gerçek yaşam örneklerini içeren dijital öğrenme materyali geliştirebilirim.)*					
3	I can use multiple tools when developing digital learning materials. *(Dijital öğrenme materyali geliştirirken birden fazla araç kullanabilirim.)*					
4	I can prepare digital learning materials that enable learners to work collaboratively. *(Öğrenenlerin işbirlikli çalışabilecekleri dijital öğrenme materyali hazırlayabilirim.)*					
5	I can develop digital learning materials that actively engage learners. *(Öğrenenleri etkin kılacak dijital öğrenme materyali geliştirebilirim.)*					
6	I can apply multimedia learning principles when preparing digital learning materials. *(Dijital öğrenme materyali hazırlarken çoklu ortam öğrenme ilkelerini uygulayabilirim.)*					
7	I can develop digital learning materials that align with my course objectives. *(Derslerimin hedeflerine uygun dijital öğrenme materyali geliştirebilirim.)*					
8	I can prepare interactive digital learning materials.					

	(Etkileşimli dijital öğrenme materyali hazırlayabilirim.)
9	I can prepare digital learning materials that support learner-instructor interaction. *(Öğrenen ile öğreten etkileşimini destekleyecek dijital öğrenme materyali hazırlayabilirim.)*
10	I can prepare digital learning materials tailored to the language proficiency level of the learners. *(Öğrenenin dil düzeyine uygun dijital öğrenme materyali hazırlayabilirim.)*
11	I can design digital learning materials that reinforce learning. *(Öğrenmeyi pekiştirici dijital öğrenme materyali tasarlayabilirim.)*
12	I can easily learn newly encountered digital learning material development tools. *(Yeni karşılaştığım dijital öğrenme materyali geliştirme araçlarını kolaylıkla öğrenebilirim.)*
13	I can collaborate with subject matter experts to develop digital learning materials for various disciplines. *(Alan uzmanları ile birlikte çalışarak farklı disiplinler için dijital öğrenme materyali hazırlayabilirim.)*
14	I can design digital learning materials that support self-regulated learning. *(Öğrenenlerin kendi kendilerine öğrenmelerini destekleyecek dijital öğrenme materyali tasarlayabilirim.)*
15	I can digitalize non-digital learning materials. *(Dijital olmayan bir öğrenme materyalini dijitalleştirebilirim.)*
16	I can create digital learning materials for assessment purposes. *(Ölçme değerlendirme amacıyla dijital öğrenme materyali hazırlayabilirim.)*
17	I can develop digital learning materials in accordance with instructional material development principles. *(Öğretim materyali geliştirme ilkelerine uygun dijital öğrenme materyali geliştirebilirim.)*
18	I can solve the problems I encounter while developing digital learning materials. *(Dijital öğrenme materyalleri geliştirirken karşılaştığım sorunları çözebilirim.)*

19	I can prepare digital learning materials that support learners' creative thinking skills. *(Öğrenenlerin yaratıcı düşünme becerilerini destekleyici dijital öğrenme materyali hazırlayabilirim.)*
20	I can prepare digital learning materials that support learners' problem-solving skills. *(Öğrenenlerin problem çözme becerilerini destekleyici dijital öğrenme materyali hazırlayabilirim.)*
21	I can prepare digital learning materials that help learners connect new information with their prior knowledge. *(Öğrenenlerin var olan bilgileri ile bağlantı kurmalarını destekleyici dijital öğrenme materyali hazırlayabilirim.)*
22	I can develop digital learning materials that provide feedback to learners. *(Öğrenene geribildirim sunan dijital öğrenme materyali geliştirebilirim.)*
23	I can prepare digital learning materials that allow learners to monitor their own progress. *(Öğrenenlerin kendi gelişimlerini izleyebilecekleri dijital öğrenme materyali hazırlayabilirim.)*
24	I can find relevant tools for creating digital learning materials that align with the course objectives. *(Dersin hedeflerine uygun dijital öğrenme materyali hazırlama araçlarını bulabilirim.)*
25	I can adapt existing digital learning materials to my course. *(Hazır dijital öğrenme materyallerini dersime uyarlayabilirim.)*
26	I can update a digital learning material. *(Bir dijital öğrenme materyalini güncelleyebilirim.)*

The Impact of ChatGPT on Academic Writing Development in Social Sciences and Humanities Education

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Abstract

In Social Sciences and Humanities education, academic writing is a core skill for students as it requires critical thinking, generating ideas, and a clear structure of sentences. But technology, especially ChatGPT, is being used by students in this regard. Despite its effectiveness, students face some challenges, like sometimes ChatGPT produces incorrect information and giving the same response again and again. Moreover, sometimes they copy responses from ChatGPT without understanding the concept, which affects their long-term learning. This study aims to investigate students' perceptions of the effectiveness and challenges of using ChatGPT in academic writing. It employs mixed-method approaches using semi-structured interviews and an online survey. This study finds that most of the students use ChatGPT to support their academic writing skills for correcting grammar, brainstorming ideas, understanding difficult academic concepts, summarizing, and paraphrasing. This study suggests that ChatGPT can be a helpful learning tool, but students need guidance from teachers and institutions on using ChatGPT, and instead of copying answers, they should understand the concept and verify the answers before writing.

Keywords: Academic writing, ChatGPT, effectiveness, challenges

1. Introduction

1.1 Background of the Study

Academic writing plays an important role in the social sciences and humanities education. Students may have to write research papers, essays, reports, etc. Nowadays, the whole world is fully dependent on technology. Generative AI is one of the most powerful tools now, people use it for different purposes. Students mainly use it for generating ideas and organizing ideas rather than generating full text.

Day by day, students are increasingly dependent on ChatGPT. Students use it for different parts of academic writing, which include brainstorming, preparing outlines, developing arguments, paraphrasing, summarizing, and revising academic written texts. ChatGPT can support academic writing development by helping students improve their grammar, fluency, accuracy, and overall writing quality, as examined by Alkamel and Alwagieh (2024). Also, Limna and Kraiwanit (2024) similarly identified its usefulness in language editing and improving writing efficiency among Social Science students.

In spite of these advantages, the growing use of ChatGPT has many challenges. Based on Lendvai's (2025) discussion, he discussed issues associated with AI-generated academic content, including unreliable information and references. Students sometimes more depends on ChatGPT. They directly copy from ChatGPT and paste it, but it is not the correct way to use AI. Students should be more careful about using ChatGPT. ChatGPT can generate ideas, but it is not correct always.

Although ChatGPT has some advantages. It can be problematic sometimes. Lendvai(2025) discussed issues related with AI- generated academic content, which are unreliable information and fabricated references.

Students who repeatedly depend on AI-generated explanations or complete responses may face some issues such as becoming less engaged in critical thinking, independent argument construction, and the development of their own writing patterns. These concerns are relevant to Social Sciences and Humanities education where academic writing involves some factors. The factors are interpretation, argumentation, originality, and critical engagement with existing knowledge background. Therefore, it is important to understand students' experiences with ChatGPT.

1.2 Research problem

1. ChatGPT can help students with grammar, idea generation, organization, and other writing tasks, it remains unclear whether it truly improves students' academic writing skills or only makes writing easier.

2. Overconfidence on ChatGPT may reduce critical thinking, originality, and independent writing.

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3. Inaccurate information, nonexistent references, plagiarism and weak verification raise concerns about responsible academic use of it.

Research Objectives

The study aims to investigate ChatGPT's impact on academic writing development among students in Social Sciences and Humanities education. From this study, students will be able:

1. To explore how students use ChatGPT for academic writing.

2. To explain ChatGPT's perceived benefits for academic writing development.

3. To identify the challenges students experience and their responsible-use practices.

1.5 Research Questions

This study focuses on the following research questions:

1. How do students in Social Sciences and Humanities use ChatGPT for their academic writing?

2. How do students perceive the usefulness and advantages of ChatGPT for their academic writing development?

3. What challenges do students have to face when they use ChatGPT for academic writing?

2 Literature review

2.1 ChatGPT and academic writing in higher education

The rise of AI has created new opportunities for academic writing in higher education. ChatGPT can explain ideas, give structure of writing, provide feedback, and help students in their academic writing. Zhao et al. (2024) examined how AI can influence in writing practices. The application of ChatGPT not only grammatical correction but also drafting and revising content. Similarly, Kotsis (2025) examined the pedagogical and ethnical aspects of ChatGPT in academic writing. The study highlights the importance of ChatGPT, which is related to academic responsibility. Overall, these studies indicate that ChatGPT should not be treated as a tool for generating text. Instead it should be considered in terms of how it influences the engagement of students with different stages of academic writing process.

2.2 ChatGPT as a tool for writing development

A commonly discussed educational use of ChatGPT is its ability to help students in developing their academic writing skills. Alkamel and Alwagieh (2024) explained that among Yemeni University EFL students, the use of ChatGPT found many benefits, mostly in grammar, accuracy, fluency and overall quality of writing. Limna and Kraiwanit (2024) investigated the views of graduate students on using ChatGPT in social sciences for language editing. Yuan et al. (2024) also explained the opportunities of using ChatGPT for English writing also added the developing content and acquiring relevant knowledge. Overall, these studies examined that ChatGPT can help students who face difficulties with academic writing. However, it is important to distinguish between using AI to improve a written text and developing a student's independent writing skills.

2.3 ChatGPT, Learning Efficiency and Knowledge Development

Academic writing includes more than constructing grammatically correct sentences. Students need to understand the academic context, organise ideas, and develop arguments based on appropriate evidence. ChatGPT can help in these areas by explaining difficult concepts, providing examples which is relevant with the concept, and offering possible ways to academic contexts. Yuan et al. (2024) found opportunities to help academic writing tasks by using ChatGPT. Similarly, Limna and Kraiwanit (2024) also highlighted its benefits for developing efficiency in language-related tasks. These applications can be beneficial for students who find it difficult to understand complex academic concepts or how to start an assignment. However, the academic benefits of ChatGPT depend on how students interact with or use its answers. There is a difference between using AI-generated explanations to understand a concept and reproducing those explanations without critically examining them.

2.4 Challenges of Using ChatGPT in Academic Writing

Although ChatGPT has several benefits, its use in academic writing also raises questions related to the accuracy of information, originality, and students' ability to learn independently. Lendvai (2025) reviewed academic literature related to academic writing and ChatGPT and contributed to ongoing discussions about the reliability

and ethical issues related to AI generated academic content. Similarly, Yuan et al. (2024) discussed problems involved in including ChatGPT in academic writing practices. A major concern is that students may depend on ChatGPT too much instead of using their critical thinking skills. Plagiarism and authorship are also important concerns, mostly when students submit AI generated content as their own work without appropriate use of AI. Therefore, for responsible use of AI students need to verify information, consult reliable sources and use their critical thinking skills for their own academic work.

2.5 Responsible AI use and institutional Guidance

The growing use of ChatGPT in academic writing produces the need for educational guidance. Palacios-Núñez et al. (2025) examined teachers' points of view on ChatGPT in academic writing education. It included its benefits and problems. Lavidas et al. (2026) investigated social science and humanities students perspectives on AI tools for academic uses with its uses, challenges and suggestions. Rather than restricting the use of AI, these studies focus on the importance of AI literacy and guidance of institutions in higher education. Educational institutions can help students by explaining its limitations, and assessing generated information. This study examines students' use of ChatGPT, including its benefits, concerns, and verification of practices.

2.6 Research gap

From the previous studies, it is shown that EFL learners use ChatGPT for improving academic writing, grammar correction and editing (Alkamel & Alwagieh, 2024), while Social Sciences graduate students use it for language editing (Limna & Kraiwanit, 2024).

Nonetheless, a few research has given attention to different use of ChatGPT including benefits and challenges in academic writing by the student of Social Sciences and Humanities. Therefore, this study addresses this gap by examining the use, benefits and challenges of ChatGPT in academic writing.

3. Research Methodology

3.1 Research Approach and Design

This study used a mixed-methods approach including quantitative and qualitative data. It examined the experience and perception of students about using ChatGPT for academic writing. The quantitative data focused on students' use of ChatGPT, including its benefits, challenges, and proper use. On the other hand, the qualitative data focused on students' personal experiences and added more explanations about it. By combining these two research approaches, the study aims to investigate both the frequency of students' responses and their perceptions of using ChatGPT for academic writing.

3.2 Study participants and Sampling Techniques

This study consists of 80 completed online surveys and face to face interview of 10 students who have experience of using ChatGPT in their academic fields. The study employed two non-probability sampling techniques. Convenience sampling was used for quantitative data to collect responses from the participants, and purposive sampling was used for qualitative data, in which participants were chosen based on their relevant experience with ChatGPT. However, the study used non-probability sampling, so the findings cannot statistically represent all social science and humanities students.

3.3 Data Collection Methods

Two primary data collection instruments were used: an online questionnaire and semi-structured interviews.

Online Questionnaire

The online questionnaire collected quantitative information about students' use of ChatGPT in academic writing.

It included frequency-based and Likert-scale questions designed to examine three main areas:

- Students' purposes and frequency of using ChatGPT for academic writing.
- Their perceptions of its benefits for writing development.
- Their experiences of challenges, academic integrity concerns, and responsible-use practices.

The questionnaire generated in numerical data that could be summarized using percentages.

Semi-Structured Interviews

Face-to-face interviews were conducted as semi-structured interviews, where 10 participants were faced the interviewed. They almost agree with the survey questions answers that ChatGPT has some benefits and challenges. Most of them use it for brainstorming, idea generate, etc but they may be more conscious of plagiarism and academic duplication.

3.4 Data Analysis

Descriptive analysis was followed for the quantitative data through Microsoft Excel. The patterns of ChatGPT use, benefits, challenges, and responsible practices were shown through percentages and frequencies.

Qualitative data were analyzed through thematic analysis. Similar ideas were categorized into themes after identifying recurring ideas according to the research objectives. The important themes included the patterns of ChatGPT use, benefits, challenges, and responsible-use practices.

4.1 Students' Use of ChatGPT for Academic Writing

Nowadays, almost every student uses ChatGPT as a supportive tool for academic writing. Using it only for creating complete answers, they not only generate ideas but also organize the ideas even they paraphrase and summarize academic writing through ChatGPT. Students mainly use ChatGPT for getting ideas for writing academic essays, reports, emails, research papers, etc. In this study, 80 completed online surveys and face to face interview of 10 students give their opinion for using ChatGPT in academic writing purposes.

Table 1: Students use ChatGPT for academic writing

Purpose of use	Percentage
Getting ideas	32.5%
Organizing ideas	23.8%
Paraphrasing and summarizing	20.0%

Table 1 shows the percentages of students' use of ChatGPT for academic writing. Here, most of the students like 32.5% of them using ChatGPT for getting ideas, because they know that ChatGPT can help them with their writing, 23.8% of students use it for organizing ideas. Students have their own ideas, but they sometimes do not know how to organize them in a proper way; that's why they use ChatGPT for organizing their ideas. Lastly, 20.0% of students use it for paraphrasing and summarizing. The Maximum number of students repeatedly use ChatGPT for grammar checking and paraphrasing or summarizing many types of activities. This proves that students rely on ChatGPT for language-related issues during their academic writing.

In this study, interview participants continuously used ChatGPT for generating ideas, brainstorming, preparing outlines, improving grammar and vocabulary, and for understanding difficult topics. Many participants said ChatGPT is useful when they struggled to organize their thoughts for the very first time. This finding supports with Zhao et al. (2024), because their study highlighted that generative AI is changing contemporary writing practices. As like that, Kotsis (2025) explained that ChatGPT has important pedagogical value when used as a supportive tool rather than as a replacement for students' own work. Limna and Kraiwanit (2024), found that students use ChatGPT mainly for language editing and improving writing efficiency, which also supports this finding. This study indicates that Social Sciences and Humanities students mainly overcome writing difficulties and improve specific areas of academic writing by using ChatGPT. Overall, the findings do not show that ChatGPT automatically develops students' independent writing abilities; instead, its educational value only depends on how students interact with AI-generated suggestions and whether they actively engage in the academic writing process.

4.2 Students' Perceptions of the Effectiveness and Benefits of ChatGPT

Students generally use ChatGPT to better understand a topic, they use it as a useful tool for supporting academic writing. The findings show that 72.5% of students use ChatGPT for understanding difficult academic topics. This is the highest percentage for perceived benefits of ChatGPT. Less then 50% or 48.8% students use it for improving their overall academic writing skills, such as they use it for correcting grammar, vocabulary, etc.

Table 2: Perceived benefits of ChatGPT

Perceived benefit	Percentage
Understanding difficult academic topics	72.5%
Starting writing	61.3%
Improving academic vocabulary	60.0%

Improving overall academic writing skills	48.8%

Table 2 demonstrated four benefits of ChatGPT from the survey of 80 students. Also, interview responses go with these four benefits. Interview participants explained that ChatGPT helped them to simplify some difficult concepts, improve sentences, correct grammatical mistakes, and create more appropriate academic vocabulary for academic writing. Most of the participants also mentioned that ChatGPT reduced the time required for searching explanations and organizing ideas for writing. Alkamel and Alwagieh (2024), reported that ChatGPT can contribute to improvements in grammar, fluency, accuracy, proofreading, and writing quality among university students, and this study aligns with the findings. Same as Yuan et al. (2024) explained that ChatGPT can support knowledge acquisition and content development in academic writing for students. The findings also create an important difference between immediate writing support by using ChatGPT. Though many students suggested that ChatGPT helped them to complete writing-related tasks, fewer students improved their overall academic writing skills. It also suggests that receiving AI assistance does not accurately develop independent writing competence.

4.3 Challenges of Using ChatGPT and Students' Responsible Use Practices

Using ChatGPT always is not right. This finding shows that there are many challenges of using ChatGPT. Students can take ideas from ChatGPT bt they may have verify every information because ChatGPT do not give accurate response always. ChatGPT helps with generating ideas; it can even give full writing assessment, but it can not write like a human. It use some patterns and that ar not like humans writing.

Table 3: Challenges and responsible-use practices

Issue	Percentage
Concern about plagiarism/academic dishonesty	58.8%
Concern about reduced critical thinking	42.5%
Verify ChatGPT-generated information	55.0%
Need teacher/university guidance	62.5%

Table 3 shows that 58.8% students need to concern about plagiarism or academic dishonesty because ChatGPT gives the writing but it always against with academic dishonesty. Interview findings provide deeper explanations of these concerns; they reported that ChatGPT sometimes provides inaccurate information, unclear explanations, or unreliable references in writing that is not always right. Some participants also explained that students may copy AI-generated responses without fully understanding the concepts or paraphrase it. These findings accurately goes with Lendvai's (2025) discussion regarding the reliability concerns of AI-generated academic content. Yuan et al. (2024) also identified challenges related to dependence, and the academic integrity of ChatGPT in learning environments. The findings supports with Palacios-Núñez et al. (2025) and Lavidas et al. (2026), who explained the importance of institutional guidance and AI literacy in higher education. Students already recognize both the advantages and limitations of ChatGPT.

6. Conclusion

This study explained students' perceptions of the effectiveness and challenges of using ChatGPT for academic writing in Social Sciences and Humanities education with a mixed-methods approach, with 80 online survey respondents and 10 interview participants. The findings showed that students use ChatGPT for different types of academic writing activities, including idea generation, organizing information, grammar and vocabulary correction, paraphrasing, summarizing, and understanding difficult academic concepts and also difficult topics. Students mainly use ChatGPT as a useful educational tool, that's why, 72.5% students reported that ChatGPT helps them to understand difficult academic topics, On the other hand, 61.3% indicated that it assists them in starting their writing for idea generating. However, students also faced several challenges. They should be more concerns regarding plagiarism, inaccurate information, excessive dependence, and reduced independent thinking. 62.5% of students believed that they need guidance from teachers and universities for the appropriate use of ChatGPT. The findings overall suggest that ChatGPT can support academic writing development when students use it to understand concepts, generate ideas, organize ideas, and improve their writing, but they need to be more serious concern about plagiarism and nonacademic writing patterns. The study concludes that the educational value of ChatGPT depends not simply on its ability to generate academic content but also on students' ability to engage critically with its responses, verify information, and maintain academic integrity.

7. Recommendation

Based on the findings of the study, the following recommendations are suggested. Universities should develop clear institutional guidelines explaining appropriate use of ChatGPT in academic writing. These guidelines should cover areas such as brainstorming, content organization, authorship, and AI assistant editing. Through authentic academic sources such as peer-reviewed journal articles, academic books, and trustable institutional publications, students should be encouraged to verify information generated by AI. They should also independently check references instead of assuming that sources provided by ChatGPT are reliable. Teachers should support independent academic writing. They should encourage students to use ChatGPT mainly for understanding difficult concepts, organizing ideas, and receiving feedback rather than blindly depending on it. Universities should incorporate AI Literacy into academic writing education. This helps students to understand the limitations of AI and use AI technologies in an ethical manner. Future research should investigate the long-term effects of ChatGPT use on students' academic writing skills, independent thinking skills, understanding difficult concepts, and originality. Longitudinal and experimental research could provide stronger evidence of whether ChatGPT improves students' academic writing skills over the long term.

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Effects of Social Media on English Vocabulary Development of Tertiary-Level Students

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Abstract

Nowadays, social media has become one of the primary modes of daily communication for learners, which has also impacted their learning habits. Hence, learners' vocabulary acquisition has been affected both positively and negatively by exposure to social media platforms like Facebook, Instagram, and TikTok, with significant English content consumption. The main objective of this research paper is to examine the influence of social media use among tertiary-level students and to understand learners' perceptions of this influence. The study uses a mixed-method approach, collecting data from tertiary-level students through surveys and vocabulary-related questionnaires. The survey heavily focused on how frequently learners use social media, the kinds of applications they use, and how they use social media to help them learn new vocabulary. The findings of this research indicate that social media plays a crucial role in intensifying informal vocabulary learning. The learners revealed learning new words, slang, and expressions through daily online exposure. Nevertheless, constant usage of social media may negatively impact the use of standard English in academic contexts. Overall, the research suggests that social media can be an additional tool for vocabulary development when used in a balanced and guided manner.

Keywords: Vocabulary, Social media, Tertiary level

1. Introduction

1.1 Background of the Study

Language is being reshaped through digital communication, changing its way of exposure, learning, and use. University going students use social media platforms like Facebook, Messenger, Instagram, YouTube, WhatsApp, TikTok etc frequently in regular life. These platforms basically function as a source of entertainment, a way of communication, and interaction. However, students see posts, comments, memes, videos, etc and get exposed to written and spoken English words. These platforms provide an extended version of language beyond the physical and traditional classrooms. Social media has been remarkably seen as a second and foreign language learning environment (Barrot, 2022). In the same way, Kabilan et al. (2010) stated that Facebook is an opportunity for university students to learn the English language by interacting and communicating.

Students need vocabulary knowledge in both written and spoken language. Primarily, textbooks, lectures, and dictionaries provide this lexical knowledge. Nowadays, digital platforms provide vast opportunities to get exposed to new, unfamiliar words for the learners. Abbas et al. (2019) found that YouTube and Facebook help ESL learners to acquire vocabulary, whereas Hasan et al. (2022) highlight better performance of EFL students in Bangladesh because of WhatsApp-influenced vocabulary. Moreover, media-assisted vocabulary enhances both intentional and incidental vocabulary acquisition of a foreign language (Nguyen, 2021).

However, social media exposes different patterns from formal environments, as online learning is quite varied worldwide. Students may not only acquire formal expressions but also informal expressions such as abbreviations, slang, short forms, colloquial words, etc. Internet-based interaction exposes different forms of language use with linguistic practices (Crystal, 2011).

Social media can project a dual impact on the vocabulary development of learners. Primarily, it can extend the lexical range with contextual knowledge and meaning. Simultaneously, too much exposure to informal expressions may create challenges in differentiating the appropriate language tone according to the settings for tertiary-level learners. Social media platforms influence both formal and informal language learning, and there should be careful investigation between these two (Zainuddin & Yunus, 2022).

1.2 Research Problem

Tertiary-level students are getting opportunities to learn diverse vocabulary outside the traditional classrooms through social media captions, posts, videos, etc. However, these platforms may provide informal expressions along with the formal expressions appropriate for academic settings, creating challenges for students to distinguish

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between formal and informal vocabulary. Therefore, this study examines how tertiary-level students use social media, their perceptions towards these, influencing vocabulary development and how these platforms are related to their language understanding and use of formal and informal English vocabulary.

1.3 Research Objectives

- To explore tertiary-level students' ways of using social media and their perceptions of its influence on English vocabulary development.
- To investigate the effect of social media on tertiary-level students' understanding and use of formal and informal English vocabulary.

1.4 Research Questions

- What are the ways tertiary-level students use social media, and how do they perceive its influence on English vocabulary development?
- How does social media affect tertiary-level students' understanding and use of formal and informal English vocabulary?

2. Literature Review

2.1 Social Media as a Language-Learning Environment

The way social media technologies are making branches across the globe, it almost formed grey line between formal and informal language acquisition. Noticeably, learners are more exposed to target language input when they are taking part in usual online activities rather than only within classroom settings. Kabilan et al. (2010) showed that students at the university considered Facebook as a great source of learning the target language English, as it promotes interaction and communication. The significance of social media as a medium of learning language is aided by another researcher, Barrot (2022). In his systematic review, it was investigated that interest in social media for learning language promoted positive outcomes.

Social media content is diverse and has multimodal features, and can be related within a social context. Words that are written may be aided by audio, visual elements, comments, and so on. These elements provide support that helps learners make meaning and understand how vocabulary works in real communication.

2.2 Social Media and Vocabulary Development

Acquisition of vocabulary demands continuous exposure to lexical items and ways in which new words can be connected with real and meaningful contexts. With the help of social media, it is possible to be exposed to new and popular words and expressions across different elements like posts, videos, captions, advertisements, memes, comments, and discussions. Nguyen (2021) found that exposure to media is beneficial for foreign language vocabulary acquisition. Abbas et al. (2019) also presented a similar report on positive perceptions of learners regarding vocabulary learning through social media.

Learning that happens through tech-assisted platforms encourages learners in vocabulary learning rather than classroom learning. Hasan et al. (2022) found that vocabulary acquisition through WhatsApp instructions had massive positive backwash on performance and positive attitudes among learners of Bangladeshi tertiary-level EFL.

2.3 Incidental Learning, Context, and Repetition

A huge part of vocabulary exposed to learners on social media is likely to be learned on the spot. It might not be the case that students will deliberately open social-media apps to study vocabulary only, but they can nevertheless notice unfamiliar words while watching videos, reading news, browsing memes, or interacting with others. During such challenges context has a big role to play its part in supporting this process. Elements like images, audio, captions, facial expressions or gestures, comments, and repeated examples may help learners make meaning without immediately consulting formal reference materials. Continuous exposure to the same vocabulary may further strengthen recognition.

In this case, however, contextual understanding alone does not guarantee complete lexical knowledge. For example, a learner might comprehend the close meaning of a word without being aware of its pronunciation,

grammatical behavior, collocations, connotations, or level of formality. Likewise, incidental exposure may be especially beneficial as an early phase of vocabulary acquisition but will require to be aided by verification and guided and consistent practice.

2.4 Informal Digital English and Register

One of the key characteristics of social media language is the commonness of informal and digital expressions. Slang, abbreviations, shortened forms, conversational writing, unusual spellings, and memes are some typical features of online communications. Crystal (2011) says that digital communication has come up with distinctive linguistic habits that have an effect on the communicative needs and requirements of the digital ecosystem. Speed, brevity, sarcasm, group identity, and creativity can prompt forms of language that differ from traditional and typical academic writing.

For learners at the tertiary level, familiarity with such vocabulary can be beneficial because it improves understanding of new-age digital communication. However, issues may occur if learners borrow informal expressions into contexts that require formal language. That's why register awareness becomes critical. Zainuddin and Yunus (2022) investigated to find out that social media sites are responsible for contributing to both formal and informal English learning. Their review also prescribes the requirement for clearer attention to how learners deal with these overlapping linguistic conditions and challenges.

2.5 Conceptual Orientation of the Present Study

The current study sees social media vocabulary learning happening with the help of the interaction of three processes: exposure, comprehension, and implementation. Exposure means the learners' contact with the target vocabulary through the context of social media. Comprehension is the understanding of unfamiliar words that occurs through contextual clues and continuous exposure. Implementation happens when learners have the ability to use vocabulary appropriately, especially when making a difference between informal virtual communication and formal academic contexts.

This encourages the study to investigate both benefits and hurdles of social media vocabulary learning rather than using vocabulary development just as an increment in the number of words learnt or memorized.

2.6 Research Gap

From the previous studies, it is shown that social media provides a learning platform for the English language through Facebook, YouTube, and WhatsApp (Kabilan et al., 2010; Abbas et al., 2019; Hasan et al., 2022). However, the association between social media platforms and vocabulary development of tertiary-level students has been given limited attention.

Additionally, the pattern of learning English and the use of formal-informal vocabulary needs to be explored (Zainuddin & Yunus, 2022). Hence, this study addresses this gap by exploring students' perceptions of learning and use of formal-informal vocabulary.

3 Methodology

3.1 Research Design

The study followed a mixed-method approach including both qualitative and quantitative data. The qualitative part examined students' experiences and examples of vocabulary learning along with their opinions about appropriate social media use. The quantitative part explored the perceptions and patterns of social media use for vocabulary development, along with concerns about formal and informal vocabulary.

3.2 Participants

This study includes 56 tertiary-level students from a university from different levels of education. The participants were from different academic disciplines using different platforms of social media.

The study aimed at this group of participants as tertiary-level students frequently use social media. Moreover, they need to use English both in formal and informal contexts, distinguishing between different genres.

3.3 Data Collection Instrument

The study used a structured questionnaire to collect both qualitative and quantitative data. The research objectives and research questions were followed to develop the questionnaire. In the questionnaire, there were open-ended questions, closed-ended questions, Likert-scale statements, and vocabulary-related multiple-choice questions.

The questionnaire included preferred social-media platforms with duration of daily use and patterns, frequency and types of content, perceptions toward vocabulary development, formal and informal vocabulary, and students' experiences of learning. The vocabulary-related questions helped to understand students' level of defining the meanings and distinguishing between formal and informal genres, whereas the open-ended questions asked about examples and the ways, teachers could follow to make the learning more appropriate.

3.4 Data Analysis

For the qualitative responses, thematic analysis was followed. Similar ideas were categorized after identifying the recurring responses for the open-ended questions, such as experiences, opinions, suggestions, etc.

For the quantitative responses, descriptive analysis was followed using percentages, mean scores, and frequencies to explain vocabulary learning strategies, social-media usage patterns, and comprehension of vocabulary. Multiple-choice questions were analyzed using percentages and frequencies, whereas five-point Likert-scale statements were analyzed through mean scores.

4. Findings & Discussion

4.1 Theme 1: Everyday Social-Media Use Creates Continuous Exposure to English

The findings show that the participants use different platforms of social media daily. 87.5% of the participants (49 out of 56), reported using social media for at least two hours per day and getting scope of English language beyond traditional classroom settings. A majority of students (76.8%) also reported getting exposure to English content often or very often, mostly through Facebook, Instagram, WhatsApp, and Messenger.

The type of content is directly associated with vocabulary learning. The content used for entertainment purposes, such as videos, memes, movies, etc was given more importance, whereas a small portion of participants stated educational content as their source for learning the English language through social media. These results show that students encounter English more while interacting or seeking recreation rather than deliberately studying or exploring the language.

Barrot (2022) found social media to be an effective environment for language learning outside the traditional classroom. Additionally, according to Kabilan et al. (2010), English learning can be easier by interacting through social platforms. This finding agrees with both of the ideas, including the matter of learning through multiple platforms rather than one. This finding addresses Research Question 1, identifying the patterns of using social media to expose English vocabulary.

4.2 Theme 2: Context, Repetition, and Independent Engagement Support Vocabulary Learning

Generally, social media provides the scope for understanding and learning new and unfamiliar English words. 66.1% of the participants (37/56) agreed or strongly agreed that they were able to understand new word meanings through context using social media, showing a mean score of 3.82 out of 5. Multimodal information on social media, such as videos, captions, pictures, etc. leaves hints for learners to infer the meaning from the context. One more important way of learning is repetition. 42 participants agreed or strongly agreed that they could remember English words by encountering those words repeatedly on social media. Moreover, they also follow contextual guessing and online searching when facing totally unfamiliar words, and this enhances independent learning. However, contextual guessing needs special attention as there may be a lack of information about collocation, genre, or register.

Hasan et al. (2022) reported that repeated exposure to online content benefits learners' learning, while Nguyen (2021) highlighted the potential of media environments in vocabulary learning. This finding agrees with both of the ideas and addresses Research Question 1, explaining the importance of repeated and contextual exposure in vocabulary development.

4.3 Theme 3: Social Media Expands Vocabulary, Particularly Informal and Contemporary English

The findings consider social media as a source of new vocabulary. 64.3% of the participants (36 out of 56) agreed or strongly agreed that they were able to learn and use new English vocabulary, with a mean score of 3.73 out of

5. Open-ended responses projected the diverse areas of vocabulary where students mentioned various abbreviations such as POV, IMO, TBH, LOL, etc. They also mentioned contemporary words such as ragebait, rizz, slay, and clickbait, which demonstrates the prominence of learning informal vocabulary. In this matter, 67.9% of the participants agreed or strongly agreed that they also learned slang and abbreviations along with formal words through social media. 50 and 52 participants could correctly identify LOL as an informal expression and interpreted IMO as in my opinion, respectively.

Abbas et al. (2019), reported learners' positive perceptions of acquiring vocabulary through YouTube and Facebook, while Crystal (2011) described digital communication as an evolving process in terms of language practices. The findings reflect with both of the ideas, highlighting more influence on informal expressions rather than formal exposure. This theme addresses both of the Research Questions, reflecting students' perceptions of using social media for vocabulary development while also showing the association with learners' understanding and use of informal vocabulary.

4.4 Theme 4: Students Demonstrate Register Awareness but Experience Some Informal-Language Interference

The findings demonstrated that many students were able to differentiate between informal and formal vocabularies, as 64.3% of the participants (36 out of 56) agreed or strongly agreed that they could use two different genres of vocabulary for different purposes. 47 participants were able to correctly identify the sentence 'social media may contribute to students' vocabulary development' as the most appropriate option for academic writing, whereas only 39 participants could select the correct option of 'many students' as the formal expression of 'a lot of students'. This finding suggests that students may get confused with formal and informal words having smaller differences rather than the clear ones. 27 participants reported of getting affected in academic writing because of social media language exposure while 52 participants were able to correctly identify the closest meaning of reliable. From this finding, it is clear that only awareness about words cannot fully prevent from mixing up formal and informal words.

Despite of having awareness about informal expressions, students may use informal words in their writing because of frequent exposure through social media. Crystal (2011) demonstrated that language practices become different than traditional writing through digital communication. It also reflects the idea of Zainuddin and Yunus (2022), highlighting the importance of differentiating between informal and formal words. Therefore, the findings show a dual pattern of social media, creating awareness while leaving the possibility of using inappropriate register. This theme addresses Research Question 2, exploring understanding and use of formal and informal vocabulary.

4.5 Theme 5: Effective Vocabulary Learning Requires Selective Use, Verification, and Guidance

Students describe that they do not see social media as only beneficial rather, they also mention about the importance of being alert while using it. They suggest to following more educational content and checking unfamiliar words before using it blindly. Additionally, they mention about teacher guidance through qualitative responses, suggesting for arranging activities, discussions etc to provide a bridge between students' formal and informal learning. Participants also suggested to use social media as a supporting tool rather than an independent source. This idea reflects with Hasan et al. (2022), showing the importance of guided and structured learning, while; Zainuddin and Yunus (2022), mention the association between informal and formal words through digital platforms. This theme addresses both the Research Questions suggesting for proper use with guidance while learning.

5. Pedagogical Implications and Recommendations

The findings have many implications for tertiary-level English teaching and independent vocabulary learning.

First, the teachers may show positive attitudes in encouraging learners to use social media with a purpose by following authentic and reliable sources of English-learning pages, news platforms, language teacher creators, and high-quality English-language content. This will allow everyday social-media exposure to include more accurate and educational language input. Second, incidental exposure can be combined with conscious and guided vocabulary-learning strategies. Learners need to cross-check unfamiliar words through authentic dictionaries, note down useful vocabulary, review it periodically, and practice using it in meaningful sentences, conversations, and academic writing. Third, special explicit attention can be given to register. Teachers can help students make specific distinctions among slang, abbreviations, conversational expressions, standard vocabulary, and academic vocabulary. Finally, implementing selective social-media content in classroom instruction is highly advisable. Elements like posts, videos, captions, vocabulary quizzes, visual flashcards, and word-of-the-day activities can reflect students' existing digital encounters with guided language learning.

6. Limitations and Directions for Future Research

There are many drawbacks and limitations that should be kept in mind when interpreting the findings.

The study involved only 56 tertiary-level students from one university, which automatically limits the extent to which the findings can be generalized to all tertiary-level students in Bangladesh or other contexts. The study also relied heavily on self-reported perceptions and reported language behavior. Although vocabulary-related multiple-choice questions showed some objectivity in the evidence of vocabulary and register awareness, the research failed to incorporate an experimental pre-test/post-test design or long-term measurement of the progress of vocabulary. In subsequent times, research could involve diverse samples from several universities. In the upcoming years, examination of particular platforms in studies could be conducted separately with greater depth, with comparative self- reported register awareness with reliable sources of samples of students' academic or form-focused writing.

7. Conclusion

The above research study investigated the effects of social media on English vocabulary development among tertiary-level students, focusing on students' everyday social-media practices, perceptions of vocabulary learning, and comprehension and usage of formal and informal English vocabulary. The findings primarily demonstrate that social media has a positive influence on learners, but it comes with a conditional perceived effect on vocabulary development. Exposure to large amount of English through their everyday internet activities, and this exposure can aid in contextual understanding, repeated encounters with vocabulary, retention, independent searching, and awareness of contemporary English. The strongest effect was found in informal and digitally motivated vocabulary. A substantial amount of familiarity with slang, abbreviations, and emerging internet expressions was exhibited by the learners. At the same time, most demonstrated awareness of differences between formal and informal vocabulary. Nevertheless, this awareness did not completely rule out the probability of informal-language interference. It was also reported that nearly half of the respondents indicated that informal social-media language sometimes affected their academic writing. Consequently, vocabulary development through social media should be considered not only in terms of vocabulary expansion but also in terms of accuracy, register, and context-appropriate use. Thus, social media is an available asset when used as an extra element of a vocabulary-learning environment rather than as a complete replacement and the only resort alternative for dictionaries, academic reading, classroom instruction, and other formal resources. Need-based involvement with dependable content, cross-checking of foreign vocabulary, active practice, and teacher guidance can help students benefit from the extensive language exposure offered by social media while eliminating inappropriate exchange of informal language into formal academic contexts.

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Green Skills and Transnational Peer Training: A Case Study in Student Mobility

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Abstract

Developing sustainable mindsets requires more than classroom instruction; it requires active collaboration and the exchange of ideas across borders. As environmental challenges grow increasingly complex, educational initiatives must move beyond traditional pedagogies and embrace interdisciplinary, cross-cultural approaches that prepare students for real-world problem-solving. This study analyzes the peer training model developed within the EcoAI EduNetwork Initiative (EAIEN), an Erasmus+ KA220-SCH cooperation partnership that brings together schools and institutions from Türkiye, Romania, and Greece. By connecting students from diverse educational and cultural backgrounds, the project creates a "living laboratory" for environmental and digital skill acquisition through both physical and virtual mobility activities. The core of this study is the evaluation of two mobility events held in Eskişehir, Türkiye and Santana, Romania, where students engaged in hands-on training focused on ecological challenges and AI-based solutions. During these events, participants collaborated in mixed international teams to explore sustainability topics and the application of artificial intelligence tools to create open educational resources to train their peers and raise awareness in the local community. Using a mix of qualitative feedback and quantitative surveys collected before and after each mobility, we examine how the peer-training methodology affects student confidence, cultural awareness, and environmental stewardship. Preliminary findings suggest that the combination of cross-border interaction and project-based tasks contributes meaningfully to both attitudinal shifts and skill development among participants. The study highlights the importance of "Green Skills" not just as technical knowledge, but as a holistic competency encompassing critical thinking, civic responsibility, and adaptability for a circular economy and how these are best fostered through collaborative, problem-based learning in authentic settings. We argue that peer training, in which students teach and learn from one another, serves as a particularly effective mechanism for internalizing these competencies. This case study offers valuable insights for educators and policy-makers interested in the practicalities of designing and managing transnational Erasmus+ mobility programs that combine social inclusion objectives with high-tech learning goals in the service of environmental sustainability.

Keywords: Green skills, peer training, cascade training, student mobility, Erasmus+, artificial intelligence in education

Introduction

European policy is unusually explicit about where green skills belong. The Council Recommendation on learning for the green transition and sustainable development (Council of the European Union, 2022) does not ask member states to add a sustainability course; it asks them to embed sustainability across the curriculum and the whole institution. GreenComp, the European sustainability competence framework, was designed to the same specification as a cross-curricular reference built around values, systems thinking, futures thinking and action rather than around a single discipline (Bianchi et al., 2022). The labour-market case points the same way: the green transition depends less on a small set of specialist occupations than on the greening of ordinary ones, so the competence has to reach every learner rather than those who choose a science pathway (Cedefop, 2021).

The argument for embedding rather than adding is also pedagogical. Sterling (2001) distinguishes education *about* sustainability, which can be delivered as content, from education *for* and *as* sustainability, which changes how teaching itself is organised. Whole-school research similarly finds that sustainability practice becomes durable when it is carried by the ordinary work of the school rather than by a designated unit (Mogren et al., 2019; UNESCO, 2020). Green skills understood in this way are a holistic competence combining critical thinking, civic responsibility and adaptability, and they are practised rather than delivered. This creates a practical bottleneck: if green competence is to appear in language, mathematics and vocational lessons, then those teachers must hold it too. Embedding is, first of all, a teacher development problem, and only then a student learning problem.

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Cascade and Peer Training

Cascade, or training-of-trainers, models promise to solve exactly this problem of reach: a small group is trained and then trains others locally. The research record is candid about how often the promise thins out. Hayes (2000) and Wedell (2005) document message loss at each transmission, with content reaching the classroom stripped of its rationale, and Bett (2016) reports the same decay in a national in-service system. The recurring diagnosis is that cascades fail when lower tiers are positioned as recipients of a fixed message rather than as adapters of it.

That diagnosis implies its own remedy, which is the design hypothesis examined here: if dilution comes from passive transmission, a cascade in which every tier must produce something for an audience of its own should resist it. This is where the cascade literature meets the peer learning literature. Learning by teaching obliges the trainer to retrieve, reformulate and adapt material for a specific audience (Topping, 2005), and successful performance of that role is a primary source of self-efficacy (Bandura, 1997). Problem-based learning applies the same logic to task design by starting from authentic, ill-structured problems (Hmelo-Silver, 2004). When the audience is international, the task also creates the conditions of cooperative, equal-status contact that intergroup contact theory associates with reduced prejudice and greater intercultural understanding (Allport, 1954).

This paper therefore asks how a three-tier peer training cascade, completed through transnational student mobility, relates to students' confidence, cultural awareness and environmental stewardship, and which design conditions appear to strengthen or weaken it.

Methodology

The Case: EAIEN and its Three-Tier Cascade

EAIEN (2024-1-TR01-KA220-SCH-000256580) is a 24-month Erasmus+ KA220-SCH cooperation partnership (September 2024–August 2026) coordinated by Anadolu University (Türkiye), with Özel Çağdaş Fen Lisesi (Türkiye), Liceul Tehnologic Ştefan Hell Santana (Romania), Future Learning (Greece) and Universitatea Politehnica Timişoara (Romania). The two partner schools differ in type and setting, a private science high school in a Turkish city and a technological high school in a small Romanian town, which gave the partnership its social inclusion dimension: the same learning goals had to work for students from different educational pathways and cultural backgrounds.

The project was organised as a three-tier cascade in which no tier received a finished package. In **Tier 1**, five teachers from each school (ten in total, deliberately not only science teachers) were trained online by the project partners in sustainability concepts, AI tools and open educational resource (OER) production. In **Tier 2**, those teachers trained twenty-one students in each of their own schools face to face; students worked in assigned roles (coordinator, researcher, designer, AI tool user) and produced materials. In **Tier 3**, the resulting 42 Student Green Ambassadors trained each other and local peers during two physical mobilities, summarised in Table 1. Virtual components, including the multilingual Moodle course *AI-Empowered Green Skills Education* and the project OER platform in English, Turkish, Romanian and Greek, supported all three tiers.

Table 1. The two mobility events (Tier 3).

	Mobility I – Eskişehir, Türkiye	Mobility II – Santana, Romania
Dates	2–9 March 2026	29 March–4 April 2026
Host school	Özel Çağdaş Fen Lisesi	Liceul Tehnologic Ştefan Hell
Participants	42 students, 10 teachers	42 students, 10 teachers, 2 university staff
Pedagogical model	Co-design → delivery	Observation → synthesis → action
Authentic settings	Municipal sustainability masterclass, university campus, waste-to-energy plant	Local authorities visited by bicycle, aluminium plant, university campus
Peer training	7 rotation sessions; 171 local students	4 awareness sessions; 96 local students

The two mobilities were deliberately different. In Eskişehir, mixed Turkish–Romanian teams co-designed quizzes, presentations, posters and interactive activities, using AI tools, and then delivered them in rotation to classes at the host school. In Santana, participants first spent three days documenting local sustainability practice with a structured observation booklet covering waste, transport, green space, energy and consumption, and only then turned their own field notes into materials and taught from them.

Data Collection and Analysis

The study is a qualitatively driven single case study (Yin, 2018), with survey data in a supporting role. Feedback forms were administered at the end of the training tiers, that is before the mobilities (7 teachers and 36 students),

and after each mobility: 8 teachers and 39 students responded after Mobility I (student response rate 92.9%), and 9 teachers from three partner institutions and 23 students after Mobility II (54.8%). Each form combined Likert or agreement items with open-ended questions, and the open-ended responses were coded thematically following Braun and Clarke (2006).

Three limitations frame the findings. The instruments were developed as project quality tools and differed across events (Mobility I used an 18-item five-point Likert scale, Mobility II a three-point agreement scale), so values are reported as within-event descriptives and are not compared across events. There was no matched pre-test and post-test on a common instrument, so outcomes are perceived rather than measured competence gains. Finally, pronounced ceiling effects carry the familiar risks of social desirability and common method bias in single-source self-report data (Podsakoff et al., 2003). Participation was voluntary and anonymous, no identifiers were collected, and extracts are attributed only by role and country; as participants were minors, school-mediated consent procedures applied.

Results

Before the Mobilities: Teachers and Students as Producers

Teacher ambassadors rated the online Tier 1 training very highly (mean 4.93/5.00). More informative than the score was what teachers said it changed: they described themselves as readier to guide AI-supported tasks in their own lessons, which is the entitlement the embedding argument requires of non-science teachers. Two difficulties surfaced immediately and recurred at every later tier: uneven prior digital and AI literacy within the group, and too little hands-on practice relative to input. Tier 2 students evaluated their school-based training equally positively (4.96/5.00 equivalent). Because students worked in defined roles and were responsible for producing materials, this tier functioned less as a second transmission than as a first production.

During the Mobilities: Peer Training Across Borders

Across the two mobilities, student ambassadors delivered eleven peer training sessions to 267 local students, roughly six times the size of the ambassador cohort. Table 2 summarises the post-mobility evaluations.

Table 2. Post-mobility evaluation (within-event descriptives).

	Mobility I – Eskişehir	Mobility II – Santana
Respondents	8 teachers, 39 students	9 teachers, 23 students
Scale	5-point Likert, 18 items	3-point agreement
Teachers	5.00 on all 18 items	97.8% agreement
Students (overall)	M = 4.25	89.5% agreement (95.8% excluding one outlier)
Highest-rated area	Cultural exchange and overall experience (M = 4.47)	Cultural perspectives, recommendation, overall value
Host vs. visiting students	4.63 vs. 3.88	100% vs. 91.7% on the three items above

Teachers were unanimous in judging the model effective, while student ratings were strongly positive but more differentiated. The clearest pattern concerned position rather than person. In Eskişehir the host students reported markedly stronger outcomes than their visiting peers, and the widest gaps fell on precisely the items describing the trainer role: explaining sustainability to others (4.58 vs. 3.30) and confidence in using AI tools (4.47 vs. 3.65). In Santana the delegations swapped roles and the pattern swapped with them, with the now-hosting Romanian students recording full agreement where their visiting Turkish peers did not. The difficulty therefore appears to lie in standing in front of an unfamiliar class in a second language, not in the characteristics of either group.

What the Peer Training Produced

Four themes recurred in the open-ended data. **First, content was re-authored rather than relayed.** Because each tier built materials for a new audience, the adaptation that cascades usually lose became the assigned task. Teachers observed that student-made materials were more concise and more accessible to other students than adult-made materials would have been.

"The most successful aspect of this exchange was that students could show their colleagues who were not part of the project what they learned about waste recycling and why this is so important." (Teacher, Romania)

Second, teaching built the teachers' confidence. Students reported that explaining sustainability to younger learners deepened their own understanding, and named the cross-school preparation of materials as the most

valuable element of the experience, which is the learning-by-teaching effect operating where the design placed it (Topping, 2005). **Third, stewardship was rescaled from global to local.** The clearest attitudinal shift followed the observation-based mobility, in which students gathered their own evidence before teaching from it.

"This experience made me realize that environmental protection is not just about big global actions but also about small and consistent habits in everyday life." (Student, Romania)

Fourth, the relational outcome outranked the technical one. Asked what mattered most, most students across both schools named friendship, cultural understanding or teamwork ahead of any tool or topic. Cultural exchange was the highest-rated area in both mobilities and the one least affected by the host–visitor gap, consistent with the conditions of cooperative, equal-status contact built into mixed-team tasks (Allport, 1954).

Where the Model Strained

Language, alongside holding the attention of younger local classes, was the challenge student trainers named most often, since they worked and taught in English as a shared lingua franca. Views on AI diverged: most students found that the tools made their materials faster to produce and more professional, teachers added that supervision was still needed for accuracy and critical thinking, and a minority of students remained openly unconvinced. This reservation is itself a healthy sign; uniform enthusiasm among adolescents would raise doubts about whether critical evaluation had been taught, and it is consistent with the emphasis on human oversight in UNESCO's (2021) guidance. Finally, the host advantage means that a mobility scheme running in only one direction distributes the hardest formative experience unequally.

Conclusions

Green skills belong in every classroom rather than in one slot on the timetable, and this places the burden on teachers before it reaches students. A cascade is the obvious structure for reaching them at scale, and the literature is right to warn that cascades dilute. The EAIEN case suggests that the dilution is not intrinsic to the structure but to a particular use of it: cascades thin out when lower tiers receive, and hold their strength when every tier produces something for a real audience. Transnational mobility completes such a cascade well, because it supplies both a real audience and the intercultural contact that participants valued most.

Five design principles follow for those planning similar Erasmus+ partnerships: (1) give every tier something to make, whether a lesson plan, a resource or a training session; (2) recruit teacher trainers from across subjects so that embedding does not begin and end in the science department; (3) let students gather their own local evidence before they teach, since the observation-based mobility produced the clearest attitudinal shift; (4) make hosting reciprocal, or, where only one direction is possible, support the visiting group with rehearsal and co-delivery; and (5) level digital and AI literacy at the top of the cascade, because unevenness left there reappears, magnified, at the bottom.

Given the self-reported, non-comparable nature of the data, these findings should be read as preliminary. Future work should use a common instrument with matched pre- and post-measures across mobilities and follow whether trained teachers continue to embed green skills in non-science lessons after the project ends. The broader implication is practical: mobility is usually justified by its intercultural value, which participants confirmed, but the same design can also carry a curriculum goal, provided that the trainer role is treated as a position to be designed and supported rather than a capability to be assumed.

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Empowering Learners through Open Educational Resources: The EAIEN Digital Learning Ecosystem

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Abstract

In the era of digital transformation, Open Educational Resources (OER) play a pivotal role in democratizing access to high-quality learning materials. The EcoAI EduNetwork Initiative (EAIEN) leverages digital technology to create an innovative learning ecosystem focused on AI literacy and environmental sustainability. This paper examines the design and implementation of the EAIEN digital platform, which serves as both a repository for student-created content and a collaborative workspace for peer-to-peer training. The study focuses on the pedagogical transition from passive consumption to active content creation. Within the EAIEN framework, students are not only learners but also "knowledge producers," developing OERs that integrate AI-driven environmental solutions. This approach utilizes a "Peer Training Exchange" model, where digital tools facilitate cross-border mentorship and knowledge sharing among high schools and universities. We discuss the technical challenges of maintaining an open-access platform that adheres to the project's strict ethical and quality assurance guidelines, including data privacy and inclusivity. Results from the early implementation phases suggest that the use of localized yet digitally shared resources enhances student motivation and technological self-efficacy. The paper describes the platform's features and discusses how the integration of AI tools within OERs can foster a more resilient and tech-savvy generation of European students.

Keywords: Open educational resources, OER-enabled pedagogy, AI literacy, green skills, peer training, Erasmus+

Introduction

Open Educational Resources are usually justified by access: materials released under open licences can be used, adapted and redistributed without cost, and UNESCO's (2019) Recommendation on OER frames them as a means of making quality learning materials available to all. Yet access alone has proved a weak engine of change. Much OER research has concentrated on cost and substitution, asking whether open materials perform as well as commercial ones (Hilton, 2016), while the pedagogical potential of openness has received less attention. A second, persistent problem is reuse. Project-funded repositories are frequently organised around the project that produced them rather than the teacher who might use them, and many outputs are archived rather than adopted once funding ends.

Two strands of work suggest a different starting point. OER-enabled pedagogy asks what becomes possible when learners are permitted to revise, remix and publish materials themselves, so that assignments produce artefacts with value beyond the classroom (Wiley & Hilton, 2018). Open educational practices extend this to the social level, treating openness as a stance towards collaboration and participation rather than as a licensing status (Cronin, 2017). Both converge with the knowledge-building tradition, in which learners contribute to a shared, improvable body of ideas rather than consuming finished ones (Scardamalia & Bereiter, 2006), and with the peer learning literature, in which explaining to others deepens the explainer's own understanding (Topping, 2005).

This shift matters particularly for the two agendas EAIEN brings together. AI literacy involves more than tool use: it includes understanding what AI can and cannot do, evaluating its outputs critically and using it ethically (Long & Magerko, 2020; Ng et al., 2021), and European frameworks place these capacities within digital competence more broadly (Vuorikari et al., 2022). Green skills, as defined by GreenComp, are likewise dispositions to be practised rather than facts to be delivered (Bianchi et al., 2022). Both are poorly served by materials that learners only read, and both are well suited to tasks in which learners must produce something for a real audience. Producing for others is also a plausible route to motivation and self-efficacy, since it combines autonomy and ownership (Ryan & Deci, 2000) with mastery experience (Bandura, 1997).

This paper therefore examines the EAIEN digital learning ecosystem as a case of OER designed around learner production. It asks how the platform was designed to support the move from consumption to creation, what the

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early implementation phases suggest about student motivation and technological self-efficacy, and what practical challenges arise in keeping such a platform open while meeting ethical and quality assurance requirements.

Methodology

Context

EAIEN (2024-1-TR01-KA220-SCH-000256580) is a 24-month Erasmus+ KA220-SCH cooperation partnership (September 2024–August 2026) coordinated by Anadolu University (Türkiye), with Özel Çağdaş Fen Lisesi (Türkiye), Liceul Tehnologic Ştefan Hell Sântana (Romania), Universitatea Politehnica Timişoara (Romania) and Future Learning (Greece), the partner leading the platform's development. Its outputs include the online course *AI-Empowered Green Skills Education*, a Teacher's Handbook, a student training pack, a quality management handbook and the Green Skills OER Platform, all published in English, Turkish, Romanian and Greek under Creative Commons licences.

The two partner schools differ in ways that matter for transferability. Çağdaş is a science high school within an examination-oriented national system. Ştefan Hell is a technological high school offering mechanical, economic and social science profiles, partly taught in German, in a multi-ethnic small-town community where many students commute from rural areas. The two universities contributed teacher training, campus-based observation and academic mentoring.

Design and Data

The study is a descriptive and interpretive single case study (Yin, 2018). It draws on three sources: project documentation describing the platform's design decisions; the resources published on the platform; and feedback collected during the implementation phases. Feedback forms were completed after the online teacher training (7 teachers), after the school-based student ambassador training (36 students), and after each of two cross-border mobilities in March and April 2026 (8 teachers and 39 students after the first; 9 teachers and 23 students after the second). Each instrument combined closed items with open-ended questions, and open responses were analysed thematically (Braun & Clarke, 2006). Because the instruments were designed as project quality tools and used different response scales, closed-item results are reported only as within-event descriptives, and all outcomes are self-reported. Participation was voluntary and anonymous, and school-mediated consent procedures applied to participating minors.

Results

An Ecosystem Organised for Use

The first and most consequential design decision was to build a repository rather than an archive. A project archive answers the question "what did this partnership do?" and is filed by work package and partner; a repository answers the question a teacher actually asks, "what can I use in my lesson this week?", and is organised by subject, level, time required and equipment. Around this decision, the ecosystem was structured in three layers (Table 1).

Table 1. Layers of the EAIEN digital learning ecosystem.

Layer	Function	Main components
Learning	Structured training for teachers and students	Moodle course with 21 instructional videos, teacher guides, activities, discussion boards and assessment on AI literacy, green skills, AI tools for teaching and OER creation
Production	Collaborative workspace for building resources	Shared drafting, versioning and review by mixed student and teacher teams, including during mobilities
Commons	Open publication and reuse	Green Skills OER Platform: teacher- and student-created resources, CC-licensed, searchable, no registration required, in four languages

Three further decisions shaped the commons layer. All resources carry Creative Commons licences, so adaptation and translation require no permission. Nothing sits behind a login, because an account requirement is effectively a tax on reuse. And teacher-created and student-created resources are published side by side. The published material falls into four families: integrated subject sequences that place a green competence inside an existing

subject (for example an energy audit in physics or life-cycle and cost analysis in economic streams); AI-supported teaching materials; student-produced explainers such as posters, videos, podcasts, quizzes and presentations; and printable activity cards drawn from the Teacher's Handbook. Every AI-supported activity includes an explicit verification step in which learners check AI output against a measurement or a primary source, so that critical evaluation is built into the task rather than added as a disclaimer.

From Consumers to Producers: The Peer Training Exchange

The Peer Training Exchange turned the platform from a store of materials into a cycle of production. Ten teacher ambassadors, five per school and deliberately drawn from different subject areas, completed the online course. They then trained 42 student Green Skills Ambassadors face to face in their own schools, where students worked in defined roles (coordinator, researcher, designer, AI tool user) to create OERs. During the two mobilities, mixed Turkish–Romanian teams co-designed further materials and delivered peer training sessions in local classrooms, reaching 171 students in Eskişehir and 96 in Santana. Universities contributed at both ends: as trainers of the teacher cohort and as authentic settings for campus observation, giving secondary students cross-border mentorship from higher education.

Whether student work should sit beside teacher work was the most contested decision in the partnership. The argument against was that student material is uneven and busy teachers should not have to sift it. The argument that prevailed was that students explaining a concept to other students reach a register that professionally produced material rarely achieves. The resulting compromise was a narrow screening remit: student resources are reviewed for factual accuracy and safety, but are not rewritten into an adult voice.

Localized yet Shared

The two partner schools used substantially the same resources but adopted them for different reasons (Table 2). This comparison is itself a finding: a resource that carries only one built-in rationale does not travel, whereas small, modular units whose rationale can be supplied locally were adopted in both settings.

Table 2. Adoption patterns in the two partner schools.

	Özel Çağdaş Fen Lisesi (Türkiye)	Liceul Tehnologic Ştefan Hell (Romania)
Main constraint	Curriculum time committed to national examinations	Limited traction of abstract environmental awareness
What was adopted	Activities also defensible as teaching examinable content, e.g. AI-supported analysis of building energy data	Content framed as professional competence: efficiency, maintenance, materials, waste and cost
Rationale supplied locally	Academic achievement	Employability in vocational fields

Motivation and Technological Self-Efficacy

Evaluation of the early implementation phases was consistently positive. Teachers rated the online training at 4.93 out of 5, and students rated the school-based ambassador training equally highly (4.96 on an equivalent five-point scale). After the first mobility, teachers gave the maximum rating on all 18 items and students reported an overall mean of 4.25; after the second, 97.8% of teacher and 89.5% of student item responses recorded agreement (95.8% excluding one clearly anomalous response set). Qualitatively, engagement was highest wherever students carried production responsibility, that is, when they built a resource, prepared a session or explained something to peers who would notice an error. Students most often named the preparation of materials with peers from the other school as the most valuable part of the experience.

Technological self-efficacy was most visible, and most unevenly distributed, in the trainer role. In the first mobility, students from the host school reported markedly higher confidence in using AI tools than visiting students (4.47 vs. 3.65) and in explaining sustainability to others (4.58 vs. 3.30), a pattern that reversed when the schools exchanged host and visitor roles. Confidence thus appeared to depend less on prior skill than on the conditions of production and delivery. Students were also less deferential to AI than adults expected: they returned repeatedly to questions of accuracy, ownership and consequence, and several teachers reported being asked questions they could not answer, which the partnership regarded as an encouraging sign rather than a problem.

Keeping an Open Platform Ethical and Sustainable

Four challenges defined the operational side of the ecosystem. The first was privacy. The platform collects no personal data from users, and student outputs are published with consent and without identifying details, in line

with the General Data Protection Regulation (Regulation (EU) 2016/679) and the project's quality management procedures. The second was inclusivity: resources are offered in visual, textual and interactive formats and as printable materials, so that unequal equipment does not become unequal access. The third was multilingual publication, which proved far more demanding than a formatting step. A correction to one paragraph becomes four corrections, and publication moves at the pace of the slowest language. Three mechanisms kept it manageable: a shared terminology list agreed early, translation by the partner whose community would use each version, and a final structured check against a common checklist. Localization went beyond translation to replacing examples, units and curricular references. The fourth was platform risk: the original course host experienced technical failures, and the course had to be rebuilt on Moodle, a reminder that open resources are only as durable as the infrastructure that hosts them.

Conclusions

The EAIEN case suggests that the value of OER depends less on openness as a licensing condition than on who is allowed to produce them and how they are organised for use. Designing the platform as a repository for lessons rather than an archive of project outputs, publishing student work beside teacher work, and building verification into every AI-supported task turned the ecosystem into a space where learners act as knowledge producers. Early evaluation indicates high satisfaction, and the qualitative evidence links engagement and technological self-efficacy to production responsibility, consistent with OER-enabled pedagogy (Wiley & Hilton, 2018) and with learning-by-teaching accounts (Topping, 2005). The contrast between the two partner schools adds a practical lesson for transnational OER: shared resources travel when they are modular enough for each school to supply its own rationale.

For practitioners, four recommendations follow: organise repositories around teaching needs rather than project structure; let students publish, screening for accuracy and safety without polishing away their voice; treat translation and localization as activities with their own timeline and quality checks; and plan for platform failure from the outset. These findings are preliminary, given that they rest on self-reported data from instruments that differed across events. Future work should track actual reuse of resources beyond the partnership and examine, with common pre- and post-measures, whether producing AI-supported OERs changes students' AI literacy and self-efficacy over time. The integration of AI tools within OERs can contribute to a more resilient and tech-savvy generation of European students, but only where learners are asked not just to use those tools, but to question and publish what they make with them.

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The Educational Pathways of Unaccompanied Minors Through Identity, School, and the New Educational Frontiers of Artificial Intelligence

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Abstract

This theoretical paper aims to reflect on the journey of unaccompanied minors, focusing on three particularly significant aspects: the identity construction, the role of school as a positive support network, and the educational potential of Artificial Intelligence (AI). The issue of unaccompanied continues to represent a highly sensitive educational and social challenge, as it concerns young people who often find themselves living in conditions of extreme vulnerability, marked by disruptions in their life stories, emotional discontinuity and fragility in the processes of recognition. From this perspective, this paper aims to highlight how these young people's identity pathways cannot be interpreted in a linear manner, but instead take the form of complex processes, marked by transitions, redefinitions, and a strong need for recognition. Within this framework, school is viewed as an educational and relational space capable of having a tangible impact on their development, rather than merely a place of instruction. In particular, for unaccompanied minors, who often cannot rely on family or social support networks, the school experience can represent a fundamental context for building meaningful bonds, for experimenting with forms of belonging, for feeling welcomed, for accessing real opportunities for participation, and for preventing isolation and marginalisation.

Within this same framework lies the consideration of AI, viewed here not merely as a digital technological tool, but as a potential educational resource. Indeed, when used responsibly and critically, it can facilitate language mediation, support the personalisation of learning pathways, and offer opportunities for social interaction. Used in this way, AI can help strengthen inclusion processes by providing innovative tools for the narrative reconstruction of the self. By allowing minors to organize and re-elaborate their life stories through digital languages, AI supports them in building identity, connections and opportunities for participation.

At the same time, it is important to avoid simplistic interpretations or uncritical positive or negative views of technology, and instead frame its use within a pedagogical perspective attentive to individual experiences and contexts. It is also very important to consider that inside this context, the pedagogical guidance can operate as a critical filter against the risks of cultural misrepresentation and algorithmmic biases that can be reproducted by the AI systems: those systems are in fact not neutral, but reflect the data and cultural models on which they are trained. From this perspective, intercultural education can provide the framework within which schools and digital technologies are reinterpreted not as separate elements, but as resources which, if pedagogically guided, can support processes of recognition, inclusion and participation among unaccompanied minors.

Keywords: unaccompanied minors, identity construction, intercultural education, school support network, artificial intelligence.

Introduction

In recent years, migration flows have become a defining feature of our society's history, taking the form of complex processes influenced by a multitude of interrelated economic, social, political, and individual factors (de Haas, 2021). These phenomena have recently seen an increase in numbers, beginning to diversify in terms of place of origin, destination, as well as the characteristics and identity of those involved. They have also begun to involve an ever-increasing number of minors who undertake migration journeys independently. For this reason, we can speak of unaccompanied minors.

Under the most recent European regulatory framework, an unaccompanied minor is defined as a minor who enters the territory of the Member States without being accompanied by an adult who is responsible for them under the law or practice of the State concerned, until they are effectively entrusted to such an adult; the definition also includes minors who are left alone or abandoned after entry (European Union, 2024, Art. 2). The presence of these minors has become one of the most significant issues in the European migration landscape; in fact, in 2025, the European Union received 21,125 asylum applications from unaccompanied minors, a figure that confirms the

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persistent relevance of the phenomenon in the European context (Eurostat, 2026). The decision to migrate, particularly for a minor, is frequently rooted in conditions of profound hardship, characterized by poverty, dysfunctional family dynamics, wars, etc.; all elements that ultimately create a context driving young people to seek better life prospects elsewhere (Pucciarelli, 2024; Quiroga, Chagas & Palacín, 2018). In this sense, unaccompanied minors often find themselves in a particularly vulnerable position, exposed to the risk of social marginalization and, at times, to public portrayals that associate them with integration or security issues, to the point of symbolically placing them in a sort of international underclass (Santagati et al., 2024). This complexity takes on even greater significance when one considers that these minors experience migration during adolescence—a phase of life already characterized by transitions, redefinitions of the self, and a need for recognition.

Their journeys are often marked by biographical ruptures, emotional discontinuities, relational fragility, and difficulties in finding a sense of belonging—elements that make the construction of identity an even more delicate process than it already is. Similarly, migration can be interpreted as a rite of passage, a process of symbolic and physical change that marks the path toward maturity. This journey, often long and dangerous, becomes an initiatory experience that not only alters the child's geographical location but also profoundly transforms their identity. This framework shows how the journey of unaccompanied minors does not concern migration in the strict sense alone, but touches more deeply on identity construction, the need for recognition, and the possibility of finding new points of reference. Precisely for this reason, it becomes necessary to also examine the educational contexts within which these journeys take shape, reorganize themselves, and can find opportunities for recognition and participation.

In this direction, this theoretical contribution, drawing on pedagogical and intercultural theoretical approaches and on a review of the relevant literature, focuses on three interconnected dimensions: identity construction, the role of school as a positive network, and the educational potential of Artificial Intelligence, with the aim to offer a theoretical analysis of the educational conditions that may support, or hinder, processes of belonging, recognition and participation among unaccompanied minors.

Identity construction and digital environments in the pathways of unaccompanied minors

In the journeys of unaccompanied minors, the construction of the self unfolds in a state of limbo between the past (their culture of origin) and the future (their integration into a new social context). For this reason, identity can be interpreted as a situated and relational process that develops through the experiences and social practices encountered in various life contexts (Esteban-Guitart, 2021). This perspective is even more significant in the case of individuals who are both adolescents and migrants, and who therefore face an already complex challenge in an amplified form. It is of utmost importance to recognize that these young people are going through a delicate period of transition, in which identity construction and the negotiation of various affiliations—both of origin and new—are intimately intertwined (Deluigi et al., 2024; De Micco, 2019; Shahimi, Block & Alisic, 2024).

In contexts characterized by cultural diversity and migratory mobility, these identity-forming processes are often marked by dynamics of continuous renegotiated and transformation. For unaccompanied minors, this means grappling both with the need to give continuity to their own history and with the need to redefine their place in the world within social, linguistic, and cultural frameworks that are often unstable. In contemporary societies, these processes do not unfold solely within family, community, or school contexts but increasingly involve digital environments and technology-mediated communication spaces as well. Online interactions and digital platforms, in fact, help shape the ways in which young people represent themselves, recount experiences, and build social relationships. Digital environments can therefore be understood as new social spaces in which individuals participate in the construction of their identities and the definition of their affiliations through technology-mediated forms of interaction (boyd, 2014; van Dijk, 2020).

In this context, AI-based tools are also progressively entering processes of communication, learning, and content production, helping to redefine the ways in which people narrate and rework their own experiences. Generative AI technologies, in fact, expand the possibilities for narrative reflection and symbolic self-construction, opening new spaces through which lived experience can be organized, expressed, and reinterpreted (Joseph, 2025; Kvietkute, 2026). This dimension echoes the perspective of narrative identity, according to which the construction of the self also occurs through the stories that individuals develop over time to give coherence to their life experiences (Ricœur, 1988).

For unaccompanied minors, these spaces can take on particular significance, allowing them to maintain ties with their cultural contexts of origin, access linguistic and cultural resources, and experiment with new forms of social participation. However, the construction of identity and a sense of belonging remains a complex process, given that it unfolds in social contexts where individuals risk being perceived primarily as "others".

School as a positive educational network in the age of Artificial Intelligence

For unaccompanied minors, the ability to develop a positive and integrated identity also depends on the quality of the educational environments they encounter in the host country. From this perspective, school can be more than just a place of instruction: it can become an educational, relational, and community space, capable of offering stability, guidance, and recognition during a phase of life often marked by emotional disruption, uprooting, and uncertainty (Barzaghi & Ferrari, 2024; Bolognesi, 2018; Dryden-Peterson, 2017; Pavesi, 2020). For unaccompanied minors, the school experience can therefore serve as a fundamental point of reference, contributing both to the acquisition of skills and to the development of more solid integration pathways on a personal and social level.

In this sense, school can be viewed as a space for social advancement where young migrants acquire cultural and relational tools useful for navigating the new sociocultural context and gradually establishing their place within the host society (Mantovani, 2011; Orioles, 2014; Dryden-Peterson et al., 2019). This does not imply a process of cultural assimilation, but rather the recognition and appreciation of the personal histories, migration experiences, and resources that students bring with them. From this perspective, moving beyond a transmissive conception of school means embracing it as an environment capable of generating shared meanings, relationships, and a sense of belonging.

For this to be possible, inclusion must not be understood as a simple adaptation of teaching strategies to the needs of students with migrant backgrounds, but as a deeper transformation of the school itself. In an inclusive pedagogical perspective, in fact, it is not the students who must adapt to the system, but the system that must reorganize itself to embrace diversity (Leiva Olivencia, 2016), building educational cultures, policies, and practices capable of promoting the active participation of all students in the life of the school community. In this context, intercultural education represents the pedagogical perspective necessary to give concrete form to the principle of inclusion: not an external addition to the curriculum, but a way of rethinking education starting from the cultural complexity of contemporary reality, valuing differences as a resource and promoting cultural negotiation, reciprocity, and the construction of shared meanings among students (Escarbajal Frutos, 2010; Gaspari, 2023; Leiva Olivencia, 2016). In this direction, school can become a positive educational network and a decisive protective resource for unaccompanied minors. An inclusive school, for everyone, where all stakeholders—students, teachers, families, and social agents—can form a community and an open, interconnected educational network, where meaningful relationships can be established (Benelli, 2020; Leiva Olivencia, 2011; Pucciarelli, 2024). It is through these networks that minors can experience trust, recognition, and belonging, escaping isolation and the risk of becoming involved in deviant behaviors, and finding in the educational relationship not only a formative function but also a protective function against the potential risk of marginalization and deviance (Barzaghi et al., 2024).

From this perspective, the school can be conceived as a place that welcomes every student with a migrant background—each with their own needs, resources, and feelings—to foster a sense of belonging and the development of their own identity. In this sense, educating does not merely mean transmitting knowledge, but also recognizing the child as an active part of a community, accompanying them in building a shared path of participation and responsibility.

Artificial Intelligence between educational inclusion and new inequalities

When viewed as a positive support network, AI and digital technologies can become useful tools for promoting the inclusion of unaccompanied minors, provided they are grounded in a clear pedagogical framework. Artificial Intelligence in Education (AIED), in fact, has been developed with the aim of designing systems capable of supporting personalized learning, offering feedback, guidance, and adaptive pathways that are better aligned with students' needs (Panciroli & Rivoltella, 2023; Hwang et al., 2020). In this sense, adaptive learning environments, intelligent tutoring systems, and the latest generative AI tools make it possible to move beyond standardized teaching models and promote learning pathways that are more adaptable to students' individual characteristics (Göksel & Bozkurt, 2019).

From this perspective, even the latest forms of generative AI—through tools such as ChatGPT, Gemini, Deepseek, and other systems capable of generating content based on user input—can represent a significant resource in educational contexts characterized by strong linguistic and cultural diversity. In particular, these tools could allow students with migrant backgrounds to personalize their learning in relation to their linguistic, social, and educational needs.

The daily use of generative AI would enable both the real-time adaptation of instructional content (Panciroli, Rivoltella, Gabbrielli & Richter, 2020; Yang, Dong & Yu, 2024; Ranieri, 2024) and the collection and analysis of meaningful data regarding students' learning processes, such as class attendance, requests for simultaneous and

non-simultaneous translation, punctuality of assignments, and other types of educational needs. Access to such information would enable schools to design more inclusive and targeted educational interventions (Jiménez Perona et al., 2024; Pucciarelli, 2024; Ranieri, 2024; Yang, Dong & Yu, 2024). From this perspective, AI could contribute not only to improving learning but also to the early identification of situations of vulnerability, such as persistent difficulties, risk of dropping out, or social marginalization, enabling the implementation of preventive and timely educational strategies (Agrusti, Bonavolontà, & Mezzini, 2019; Rienties, Simonsen, & Herodotou, 2020; Panciroli & Rivoltella, 2023). However, these possibilities cannot be taken at face value. The use of AI in educational contexts can in fact produce new forms of digital exclusion, especially when students do not have access to technologies under the same conditions. The digital divide does not, in fact, concern only the availability of technological tools, but also involves digital skills, concrete opportunities for using technologies, and the social conditions that allow for full participation in digital environments (van Dijk, 2020; Helsper, 2021). In the case of unaccompanied minors, difficulties in using AI may be exacerbated by the fragility of their social support networks, limited language proficiency, and migration trajectories often marked by educational discontinuity. Under these conditions, the risk is that digital tools, rather than bridging gaps, end up reproducing or amplifying existing inequalities. Added to this is a further critical issue, linked to the fact that digital environments can become spaces of discrimination, stereotyping, and hostile discourse toward young people with a migrant background (Matamoros-Fernández, 2017; Farkas, Schou, & Neumayer, 2018). Furthermore, AI systems are not neutral tools but reflect the data and cultural models on which they are trained, with the risk of incorporating and reproducing biases, stereotypes, and implicit discrimination present in the relevant social contexts (Agrusti, 2023; Tommasi, 2020), which could reproduce or amplify forms of discrimination in digital contexts (Noble, 2018; Crawford, 2021; Mehrabi et al., 2021). This raises a central educational question: while AI can offer significant opportunities for inclusion, it also requires critical reflection on the conditions and logic under which it is introduced.

For this reason, the role of schools remains decisive. Schools are not simply called upon to introduce new tools into teaching processes, but to mediate their use through a clear educational purpose, guiding students and teachers in understanding the mechanisms that govern digital environments and promoting a critical, informed, and responsible use of technologies. Only within a pedagogical framework capable of balancing technological innovation with educational responsibility, AI can become a genuine resource for strengthening relationships, opportunities for participation, and pathways to recognition, especially for individuals in particularly vulnerable situations, such as unaccompanied minors (Orazi & Moriconi, 2024).

Conclusions

The journey of unaccompanied minors raises profound questions about the meaning of education and the kind of human, relational, and formative space that host societies are able to create for those who arrive bearing with them experiences of disruption, expectations, and vulnerability. In these contexts, identity cannot be conceived as something imposed from the outside, but as a process that is built over time, through relationships, mutual recognition, and the possibility of finding new points of belonging. From this perspective, school can play a decisive role. It is not merely a place of instruction but can become a positive educational network, capable of offering stability, meaningful relationships, and concrete opportunities for participation. For unaccompanied minors, who often lack family ties and stable social networks, the school experience can be a fundamental starting point for building future paths.

At the same time, in educational contexts increasingly shaped by digital technologies, it becomes necessary to also question the role of artificial intelligence. When integrated into a thoughtful pedagogical framework, it can support language mediation, the personalization of learning paths, and access to educational opportunities. However, its inclusive value cannot be taken for granted: AI can contribute to processes of recognition and participation only if guided by an educational vision attentive to the relationships, needs, and vulnerabilities of those involved.

The future of education, therefore, does not depend simply on the introduction of new technologies, but on the school's ability to use them to build educational contexts that are more equitable, inclusive, and sensitive to the experiences of young people with migrant backgrounds. It is in this direction that schools, relationships, and artificial intelligence can work together to build pathways of recognition, belonging, and participation for unaccompanied minors.

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Global Analysis of Architectural Education Research: A Comparison of Developed and Developing Countries (2016–2025)

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Abstract

Research into architectural education has diversified significantly over the past decade, influenced by global developments such as digital transformation, sustainability, and the pandemic. The dataset comprises 408 peer-reviewed articles, which correspond to 493 country-based publication records when countries represented in authors' affiliations are counted separately. However, how this research differs between developed and developing countries has not been sufficiently examined in a systematic manner. This study aims to compare publication trends and thematic focuses between developed and developing countries by analysing 408 articles indexed in the Web of Science (WoS) database between 2016 and 2025, using systematic literature review and thematic content analysis methods. The findings indicate that developing countries accounted for 254 country-based publication records, compared with 239 for developed countries. From a thematic perspective, the most prevalent area of research in developing countries was 'Studio Pedagogy and Design Education' (65 country-based publication records, 25.6%), whilst in developed countries, 'Sustainability, Climate and Environmental Design' (46 country-based publication records, 19.2%) was the most prevalent theme. Furthermore, studies focusing on Historical, Theoretical and Critical Pedagogy, as well as Alternative, Experimental and Learning-by-Doing approaches, were more prevalent in developed countries, whereas research focusing on Pandemic and Flexible Learning Models, Studio Pedagogy and Design Education, and Digital and Computational Technologies was more prevalent in developing countries. These differences may reflect variations in digital infrastructure, educational priorities, and institutional contexts across countries. Consequently, by comparatively examining the literature on architectural education across different levels of development, the study highlights thematic differences within the field and provides insights for future research and educational policy discussions.

Keywords: Architectural Education, Developed and Developing Countries, Global Knowledge Production, Systematic Literature Review, Thematic Analysis

1. Introduction

Over the past decade, architectural education has undergone significant changes, including pedagogical transformations in the design studio (Saghafi & Crowther, 2021), sustainability-oriented curriculum reforms (Boarin et al., 2020), and remote learning models necessitated by the COVID-19 pandemic (Metinal & Gümüşburun Ayalp, 2022). This process has led to the increasing prominence of themes such as digitalisation, studio pedagogy, sustainability, and online learning in architectural education research. However, how this transformation has differed globally and how countries' levels of development relate to research agendas and priorities have not been sufficiently clarified. The existing literature includes numerous studies addressing the reconsideration of the design studio and studio pedagogy (Saghafi & Crowther, 2021; Pasin, 2017), sustainability-oriented educational approaches (Boarin et al., 2020), pedagogical approaches and knowledge frameworks in architectural education (Olweny, 2020), and the transformation of architectural education during the pandemic (Metinal & Gümüşburun Ayalp, 2022). Nevertheless, most of these studies have focused on specific themes, technologies, or country cases; studies that examine, in a holistic and comparative manner, how priorities in architectural education research differ according to countries' levels of development remain limited. This study aims to compare publication trends and prominent thematic research areas in developed and developing countries by analysing architectural education articles indexed in the Web of Science (WoS) database between 2016 and 2025. In this context, the study seeks to answer the following research questions: How do publication trends in architectural education research differ between developed and developing countries? What are the prominent thematic research areas in these two country groups? By revealing global priorities and thematic orientations in architectural education research in relation to levels of development, the study is expected to contribute to future research, curriculum development discussions, and evaluations of educational policies.

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2. Method

This study is a quantitative systematic literature review aimed at comparing publication trends and thematic foci in architectural education research in the context of developed and developing countries. Data were systematically collected and classified, and publication trends were examined through descriptive quantitative analysis. A systematic coding process based on qualitative content analysis was conducted to develop thematic categories and assign articles to these categories.

2.1 Systematic Literature Review

The data collection process was carried out using the Web of Science (WoS) database. The search was conducted using the query "architectural education" OR "architecture education" within the "All Fields" category. Alternative terms such as "architectural pedagogy" were tested in pilot searches; however, as these were found to unnecessarily broaden the scope of the study, the final query was limited in this way. The search criteria included the document types 'Article', 'Review Article' and 'Early Access'; the indices AHCI, SSCI and SCI-EXPANDED; and the languages English and Turkish. The time frame was set as 2016–2025. The titles, abstracts and keywords of the publications obtained from the search were examined; studies not directly related to architectural education were excluded, and as a result of this process, the final sample was determined to consist of 408 articles. The study covers publications indexed in the Web of Science database as of the end of December 2025 that meet the specified inclusion criteria.

2.2 Data Analysis

The final sample of the study consists of 408 articles. In the case of internationally co-authored studies, as each country represented in an article was considered a separate country-based publication record, a total of 493 country-based publication records were obtained for the analyses. Consequently, the totals for country groups may be higher than the number of 408 articles included in the final sample. The data analysis was carried out in three stages. In the first stage, each article was classified according to the country information specified in the authors' affiliations. The UNDP's 2023–2024 Human Development Index (HDI) data were used as the basis for classifying countries' levels of development; countries with an HDI value of 0.800 or above were classified as developed, whilst those below this value were classified as developing countries (UNDP, 2024). In the second stage, the annual publication counts of the country groups were compared. In the third stage, the thematic focuses of the articles were determined using an inductive content analysis approach (Hsieh & Shannon, 2005). Within this framework, a total of 10 thematic categories, clustered around common themes, were established by examining the abstracts, keywords and, where necessary, the full texts of studies representing different years and country groups within the sample (Table 1). The thematic categories established were subsequently applied to the entire sample (408 articles). The classification process was carried out independently by two researchers; any discrepancies that arose were discussed in joint evaluation meetings and resolved through consensus. This process was undertaken to enhance the consistency of the thematic classification.

2.3 Scope and Limitations

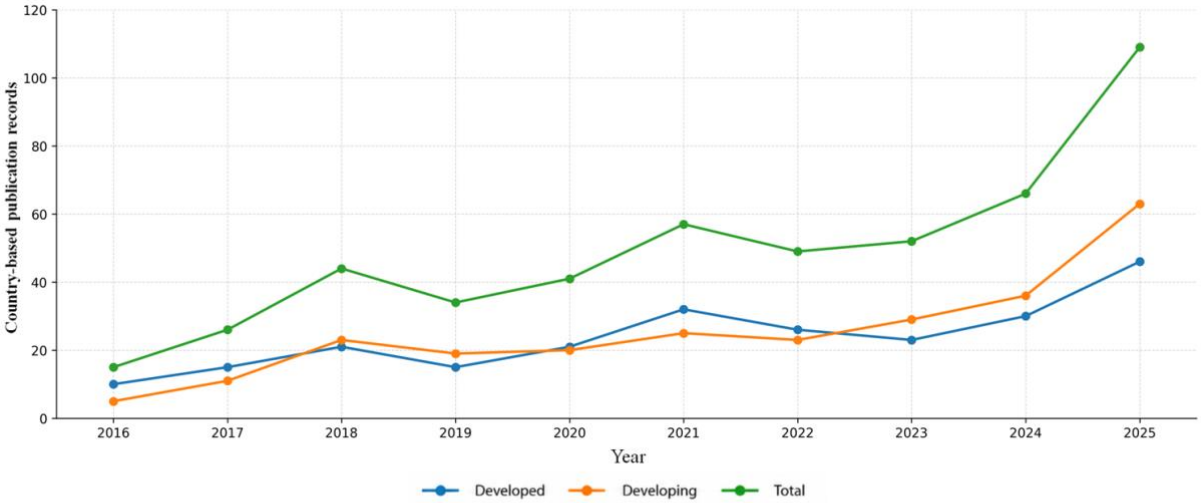
This study covers publications indexed in the Web of Science (WoS) database between 2016 and 2025, published in English or Turkish, and directly addressing architectural education. The main limitations of the study are that the research is restricted solely to the Web of Science database and the specified document types and languages, the fact that, in international co-authored studies, each country is counted as a separate country-based publication record, resulting in country-based totals being higher than the number of unique articles; and the fact that the classification of countries' levels of development is based on 2023–2024 HDI values for the entire 2016–2025 review period, meaning that any potential changes during this period have not been reflected in the analysis.

3. Findings

3.1 Publication Trends by Year

Figure 1 shows the annual distribution of country-based publication records relating to research on architectural education in developed and developing countries between 2016 and 2025. During the period under review, developing countries recorded 254 country-based publication records, whilst developed countries recorded 239, showing a similar distribution. Although fluctuations were observed in both groups over the years, the general trend is upwards. Whilst a decline was observed in developed countries during the 2022–2023 period following a marked increase in 2021, a more pronounced rise is evident in developing countries, particularly after 2023. By 2025, both groups had reached their highest figures for the period under review; the number of records rose to 63 in developing countries and to 46 in developed countries. These findings indicate that research into architectural

education is attracting increasing interest in both groups of countries, although the recent growth has been more pronounced in developing countries.



	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Toplam
Developed	10	15	21	15	21	32	26	23	30	46	239
Developing	5	11	23	19	20	25	23	29	36	63	254
Total	15	26	44	34	41	57	49	52	66	109	493

Figure 1. Distribution of Research on Architectural Education in Developed and Developing Countries by Year (2016–2025)

3.2 Distribution of Thematic Focuses

Table 1 shows the distribution of thematic focuses in research on architectural education according to groups of developed and developing countries. When examining the shares within each group, Studio Pedagogy and Design Education (25.6 per cent) accounts for the highest share in developing countries, followed by Digital and Computational Technologies (17.7 per cent) and Sustainability, Climate and Environmental Design (15.7 per cent). In developed countries, however, Sustainability, Climate and Environmental Design (19.2 per cent) ranks first, followed by Studio Pedagogy and Design Education (15.9 per cent) and Digital and Computational Technologies (13.8 per cent). When the distribution within themes is examined, more pronounced differences are observed in other themes. Whilst 55.8 per cent of studies on Student Psychology, Cognition and Embodiment originate from developed countries, this proportion rises to 80.0 per cent in the Historical, Theoretical and Critical Pedagogy theme. In contrast, 67.6 per cent of studies on the Pandemic and Flexible Learning Models originate from developing countries. Whilst 66.7 per cent of studies on Alternative, Experimental and Learning-by-Doing are based in developed countries, the share of developing countries is higher in the themes of Professional Practice and Education-Practice Integration (54.5 per cent) and Virtual and Augmented Reality (XR) (57.6 per cent). In the Cultural Heritage, Local Context and Decolonisation theme, whilst the distribution is relatively balanced, the share of developed countries stands at 53.3 per cent.

Overall, the findings indicate that application- and technology-focused themes such as Studio Pedagogy, Digital and Computational Technologies, the Pandemic and Flexible Learning Models, and XR are more highly represented in developing countries; whilst theoretical, pedagogical and student-centred themes such as Historical, Theoretical and Critical Pedagogy, Alternative and Experimental Learning, and Student Psychology have a higher share in developed countries. The Sustainability theme is a strong area of research in both groups, but carries a more pronounced weight in developed countries.

Table 1. Distribution of thematic focuses by developed and developing country groups (2016–2025)

Theme	Developing (within-theme %)	Within-group %	Developed (within-theme %)	Within-group %	Grand total	Overall %
Studio Pedagogy and Design Education	65 (63.1%)	25.6	38 (36.9%)	15.9	103	20.9
Sustainability, Climate and Environmental Design	40 (46.5%)	15.7	46 (53.5%)	19.2	86	17.4
Digital and Computational Technologies	45 (57.7%)	17.7	33 (42.3%)	13.8	78	15.8

Student Psychology, Cognition and Embodiment	19 (44.2%)	7.5	24 (55.8%)	10.0	43	8.7
Historical, Theoretical and Critical Pedagogy	7 (20.0%)	2.8	28 (80.0%)	11.7	35	7.1
Pandemic and Flexible Learning Models	23 (67.6%)	9.1	11 (32.4%)	4.6	34	6.9
Alternative, Experimental and Learning-by-Doing	11 (33.3%)	4.3	22 (66.7%)	9.2	33	6.7
Professional Practice and Education–Practice Integration	18 (54.5%)	7.1	15 (45.5%)	6.3	33	6.7
Virtual and Augmented Reality (XR)	19 (57.6%)	7.5	14 (42.4%)	5.9	33	6.7
Cultural Heritage, Local Context and Decolonisation	7 (46.7%)	2.8	8 (53.3%)	3.3	15	3.0
Total	**254 (51.5%)**	**100,0**	**239 (%48.5)**	**100.0**	**493**	**100.0**

4. Discussion

4.1 Shifting Patterns in Publication Output

Whilst research on architectural education generally showed an upward trend during the 2016–2025 period, developing countries recorded a slightly higher total number of country-level publication records than developed countries. In particular, the marked increase observed in developing countries since 2023 indicates that this group of countries is making an increasingly significant contribution to research on architectural education. This finding is significant in terms of the contribution of different regional contexts to the literature on architectural education. Indeed, Olweny (2017) highlights the importance of regional and socio-cultural context in understanding architectural education processes, using architecture schools in East Africa as a case study. Viewed from this perspective, the increase in publications observed in developing countries in the present study indicates that these countries' contribution to the literature on architectural education is strengthening.

4.2 Thematic Differences in Research Priorities

The findings indicate that there are distinct thematic differences in the research agendas of developed and developing countries. When examining the shares within each group, 'Sustainability, Climate and Environmental Design' ranks first in developed countries with 19.2 per cent, whilst 'Studio Pedagogy and Design Education' has the highest share in developing countries at 25.6 per cent. In his study examining three architecture schools in Turkey, Pasin (2017) questions the central role of the design studio in architectural education and emphasises the need to reassess the studio-centred educational structure in the face of changing social, economic, ecological and technological conditions. Another difference in terms of shares within the group is observed in the 'Digital and Computational Technologies' theme. The share of this theme stands at 17.7 per cent in developing countries, whilst it is 13.8 per cent in developed countries. Köse and Gümüşburun Ayalp (2026) have demonstrated that publications on technological developments in architectural education have increased significantly, particularly since 2017, and that developing countries such as Turkey, Egypt and Iran are active in this field of research. When the distribution within themes is examined, the differences become even more pronounced. 67.6 per cent of the publications under the theme 'Pandemic and Flexible Learning Models' originate from developing countries. This concentration may be linked to the fact that issues relating to online education, remote studio work and digital technologies became more prominent on the research agenda during the pandemic. Metinal and Gümüşburun Ayalp (2022) demonstrate that the transition of architecture education to an online environment during the COVID-19 period created various challenges, and that topics such as online learning, virtual design studios, technology and the student experience have become significant areas of research. In contrast, within the thematic distribution, 80.0 per cent of studies on 'Historical, Theoretical and Critical Pedagogy' and 66.7 per cent of those on 'Alternative, Experimental and Learning by Doing' originate from developed countries. Nevertheless, critical and transformative pedagogical discussions are also evident in the contexts of developing countries. Olweny (2020) questions the pedagogical approaches and knowledge systems inherited from the colonial era in architectural education in sub-Saharan Africa; she discusses the need to recognise alternative forms of knowledge, decolonisation and transformation in education.

Overall, the findings suggest that, rather than the two groups of countries focusing on entirely different research areas, common themes take on varying degrees of prominence. Whilst sustainability and theoretical and alternative pedagogical approaches are represented to a greater extent in developed countries, studio pedagogy, digital and computational technologies, the pandemic and flexible learning models, and XR account for a higher proportion in developing countries.

4.3 The Global Rise of Sustainability

Research findings indicate that the theme of 'Sustainability, Climate and Environmental Design' is one of the leading areas of research in both developed and developing countries. When examining the distribution within each group, this theme ranks first in developed countries with 46 country-based publication records (19.2 per cent), whilst it features prominently in developing countries with 40 records (15.7 per cent). This distribution demonstrates that sustainability is not confined to a specific group of countries and is one of the common priorities in architectural education research. The importance of sustainability within architectural education has made the integration of design principles into the curriculum and design studios a significant area of research. In their study comparing architecture programmes across three different continents, Boarin et al. (2020) examined the place of sustainability education within the curriculum and found that almost all participating students regarded sustainability as a key component of their education. Mohamed and Elias-Ozkan (2019), meanwhile, developed an experimental pedagogical approach aimed at integrating sustainability principles into architectural design studios and demonstrated that the studio model implemented contributed to students' ability to incorporate sustainable design elements into their projects. Consequently, the findings indicate that sustainability is one of the common themes in architectural education research, regardless of the level of development.

4.4 The Pandemic, Digital Transformation and Future Trends

Research findings indicate that the pandemic and digital transformation have taken on significant importance in research on architectural education. Upon examining the distribution within this theme, it is observed that 67.6 per cent of the country-based publication records under the theme 'The Pandemic and Flexible Learning Models' relate to developing countries. Metinal and Gümüşburun Ayalp (2022) highlight that the transition of architectural education to an online environment during the COVID-19 period created various challenges, and that topics such as online learning, virtual design studios, technology and the student experience have become important areas of research. The pandemic experience has also brought to the fore more flexible and adaptable models for the future of architectural education. Salama and Crosbie (2020) emphasise the need to integrate change, flexibility and adaptability into the curriculum, design studios and teaching-learning processes. Al Maani et al. (2021), in their study conducted with students participating in online design studios at 15 universities in Jordan, found that whilst online studios support certain learning skills, they also present significant challenges in terms of feedback, communication and peer interaction. In this regard, the authors propose a more flexible design studio model that combines online activities with direct student–tutor interaction. Drawing on their experiences of online education during the pandemic, Varma and Jafri (2021) also highlight the future potential of blended/hybrid learning in architectural education and recommend that this approach be integrated into the curriculum and pedagogical frameworks. Similarly, Megahed and Hassan (2022) propose a blended learning approach that integrates face-to-face and online learning formats for post-pandemic architectural education, emphasising the importance of addressing content, pedagogy and technology in an integrated manner. In this regard, the findings indicate that the digital transformation, which has gained momentum due to the pandemic, has made not only the use of technological tools but also how these tools can be integrated with pedagogical approaches, studio practices and face-to-face learning experiences a significant area of research in architectural education.

5. Conclusion

This study examined publication trends and thematic differences in architectural education research by analysing 408 articles indexed in the Web of Science database between 2016 and 2025. These articles corresponded to 493 country-level publication records when each country represented in internationally co-authored studies was counted separately. The findings reveal three key conclusions. Firstly, developing countries recorded a slightly higher total number of country-level publication records than developed countries. Secondly, distinct thematic differences were identified between the two groups of countries. Whilst sustainability, climate and environmental design feature prominently in developed countries, studio pedagogy and design education have been the most intensively researched areas in developing countries. Thirdly, the fact that the theme of sustainability ranks highly in both country groups indicates that this topic is one of the common agendas in architectural education research. This study provides a comparative analysis of the architecture education literature from the perspective of development level, thereby highlighting research priorities and thematic trends across countries. The findings reveal that digital transformation, sustainability and pedagogical approaches are key areas of focus in architecture education research. In future research, including different databases, conference papers and postgraduate theses in the analysis could yield more comprehensive results. The fact that this study was limited to English and Turkish publications indexed in the Web of Science database, and that countries' levels of development were classified based on 2023–2024 HDI values, should be taken into account when interpreting the findings.

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Bibliometric, Thematic, and Temporal Trend Analysis of Graduate Theses on the Diagnosis of Misconceptions in Science Education in Türkiye (2006–2024)

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Abstract

This study aimed to examine the bibliometric, thematic, and temporal trends of graduate theses conducted in Türkiye between 2006 and 2024 on the diagnosis of misconceptions in science education. The study was conducted using document analysis within the framework of a qualitative research approach. The data were obtained from the National Thesis Center of the Council of Higher Education in Türkiye. Following the search and screening process based on predetermined inclusion and exclusion criteria, 70 graduate theses, comprising 63 master's theses and seven doctoral dissertations, were included in the study. Bibliometric and descriptive analyses were used to examine the theses in terms of publication year, degree type, science discipline, research purpose, research method, sample level, and data collection tools, while content analysis was employed to examine their purposes and main findings. Temporal trends in the development and use of multi-tier diagnostic tests were also investigated. The findings showed that the majority of the studies were master's theses and that research on the diagnosis of misconceptions became more prominent particularly from 2017 onward. The theses were predominantly concentrated in physics, chemistry, and biology, whereas relatively few studies focused on environmental education, astronomy education, and earth science education. Quantitative methods were the most frequently employed research approach, and preservice teachers and middle school students were the most commonly studied groups. One-tier tests were the most frequently used data collection tools. However, the temporal analysis of diagnostic test development indicated an increasing tendency toward multi-tier diagnostic instruments, particularly four-tier tests. The findings also showed that misconceptions were frequently identified across the theses and that most instructional interventions aimed at addressing misconceptions were reported to have positive effects. Overall, the results reveal the methodological and thematic tendencies of graduate research on the diagnosis of misconceptions in science education in Türkiye and highlight comparatively underexplored areas for future research.

Keywords: Misconceptions; science education; diagnostic tests; bibliometric analysis; thematic analysis; graduate theses

Introduction

One of the fundamental aims of science education is to enable students to construct scientific concepts in a meaningful and interconnected manner. However, students enter learning environments not only with knowledge acquired through formal instruction but also with prior knowledge developed through their everyday experiences, previous learning, and the language they use. Although such prior knowledge provides an important starting point for learning new concepts, it may hinder students' conceptual learning when it is inconsistent with scientific knowledge. Therefore, taking students' existing conceptual structures into consideration in science teaching is important for promoting meaningful learning (Altay 2021; Şensoy et al., 2005; Uyanık, 2019).

Students' ideas that are inconsistent with scientifically accepted explanations and exhibit a certain degree of consistency are addressed as misconceptions in the science education literature. Misconceptions are not merely incorrect answers; because they may be associated with students' existing knowledge structures, they can also influence subsequent learning. Therefore, identifying misconceptions before or during instruction is important for understanding students' conceptual difficulties and adapting instruction accordingly. Indeed, research indicates that students' prior knowledge and alternative conceptual structures should be taken into account in science learning and that diagnostic assessments can be used to identify these structures (Butler & Simmie, 2015; Rebich & Gautier, 2005).

When there is a consistent relationship between students' prior knowledge and the new concepts they learn, lasting and effective concept learning can be achieved (Aydoğan et al., 2003). It is very difficult to achieve conceptual change in science education without first identifying students' prior knowledge, determining whether it is scientifically accurate, and addressing any existing misconceptions (Aydoğan et al., 2003). In the literature, misconceptions have been described as understandings that students develop through experience, that conflict with scientific knowledge, and that make the learning of scientific knowledge more difficult (Çakır & Yörük, 1999).

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Misconceptions should not be confused with scientific errors. If a student provides a scientifically incorrect answer when asked about a concept but subsequently learns and accepts the scientifically correct explanation following feedback and correction, this is considered a scientific error. However, if a student gives a scientifically incorrect answer when asked to define a concept and, despite feedback and correction, does not learn the correct explanation and persists in the incorrect understanding, this is considered a misconception (Karakuyu, 2006). Therefore, although all misconceptions can be regarded as scientific errors, not all scientific errors can be regarded as misconceptions (Yenilmez & Yaşa, 2008). Students who hold misconceptions attempt to construct schemas in their minds by drawing on their existing incorrect conceptions when encountering new situations; however, they are unable to accomplish this successfully. Therefore, concept learning cannot occur in a student who holds misconceptions (Meşeci, Tekin, & Karamustafaoğlu, 2013).

Science education is a fundamental field of learning that contributes to students' ability to understand events and phenomena in the natural world from a scientific perspective, relate scientific knowledge to everyday life, and develop evidence-based solutions to the problems they encounter (Alberts, 2022; Tal & Dierking, 2014). Therefore, identifying and addressing students' misconceptions is of great importance (Aşçı, Özkan, & Tekkaya, 2001). To address students' misconceptions, it is necessary to understand the factors that give rise to them (Yılmaz, 2023). Misconceptions may persist within students' cognitive structures and may be resistant to traditional instructional practices; therefore, addressing such misconceptions is not always straightforward (Daines et al., 2019). Accordingly, it is important to employ contemporary instructional approaches that encourage students to question their existing ideas and support conceptual change in addressing misconceptions (Güneş, 2005).

Traditional assessment tools that rely solely on whether a student's response is correct or incorrect may be limited in their ability to distinguish whether an incorrect response results from a lack of knowledge or from an established misconception. Failure to identify and address such misconceptions makes it difficult for students' incorrect conceptions to be recognized during the learning process. Consequently, students may not have the opportunity to consciously recognize and correct their erroneous understandings (Baki, 1999, as cited in Yılmaz, 2007).

Various data sources based on written responses, verbal communication, and observation can be used to identify students' misconceptions. In observation-based assessments, researchers may directly observe students' behaviors or record them using a camera. In verbal assessments, data are collected through interviews conducted with students. Written assessments generally involve objective or conventional types of questions or concept-mapping techniques (Eryılmaz & Sürmeli, 2002). A variety of assessment tools, including open-ended tests, interviews, one-tier diagnostic tests, two-tier diagnostic tests, three-tier diagnostic tests, and four-tier diagnostic tests, are used to identify students' misconceptions across different fields and topics (Kaltakçı, 2012).

An interview is a method of obtaining information within the scope of a study by collecting data from participants through questions asked during a conversation involving two or more individuals (Büyüköztürk et al., 2014). Interviews can be used to reveal students' levels of conceptual understanding and their misconceptions (Karataş et al., 2003). Because interviews are useful for identifying misconceptions, they are widely used for this purpose (Osborne & Gilbert, 1980). However, both the interview process and the subsequent analysis are time-consuming. Open-ended tests are also used to identify students' misconceptions. Open-ended questions do not include response options and cannot be answered with brief responses such as "yes" or "no." Rather, they consist of conventional questions that require written responses (Kaltakçı, 2012; Önsal, 2016). When answering such questions, students are expected to explain the concepts in their minds together with the reasons underlying their responses (Eryılmaz & Sürmeli, 2002). Open-ended tests are also time-consuming because their analysis requires considerable time. In addition, students may be reluctant to answer the questions. In such cases, identifying students' misconceptions may become more difficult (Kaltakçı, 2012; Önsal, 2016).

Compared with open-ended tests and interviews, one-tier tests make it possible to collect data on a greater number of topics in less time (Kaltakçı Gürel et al., 2015). In one-tier tests, students are expected to select the correct answer from multiple response options for each question. Students do not have the opportunity to provide explanations while answering questions in one-tier tests. These tests are economical for researchers in terms of both administration and analysis (Kaltakçı, 2012).

The first tier of two-tier diagnostic tests consists of a multiple-choice question with response options related to the topic being assessed (Treagust, 1988, as cited in Tüysüz, 2009). In the second tier, students are asked to select the reason for the answer they provided in the first tier (Chen et al., 2002; Karataş et al., 2003). The first tier of the test includes the correct answer, misconception-based options, and distractors. When determining the misconception-based options, alternative misconceptions identified in previous studies in the literature are utilized (Treagust, 1988, as cited in Tüysüz, 2009). In two-tier tests, students who select misconception-based options in both tiers are considered to hold a misconception. Although the development of two-tier tests is time-consuming, they are widely used because they are practical and economical in terms of administration and analysis, reduce the

effect of guessing compared with one-tier tests, and are considered to have high validity and reliability (Canpolat et al., 2011; Çakır & Aldemir, 2011; Karataş et al., 2003)

Three-tier diagnostic tests were developed to address the limitation of two-tier diagnostic tests in that they do not assess students' confidence in their responses. In the first tier of these tests, students are presented with a multiple-choice question that includes misconceptions about the relevant concept reported in the literature. The second tier includes explanations intended to identify the reasoning underlying the response given in the first tier. In the third and final tier, students are asked to indicate how confident they are in the responses they provided in the first two tiers (Altun, 2009; Demirci & Efe, 2007; Kaltakçı, 2012). If a student selects misconception-based options in both the first and second tiers and indicates confidence in these responses in the third tier, the student is considered to hold a misconception (Eryılmaz, 2010).

Four-tier diagnostic tests were developed to address the limitation of three-tier diagnostic tests in which the confidence level for each response is not assessed separately. Four-tier tests have been used as the most recent method for identifying misconceptions (Eren, 2019). In recent years, these tests have gained considerable importance in the identification of misconceptions. In four-tier misconception diagnostic tests, the first tier consists of a four-option multiple-choice question including the correct answer, distractors, and a misconception identified based on the literature. The second tier is the confidence tier, which assesses whether students are confident in the answer they provided to the question in the first tier. The third tier consists of four multiple-choice options representing the reasons underlying students' responses in the first tier. The fourth tier is the second confidence tier, which assesses how confident students are in the response they provided in the third tier. Four-tier tests provide more concrete and realistic results than other diagnostic tests (Taşlıdere, 2016).

An examination of studies aimed at identifying misconceptions in science education reveals that numerous studies have been conducted across different science disciplines, with different sample groups, and using various data collection tools. The use of one-, two-, three-, and four-tier diagnostic tests, in addition to methods such as interviews and open-ended questions, indicates that assessment approaches for identifying misconceptions have diversified over time. In particular, multi-tier diagnostic tests take into account not only students' answers but also the reasoning underlying their answers and, in some types of tests, their confidence levels, thereby enabling misconceptions to be distinguished from a lack of knowledge (Arslan et al., 2012; Yang & Lin, 2015).

Nevertheless, although individual studies provide detailed information about a particular topic, sample, or assessment tool, the absence of an integrated examination of these studies makes it difficult to identify overall research trends in the field and how these trends have changed over time. In particular, there is a need to examine collectively how graduate theses focusing on the diagnosis of misconceptions in science education in Türkiye are distributed according to year, science discipline, research purpose, research method, sample level, and data collection tools, as well as how the use of two-, three-, and four-tier diagnostic tests has changed over time. Accordingly, examining graduate theses focusing on the diagnosis of misconceptions in science education in Türkiye from a holistic perspective is important for revealing the development of the field from past to present, identifying the science disciplines and sample groups in which research has been concentrated, tracing the temporal evolution of the diagnostic tools used, and identifying relatively underexplored areas. In addition to systematically presenting the existing body of research, such an examination is expected to provide guidance for future studies on misconceptions with respect to the selection of research topics, samples, methods, and assessment tools.

In this context, the aim of this study is to examine the bibliometric and thematic characteristics of graduate theses conducted in Türkiye between 2006 and 2024 on the diagnosis of misconceptions in science education. Accordingly, the research questions are as follows:

1. What is the distribution of graduate theses on the diagnosis of misconceptions in science education in Türkiye by year?
2. What is the distribution of these theses by degree type (master's/doctoral)?
3. What is the distribution of these theses across science disciplines (physics, chemistry, biology, environmental education, and astronomy education)?
4. What is the distribution of the theses according to their research purposes?
5. What is the distribution of the research methods employed in the theses?
6. What is the distribution of the theses according to sample level?
7. What is the distribution of the types of data collection tools used in the theses?
8. What is the distribution by year of the theses conducted for the purpose of diagnostic test development?
9. What are the temporal trends in the types of diagnostic tests (two-tier, three-tier, and four-tier)?

10. What are the trends in the main findings reported in the theses?

Method

Research Design

This study, which aimed to identify the bibliometric, thematic, and temporal trends of graduate theses on the diagnosis of misconceptions in science education in Türkiye between 2006 and 2024, was conducted using a document analysis design within the framework of a qualitative research approach. Document analysis is a data collection and analysis method that enables the systematic examination, classification, and interpretation of written materials related to the phenomenon under investigation. This process involves identifying, accessing, and examining relevant documents, recording the data, and analyzing the collected data (Karasar, 2005).

In this study, a descriptive research approach based on document analysis was adopted to determine the bibliographic characteristics, thematic structures, and temporal trends of graduate theses completed in Türkiye between 2006 and 2024 on the diagnosis of misconceptions in science education. Bibliometric, descriptive, and thematic analyses were used in a complementary manner.

Within the bibliometric component of the study, bibliographic indicators of the graduate theses retrieved from the National Thesis Center of the Council of Higher Education, such as year of publication and degree type, were examined, and their frequency and percentage distributions were determined. In addition, the science disciplines, research purposes, research methods, sample levels, and data collection tools used in the theses were classified and analyzed descriptively. The temporal trend analysis examined the distribution of the theses by year, with particular attention to changes over time in the use of two-, three-, and four-tier tests developed for diagnosing misconceptions. The research purposes and reported main findings of the theses were coded through content analysis and classified into themes.

In this study, bibliometric analysis did not encompass science-mapping techniques involving citation analysis, co-authorship analysis, co-citation analysis, or keyword co-occurrence networks. The bibliometric component was limited to quantitatively describing the graduate theses included in the study in terms of the specified bibliographic indicators and identifying the distributions of these indicators over time. Thus, the study combined a quantitative description of the bibliographic characteristics of graduate theses with a thematic examination of their content.

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Document Retrieval and Search Process

The data collection process was conducted using the National Thesis Center database of the Council of Higher Education. The searches were performed using the "Advanced Search" function. The following keyword combinations were used in the search process:

"misconception" AND "diagnosis"; "misconception" AND "identification"; "misconception" AND "diagnostic test"; "misconception" AND "identification test"; "misconception" AND "two-tier test"; "misconception" AND "three-tier test"; "misconception" AND "four-tier test."

The records retrieved through the searches were examined in accordance with the purpose of the study, and theses relevant to the field of science education were identified. The initial search yielded a total of 75 graduate theses published between 2006 and 2024.

Inclusion and Exclusion Criteria

The theses to be included in the study were determined according to the following criteria.

Inclusion Criteria

To be included in the study, a thesis was required to meet all of the following criteria:

- to have been completed between 2006 and 2024;
- to be a master's thesis or doctoral dissertation completed in Türkiye;
- to have been conducted in the field of science education (Science Education, Physics Education, Chemistry Education, Biology Education, Environmental Education, or Astronomy Education);
- to focus on the diagnosis, identification, or detection of misconceptions;

- to include at least one assessment tool used to identify misconceptions (e.g., a two-tier test, three-tier test, four-tier test, or concept inventory); and
- to have its full text available.

Exclusion Criteria

Theses with any of the following characteristics were excluded from the study:

- studies that examined only the effect of an instructional method and did not include an assessment tool for diagnosing misconceptions;
- theses conducted in the fields of mathematics education, social sciences education, or language education;
- studies focusing solely on the development of an achievement test or attitude scale, or examining only academic achievement;
- studies that referred to misconceptions but did not include any assessment tool for diagnosing them;
- duplicate records of the same thesis retrieved through different keyword searches; and
- theses for which the full text was unavailable.

However, studies that first identified misconceptions using assessment tools designed for diagnosing misconceptions and subsequently implemented an instructional intervention were included in the study. This was because such studies provided data relevant to the primary focus of the research, namely the diagnosis of misconceptions.

Following the search and screening process, a total of 70 theses, comprising 63 master's theses and 7 doctoral dissertations, met the eligibility criteria and were included in the study.

Data Analysis

Descriptive analysis and content analysis were used together to analyze the data obtained within the scope of the study.

Bibliographic information regarding the publication year, degree type, university, research method, research design, research topics, assessment tools used, study group, and data collection tools of the theses was analyzed descriptively using frequency and percentage values and presented in tables. In addition, data concerning the purposes and findings of the theses were examined through content analysis. Accordingly, the relevant data were first coded, similar codes were grouped to form subcategories, and these subcategories were subsequently classified under themes based on their common characteristics. The resulting findings were presented in tables and interpreted.

Coding Process and Reliability

To evaluate consistency in the coding process, 10 theses were randomly selected from the 70 theses included in the study and independently coded by two coders. The classifications made by the two coders were compared, and the percentage agreement between the coders was calculated using the formula proposed by Miles and Huberman (1994): "Agreement / (Agreement + Disagreement) × 100." The percentage agreement between the coders was found to be 84.3%. Codes on which the coders disagreed were re-examined, and consensus was reached through discussion. Following this process, the coding framework was finalized, and the remaining theses were coded by the [first researcher/researcher] in accordance with the final coding framework.

Results

In this study, master's theses and doctoral dissertations completed between 2006 and 2024 were reviewed. The findings are presented in tables below in accordance with each research question.

Table 1. Distribution of theses on the diagnosis of misconceptions in science education by year

Year	Master's Theses	Doctoral Dissertations
2006	3	1
2007	3	0
2008	5	0
2009	1	0

2010	4	0
2011	1	0
2012	0	1
2013	3	1
2016	3	0
2017	6	1
2018	6	0
2019	6	1
2020	5	0
2021	4	0
2022	3	1
2023	4	1
2024	6	0
Total	**63**	**7**

As shown in Table 1, the distribution by year of graduate theses on the diagnosis of misconceptions in science education between 2006 and 2024 is presented. Based on these data, the number of theses conducted on this topic appears to be relatively limited. The highest number of graduate theses was recorded in 2017 and 2019, with seven theses completed in each of these years. In contrast, 2009 and 2011 had the lowest number of theses, with only one graduate thesis completed in each year.

Table 2. Distribution of theses on the diagnosis of misconceptions in science education by degree type

Graduate Theses	Master's Theses	Doctoral Dissertations
Total	63	7

As shown in Table 2, the distribution of graduate theses on the diagnosis of misconceptions in science education between 2006 and 2024 according to degree type is presented. A total of 70 theses were examined, of which 63 (90%) were master's theses and 7 (10%) were doctoral dissertations

Table 3. Distribution of theses on the diagnosis of misconceptions in science education by subject area

Subject Area	Master's Theses	Doctoral Dissertations
Physics	24	4
Chemistry	18	1
Biology	14	3
Environmental Education	3	1
Earth Science Education	1	0
Astronomy Education	4	0
Total	**64**	**9**

As shown in Table 3, among the graduate theses on the diagnosis of misconceptions in science education conducted between 2006 and 2024, physics was the most frequently studied subject area, with a total of 28 theses, comprising 24 master's theses and 4 doctoral dissertations. This was followed by chemistry with 19 graduate theses and biology with 17 graduate theses. Earth science education was the least frequently studied subject area, with only one master's thesis.

Table 4. Distribution of theses on the diagnosis of misconceptions in science education by research purpose

Research Purpose	Master's Theses	Doctoral Dissertations
Intervention Effects	24	3
Descriptive Assessment	30	1
Assessment Instrument Development	17	4

Examination of Relationships	2	1
Total	**63**	**7**

As shown in Table 4, the numbers of doctoral dissertations and master's theses according to specific research purposes are presented. An examination of the data indicates that descriptive assessment was the most frequently identified research purpose, with a total of 31 theses, comprising 30 master's theses and 1 doctoral dissertation. This was followed by studies examining intervention effects, with a total of 27 theses, comprising 24 master's theses and 3 doctoral dissertations. The least frequently identified research purpose was the examination of relationships, with a total of three theses, comprising two master's theses and one doctoral dissertation.

Table 5. Distribution of theses on the diagnosis of misconceptions in science education by research method

Research Method	Master's Theses	Doctoral Dissertations
Quantitative	45	4
Mixed Methods	13	3
Qualitative	5	0
Total	**63**	**7**

As shown in Table 5, quantitative research was the most frequently employed method in graduate theses on the diagnosis of misconceptions in science education conducted between 2006 and 2024. A total of 49 theses, comprising 45 master's theses and 4 doctoral dissertations, employed quantitative research methods. Mixed methods were used in 16 theses, including 13 master's theses and 3 doctoral dissertations. Qualitative research was the least frequently employed method, with only five master's theses. Overall, the findings indicate that the majority of the theses examined were master's theses employing quantitative research methods.

Table 6. Distribution of theses on the diagnosis of misconceptions in science education by sample level

Sample Level	Master's Theses	Doctoral Dissertations
Primary School Students	3	0
Middle School Students	29	1
High School Students	6	1
Preservice Teachers	29	5
Total	**68**	**7**

As shown in Table 6, preservice teachers constituted the most frequently selected sample group in graduate theses on the diagnosis of misconceptions in science education conducted between 2006 and 2024. Preservice teachers were included in a total of 34 theses, comprising 29 master's theses and 5 doctoral dissertations. This group was followed by middle school students, who were included in 30 theses, comprising 29 master's theses and 1 doctoral dissertation. Primary school students were the least frequently selected sample group, appearing in only three master's theses.

Table 7. Distribution of theses on the diagnosis of misconceptions in science education by type of data collection tool

Data Collection Tool	Master's Theses	Doctoral Dissertations
One-Tier Test	34	1
Two-Tier Test	8	1
Three-Tier Test	5	0
Four-Tier Test	12	3
Interview	9	4
Diagnostic Branched Tree	1	0
Structured Grid	1	0
Word Association Test	1	0
Observation	1	0
Questionnaire	6	1
Open-Ended Test	9	0
Total	**87**	**10**

As shown in Table 7, the distribution of master's theses and doctoral dissertations according to the types of data collection tools used is presented. Among the theses on the diagnosis of misconceptions in science education

conducted between 2006 and 2024, one-tier tests were the most frequently used data collection tool, appearing in a total of 35 graduate theses. One-tier tests were followed by four-tier tests, which were used in 15 theses. Observation, word association tests, structured grids, and diagnostic branched trees were the least frequently used data collection tools, each appearing in only one thesis.

Table 8. Distribution by year of theses on diagnostic test development for ıdentifying misconceptions in science education

Year	Master's Theses	Doctoral Dissertations
2008	1	0
2012	0	1
2013	0	1
2016	1	0
2017	3	0
2019	3	1
2020	3	0
2021	1	0
2022	2	1
2023	2	0
2024	1	0
Total	**16**	**4**

As shown in Table 8, the distribution by year of theses focusing on the development of diagnostic tests for identifying misconceptions in science education between 2006 and 2024 is presented. Based on these data, the number of theses conducted on this topic was relatively limited. The highest number of diagnostic test development theses was recorded in 2019, with four graduate theses. In contrast, 2012, 2013, 2016, 2021, and 2024 each had only one graduate thesis focusing on the development of diagnostic tests for identifying misconceptions.

Table 9. Distribution of the types of diagnostic tests developed in science education by year

Year	Two-Tier Test	Three-Tier Test	Four-Tier Test
2008	1	0	0
2012	0	0	1
2013	1	0	0
2016	0	0	1
2017	1	0	2
2019	0	1	3
2020	0	0	3
2021	0	0	1
2022	1	1	1
2023	0	1	1
Total	**4**	**3**	**13**

As shown in Table 9, the distribution by year of the types of diagnostic tests developed in theses on the diagnosis of misconceptions in science education between 2006 and 2024 is presented. Based on these data, four-tier tests were the most frequently developed type of misconception diagnostic test, whereas three-tier tests were the least frequently developed. The first four-tier diagnostic test identified within the scope of this study was developed in 2012, and an increase in the development of four-tier diagnostic tests was observed in 2019 and 2020. Three-tier diagnostic tests began to appear in the theses examined from 2019 onward.

Table 10. Distribution of the main findings reported in theses on the diagnosis of misconceptions in science education

Main Findings	Master's Theses	Doctoral Dissertations
Identification of a High Prevalence of Misconceptions	29	1
Positive Intervention Effect	22	3
Negative Intervention Effect	4	0
Development of a Valid and Reliable Test	18	3
Total	**73**	**7**

As shown in Table 10, the distribution of the main findings reported in theses on the diagnosis of misconceptions in science education between 2006 and 2024 is presented. Based on these data, a high prevalence of misconceptions among students was identified in the findings of 30 graduate theses. In 25 graduate theses, the interventions implemented to address misconceptions were reported to be effective, whereas in four graduate theses, the interventions were reported to be ineffective in addressing misconceptions. In 21 graduate theses, the development of a valid and reliable misconception diagnostic test was reported.

Discussion

In this study, a search was conducted in the National Thesis Center database of the Council of Higher Education using the "Advanced Search" function and specified keywords. The search yielded a total of 75 studies, of which 70 met the inclusion criteria and were examined within the scope of the bibliometric analysis. The analysis addressed the following dimensions: the distribution of graduate theses on the diagnosis of misconceptions by year, degree type, and science discipline; the distribution of the theses according to their research purposes, research methods, sample levels, and types of data collection tools; the distribution by year of theses conducted for diagnostic test development; temporal trends in the types of diagnostic tests; and trends in the main findings reported in the theses.

The rationale for examining theses on the diagnosis of misconceptions published between 2006 and 2024 was the adoption of the constructivist approach in the Turkish education system during the 2005–2006 academic year. The literature also indicates a significant increase in the number of publications beginning in 2006 (Çetin & Bolulu, 2025). An examination of theses on the diagnosis of misconceptions showed that the number of studies remained relatively low and fluctuated until 2016, gained momentum in 2017, and reached its highest levels in 2017, 2019, 2023, and 2024. The increase in the number of studies in 2017 and 2019 may be interpreted as reflecting a growing interest in the diagnosis of misconceptions and conceptual change (Kılıçoğlu, 2022). Similarly, the bibliometric review conducted by Karaca et al. (2023) reported a substantial increase in scientific studies focusing on misconceptions, particularly in recent years.

The revision of the Science Curriculum in 2018 represents one of the developments that should be taken into consideration when evaluating research topics and trends in science education. However, additional evidence is needed to conclude that this curricular change directly led to an increase in the number of studies on misconceptions. Therefore, the studies observed in 2018 and thereafter may be interpreted as an indication that concept learning and misconceptions continued to maintain their place in science education research during the period in which the curricular change occurred.

In addition, the absence of any studies on the diagnosis of misconceptions in science education in 2015 may be explained by the increasing prevalence of research on STEM education and practices in Türkiye beginning in 2014 (Alkış Küçükaydın, 2020). Meta-synthesis research examining STEM education practices in 2015–2016 revealed a marked increase in studies on STEM education (Herdem & Ünal, 2018). However, it is not possible to establish a direct causal relationship between this increase in STEM research and the absence of theses on the diagnosis of misconceptions in 2015. Therefore, it appears more appropriate to interpret the finding for 2015 as part of the annual fluctuations in research on misconceptions.

The considerably smaller number of doctoral dissertations compared with master's theses may, among other reasons, be attributable to doctoral dissertations being subject to delayed public access (İdil & Kaptan, 2017). Accordingly, because theses that could not be accessed were excluded from the study, the number of doctoral dissertations available for examination within the scope of the research remained limited. In addition, another possible explanation for this finding is that master's degree programs generally require less time and may be easier to complete than doctoral programs.

With regard to the themes related to research purposes, the studies examined in this research were found to focus most frequently on investigating the effects of interventions involving methods used to identify and address misconceptions on various variables. The relatively high number of studies within this theme may be associated with the need to identify different methods and techniques for enhancing the effectiveness of concept teaching in science education.

When the distribution of the theses by subject area was examined, no substantial differences were observed among the fields; however, physics topics were investigated in a greater number of studies than biology and chemistry topics. This may be attributable to the various conceptual difficulties students experience in understanding physics topics and to misconceptions emerging as an important barrier to the effective understanding of physics concepts. The literature indicates that students have persistent misconceptions particularly in physics topics such as force and motion, optics, and energy, and that these misconceptions make conceptual learning more difficult (Singh & Schunn, 2009; Wells et al., 2020). In addition, the number of studies conducted in the field of environmental

science was found to be relatively low. Therefore, further studies focusing on the diagnosis of misconceptions related to environmental science are needed (Alkış Küçükaydın, 2020).

The majority of the studies examined were found to have adopted quantitative research methods, whereas qualitative research designs were used to a more limited extent. An evaluation of the studies in the literature reveals similar findings. Various reviews conducted by different researchers have shown that quantitative research methods are more commonly employed than other research methods in studies in the field of science education (Altıparmak & Nakiboğlu, 2005; Arık & Türkmen, 2009; Göktaş et al., 2012; Gürdal et al., 2005; Sozbilir et al., 2012). Accordingly, the findings of these studies can be considered consistent with those obtained in the present study (Kiras & Bahar, 2021).

When the sample levels of the studies were examined, preservice teachers were found to be the most frequently selected group, followed by middle school students. The more frequent selection of preservice teachers as participants may be associated with researchers' easier access to this group. The fact that middle school students constituted the second most frequently studied group may be explained by the need to investigate students' concept learning and their understanding of concepts following the implementation of the revised science curricula (MEB, 2013; 2017;2018). The studies examined did not include in-service teachers as a sample group. However, further research incorporating the experiences and views of teachers, who plan instructional processes, select appropriate methods and techniques for concept teaching, and play an active role in the teaching process, is recommended (Alkış Küçükaydın, 2020). Within the scope of the present study, the number of studies conducted with primary school students was found to be quite limited, with only three studies identified. However, the process through which concepts are formed and constructed in students' minds begins at an early age (Riche, 2000). Therefore, an increase in the number of studies focusing on concept teaching and the diagnosis of misconceptions at the primary school level is recommended.

One-tier tests were found to be the most commonly used data collection tools in the studies, followed by four-tier tests. Three-tier and four-tier diagnostic tests were used less frequently than one-tier tests for identifying misconceptions. Based on this finding, there appears to be a need for further studies in which three-tier and four-tier diagnostic tests are used or developed to identify and address misconceptions. Studies in the field of science education were also found to commonly employ one or more methods of concept teaching. In this context, methods and techniques used in concept teaching, such as word association tests, concept cartoons, diagnostic branched trees, structured grids, and POE (Predict–Observe–Explain), were also identified as data collection tools used in research.

When the theses included in the study were examined in terms of their findings, intervention studies aimed at addressing misconceptions most frequently employed computer-assisted conceptual change texts. In science education, the use of methods, techniques, and strategies such as cooperative learning, problem-based learning, drama, the 5E instructional model, active learning, the Know–Want–Example–Learn technique, project-based learning, graphical materials, demonstration experiments, experimental methods, POE (Predict–Observe–Explain), computer-based materials, refutation techniques, drawing techniques, educational games, storytelling, GeoGebra applications, concept wheels, augmented reality, and argumentation was reported to be effective in addressing misconceptions. In studies employing methods, techniques, and strategies such as concept cartoons, computer-assisted conceptual change texts, conceptual change texts, and diagnostic branched trees, some studies reported positive outcomes, whereas others reported negative outcomes. In all studies involving the development of misconception diagnostic tests, the researchers concluded that valid and reliable assessment tools had been developed.

Conclusion

In this study, graduate theses conducted in Türkiye between 2006 and 2024 on the diagnosis of misconceptions in science education were examined in terms of bibliometric, thematic, and temporal trends. The findings revealed that the vast majority of the studies examined were conducted at the master's level, whereas the number of doctoral dissertations remained limited. An examination of the distribution of theses by year showed that the number of studies varied across different periods and that research on the diagnosis of misconceptions became more prominent particularly from 2017 onward.

In terms of science disciplines, the studies were predominantly concentrated in the fields of physics, chemistry, and biology, whereas environmental education, astronomy education, and particularly earth science education received comparatively limited attention. Regarding the purposes of the studies, research aimed at identifying the existing state of misconceptions and examining the effects of different instructional interventions on misconceptions was prominent. In contrast, studies investigating relationships between variables were more limited.

From a methodological perspective, quantitative research approaches were clearly predominant in the theses, whereas qualitative research remained relatively limited. Regarding sample groups, participants at the higher education level and middle school students were prominent, while fewer studies were conducted with primary school students. These findings indicate that research on misconceptions in science education has been concentrated within particular methodological approaches and sample groups, highlighting the need for greater methodological diversity.

With regard to data collection tools, one-tier tests were the most frequently used instruments; however, two-, three-, and four-tier diagnostic tests were also employed. The temporal distribution of test development studies indicates a trend toward multi-tier diagnostic tests, particularly in recent years. The prominence of four-tier tests among the diagnostic tests developed may be interpreted as reflecting a tendency toward identifying misconceptions in greater detail by considering not only whether students' answers are correct or incorrect but also the reasoning underlying their answers and their confidence levels.

Recommendations

Based on the findings of this study, the following recommendations are proposed for future research on the diagnosis of misconceptions in science education:

1. Considering that studies have predominantly focused on the fields of physics, chemistry, and biology, further research should be conducted in comparatively underexplored fields such as environmental education, astronomy education, and particularly earth science education.
2. Given the limited number of studies conducted at the primary school level, greater emphasis should be placed on research involving primary school students in order to identify misconceptions at earlier stages of education.
3. Considering the predominance of quantitative research, more qualitative and mixed-methods studies should be conducted to provide a more in-depth understanding of the factors underlying the development of students' misconceptions.
4. To more clearly distinguish misconceptions from a lack of knowledge, three- and four-tier diagnostic instruments that assess students' reasoning and confidence levels should be developed and used rather than relying solely on one-tier tests.
5. Longitudinal studies should be conducted that focus not only on identifying students' misconceptions but also on determining their sources, addressing them, and monitoring the persistence of conceptual change after instructional interventions.
6. Given that instructional methods used to address misconceptions may produce different outcomes, experimental studies comparing different intervention methods within the same conceptual domain should be conducted.
7. Future review studies should include not only graduate theses but also national and international peer-reviewed journal articles, thereby enabling trends in Türkiye to be compared with international research trends.

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Unveiling The Impact of GenAI on University Education A Survey Identifying Key Factors

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Abstract

The use of generative AI (GenAI) tools like ChatGPT, Gemini, Claude, and DeepSeek are now a part of the university curriculum, but the conditions influencing responsible adoption of these technologies are not sufficiently explored in the context of South Asian Higher Education. To explore key factors influencing the uptake of GenAI, perceptions of academic integrity, and the preferences of policies, this study polled 599 respondents (552 students and 47 faculty) from four departments (Science and Engineering, Business, Arts and Social Science, Medical and Pharmacy) at a private university in Bangladesh. There is a significant correlation between frequency of use and self-reported proficiency with prompting ($\chi^2 = 31.29$, $p < .001$), a strong correlation between clear understanding of the guidelines and the perception of GenAI as a form of cheating ($\chi^2 = 79.43$, $p < .001$), a strong correlation between self-reported proficiency with prompting and fact-checking behavior ($\chi^2 = 112.22$, $p < .001$), and a significant correlation between self-reported role as respondent and perception of GenAI as lowering critical thinking ($\chi^2 = 18.29$, $p = .001$), with faculty having more polarized perspectives than students. There were no significant relationships between any of the demographics and job-security worries or critical-thinking belief. Almost three-quarters (74.6%) said GenAI will diminish critical thinking, and a similar proportion (73.0%) believes that GenAI literacy will be a requirement by 2030. The results indicate that the factors that will drive responsible use of GenAI are not necessarily demographic, but rather the clarity of the instruction, digital literacy, and the role of the institution. The paper concludes with recommendations for uniform guidelines, integrity education, and fair access to GenAI.

Keywords: Generative AI, GenAI literacy, higher education, learning process, academic integrity, university education

Introduction

The rise of large language model (LLM) tools like ChatGPT, Gemini, Claude, and DeepSeek have transformed the way university students are working with academic content, including everything from creating essays to debugging code to preparing for exams. It started as a novelty at the end of 2022, and in just a few academic terms, it has become a regular part of the academic life of students and faculty in almost every discipline (Stefanova & Kalmukov, 2025). This transition was not the result of institutional design, it was a bottom-up development, faster than universities could form policy in response to students and teachers using freely available tools. We have found ourselves in a strange present in higher education where a great technology that has the potential to transform student learning, teaching and assessment has now been normalized in classrooms without most institutions having reached agreement on how it is to be used in the normed form (Gomes et al., 2026).

This normalization creates necessary and interdependent queries. The issue with academic integrity is that GenAI can make it hard to tell the difference between using AI for help and handing someone a finished essay, especially when detection methods are not foolproof and are not used uniformly (Weber-Wulff et al., 2023). The concern about assessment validity is that traditional forms of assessment (essays, problem sets, literature summaries) may no longer adequately assess the competencies these were designed to assess once students can write a fluent draft in a matter of seconds. The concern is that as GenAI is more frequently able to do the cognitive work of synthesis, argumentation, and problem-solving for a student, the practice that helps develop these skills could be shortened (Lin & Sohail, 2026). Equity is a concern because if the capability of GenAI tools continues to be tied to the tier of subscription, then unequal access to these might equate to unequal learning capabilities for students who need them the most.

The pressure on universities to formulate policies is now greater than ever to not only prohibit the use of a tool that is already popular, but also to allow unchecked replacement of human learning with the machine's output (Chan & Hu, 2023; Cotton et al., 2024; Dwivedi et al., 2023). Very little of the empirical literature to date regarding the use of GenAI in the university has been conducted in the context of other regions of the world and tends to assume that student and faculty perceptions are uniform groups (Kasneci et al., 2023).

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There is comparatively few survey-based evidence from South Asian universities, where the context in which GenAI affects the classroom has some differences to the better understood contexts. English is often a second or third language for students, and this influences not only the use of GenAI (as a language-support text, rather than just a productivity tool) but also the performance of the automated AI-text detectors, which have been found to give poorer results on non-native English writing (Liang et al., 2023).

The policy infrastructure, typically at the institutional level, is often less robust, and guidance on the use of GenAI more often is subject to the discretion of individual instructors than to a university-wide or national-level policy. Adoption of AI tools among engineering and computer science undergraduate students in the region also looks high, as the usefulness of the tools in coding, debugging, and technical writing (which are integral parts of engineering and computer science programs) is clear. The regional particularities warrant caution in generalizing findings from the West and East Asian contexts to the South Asian higher education context, and the need for empirical institution-specific evidence that will support policy decisions currently being made using limited local data.

This study aims to fill that gap by conducting a well-structured survey at a private university of Bangladesh. The study does not focus on the general question of whether GenAI is beneficial or detrimental to learning, as is often reported in the literature, but on recognizing key factors that can reasonably impact the use and perception of GenAI: frequency of use, clarity of instructor guidance, self-reported skill at prompting, fact checking behavior, and the role of the respondent. A single overall conclusion about the good or bad of GenAI for higher education is less actionable than being able to isolate those factors and to test those that are statistically correlated with attitudes towards academic integrity, critical thinking, and the role of GenAI in higher education in the future.

The identification of any behavioral or institutional factors that might be more important than broad demographic factors has direct implications for the direction of limited policy and training resources at universities. This paper is mainly guided by two research questions:

RQ1. What are the patterns of GenAI use, institutional factors, and demographic factors related to the perceptions of academic integrity, critical thinking, and workforce readiness of students and faculty?

RQ2. What are the statistically significant associations and what do the associations mean for university GenAI policy?

The rest of this paper is organized as follows. In section 2, the literature on GenAI adoption, academic integrity, critical thinking, and equity in higher education are summarized. The study instrument, sample, and analysis method are described in section 3. Descriptive and inferential results are provided in Section 4. These findings are discussed in the context of the research questions and literature in Section 5. Policy recommendations, limitations and concluding remarks are included in sections 6-8, respectively.

Literature Review

GenAI Adoption in Higher Education

The use of GenAI has been extensively studied across the lenses of technology acceptance among university students. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT), the four determinants of behavioral intention to use a technology are performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). The recent studies on the adoption of GenAI among university students based on UTAUT have found performance expectancy and effort expectancy to be consistently significant predictors of adoption intention, while social influence is a comparatively weaker predictor. Thus, the adoption of GenAI in academic settings is more influenced by perceived personal utility rather than peer pressure. While social influence is a relatively weak predictor of intention to adopt GenAI, which may indicate that university students are more likely to embrace it due to its perceived benefits to them personally than to their peers, performance expectancy and effort expectancy are consistently found to be significant predictors of intention to adopt GenAI.

Kasneci et al. (2023) also claim that LLM use is generally bottom-up and that their ability to provide explanations, brainstorming and personalized tutoring gives students a clear advantage to their use. This pattern of technology overshadowing institutional readiness is not unique to GenAI. Zawacki-Richter et al. (2019), in a systematic review of AI applications in higher education prior to the GenAI era, found that educator perspectives were consistently underrepresented in the literature relative to technical and system-design perspectives. The current study aims to help redress this gap by foregrounding both student and faculty voices.

Academic Integrity and Instructor Guidance

In previous literature, there is often a sense of uncertainty about what is allowed when using GenAI to assist in completing work. Chan & Hu (2023) discovered that students know that it is not acceptable to submit directly generated AI text without proper editing and review, but that lighter uses of AI, such as brainstorming or grammar checking, are acceptable. Cotton et al. (2024) also stated that there remains a lack of clarity within students and teachers regarding the boundaries between acceptable support and plagiarism, and that such clarity, rather than total ban, is more appropriate in this context. Sullivan et al. (2023) extend this, arguing that universities should think of integrity in the ChatGPT age not as a static list of forbidden actions, but instead as an evolving teaching discourse between faculty and students about disclosure and acceptable use. This reframing draws on a longer tradition in academic integrity scholarship.

Chesney (2009) argues that integrity is best understood as a teaching-and-learning imperative rather than a purely disciplinary matter, and Bretag (2016) frames integrity as a whole-of-institution responsibility that encompasses policy clarity, assessment design, and student education. Perkins (2023) uses this approach explicitly for large language models and warns that a binary view of GenAI use as a violation may hide the wide range of support types (from generating ideas to replacing text entirely) that students say they are using. Surveying students and faculty at a Latin American university, Carvajal et al. (2026) suggest that norms of disclosure, not bans, should be observed at the course level to bridge this gap between the perceptions of faculty and students when using GenAI in courses.

AI Literacy as a Framework for Responsible Use

An increasing amount of research suggests that the risks associated with GenAI are best mitigated not by implementing restrictions, but via systematic AI literacy education. Long & Magerko (2020) define AI literacy as a set of competencies that involve understanding what artificial intelligence systems can and cannot accomplish, how outputs are generated, and critically evaluate AI produced information rather than to take it as authoritative. This framework is particularly related to the present study's interest in fact-checking behavior as a measurable, trainable part of responsible GenAI use, rather than an incidental attribute of some users.

Critical Thinking, Skill Development, and Verification Behavior

A related issue in the literature is the potential decline in critical thinking and proof-checking skills when using GenAI. Weber-Wulff et al. (2023) shows that AI generated text detection systems are still not reliable, which means that it is increasingly up to students and instructors to consider the output of GenAI systems and not depend on automatic text detection. In addition, Liang et al. (2023) demonstrate that these detectors are systematically biased against non-native English writers, which can have direct implications for non-Anglophone academic settings, like Bangladesh, where flagging for stylistic irregularity has the potential to unfairly penalize multilingual students. The body of work indicates that "fact-checking and verification behavior" and not the use of GenAI itself is a more robust measure of responsible use than the frequency of use.

Equity and Institutional Policy

Finally, there are several studies that raise equity concerns around differential access to premium GenAI subscriptions, in that if there are meaningfully better output qualities in paid tiers, then differential access could lead to differential academic advantage (Kasneci et al., 2023). This concern drives the focus of the equity-focused survey item included in the present study and contextualizes the institutional GenAI-subscription policy in the wider literature on digital equity in higher education.

Universities should build such policy that does not create any bias among students, if they provide subscription based GenAI applications it should be given to everyone.

Methodology

Research Design

The study adopted quantitative, cross sectional survey design. The instrument was sent online with a structured questionnaire (Google Forms), and 599 valid answers from precipitants were received between April and June 2026. The survey was anonymous and targeted individuals with some basic working knowledge of GenAI tools, not the general population of the university, as the study purpose was to study GenAI-literate users rather than the general university population. The survey was sent to 607 students and 65 faculty members from different departments to collect different views from diverse disciplines. 552 students (90.1%) and 47 faculty members (72.3%) participated and shared their answers.

Instrument

The questionnaire consisted of four parts. Demographic data (age group, gender, education, education field, role) was gathered in Section A. In Section B (students only), they captured the frequency of use of GenAI, type of use, attitudes toward academic dishonesty, exposure to instructor guidelines, and job-security concern. Section C (faculty only) was able to capture curriculum integration, assessment modification, teaching confidence, workload impact, and policy preference. The data in Section D (all respondents) reflected beliefs about critical thinking, self-rated ability to prompt, how often they fact-check, their perceptions of equitable access to paid GenAI tools, and their expectations for GenAI literacy by 2030.

Sample

The final sample (N = 599) comprised 552 students (92.2%) and 47 faculty members (7.8%). The sub-sample of students was mainly undergraduate (99.5% undergraduate, 0.5% post-graduate) and included students from Business Administration (14.7%), Arts and Social Science (9.0%), Medical and Pharmacy (6.5%) and Science and Engineering (69.8%). The faculty member sub-sample was mainly post-graduate (76.6% post-graduate, 23.4% PhD) and included faculty members from Business Administration (12.8%), Arts and Social Science (8.5%), Medical and Pharmacy (4.3%) and Science and Engineering (74.4%). The faculty member sub-sample is sufficiently large to describe faculty-specific items with reasonable confidence but is not as large as the student sub-sample, so faculty-only inferential comparisons should be interpreted with caution.

Data Analysis

All items were analyzed using descriptive statistics (frequency and percentage). A series of chi-square tests of independence were used to evaluate and determine whether there were differences in attitude and behavior with regard to aspects of GenAI that were of theoretical interest: frequency of use, prompting ability, fact-checking behavior, clarity of instructor guidelines, perception of cheating, gender, age group, and worry regarding job security. The α level chosen for significance was .05. Data analysis was done in Python with the help of pandas and SciPy.

Results

Sample Demographics

Demographic data like age group, gender, education, education field, and current role was collected from the survey participants to identify and analyze groups within the research's context. This data will help this research to cluster the participants of this research.

Table 1 summarizes the demographic composition of the collected sample from the survey. According to the demographic profile of the sample (N = 599), most of the respondents were students (92.2%, n = 552), while faculty members made up the remaining 7.8% (n = 47). In terms of age distribution, the sample was predominantly young, with 78.3% (n = 469) aged between 15 and 25 years, followed by 20.2% (n = 121) aged 25 to 40 years, and only 1.5% (n = 9) in the 40 to 55 age brackets. Most of the respondents of this survey were male (73.8%, n = 442) with females accounting for 26.2% (n = 157). When asked about their level of education, most of the respondents were undergraduate students (91.7%, n = 549), followed by postgraduate (6.5%, n = 39), and PhD (1.8%, n = 11). Finally, across academic disciplines, Science & Engineering was the most represented field (69.8%, n = 418), followed by Business Administration (14.7%, n = 88), Arts & Social Science (9.0%, n = 54), and Medical & Pharmacy (6.5%, n = 39).

Table 1. The demographic composition of the sample.

Variable	Category	n	%
Role	Student	552	92.2
	Faculty Member	47	7.8
Age group	15–25	469	78.3
	25–40	121	20.2
	40–55	9	1.5
Gender	Male	442	73.8
	Female	157	26.2
Education level	Undergraduate	549	91.7

	Post-graduate	39	6.5
	PhD	11	1.8
Education field	Science & Engineering	418	69.8
	Business Administration	88	14.7
	Arts & Social Science	54	9.0
	Medical & Pharmacy	39	6.5

GenAI Usage Patterns

Nearly all respondents used GenAI, where 69.0% of the respondents used it daily, and another 24.6% used it two or three times a week, resulting in 93.6%. Explanation of complex or difficult concepts (72.1%) was the most frequent use case, followed by brainstorming of ideas and outlines (37.2%), checking or debugging code or grammar (22.2%), summarizing of readings (10.7%) and drafting of entire paragraphs or essays (4.3%). Only 0.7% reported not using GenAI for coursework at all.

Academic Integrity Perceptions

When asked if it's academic cheating to use GenAI to create a first draft, the plurality of respondents (46.6%) said it depends on whether or not the student edits the draft extensively or not, 25.9% said it depends on the instructor's provided specific rules, 15.9% said it's always cheating no matter what, and 11.6% said it's legitimate to use as the starting point. When asked about guidance from instructors, 14.7% of respondents said all their instructors had given them clear GenAI guidelines, 43.8% said some instructors had provided clear GenAI guidelines, and 10.3% said that no instructors had provided clear GenAI guidelines. Therefore, it is obvious that faculty members are already considering GenAI and are offering students guidelines so that students have an ideal idea of what extent they can use GenAI.

Critical Thinking, Prompting Skill, and Verification

In the survey question, when asked about GenAI's impact on critical thinking in higher education, 74.6% of the total sample agreed or strongly agreed that GenAI diminishes the importance of critical thinking, with 10.9% disagreeing or strongly disagreeing with this opinion. This belief was quite distinct among different role groups, faculty had more polarized attitudes, with higher agreement rate (80.8% vs. 74.1%) and a significantly higher strong-disagreement rate (12.8% vs. 2.9%). Across the entire sample, the distribution of self-rated prompting ability was: 51.8% proficient, 29.7% basic, 17.4% expert, and 1.2% novice. Checking the output of GenAI was more diverse, 40.1% said that they did check the GenAI output often, 30.9% said they did check the output always, 24.4% said they did check the output sometimes, and only a few (4.6%) rarely or never check the output generated by GenAI.

Faculty Member Perspectives

Table 2: Faculty member responses on curriculum integration, assessment change, teaching confidence, workload, and policy preference.

Item	Response category	%
GenAI integrated into teaching	Policy included, not used for teaching	53.2
	Considering adoption next semester	21.3
	Actively used for lesson planning / activities	12.8
	No plans to integrate	12.8
Assessment modified	Moved to more in-class exams / oral vivas	63.8
	Requires more process-based work	21.3
	Unchanged	14.9
Teaching confidence (1–10 scale)	4–6 (Moderate / self-taught)	38.3
	7–8 (High)	34.0
	9–10 (Expert)	21.3
	1–3 (Low / needs training)	6.4
Grading/monitoring workload	Slightly increased	59.6
	Significantly increased	25.5

	Slightly decreased	14.9
	Common national standard (UGC)	59.6
Policy preference	University-wide standardized policy	27.7
	Department / instructor discretion	12.8

The majority of faculty member (53.2%) indicated they had incorporated a GenAI policy into their course syllabus but were not currently actively using GenAI for teaching and learning, 21.3% were planning to use GenAI for the next semester, 12.8% were using GenAI to plan their lessons or use in class, and 12.8% indicated no plans to adopt GenAI. In response to GenAI, 63.8% of faculty had shifted to more in-class examinations or viva voce and 21.3% had increased requirement for more process work, with 14.9% retaining their assessment methods as it was. The majority of faculty (59.6%) felt that they are moderate or self-taught in teaching the proper use of GenAI (rated 4-6 on a scale of 1-10, 38.3% rated 7-8 and 21.3% rated 9-10), while only 6.4% felt they require training. A large majority (85.1%) reported that GenAI had increased their grading and academic-integrity-monitoring workload (59.6% slightly, 25.5% significantly), with only 14.9% reporting a decrease. Regarding policy preference, 59.6% of faculty wanted a common national standard set by the University Grants Commission, 27.7% wanted a university-wide standardized standards policy, and 12.8% wanted a policy that would be left at the discretion of the department or instructor.

Equity and Future Outlook

When asked about the university offering paid GenAI tools for all students, 47.4% voted in favor, 35.6% in favor of GenAI tools for students in AI-heavy courses, and 17.1% opposed the idea of subscription in any form. In the future, 73.0% of respondents agreed or strongly agreed that GenAI literacy will be required at university level to have a degree without it.

Key Factors: Chi-Square Test Results

Table 3: The chi-square tests of association conducted to identify statistically significant key factors.

Variable pair	χ^2	df	p	Result
Frequency of use × prompting ability	31.29	9	< 0.001	Significant
Instructor guidelines × cheating perception	79.43	9	< 0.001	Significant
Prompting ability × fact-checking behavior	112.22	12	< 0.001	Significant
Role × critical-thinking belief	18.29	4	0.001	Significant
Frequency of use × critical-thinking belief	7.38	12	0.832	Not significant
Gender × job-security worry	4.11	4	0.392	Not significant
Age group × job-security worry	1.44	4	0.838	Not significant
Education field × critical-thinking belief	9.56	12	0.655	Not significant
Education field × frequency of use	12.04	9	0.211	Not significant

There were four significant associations. First, for frequency of GenAI use, there was a significant association with self-reported ability to prompt ($\chi^2(9, N = 599) = 31.29$, $p < .001$). 53.0% of daily users rated themselves as proficient and 19.7% as experts, compared with just 32.1% who rated themselves as proficient and 3.6% who rated themselves as expert on once-a-week use of GenAI, indicating that prompting ability is developed through repeated use and is not a fixed trait.

Second, students' perceptions of the clarity of the instructors' guidelines positively correlated with their perception of whether GenAI-assisted drafting is considered cheating ($\chi^2(9, N = 599) = 79.43$, $p < .001$). Interestingly, students with all of their instructors who set clear rules were the most likely to feel “always cheating” (46.9%), whereas those with only some instructors were the least likely to feel that (7.9%) and the most likely to say, “depends on the specific rules set by the instructor” (32.2%). The pattern indicates that more explicit and consistent guidance is linked with more stringent default perspectives on how GenAI can assist with drafting, while less cohesive guidance or inconsistency is linked with more conditional and rule-dependent perspectives of how GenAI can assist with drafting.

Last, self-reported prompting ability was positively related to fact-checking behavior ($\chi^2(12, N = 599) = 112.22$, $p < .001$). More expert users (50.0%) said they always fact check GenAI output compared to 19.1% of basic users, and basic users were much more likely to state that they “sometimes” (7.7% vs. 47.2% of experts). The finding

suggests that the more proficient one feels with GenAI tools, the more consistently they verify, rather than they feel complacent.

Finally, the belief that GenAI diminishes critical thinking was significantly associated with respondent role ($\chi^2(4, N = 599) = 18.29$, $p = .001$). Faculty had a higher level of agreement ("agree" + "strongly agree") than students (80.8% vs. 74.1%) but faculty were also more than four times as likely to strongly disagree (12.8% vs. 2.9%). This means that there is not just an increase in overall concern among the faculty, but a more polarized distribution.

Five associations tested were not statistically significant, however, by comparison. Frequency of GenAI use was not significantly associated with belief that GenAI reduces critical thinking ($\chi^2(12, N = 599) = 7.38$, $p = .832$). Neither gender ($\chi^2(4, N = 599) = 4.11$, $p = .392$) nor age group ($\chi^2(4, N = 599) = 1.44$, $p = .838$) was significantly associated with concern about GenAI's impact on future job security. Education field was not significantly associated with either critical-thinking belief ($\chi^2(12, N = 599) = 9.56$, $p = .655$) or frequency of use ($\chi^2(9, N = 599) = 12.04$, $p = .211$). With the more heterogeneous sample, these null results indicate that the concern over critical-thinking erosion, job-security anxiety, and usage intensity is not only limited to certain sub-groups of students, it is not necessarily found in any specific group of disciplines.

Discussion

The findings suggest that not only demographic factors, but also instructional clarity and digital literacy are important components in the responsible use of GenAI in this sample. The high correlation between instructor guideline clarity and cheating perception (RQ1, RQ2) aligns with the Cotton et al. (2024) argument that it is not the availability of GenAI that is the main cause of inconsistent student perceptions of acceptable use, but rather the clarity of guidelines. The results are interesting because the "all instructors clear" students were the most likely to say that GenAI-assisted drafting was "always cheating," showing that it is not the case that students' attitudes toward cheating become more permissive when they are not informed about the use of AI. This aligns with recommendation of Carvajal et al. (2026) for explicit and course-level disclosure norms to help bridge the gap between students and instructors.

Literature on detection tools may give a gloomy view of the relationship between prompting and fact checking, but this is not the case here. More proficient users in this sample confirmed more consistently with the output of GenAI, supporting the perspective that true GenAI literacy goes beyond fluent use of a tool, but also entailed critical evaluation skill (Weber-Wulff et al., 2023) . This indicates that the ability of checking the source and verifying content should be taught from the beginning of the university's GenAI-literacy, and not simply be regarded as a skill acquired through the learning of the prompting technique.

The high overall agreement (72.5%) that GenAI decreases critical thinking and the null association between frequency of use and the belief that GenAI decreases critical thinking is an interesting mix. It implies that even the heaviest users of the tool have the same concern over their own use as infrequent users have. Self-awareness may be a tool that universities can leverage, rather than having to make a point of convincing heavy users that they have a problem in which they have no perception, they may need to somehow translate a pre-existing concern into actual practice and verification and independent-practice.

This result does not align with some technology-acceptance research which reports that gender, age, or education-field differences can be seen in the intention to adopt GenAI. The education-field effect is not identified within this expanded, more diversified (by discipline) sample, which spans across the four fields of study (Science and Engineering, Business Administration, Arts and Social Science, and Medical and Pharmacy). This finding is stronger than it would be if the sample had been drawn from only one field of study.

However, the important role effect on critical-thinking belief makes a usage-driven one more complicated. Students' responses were more clustered than faculty's responses in both agreeing and strongly disagreeing that GenAI decreases critical thinking. The polarization might stem from the fact that those faculty who have incorporated GenAI into their own teaching (12.8%) see this as being compatible with, or even a benefit to, critical thinking (provided it is done purposefully), while faculty who have yet to integrate GenAI into their teaching experience may view it in terms of potential displacement risk. This aligns with Carvajal et al. (2026), who found that professors see GenAI in terms of assessment validity and authorship, rather than the more instrumental and supportive view of GenAI that students hold.

Recommendations

The following recommendations are proposed for University policies and pedagogy considering the identified key factors:

1. Standardize instructor guidance. Considering that guideline clarity is the top predictor of student judgements of the use of GenAI in drafting, universities should adopt baseline level of disclosure guidelines for students in a course syllabus, even if guidelines can be adapted to a specific course or discipline.
2. Embed verification skills in GenAI literacy training. Prompting competency should be integrated into fact-checking competency to achieve more consistent fact-checking and should be taught alongside source verification and output assessment as part of the same competency rather than as separate skill tracks for GenAI orientation programs.
3. Re-think the assessment so that it emphasizes the process rather than the perfect output. Given the trend of faculty respondents towards in-class exams and oral vivas, departments should include process-based evidence (such as rough drafts, oral defenses, annotated reasoning) into assessment design to ensure that the evidence value of student submission is not lost.
4. Act intentionally to tackle inequity in access to GenAI. Subscription-based access to paid GenAI tools is not a luxury but a necessary consideration of fairness for the university community, especially when it comes to AI-focused disciplines like computer science and engineering, where access is likely to be a necessity rather than a choice.
5. Educate faculty members for Gen AI classroom. Reported increase in workload for grading and integrity monitoring indicates that the institution should provide support to continue with assessment redesign, through training, revision of rubrics and workload recognition.

Limitations

This study has several limitations. Although the sample is diverse, it is skewed toward students (92.2%) and Science and Engineering respondents (69.8%). Faculty-related findings (n = 47) are large enough to report descriptively with reasonable confidence but smaller than the student sub-sample and should still be interpreted with some caution in inferential comparisons. The sample was obtained through non-probabilistic, convenience-based distribution, which limits generalizability beyond similar populations. All measures (usage frequency, prompting ability, fact-checking behavior) were self-reported and were not independently verified, introducing potential social-desirability or self-assessment bias. The cross-sectional design permits identification of statistical association but not causal direction (for example, greater prompting skill and more consistent fact-checking may reinforce one another bidirectionally rather than one causing the other). The significant role effect on critical-thinking belief was tested only bivariately. It may be confounded with unmeasured differences between students and faculty (for example, disciplinary training, years of GenAI exposure) that a multivariate model could disentangle. The instrument was not a previously validated psychometric scale, which limits direct comparability with instruments used in other GenAI-in-education studies.

Conclusions

This study surveyed 599 respondents from a Bangladeshi private university across four academic disciplines, including students as well as faculty members, to uncover the primary determinants affecting GenAI use, views of academic integrity, and preferences for institutional policy in university education. This study discovered near universal and high frequency use of GenAI, although mostly for clarifying concepts and brainstorming, rather than straight essay generation. Four key factors were statistically significant. The frequency of use was associated with self-rated proficiency in prompting, instructor guideline clarity was strongly associated with how students judge GenAI-assisted drafting, prompting proficiency was strongly associated with more consistent fact-checking behavior, and respondent role was significantly associated with (more polarized) belief that GenAI reduces critical thinking. None of the demographic variables (gender, age, and education field) were significantly associated with either job-security worry, critical-thinking belief, and usage frequency, suggesting that behavioral, institutional, and role-based factors, rather than broad demographic traits, are the more meaningful levers for policy intervention. The research supports a policy direction that emphasizes standardized, clear instructor guidance and integrated GenAI-literacy training that combines prompting skill development with verification habits, as well as targeted faculty development that addresses more polarized views among instructors. Future research should extend this survey with validated psychometric scales, multivariate modeling of the role influence on critical-thinking belief, and longitudinal designs to explore how these important factors shift as GenAI tools and institutional policy become more advanced.

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this study possible. Special thanks to the faculty responders who took time out of teaching and research activities to reflect in detail on curriculum integration, assessment redesign and policy preferences. All responses to the survey were collected anonymously in compliance with established ethical practice for educational research and no personally identifying information is presented in this publication.

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An Explainable AI Framework for Identifying Factors Influencing Student Academic Performance

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Abstract

Traditional machine learning models frequently operate as black boxes, making accurate predictions but lacking the openness required for practical intervention as educational datasets become more complicated. Teachers are unable to fully understand the specific behavioral and demographic factors that influence students' success or failure due to this lack of understanding. This paper develops an explainable artificial intelligence (XAI) framework to analyze student academic performance using the Student Performance Prediction dataset, whose attributes span demographic, behavioral, and academic factors such as study hours per week, attendance rate, parental education level, internet access, and extracurricular activities. A four-learner stacking ensemble combining Random Forest, XGBoost, LightGBM, and Extra Trees with a logistic-regression meta-learner is proposed to classify students as Pass or Fail, and impurity-based feature importance together with SHAP (SHapley Additive exPlanations) value analysis is applied to identify and explain the factors driving that classification. The proposed model achieves a test accuracy of 82.39%, precision of 82.40%, recall of 82.39%, F1-score of 82.39%, and an AUC of 0.891, outperforming twelve widely used baseline classifiers trained under an identical pipeline. Both explanation methods converge on engineered study–attendance interaction features as the dominant predictors of academic outcome, with behavioral factors substantially outranking demographic attributes, results that support data-informed, fairness-aware early-intervention strategies in higher education

Keywords: explainable AI, SHAP, stacking ensemble, higher education, academic performance prediction, student analytics, feature engineering

Introduction

One of the most persistent challenges in educational research is effectively predicting and explaining students' academic success. Universities and colleges acquire a large amount of behavioral, demographic, and academic data, but the challenge is to convert that information into useful insights for instructors and administrators. Over the recent decade, machine learning (ML) has been increasingly used in Educational Data Mining (EDA) and Learning Analysis (LA) to predict outcomes such as pass/fail status, dropout likelihood, and final grades. These challenges have been proven to improve predictive accuracy by employing a variety of ensemble approaches (e.g., Random Forest, Gradient Boosting, XGBoost, LightGBM, CatBoost) and deep neural network frameworks. However, the properties that make these models accurate also prevent them from being transparent. Its characteristics include high dimensionality, non-linear relationships, and extensive ensembling possibilities. Teachers and academic counselors are occasionally provided a single number indicating a predicted risk of failure, but they are not given the reasoning that connects the forecast to potentially modifiable behaviors (for example, attendance, study habits).

The problem of the 'black-box' is the lack of transparency is a barrier to the wider adoption of predictive analytics in practical educational practice. Instructors are reluctant to go ahead with a plan they cannot examine, and institutional review standards are increasingly mandating that automated decisions affecting students be verifiable and understandable. To address this challenge, the cure of Explainable Artificial Intelligence (XAI) has been emerged. It offers a suite of post-hoc and inherently interpretable methods, in particular SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), which quantify the extent to which each input feature contributes to a given prediction (Lundberg & Lee, 2017, Ribeiro et al., 2016). When these techniques are used in an EDM pipeline, they allow a model to not only signal the student is at danger, but also the model can explain the reasons for the risk, which may be used by teachers to make appropriate interventions.

This research proposes an explainable artificial intelligence framework to classify university students as Pass or Fail and to discover the behavioral, intellectual and demographic elements that contribute to this classification. The framework's cornerstone is a custom four-learner stacking ensemble. The base learners of this ensemble are Random Forest, XGBoost, LightGBM and Extra Trees, while the meta-learner is a regularized logistic regression. The model is based on the feature-optimized version of the Student Performance Prediction dataset. For example,

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10 domain-specific interaction, non-linear, and threshold features created from six raw variables include a weighted score for study attendance, a product of study attendance, and squared and logarithmic transformations of study hours and attendance. These features include gender, weekly study hours, attendance %, parents' education level, home internet access, and participation in extra-curricular activities. To minimize the lingering class imbalance, the training subset is oversampled via the Synthetic Minority Oversampling Technique, also called SMOTE. Additionally, SHAP values are integrated with impurity-based feature importance to provide both global and local explanations of the generated predictions.

This research has three focused aims: (i) to develop and train a high-efficiency stacking ensemble classifier for the binary Pass/Fail prediction task and assess its performance against twelve common baseline algorithms using a uniform preprocessing pipeline, (ii) to apply SHAP-based interpretability to determine, at both the global (cohort) and local (individual student) levels, the behavioral and demographic factors that most strongly influence academic outcomes, and (iii) to translate these insights into actionable, data-driven recommendations for educators and academic advisors to support early intervention. The rest of the paper is organized as follows. Section 2 reviews the current research on machine learning and explainable AI for forecasting student achievement. Section 3 is dedicated to the dataset, the preprocessing pipeline, the feature engineering, the proposed stacking architecture and the assessment technique. Experimental data are presented and discussed in Section 4. Section 5 explores the implications and limits of the study and section 6 finishes with suggestions for future research.

Literature Review

Predictive Modeling in Educational Data Mining

There has been a lot of work applying machine learning techniques to predict student outcomes, such as final grades, at-risk classifications, and dropout rates. Several studies comparing multiple approaches often report that ensemble and boosting algorithms perform better than individual classifiers on tabular educational data. In addition, Cheng et al. (2024) combined the XGBoost classifier with a hybrid artificial-ecosystem-optimization (AEO) strategy to improve the prediction accuracy of student performance over an academic term. Asselman et al. (2023) showed that a methodology based on XGBoost improved the prediction of student achievement compared to traditional classifiers. In line with these results, the simple comparison done in this study shows that XGBoost, CatBoost and LightGBM perform better than single decision tree models, logistic regression and support vector machines, in general. This finding is in line with the current evidence in the EDM literature that gradient boosted tree ensembles are useful default learners for small to medium scale structured educational datasets.

Researchers have proposed that stacking and voting ensembles with individual classifiers can improve the predictive robustness of the system. Niyogisubizo et al. (2022) proposed a dual-layer stacked-generalization strategy to predict university attrition and showed its improved efficacy compared to individual base models. Recently, Firdaus and Sipayung (2026) used a logistic-regression meta-learner with Random Forest, Gradient Boosting and XGBoost to predict the probability of attrition of students in STEM. They achieved 90.91% accuracy and 0.957 area under curve (AUC) while maintaining interpretability by post-hoc feature significance analysis. Together, these studies motivate the stacking design that has been choosen for this particular paper. This architecture combines several tree ensembles using a regularized logistic meta-learner, in line with the classical idea of layered generalization (Wolpert, 1992). The goal of this design is to incorporate complementary decision limits while yet being adaptable to SHAP-based explanation.

Class Imbalance and SMOTE in Educational Datasets

Educational outcome databases frequently exhibit an imbalance, with a greater number of classes that have succeeded, been retained, or graduated compared to those who have failed, withdrawn, or ceased attendance. The Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al., 2002) remains the most widely employed method. This method produces artificial instances of the minority class by interpolating among the closest neighbors instead of depending on simplistic replication. Jain et al. (2025) developed a particle-swarm-optimization-weighted ensemble integrated with SMOTE for predicting student dropout. Authors indicated an accuracy of 86% and an area under the curve (AUC) of 0.959 subsequent to the balancing of the ensemble. Comparable results were presented by Masood et al. (2025), illustrated that enhanced SMOTE variants augment minority-class recall in predicting student dropout while maintaining the majority-class precision. Wang et al. (2021) conducted an additional examination of the SMOTE-driven augmentation and categorization of imbalanced datasets. This study emphasized the importance of integrating oversampling with cross-validated model selection to avert information leaking. In the present study, the SMOTE method is applied solely to the training subset following the train–validation–test division. This is done following best practice, with the objective of ensuring that no synthetic data is present in the validation or test sets used to report performance.

Explainable AI for Student Performance Prediction

One of the major trends of modern EDM research is the transition from purely predictive models to explainable ones. SHAP, a unified game-theoretic approach to feature attribution, was proposed by Lundberg and Lee (2017), satisfying the properties of local accuracy, consistency and missingness, building on past techniques such as LIME (Ribeiro et al., 2016). Since then, SHAP has become the state-of-the-art tool for explainability in student performance studies. Choi et al. (2025) applied SHAP to explain predictions of student performance and to deliver tailored, actionable recommendations. They argued that explicitly linking SHAP attributions to recommendations for intervention can help bridge the gap between prediction and educational practice. A relevant systematic review on explainable AI methods for predicting student performance in computer science and STEM education (Choi et al., 2025) found SHAP to be the dominant explainability method, while calling for a closer integration of model accuracy and actionable, dashboard-ready insights. Similarly, Guevara-Reyes et al. (2025) found that SHAP supports both global interpretabilities, through the aggregation of attributions across the entire cohort, and local interpretability, through explanations for individual predictions – a duality that is important in academic advising, where educators need insight at the cohort level and diagnostic explanations at the student level.

A number of recent studies combine ensemble learning with SHAP especially for prediction of undergraduate performance. Johora et al. (2025) used the combination of SHAP and LIME in a custom ensemble model and achieved 86.4% accuracy over 872 undergraduate records from Bangladesh. They stated attendance rate was one of the most important predictors of academic performance, always outperforming purely demographic factors. This is closely resembling the trend of the current study. Babu (2026) proposed a similar Random-Forest-plus-SHAP model using attendance, internal-assessment scores and study hours, achieving 92.3% accuracy compared to 84.5% for a decision-tree baseline, and found that the added explainability layer improved the transparency and practical interpretability of predictions for educators. Recently, Lu et al. (2026) compared SHAP-based attribution and DiCE counterfactual explanations for early detection of at-risk individuals. They found that the two techniques often ranked features differently. This limitation motivates the present study's strategy of using both impurity-based feature importance and SHAP as complementary, cross-validating sources of explanation. We argue that agreement between diverse methods, rather than dependence on a single explanation method, provides the strongest justification for selecting the features driving student outcomes.

Research Gap

Despite the rising volume of XAI research on EDM, three holes remain. First, many studies report SHAP importance for a single, often already-strong classifier without benchmarking against a large panel of baseline algorithms trained using the same pipeline, making it difficult to determine whether reported gains are due to the model or the explanation technique itself. Second, very few research specifically design domain-informed interaction and non-linear characteristics to disclose correlations to the explainability layer, instead relying solely on raw attributes. Third, while stacking ensembles have been demonstrated to beat individual learners in dropout and retention prediction, they have rarely been combined with SHAP explanation for the specific pass/fail classification task utilizing a small set of easily recoverable attendance, study-habit, and demographic characteristics. This paper fills these three gaps by (i) comparing a custom stacking ensemble to twelve baseline classifiers using a single preprocessing pipeline, (ii) explicitly engineering ten domain-informed features from six raw attributes to surface interaction effects to SHAP, and (iii) using both feature-importance and SHAP analysis on the resulting stacking ensemble to produce cohort- and student-level explanations.

Methodology

Dataset Description

In the study, the Student Performance Prediction dataset (Maree, 2025) is used. It consists of 708 student records and 10 columns. The raw feature set consists of six input attributes and one binary goal after excluding the non-predictive Student_ID identifier: Gender, Study_Hours_per_Week, Attendance_Rate, Parental_Education_Level, Internet_Access_at_Home, Extracurricular_Activities and the target Pass_Fail. Two directly outcome-leaking columns, Past_Exam_Scores and Final_Exam_Score, were deliberately excluded from the feature set since incorporating them would enable the model to trivially infer Pass/Fail from a near-deterministic scoring rule rather than the behavioral and demographic antecedents of academic performance. The goal class was perfectly balanced at record level (354 Pass, 354 Fail) as this is a dataset pre-selected for a balanced classification benchmark and there were no missing values in any column.

Data Preprocessing

Categorical attributes were label encoded. No missing data have been observed but median-imputation precaution was kept in the pipeline for robustness. For continuous attributes, outliers were clipped using the interquartile-range (IQR) rule, i.e., any value beyond 1.5*IQR from the first (or third) quartile was clipped to the corresponding bound. All continuous characteristics were then normalized to have zero mean and unit variance using a StandardScaler fitted on the training data.

Feature Engineering

An additional 10 features were engineered from the Study_Hours_per_Week and Attendance_Rate to capture the non-linear and interaction relationships between study habits and attendance. The features are Study_Attendance_Product, Study_Attendance_Ratio, Study_Hours_Sq, Attendance_Sq, Study_Attendance_Diff, Weighted_Score (60% study hours + 40% attendance rate), Study_Hours_High, Attendance_High, Both_High, Study_Log, Attendance_Log, and Norm_Study_Attendance. Feature matrix after engineering has 18 columns. All designed characteristics were re-standardized using a second StandardScaler and any remaining NaN or infinite values resulting from the ratio/normalized-difference calculations were replaced by zero.

Train–Validation–Test Split and Class Balancing

The dataset with 708 records was divided using stratified sampling to keep the Pass/Fail ratio. The training data was 60% (424 records), validation data 20% (142 records) and test data 20% (142 records). We only applied SMOTE (Chawla et al., 2002) to the training partition after the split, such that the validation and test sets are unaffected, and the stated performance is not inflated by synthetic leakage.

Baseline (Existing) Models

Twelve widely used classifiers were trained as baselines under the identical preprocessing pipeline: Logistic Regression, Decision Tree, Random Forest (Breiman, 2001), Gradient Boosting, SVM (RBF), SVM (linear), XGBoost (Chen & Guestrin, 2016), LightGBM (Ke et al., 2017), CatBoost (Prokhorenkova et al., 2018), a default multilayer perceptron, a deep multilayer perceptron, and a soft-voting ensemble of Random Forest, XGBoost, and LightGBM. Each baseline was trained on the standardized, feature-engineered training set (without SMOTE) and evaluated on the held-out validation and test partitions using identical metrics to the proposed model.

Proposed Model — Custom Stacking Ensemble

The proposed model is a custom StackingClassifier, which uses four heterogeneous tree-based base learners: Random Forest (300 estimators, max depth 12), XGBoost (300 estimators, learning rate 0.1), LightGBM (300 estimators, learning rate 0.1) and Extra Trees (Geurts et al., 2006) (300 estimators, max depth 12). Each of these base learners is trained on the SMOTE-balanced training set. The final Pass/Fail decision is performed by a logistic-regression meta-learner (L2 penalty, C = 2.0, class_weight = 'balanced'), with base-learner out-of-fold predicted probabilities acquired via 5-fold cross-validation (stack_method = 'predict_proba') as meta-features. This architecture is based on the classical stacked-generalization principle (Wolpert, 1992): heterogeneous base learners with different inductive biases (bagged trees in Random Forest and Extra Trees versus boosted trees in XGBoost and LightGBM) are combined through a simple, well-regularized meta-learner, learns how to weight each base learner's output rather than treating all base learners equally, as a majority-vote or averaging ensemble would. The whole end-to-end architecture is shown in Figure 1.

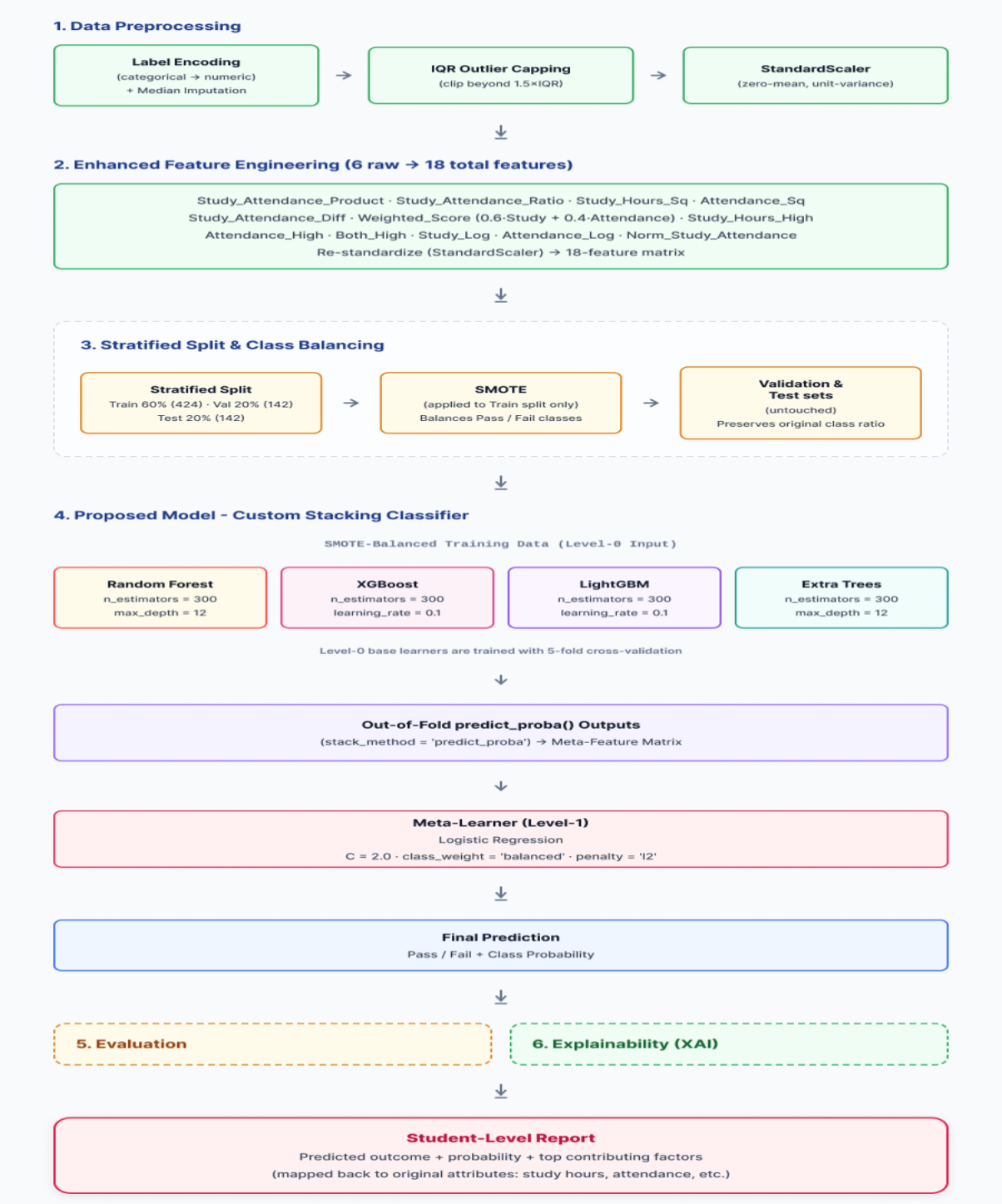


Figure 1. End-to-end architecture of the proposed model, from raw data ingestion through preprocessing, feature engineering, stratified splitting and SMOTE balancing, the two-level stacking classifier, and the evaluation/explainability layers.

Explainability Layer

For each trained model, including the proposed stacking ensemble, two complementary global explanation methods were computed: (i) impurity-based feature importance, directly extracted from each tree-based base learner and averaged across the ensemble for the stacking model; and (ii) SHAP values (Lundberg & Lee, 2017), computed with a TreeExplainer for individual tree-based baselines and, for the stacking ensemble, approximated by averaging the normalized feature-importance vectors of the four base learners over a 50-instance sample of the test set. A global feature-ranking bar chart and a summary beeswarm plot were generated using SHAP values. A custom prediction-explanation function also maps each engineering feature back to its constituent raw attributes,

such that a SHAP attribution on, for example, Weighted_Score can be communicated to an instructor as a statement about a specific student's study hours and attendance rate.

Evaluation Metrics

All thirteen models were evaluated on the held-out test set (142 records) using accuracy, weighted precision, weighted recall, weighted F1-score, area under the ROC curve (AUC), and balanced accuracy. Confusion matrices and per-class classification reports were additionally computed for the proposed model to support the fine-grained result analysis presented in Section 4.

Results

Comparative Performance of All Models

Table 1 shows validation and test performance for all thirteen models, trained and evaluated with the same pipeline. The suggested stacking ensemble scored the greatest test accuracy (0.8239), test AUC (0.8907) and test balanced accuracy (0.8239) out of all thirteen models and tied CatBoost for the highest validation accuracy (0.8803) while greatly beating it on validation AUC (0.9562 vs 0.9324). Among the baselines, CatBoost was the best single classifier (0.8169 test accuracy, 0.8867 test AUC), followed by XGBoost (0.8099 accuracy, 0.8578 AUC). Logistic Regression and both SVM variants were the weakest baselines (test accuracy 0.6549–0.7042), consistent with their failure to capture the non-linear interaction effects induced in feature engineering. The suggested model achieved a 0.9% higher test accuracy than the top performing baseline (CatBoost).

Table 1. Validation and Test Performance of the Proposed Stacking Ensemble Against Twelve Baseline Classifiers

Model	Val. Acc.	Val. AUC	Test Acc.	Test Prec.	Test Rec.	Test F1	Test AUC	Bal. Acc.
Logistic Regression	0.7465	0.8201	0.6549	0.6550	0.6549	0.6549	0.7280	0.6549
Decision Tree	0.7606	0.7722	0.7887	0.7972	0.7887	0.7872	0.8291	0.7887
Random Forest	0.8521	0.9369	0.7676	0.7720	0.7676	0.7667	0.8722	0.7676
Gradient Boosting	0.8592	0.9016	0.7606	0.7830	0.7606	0.7557	0.8841	0.7606
SVM (RBF)	0.7676	0.8442	0.7042	0.7044	0.7042	0.7042	0.7748	0.7042
SVM (Linear)	0.7535	0.8169	0.6690	0.6693	0.6690	0.6689	0.7356	0.6690
XGBoost	0.8239	0.9054	0.8099	0.8129	0.8099	0.8094	0.8578	0.8099
LightGBM	0.8521	0.9286	0.7887	0.7946	0.7887	0.7877	0.8784	0.7887
CatBoost	0.8803	0.9324	0.8169	0.8192	0.8169	0.8166	0.8867	0.8169
MLP (Default)	0.8169	0.8510	0.7676	0.7720	0.7676	0.7667	0.8342	0.7676
MLP (Deep)	0.8451	0.8887	0.7606	0.7682	0.7606	0.7588	0.8475	0.7606
Voting Classifier	0.8732	0.9316	0.7817	0.7886	0.7817	0.7804	0.8798	0.7817
Proposed Model	**0.8803**	**0.9562**	**0.8239**	**0.8240**	**0.8239**	**0.8239**	**0.8907**	**0.8239**

Proposed Model Performance in Detail

The suggested stacking ensemble properly identified 117 out of 142 students in the test set of 142 records, with an accuracy of 82.39%. Table 2 shows the per-class classification report. The model achieved near-identical precision and recall on both classes (Fail: precision 0.819, recall 0.831, F1 0.825; Pass: precision 0.829, recall 0.817, F1 0.823), suggesting that the model does not systematically favor one class over the other which is an important property considering that misclassifying an at-risk (Fail) student as Pass carries a real pedagogical cost, since such a student would not receive a timely intervention.

Table 2. Per-Class Classification Report of the Proposed Model on the Test Set

Class	Precision	Recall	F1-score	Support
Fail	0.8194	0.8310	0.8252	71
Pass	0.8286	0.8169	0.8227	71

Confusion Matrix Analysis

The confusion matrix of the suggested model on the test-set is shown in Figure 2. Of the 71 students who genuinely failed, 59 (83.1%) were accurately detected and 12 (16.9%) were misclassified as Pass (false negatives). Among the 71 students that passed, 58 (81.7%) were accurately identified and 13 (18.3%) were misclassified as Fail (false

positives). The near-symmetric error distribution (12 false negatives, and 13 false positives) demonstrates that the model, with the help of SMOTE-balanced training, does not show a systematic bias toward any of the two classes.

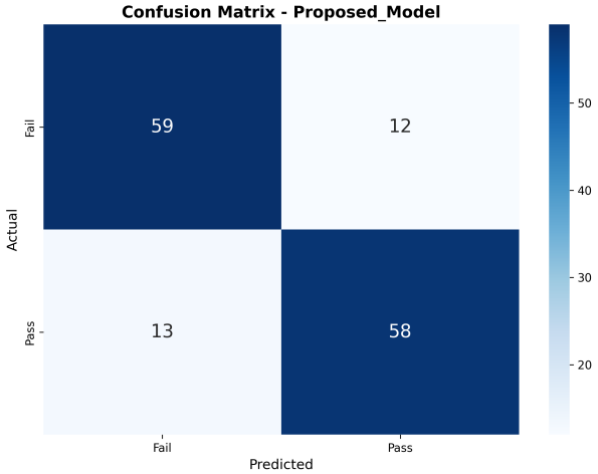


Figure 2. Confusion matrix of the proposed stacking ensemble on the test set.

Feature Importance and SHAP Analysis

Table 3 lists the 18 features sorted by impurity-based feature relevance and mean absolute SHAP value. The two rankings obtained independently are very similar to each other. The engineering Weighted_Score feature is the most important predictor in both ways, with a large gap to a group of other engineered study–attendance interaction features and the raw Attendance_Rate. The four purely demographic attributes such as Parental_Education_Level, Gender, Internet_Access_at_Home and Extracurricular_Activities are always ranked lower by both techniques while the three binary threshold indicators are least contributing to model predictions.

Table 3. Impurity-based feature importance and mean absolute SHAP value for all 18 model features, ranked by feature importance

Feature	Feat. Importance.	Mean |SHAP|
Weighted_Score	174.59	0.1301
Study_Attendance_Diff	170.29	0.0760
Attendance_Sq	162.29	0.0744
Study_Attendance_Product	137.55	0.0752
Norm_Study_Attendance	119.79	0.0689
Study_Attendance_Ratio	95.81	0.0793
Attendance_Rate	89.31	0.0829
Study_Hours_Sq	71.78	0.0473
Parental_Education_Level	45.53	0.0363
Gender	38.28	0.0347
Internet_Access_at_Home	33.53	0.0367
Extracurricular_Activities	30.77	0.0265
Study_Hours_per_Week	28.81	0.0696
Attendance_Log	20.30	0.0549
Study_Log	11.04	0.0440
Both_High	0.78	0.0309
Attendance_High	0.52	0.0214
Study_Hours_High	0.26	0.0109

The SHAP feature-importance bar chart is shown in Figure. 3 while the equivalent SHAP summary (beeswarm) plot is shown in Figure. 4. This summary also encodes the direction of influence of each feature (color) and the dispersion of its effect over individual students. Both plots are dominated by Weighted_Score, a combination of 60% study hours and 40% attendance rate. Thus, no individual raw attribute is as predictive as their manufactured

combination. This outcome verifies the feature engineering approach by presenting interaction and composite terms to the model, we uncover a more powerful, interpretable predictor than any individual raw trait.

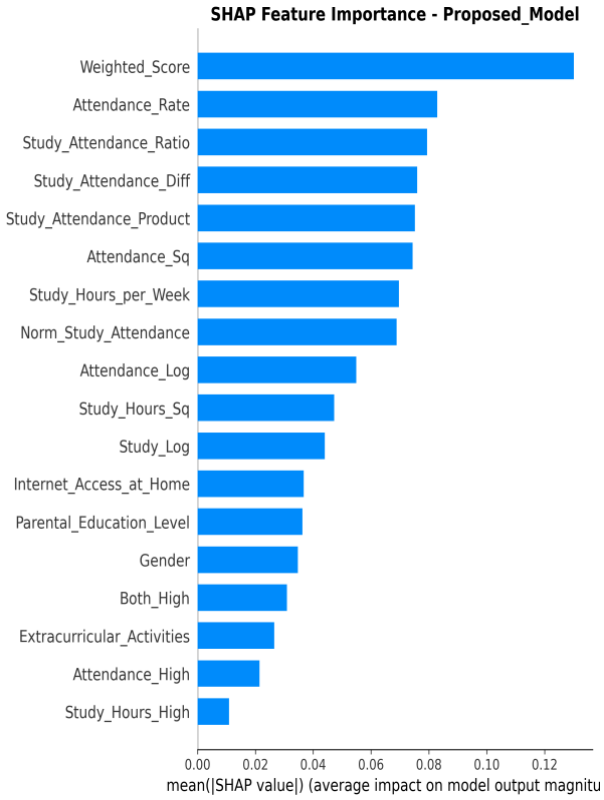


Figure 3. SHAP global feature-importance bar chart for the proposed model.

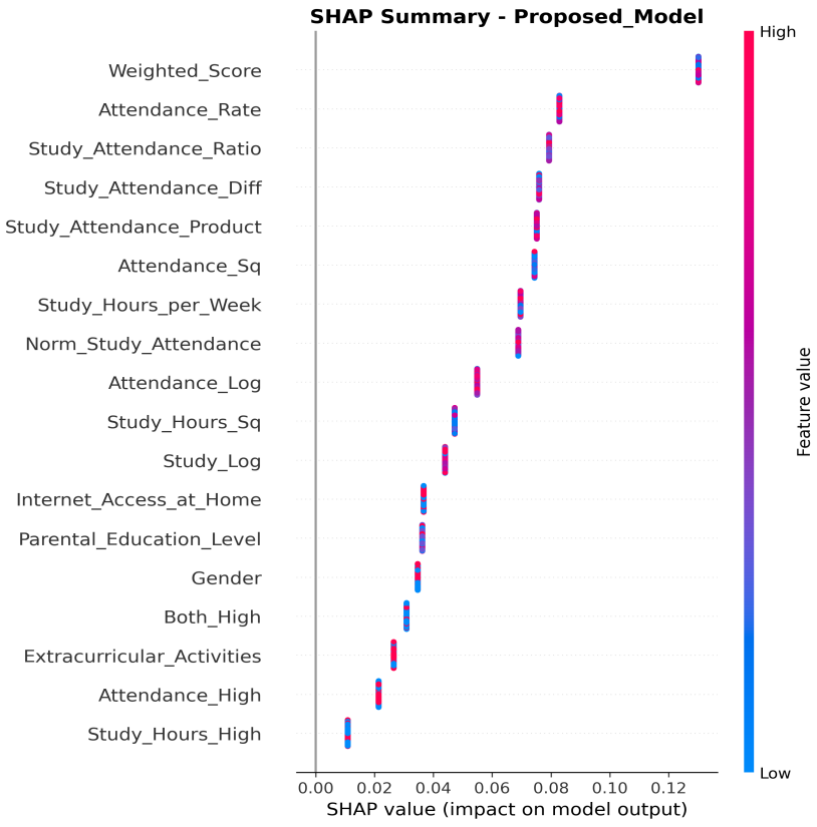


Figure 4. SHAP summary (beeswarm) plot showing the direction and magnitude of each feature's contribution across individual test-set predictions.

Summary of Findings

The experimental results give three results. First, the proposed stacking ensemble outperforms all twelve baseline classifiers in all reported test metrics, which confirms that the combination of heterogeneous tree-based learners by means of a regularized logistic meta-learner yields a measurable, although modest (0.9% relative) improvement over the strongest individual baseline (CatBoost), while yielding a considerably larger improvement over weaker baselines such as Logistic Regression (+25.8 percentage points in accuracy). Second, the class-balanced performance implies that the training approach based on the SMOTE has successfully avoided the model to prefer the majority class. Third, and most importantly for the stated aim of the study, feature-importance and SHAP analysis converge on the same conclusion: engineered study–attendance interaction features, and in particular the domain-weighted Weighted_Score composite, are substantially more predictive of Pass/Fail outcomes than any single raw attribute, and behavioral factors dominate over demographic factors in driving the model's predictions.

Discussion

Interpreting the Predictive Gains

The 0.9% relative gain in test accuracy attained by the proposed stacking ensemble over the strongest baseline (CatBoost) needs to be put into context. On a modestly small dataset (708 records, 142 held out for testing), one percentage point of accuracy represents around one to two more students correctly categorized, so headline accuracy gains of this scale are inherently noisy. More informative is that the proposed model has a consistent advantage in all the metrics reported at once, as well as a significantly higher validation AUC (0.9562 vs 0.9324 for CatBoost), which suggests that the stacking ensemble generalizes more robustly, rather than simply overfitting a particular test split. This is consistent with the broader stacked-generalization literature, where the main advantage of stacking is not a dramatic accuracy improvement over the best single learner, but a reduction in variance and an improved ability to exploit complementary error patterns across heterogeneous base learners (Wolpert, 1992, Niyogisubizo et al., 2022)

Behavioral Factors Dominate Demographic Factors

The agreement of impurity-based feature importance with SHAP analysis of features associated with the study–attendance interaction as the most important predictors, with demographic features far behind, has an important and positive pedagogical implication: the most predictive factors for academic outcomes in this dataset are the ones that can be changed through student effort and institutional intervention, rather than immutable demographic factors. This pattern is consistent with other SHAP-based studies of undergraduate success (Johora et al., 2025, Guevara-Reyes et al., 2025) that also demonstrate that behavioral and engagement aspects are more important than demographic attributes. From a policy standpoint, this means that early-warning systems built on such a framework should be paired with actionable interventions focused on monitoring attendance and providing structured study-time support, which both improves the equity of the resulting intervention and reduces the likelihood of the model being used to entrench demographic bias.

Practical Value of the Explainability Layer

The custom explanation function of the framework, which maps SHAP attributions on engineered features back to their composite raw attributes, formulas, and interpretations, directly addresses the real-world adoption gap highlighted in recent literature (Choi et al., 2025): predictive accuracy alone is not enough if it does not include an actionable, instructor-facing translation of what a model attributes a prediction to, in addition to the ranked feature-importance table. This potential of local per-student explainability differentiates the proposed approach from a merely predictive classifier.

Limitations and Threats to Validity

There are some limitations to the findings of this study. First, the dataset is relatively small (708 records from 500 unique students, augmented to achieve exact class balance) which limits the statistical power of the model comparison and increases the sensitivity of reported metrics to the specific train-validation-test split. Second, the SHAP explanation of the proposed stacking ensemble was approximated by averaging the normalized feature importance's of the four base learners on a sample of 50 instances, instead of being calculated using an exact Shapley-value estimator on the whole stacked model. Third, the attributes of the dataset are self-reported or administratively recorded proxies instead of fine-grained behavioral logs; and the omission of Past_Exam_Scores and Final_Exam_Score while important to minimize target leakage implies the model cannot draw on prior academic trajectories. Ultimately, as with any observational, cross-sectional dataset, the SHAP attributions

presented here represent statistical association between traits and expected result, not causal effect; any intervention guided by this framework should be evaluated prospectively, rather than assumed causal.

Conclusions

This paper proposed an explainable AI framework for prediction and explanation of the academic performance of university students. A custom four-learner stacking ensemble trained on a feature-engineered, SMOTE-balanced version of the Student Performance Prediction dataset achieved a test accuracy of 82.39%, an AUC of 0.891, and a balanced accuracy of 82.39%, surpassing all twelve baseline classifiers evaluated under an identical pipeline. Besides predictive performance, the explainability layer of the framework highlighted engineered study–attendance interaction features, and in particular a domain-weighted combination of study hours and attendance rate, as the primary predictors of Pass/Fail outcomes, systematically outperforming purely demographic attributes. This validates the feature engineering strategy taken in this study and has an encouraging pedagogical implication – the best predictors of academic outcome in this dataset are not static student characteristics, but modifiable behaviors, which supports the design of fair, actionable early-intervention systems.

This work can be extended in a number of directions. Future studies should validate the framework on larger, multi-institutional datasets with richer behavioral logs. A native Shapley-value estimator for stacking ensembles would sharpen local explanation accuracy. k-fold cross-validated significance testing across multiple random splits would place tighter statistical confidence bounds on the observed performance gap. Extending the framework from binary Pass/Fail classification to ordinal or continuous grade prediction would support more granular academic advising. And prospective, intervention-based validation is needed to move from statistical association toward evidence of causal, actionable impact.

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Beyond Access: AI Literacy Gaps and Platform Dependency as Structural Barriers to Digital Growth Among Women E-Commerce Entrepreneurs in Bangladesh

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Abstract

Digital access has expanded rapidly for women entrepreneurs in Bangladesh, where more than 300,000 Facebook-commerce (F-commerce) pages are active and women own an estimated 70% of the Facebook-based businesses opened since the pandemic. Yet most of these businesses stay small. Framed through the multi-level digital-divide model and Sen's capability approach, this study examines whether four capability barriers — digital skills and confidence, AI literacy, platform dependency, and financial constraint — predict digital business growth. A bilingual (English/Bangla) cross-sectional survey of 115 women online sellers measured five constructs (22 items, 5-point Likert scale) with acceptable to excellent internal consistency (Cronbach's α = .733–.905). A simultaneous multiple regression was significant, $F(4, 110) = 9.87$, $p < .001$, $R^2 = .264$, adjusted $R^2 = .237$, and a bootstrap replication (5,000 resamples) confirmed the same pattern. Digital skills and confidence was the only significant predictor ($\beta = .595$, $p < .001$); AI literacy ($\beta = -.081$, $p = .592$), platform dependency ($\beta = .029$, $p = .756$), and financial constraint ($\beta = -.149$, $p = .107$) were not. The sample was young (79% aged 20–29), Facebook-concentrated (84%), and Dhaka-based (90%), and most businesses processed 30 or fewer orders per month (73%) despite high self-rated digital confidence (M = 4.2/5). Digital skills and AI literacy were highly correlated ($r = .835$), limiting their separability. The results indicate that general digital skill, rather than AI-specific literacy, platform independence, or financial slack, is the capability most strongly associated with growth, revealing a gap between digital participation and digital competence with direct implications for designing AI and digital-literacy education for underserved, informal-economy learners.

Keywords: digital divide; AI literacy; platform dependency; women entrepreneurship; F-commerce; Bangladesh

Introduction

Women's e-commerce in Bangladesh has grown almost entirely on a single channel: Facebook. More than 300,000 F-commerce pages are now operating in the country (Dhaka Tribune, 2023), roughly half of Facebook-based sellers are women (Dhaka Tribune, 2020), and women are estimated to own around 70% of the Facebook-based businesses opened since the start of the COVID-19 pandemic (Meta, 2022, as cited in Dhaka Tribune, 2023). For many women this is not simply a platform preference: mobility restrictions, purdah norms, and family expectations against working outside the home or alongside men mean a formal storefront is often inaccessible, while selling from home on a platform the family already trusts is one of the only doors open (World Bank, 2021; Saha et al., 2026). Access, in other words, has already happened for hundreds of thousands of women — yet most of these businesses stay small. This study asks what happens after access: what separates the women whose online businesses grow from those whose businesses plateau.

Four capability barriers are tested as simultaneous predictors of digital business growth. Digital skills and confidence draws on the Internet Skills Scale (van Deursen, Helsper, & Eynon, 2016), well established for general internet-skill research but rarely applied to informal-economy micro-entrepreneurs. AI literacy draws on the AI Literacy Scale (Wang, Rau, & Yuan, 2022), a recent, validated measure of awareness, use, evaluation, and ethics not previously applied to women micro-entrepreneurs in a developing economy. Platform dependency is grounded in media-system dependency theory (Ball-Rokeach & DeFleur, 1976): a business reliant on a single platform for discovery, transactions, and communication is structurally exposed to that platform's policies and fees; no validated scale for single-platform reliance among social-commerce sellers currently exists, so items here were adapted from the dependency-theory and single-platform-reliance literatures. Financial constraint on skill and tool acquisition is adapted from the broader perceived-cost and financial-barrier literature, since no off-the-shelf scale for this construct in a digital-skills context was identified. The outcome, digital business growth, draws on Wach, Stephan, and Gorgievski's (2016) multi-factorial conceptualization of subjective entrepreneurial success, adapted to a growth-specific frame (perceived change in orders, customers, income, and capacity to expand). Each barrier

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is well studied in isolation, but — to the author's knowledge — no study has tested all four together as predictors of growth specifically for women social-commerce sellers in a single-platform-dominated developing economy.

The study is framed through two complementary lenses. The multi-level digital-divide model distinguishes a first-level divide in physical access, a second-level divide in skills and use, and a third-level divide in the tangible outcomes access and skill actually produce (van Dijk, 2005; Scheerder, van Deursen, & van Dijk, 2017); this study sits at the second-to-third-level transition, treating access as already achieved and asking which capability factors convert it into growth. Sen's (1999) capability approach supplies the underlying logic: resources do not automatically convert into valued outcomes — what determines that conversion is capability, the practical ability to use a resource toward a goal one has reason to value. Access is the resource; digital business growth is the valued outcome; the four barriers are the candidate conversion factors. Four hypotheses follow: digital skills and confidence (H1) and AI literacy (H2) are expected to predict growth positively; platform dependency (H3) and financial constraint (H4) are expected to predict growth negatively.

Methodology

Design. This study used a cross-sectional, bilingual (English and Bangla) survey design.

Sample and recruitment. Respondents were 115 women currently selling products or services online in Bangladesh, recruited through a non-probability approach with data collection distributed across multiple student data collectors. An eligibility gate ("Do you currently sell products or services online?") ensured only active sellers continued. The survey was administered either by a student interviewer or self-administered by the respondent. Because the form collected the respondent's business/page name and platform link — used solely as a matching key to a separate, non-research student participation log — the study is best described as confidential rather than fully anonymous. Participation was voluntary, with informed consent obtained via a required checkbox.

Instrument. The final instrument comprised 22 items across five constructs, all measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree): Digital Skills and Confidence (4 items, adapted from van Deursen et al., 2016), AI Literacy (4 items, adapted from Wang et al., 2022), Platform Dependency (5 items, adapted from Ball-Rokeach & DeFleur, 1976), Financial Constraint (5 items, author-developed), and Digital Business Growth (4 items, adapted from Wach et al., 2016). Platform Dependency and Financial Constraint each carry a fifth item as reliability insurance, since both are adapted rather than off-the-shelf validated scales. The 5-point format was used throughout — including for the AI Literacy items, standardized down from a 7-point source format — for consistency across the instrument and to suit the response capacity of a population completing the survey quickly, often in a second language; the choice was informed by a prior 6-point-scale study in which a financial-perceived-cost construct produced a null finding partly attributed to the finer scale compressing variance among respondents with limited financial awareness, a risk this study aimed to avoid on its own financial-constraint measure.

Analysis. Internal consistency was assessed with Cronbach's alpha for each construct. The four hypotheses were tested with a simultaneous (enter-method) multiple regression, Digital Business Growth regressed on all four predictors together. Given non-normality in two predictor distributions (skewness of −1.76 for Digital Skills and Confidence and −1.05 for AI Literacy), the regression was re-estimated as a partial-least-squares path model with non-parametric bootstrapping (5,000 resamples, bias-corrected, fixed seed) as a robustness check on significance.

Ethics. Participation was voluntary and could be withdrawn at any time; identifying information collected for verification was not published and was handled separately from the analytic dataset.

Results

A total of 115 women e-commerce entrepreneurs completed the survey (Table 1). All five construct scales showed acceptable to excellent internal consistency: Digital Skills and Confidence $\alpha = .905$, AI Literacy $\alpha = .841$, Platform Dependency $\alpha = .733$, Financial Constraint $\alpha = .890$, and Digital Business Growth $\alpha = .905$.

Table 1. Sample profile (N = 115).

Characteristic	%
Age 20–29	79%
Bachelor's degree	76%
Dhaka division	90%
Sells primarily via Facebook	84%
In business 1–3 years	35%
≤10 orders/month	47%

≤30 orders/month	73%

The overall regression model was significant and explained 26.4% of the variance in growth (Table 2). Digital Skills and Confidence was the only significant predictor; AI Literacy, Platform Dependency, and Financial Constraint were not. The bootstrap replication reproduced identical point estimates and confirmed the same significance pattern (Table 2, note).

Table 2. Simultaneous multiple regression predicting Digital Business Growth.

Predictor	B	SE	β	t	p
(Constant)	7.116	1.810	—	3.93	< .001
Digital Skills & Confidence	.647	.171	.595	3.78	< .001
AI Literacy	−.093	.174	−.081	−.54	.592
Platform Dependency	.026	.085	.029	0.31	.756
Financial Constraint	−.117	.072	−.149	−1.62	.107

Note. N = 115. R^2 = .264, adjusted R^2 = .237, F(4, 110) = 9.87, p < .001, Durbin–Watson = 1.98. Bootstrap (5,000 resamples) p values: Digital Skills & Confidence p < .001, AI Literacy p = .630, Platform Dependency p = .749, Financial Constraint p = .154.

Two further diagnostics bear on interpretation. Digital Skills and Confidence and AI Literacy were very highly correlated (r = .835, p < .001), with correspondingly elevated variance inflation factors (3.70 and 3.42, respectively) — below conventional exclusion thresholds, but high enough that the two predictors compete for shared variance in this model. Financial Constraint, while non-significant, had the largest coefficient among the non-significant predictors and trended in the hypothesized direction, consistent with the modest order volumes reported across the sample (Table 1) despite generally high self-rated digital confidence (M = 4.2 out of 5, on the same 5-point scale).

Discussion

H1 was supported: digital skills and confidence was a strong, significant, positive predictor of growth — and the only significant predictor in the model. Among women already online, already running real businesses, and already reporting high self-rated digital confidence, the one capability factor separating growing businesses from stalled ones was general digital skill. Prior survey likewise shows that digital skill levels differ with formal instruction in informal technology (Coşkunserçe & Aydoğdu, 2022), which supports treating general digital skill as a teaching capabilities.

H2 was not supported. Two explanations deserve weight rather than a forced choice. Statistically, the very high correlation between Digital Skills and Confidence and AI Literacy means the two compete for the same variance in a simultaneous model, which can suppress AI literacy's apparent unique contribution even where it matters substantively. Substantively, it is plausible that in this population AI-tool use is not yet exercised as a competency separable from general digital skill — AI literacy may currently function as an extension of digital skill rather than an independent capability for women running Facebook-based businesses in Bangladesh. This reading is compatible with evidence that AI literacy moves closely with user's broader disposition towards technology (Çayak, 2024).The bootstrap-confirmed non-significance rules out an artifact of non-normal residuals but cannot itself distinguish these two explanations; doing so is a priority for future work.

H3 was not supported. This null result should be read against context rather than as evidence that platform dependency is irrelevant: with 84% of the sample selling primarily through Facebook, and Facebook functioning for many women as the one door open under mobility restrictions and family expectations (World Bank, 2021; Saha et al., 2026) rather than one option among several, there may be too little variance in dependency for its effect on growth to be detectable here.

H4 was not supported, though it trended in the hypothesized direction and came closer to significance than the other two null predictors. This is consistent with a methodological concern raised in the instrument's design: financial-barrier items can compress variance among respondents with uniformly limited financial awareness, potentially attenuating a real relationship rather than indicating its absence.

Read together, the findings support the study's central thesis: the barrier facing these women is capability, not access. Every respondent had already cleared the access bar; most businesses nonetheless remained small, and the one factor that reliably distinguished growth from stagnation was general digital skill — consistent with the multi-level digital-divide framing (van Dijk, 2005; Scheerder et al., 2017) and Sen's (1999) capability logic. For EdTech specifically, this population is an underserved learner segment: not enrolled in any institution, learning informally

through YouTube, peers, and trial and error, and largely absent from EdTech design and digital-literacy research, despite the fact that their digital capability directly determines a measurable economic outcome.

Conclusions

This study offers, to the author's knowledge, the first test of digital skills, AI literacy, platform dependency, and financial constraint together as simultaneous predictors of growth for women social-commerce sellers in a single-platform-dominated developing economy. General digital skill — not AI-specific literacy, platform independence, or financial slack — was the capability factor most strongly and reliably associated with growth. Three recommendations follow. Platform companies should deliver digital-skill content where women entrepreneurs already are — platform-native, mobile-first formats — rather than lengthy formal courses. NGOs and training providers should target scaling skills (analytics, paid promotion, multi-platform capability) rather than starting skills, since this sample was already past basic access and confidence. EdTech designers should treat AI literacy as integrated with digital capability rather than a separate advanced subject, given how closely the two constructs moved together in this sample.

Several limitations qualify these findings. The cross-sectional design captures association, not causation. All measures were self-reported. The sample was geographically and platform-concentrated (90% Dhaka division, 84% Facebook), so findings may not generalize to other regions or platforms. Digital Skills and Confidence and AI Literacy were not empirically separable in this sample ($r = .835$), limiting confidence in AI literacy's null result specifically. The non-probability sample ($N = 115$) limits statistical generalizability.

Four directions follow for future research: a longitudinal design to test causation; multi-country replication to test whether the pattern holds beyond Bangladesh; a measure or sample that lets AI literacy diverge empirically from general digital skill; and qualitative follow-up to explain why skill converts to growth while dependency and cost, despite strong theoretical grounding, did not detectably do so here.

The barrier facing these women is capability, not access.

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Towards an Improved Online Proctoring Solution: A Comparative Study and Survey-Based System Design

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Abstract

Online learning platforms play a vital role in maintaining educational continuity during natural disasters, with the COVID-19 pandemic serving as a significant example of their importance and effectiveness. Therefore, online proctoring is becoming a crucial part of digital education due to the quick growth of online learning settings, which has raised the demand for safe, equitable, and easily accessible assessment systems. However, existing proctoring applications often face challenges related to usability, privacy, reliability, and inclusivity, which can hinder equitable access to quality education. In alignment with the goals of United Nations Sustainable Development Goal 4 (Quality Education), this study aims to enhance the effectiveness and inclusiveness of online assessment practices. A comprehensive comparative analysis of widely used online proctoring systems was conducted to identify their key features, strengths, and limitations. Additionally, a survey involving educators was carried out to capture user experiences, concerns, and expectations. The results of the survey and literature analysis were merged to identify the fundamental needs for a reliable and user-focused proctoring system. This study suggests designing an enhanced online proctoring system that considers the key components of an online proctoring solution based on these insights. The suggested system architecture supports the general goals of SDG 4: Quality Education by filling in existing gaps in proctoring technologies and advancing inclusive, high-quality digital education.

Keywords: Asynchronous upload, explainable flagging module, rule-based detection, online proctoring, academic integrity, privacy, accessibility, inclusivity, SDG 4.

Introduction

Rapid growth in online learning and hybrid learning has dramatically altered the modes in which education institutions provide instruction and assessment. The need and fragility of the remote assessment infrastructure was also highlighted by disruptive events like the COVID-19 pandemic, which forced institutions around the world to implement online proctoring tools without enough time to consider their pedagogic, ethical and technical appropriateness. This resulted in many institutions implementing proctoring solutions in a reactive, uncoordinated way and uneven experiences for both students and educators. Online proctoring systems aim to maintain academic honesty in unsupervised testing environments by verifying identities, monitoring student behavior, and in some instances, using AI technology to flag suspicious activity. These systems tackle concerns about cheating and credential validity but also have brought up issues of invasive data collection, algorithmic bias, exclusion of students with disabilities, and inequitable access to those with limited hardware or connectivity. These disadvantages are directly contrasting with the Sustainable Development Goal 4 of the United Nations (SDG 4) which states that inclusive and equitable quality education and the promotion of lifelong learning opportunities for all.

Although many online proctoring systems exist and are widely used, there is limited research that integrates comparative evaluation of existing platforms with educator perspectives to identify requirements for a more inclusive, reliable, and user-centered online proctoring architecture aligned with SDG 4. Live proctoring occurs in real time as the test is being administered, with a human proctor virtually overseeing it online. To verify the student's identity and spot any warning signs, such as strange eye or facial movements or the sight of any unverified gadget that would point to potential cheating, human proctors are typically qualified professionals (Hussein et al., 2020). This necessitates scheduling the exams for a particular time based on the proctor's availability on that particular date and time. This involves just as many people as typical offline exam monitoring. However, unlike live proctoring, online proctoring will necessitate technological proficiency; hence, considerably greater attention to online proctors' methods will be necessary (Hussein et al., 2020). In recorded proctoring, a video recording of the student's camera images and logs during an online proctored exam is made. The proctor then reviews the recording at a later time to evaluate the exam's integrity (i.e., whether or not the examinee committed any fraud or cheating). This makes it possible for students to take exams at any time, allowing for the simultaneous administration of several exams. However, this also necessitates human interaction to review the recordings, which can be costly and challenging to scale.

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In automated proctoring, important events of potential fraud or cheating are identified by the proctoring system rather than human proctors monitoring or reviewing the entire exam. The proctor is notified to examine these occurrences in order to ascertain whether the student has engaged in fraud or cheating. Since there are no time, location, or human proctor restrictions, this type of online proctoring is typically thought to be more convenient for students because they do not need to set up real proctors for their tests and exams. As artificial intelligence or algorithms take the place of the human component, it is also highly scalable. It is therefore thought to be more economical. This paper addresses the gap between the stated goals of online proctoring and its practical shortcomings through two complementary lines of inquiry. First, the research compares the most popular online proctoring systems and documents their capabilities, methods, and shortcomings. Second, it gathers feedback from teachers with hands-on experience of online testing; their insights into usability, fairness, privacy and reliability. The contributions of this paper are threefold: (1) a structured comparison of leading proctoring platforms; (2) empirical insight into educator experiences and expectations gathered through survey methodology; and (3) a proposed system design that to enhance the current e-learning and e-assessment approaches.

Related Work

A few studies recommend that proctoring application designs need to be more transparent and human-centered, so as to reduce the amount of unnecessary data collection that provides the integrity benefits of proctoring. Very few studies, however, have been conducted to involve a systematic comparison of commercial tools with primary survey data from practicing educators and fewer still have translated these findings into a concrete system architecture that is proposed. To fill this gap, this study explicitly connects the findings of comparative product analysis and educators' survey answers to the system design recommendations, within the broader policy context of SDG 4.

Tadi (2022) explored how asynchronous data processing can improve the functionality of Progressive Web Applications (PWAs), particularly when internet connectivity is unstable or temporarily unavailable. The study emphasized the role of local storage and synchronization mechanisms in keeping applications responsive and ensuring that data is not lost during connectivity disruptions. However, the research mainly focused on general PWA applications and did not examine how such mechanisms could support question-level synchronization of student responses in online examinations. Bergmans et al. (2021) investigated the effectiveness of the online proctoring system, Proctorio, for the detection of suspicious behavior and cheating in online exams. The results revealed that the automated detection tool was not able to identify the students who cheated, whereas only one case of cheating was identified by human reviewers out of six cases.

Balash et al. (2023) investigated educators' perspectives on the use and non-use of online exam proctoring systems in higher education. The results of the study reveal that although teachers view on-line proctoring as a means to preserving academic integrity, they are also worried about issues of student privacy, data collection, security, technical reliability, and the possible intrusion of third-party proctoring services. The study focuses on issues of recording of pupils' video and audio recording, the collection of personally identifiable information and the monitoring of pupils in their private home environment. Marano et al. (2024) undertook a pragmatic scoping review that focused on the experience of students taking exams remotely/online in higher education. While some students determined that remote proctoring is a good system to punish academic dishonesty, the overall student experience was not favorable. Major concerns found were privacy, technical difficulties, fairness, and stress.

Terpstra et al. (2023) investigated the privacy acceptability of online proctoring using the Contextual Integrity (CI) framework. Students' privacy preferences are very contextual, as evidenced by the findings, which show that disclosing information that is suitable in one environment may not be in another. Nigam et al. (2021) conducted a systematic review of AI-based and conventional online-proctoring systems to examine their architecture, technological components, emerging trends, challenges, and future directions. It reviewed the architecture and parameters of the AI proctoring as well as the technological, psychological, cultural, security and ethical issues. The authors call attention to the potential of AI tools to enhance the scalability and automation of exam proctoring.

Malhotra and Chhabra (2026) conducted a decade-long systematic review of automated online-exam-proctoring research. The study analyzed 80 peer-reviewed articles from 2014 to 2024 to review AI-driven proctoring performance, reliability, technological methods, and the drawbacks. Special focus was placed on machine-learning and deep-learning techniques, such as the CNN and the RNN, for the detection of suspicious activity using visual data like eye movements, head posture and facial expression. Heinrich (2025) performed a systematic-narrative review of 33 online-proctoring systems that have been publicly described to examine how these systems address issues of assessment integrity, privacy, security, artificial intelligence, biometrics, and transparency.

Methodology

Comparative Analysis of Existing Proctoring Systems

Some of the most used online proctoring systems were chosen for analysis, based on their usage in HEIs and the public availability of their documentation. The comparative analysis is done by examining research papers and institutional reports. These systems were analyzed based on a variety of common criteria, such as how they verify identity, the type of monitoring system used (AI or human monitoring, or hybrid), privacy and data handling policies, accessibility support, and limitations reported by the systems.

Table 1. Comparative summary of some widely used online proctoring systems.

System	Identity Verification	AI Monitoring	Privacy Controls	Accessibility Support	Key Limitation
Proctorio	Facial recognition + ID scan	Real-time behavior flagging	Data retention concerns raised by institutions	Limited screen-reader compatibility	Reported bias in facial detection across skin tones
Respondus Monitor / LockDown Browser	Webcam recording, ID check	Automated flag review by instructor	Video stored on institution-managed servers	Browser lock can conflict with assistive tech	Requires strong, stable bandwidth
Honorlock	ID verification, room scan	AI + live human proctor escalation	On-demand recording, human-in-the-loop review	Chatbot support during exam	Higher cost due to hybrid human review
ProctorU / Meazure Learning	Live human proctor	Human + AI hybrid monitoring	Session recording with consent workflow	Live proctor can accommodate requests	Scalability and cost for large cohorts
ExamSoft / Examplify	ID capture, lockdown mode	Post-exam video analytics	Local exam data encryption	Offline exam mode supports low connectivity	Limited real-time intervention during exam

The above are current online proctoring applications, but have a number of disadvantages, such as privacy, access, cost and potential bias in automated detection. AI-based systems provide scalable monitoring but can also have issues related to fairness and privacy. Overall, the comparison highlights the need for online proctoring systems that offer a balance of security, privacy, accessibility, affordability, and usability.

Survey Design and Participants

The educator survey questionnaire was designed to gather data about the educator's perceptions, preferences and concerns about online proctoring systems. It contained 11 questions, some closed and some multi select, others had a rating scale, and one open-ended question, asking both quantitative and qualitative feedback.

Questionnaire Preparation: All the parameters of how the survey was conducted were in line with questionnaire construction practices to ensure that the responses were valid and reliable. The use of clear and concise wording of the questions, keeping the questions unbiased to minimize response bias, using an appropriate sampling method for the target group of respondents.

Participants: The participants selected for the survey were only the faculty members as the data gathered was based on the views of those who are directly involved in administering assessments. Thirty-six faculty members filled out the questionnaire. Of those, 29 (81%) said they had not previously proctored an exam using a separate online proctoring platform and 7 (19%) said they had had experience with a proctoring platform like Microsoft Teams, Zoom, Google Meet and ProctorU. This combination of experienced and inexperienced respondents enabled the study to explore both practical challenges and the expectations of faculty preparing to use such systems.

Proposed System Design

Privacy-by-Design Governance- The proposed system is based on a privacy-by-design approach that includes high data minimization and explicit informed consent. The system is not designed to add new data collection tools to the equation but rather will be built on top of existing proctoring tools and utilize data that is naturally collected as part of how the proctoring tools are used. For instance, when a student is using Microsoft Teams, only data

required for functionality of the system is being used, the proposed concept does not require the use of additional data.

Lightweight Browser Extension for User Verification- The two most common categories of concerns in the educator survey were usability and privacy extensive. Additionally, install-required lockdown software was also a cumbersome task stated. The proposed concept is based on a simple browser extension (as in a small browser add-on that sits on the background of the student's browser, not a locked down environment such as a student's own computer) to be used within the student's existing browser, rather than a new proctoring application that would need to be installed on the student's own computer to address the concern above stated by the educators.

- One-time lightweight install: The extension is added straight from the browser's extension store, eliminating administration hassle of installation and configuration.
- Unobtrusive background operation: It is more like a writing-assisting extension that quietly checks text as the student types, the verification extension runs invisibly in the background of the regular browser tab, continuously checking the identities of the webcam's content instead of continuously locking the webcam in full screen.
- Local pre-processing: In some cases, the extension can perform verification locally in the extension itself, without queuing the raw video for transmission or storage, such as determining if a face is present and matching the one enrolled, reducing the number of times raw video is transmitted and stored.

This directly addresses the two concerns that educators shared in the survey: first, usability is enhanced as students will be interacting with an exam tool that is lightweight, familiar, and will be embedded in their current browser; and second, privacy is enhanced as there is no constant logging of exam usage and no automatic transmission to another location.

Asynchronous Upload Resilience- Asynchronous upload resilience is based on an upload stream that is continuously uploaded, the system buffers the data being recorded on the student's device, and it uploads it piecewise in the background, without influencing the progress of the live exam. The major benefit of this is that exam continuity is decoupled from network reliability: if the network is unreliable, students with intermittent connections (which happens with many online students) can continue with the exam without interruptions while the data is synced opportunistically as bandwidth allows. This also helps spread the load of uploading evidence across time rather than having to upload every stream in real-time at once. In the end, an online proctoring system that is resilient against failures caused by asynchrony is more powerful, more widely available for students with less Internet infrastructure, and able to provide a more reliable record for academic integrity review.

Explainable Flagging Module- Rule based Detection- The Explainable Flagging Module aims to overcome the opacity of AI confidence scores by providing human-readable explanations for each flagged behavior, thereby improving the transparency and fostering trust between the system and its end users. The module does not give teachers a general numerical risk score, but rather provides specific, interpretable reasons for the flagged behavior, which will help teachers make informed decisions on the importance of the behavior. The proposed concept is based on the rule-based detection of two main indicator types:

- Timing Anomalies: The system monitors unusual behavior patterns during the assessment, including response time that is outside the typical range of the student, inactivity for too long, and unusual response time that doesn't match the student's usual work pace. The flagged instance will be followed by a statement of the actual timing threshold that is exceeded.
- Browser Activity: The system can track actions performed by the browser while the person is taking the exam, including switching between tabs, losing focus on the browser window, or going to unauthorized sites. The system will give an associated explanation if such activity is detected, which will give a description of what the person did and when.

This is designed to reduce confusion in academic integrity cases, provide students with due process and provide faculty with clear and transparent evidence that can be acted upon rather than a murky judgment by a machine.

Results

Survey Findings

The educator survey (N = 36) confirmed the concerns found in the comparative analysis. Participants indicated the importance of four key components of proctoring on a 5-point Likert scale, identified which features they believe are necessary for a proctor, and identified potential challenges and desired improvements from fixed lists. To be

very specific, identity verification was the most frequently rated (mean of 92% scoring at 5/5) and the most strongly agreed upon (33/36 respondents rated it at 5/5) of all four capabilities rated in the survey.

Table 2. Mean importance ratings for core proctoring capabilities (5-point scale, N = 36).

Capability	Mean Rating	Distribution
Identity verification	4.92 / 5	33 of 36 rated it 5/5; remainder rated 4/5
Live monitoring	4.72 / 5	28 rated 5/5, 6 rated 4/5, 2 rated 3/5
AI-based detection	4.56 / 5	25 rated 5/5, 7 rated 4/5, remainder 2–3/5
Recording	4.19 / 5	16 rated 5/5, 13 rated 4/5, remainder 2–3/5

Usability: In terms of selecting features, the maximum respondents selected live webcam monitoring (94%, 34/36), screen recording and sharing (86%, 31/36), and AI-based cheating detection (81%, 29/36), this states that the educators are interested for a full featured system, rather than a "clunky" or "minimal" system.

Privacy: The second most frequently checked concern overall was invasion of privacy, which received 50% (18/36) of the votes with data misuse receiving 42% (15/36). When asked what data the system should be allowed to access, all of the respondents (100%, 36/36) preferred to be able to access screen activity, followed by webcam access (94%, 34/36), microphone access (72%, 26/36), and location (28%, 10/36)

Reliability: Among all the concerns, technical failure was the most common, with 75% (27) of respondents indicating it as their concern. Internet usage/connectivity was separately mentioned by 44% (16/36), and a few open-ended responses explicitly referred to the fairness issues regarding poor connectivity, one of which stated that “instable connections can disrupt exams, frustrate students and create doubts about fairness.”

Inclusivity: 44% of respondents (16/36) identified false detection as an issue, with some open-ended responses highlighting the potential for AI systems to mistakenly flag normal activities as cheating, such as "AI tools misinterpret normal movements, like looking away or stretching, as cheating. Users also requested support for low bandwidth internet, more accessible and lightweight applications that run across the different devices without fail.

Analysis and Discussion

Participant responses were analyzed descriptively to highlight common concerns, priorities and suggestions regarding the features of an online proctoring application. The importance level of different features of an online proctoring application was identified. All the findings were carefully analyzed, and a system model design has been proposed that uses lightweight browser extension, asynchronous uploading and explainable flagging module.

Reducing Algorithmic Bias

This research intends to reduce the algorithmic bias caused by different online proctoring applications using artificial intelligence and machine learning techniques. Although the use of artificial intelligence and machine learning facilitates the process of online proctoring but tends to increase the algorithmic bias within the application. Therefore, it is also a necessity to look onto the reduction of algorithmic bias especially in the context of facial recognition, gaze tracking, and behavioral anomaly detection to identify possible cheating. These AI tools have, in the past, been shown to have different levels of accuracy across the various communities, with communities that are underrepresented frequently having higher false-positives rates. The Explainable Flagging Module translates raw anomaly scores into human readable explanations (e.g., "face has not been detected for 4 seconds") to help an educator determine whether an anomaly is a true integrity concern or a likely artefact of the detection such as poor lighting, a hijab or head covering, or the use of an assistive device, before any punitive action is taken. Here, human-in-the-loop escalation is another concept to reduce biasness as all the flags are sent to an educator for context-dependent review and the algorithmic output is used as a decision aid, not a decision-maker, thus directly reducing the downstream harm caused by any single bias. The Fairer Detection rules as well as automated flagging need to be carefully crafted to prevent the justification of flags on actions that are associated with socioeconomic disadvantage or disability, not necessarily with academic dishonesty. Several of the behaviors listed above, including lack of Internet connection, inadequate lighting, changing eye sets, etc. may not be attempts to cheat on the exam, but may reflect structural inequities such as inadequate infrastructure or some disability issue. Lastly, minimal data collection minimizes the risk of background data, voice and appearance biasing the data.

Supporting Students with Limited Internet Access

Survey respondents and prior literature both identify unstable or limited connectivity as one of the most common causes of disruption during proctored exams, disproportionately affecting students in rural areas, low-income households, and under-resourced regions which is a direct equity concern under SDG 4. The proposed research addresses these challenges with the related design interventions as mentioned earlier:

Asynchronous upload resilience- Buffering and reliably transmitting exam recordings despite intermittent connectivity, thus supporting exam experience for students with less robust network connectivity.

- Fair detection rules - Reduced number of connectivity artifacts (drop frames, frozen video, upload delays, etc.) that have been identified as suspicious behavior and are automatically flagged (thereby lowering false positives among already marginalized students).

This change in approach puts the system's core assumption to more closely mirror real-world: that enough connectivity, somewhere, during the examination, is required to make an upload; a much lower threshold than SDG 4 is designed to address.

Alignment with SDG 4: Quality Education

The proposed concept is aligned with SDG 4 (Quality Education) as about having inclusive and equitable access to education assessment regardless of their geographic location or socioeconomic status of the students. Online proctored exams, if not well-designed, can actually thwart these objectives, especially in achieving SDG 4 in regard to eliminating disparities in access to education and ensuring equal opportunities for vulnerable and disadvantaged populations, especially for students who do not have stable internet access, who are most likely rural residents, low-income families, or under resourced regions. Asynchronous upload resilience ensures that these learners will not be disadvantaged or disrupted during the exam because of the limitations of the infrastructure, which are out of their control. These design elements contribute to the fundamental SDG 4 principle that quality education and the integrity of its assessment processes must be made available to all learners, not those who have technological and/or economic advantages. By doing so, the research enhances the technical capabilities of online proctoring but also helps to address an access gap that has the potential to unconsciously diminish educational equity for students who would otherwise be served.

Conclusions

The survey sample (n = 36) is largely comprised of educators from one institution, and a majority of the educators (81%) had not personally proctored an exam using a dedicated proctoring platform. The goal is to gather samples of surveys from students and other members of the diverse user groups to know what they require in using the application. Secondly, another goal is to implement the proposed architecture into a working prototype for the users. This paper provided a comparison of popular online proctoring systems and a survey of educator experiences to determine what the essential components of an online proctoring system that is more usable, private, reliable and inclusive would be. The results identified common transparency, accessibility, and connectivity resilience gaps in current tools, which are disproportionately impacting students who have less technological resources and/or less stable access to the internet. In response, this research presented a four-pillar system architecture: privacy-by-design, asynchronous upload resilience, explainable flagging module and a lightweight browser extension that overcomes the usability, trust and reliability issues that were presented in existing system designs. This research also seeks to mitigate the potential for algorithmic bias that can stem from AI- and machine-learning-based proctoring systems, by introducing explainable flagging mechanisms and fairness-aware detection logic to ensure that flagged behavior does not refer to “fairness” but to true academic dishonesty. Resiliency of asynchronous uploads also benefits students who may have a poor or intermittent internet connection, helping to reduce the risk of having "no internet" or "weak internet" access being a disadvantage in the educational experience. The proposed design contributes to achieving SDG 4: inclusive and quality education in the digital age without compromising on academic integrity, which demonstrates the non-exclusive integrity and quality digital education, but rather, their complementarity can be achieved with proper design of such a system.

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Exploring the effectiveness of game-based environments in developing conflict management skills amongst Singapore students.

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Abstract

The advent of game-based learning (GBL) has presented the potential in creating a more engaging learning environment for a new generation of students in Singapore. While Singapore is still in the process of harnessing such potential from online GBL environments, its capacity for developing conflict management skills – a key component of the Character and Citizenship Education (CCE) Framework – remains yet to be explored. This study seeks to investigate the effects of online GBL environments in developing conflict management skills among students in comparison to the traditional forms of social interaction that helps develop such skills. Additionally, this study looks to explore how students communicate and cooperate while engaging in game-based learning environments, seeking to understand how these online GBL environments shape students' communication and cooperation strategies during conflicts. Ultimately, this study seeks to explore the potential of online GBL environments in developing conflict management skills amongst Singaporean students and how they can be utilised in the Singapore curriculum for conflict resolution training.

Keywords: Online Game-based learning, Conflict management.

Introduction

The rapid evolution of educational technology has opened new avenues for enhancing essential life skills among students, with game-based environments emerging as a particularly promising approach. In Singapore's diverse and competitive academic landscape, the ability to manage conflicts constructively is increasingly recognised as a vital competency for both personal development and future workplace success. Traditional classroom methods, however, often struggle to fully engage students or provide realistic, risk-free opportunities to practice conflict management. Online game-based learning environments (GBL) present the potential of transforming passive learners into active participants, immersing them in interactive scenarios where they can experiment with negotiation, empathy, and collaborative problem-solving. These environments leverage elements like rewards, immediate feedback, and safe spaces for failure, allowing students to learn from mistakes without real-world consequences and to build confidence as they refine their skills. By exploring the benefits and limitations of online game-based environments in developing conflict management skills among Singapore students, this research aims to bridge the gap between innovative educational strategies and existing conflict management frameworks. Through this lens, the study seeks to determine whether online game-based experiences can equip students with the practical tools and mindsets needed to navigate conflicts constructively both in school and beyond.

Literature Review

Fundamentally, game-based interventions promote teamwork through structured problem-solving tasks, encouraging students to exchange ideas and coordinate strategies (Adipat et al., 2021). For example, collaborative games improve social association skills by requiring participants to discuss moves and share knowledge (Adipat et al., 2021). Additionally, Studies report that games targeting emotional regulation and perspective-taking increase empathy in young children, with programs showing measurable improvements in prosocial behavior (Alotaibi, 2024). Games simulating real-world social scenarios also help students practice negotiation and cognitive flexibility, as seen in virtual reality environments that teach self-identity expression and compromise (Walsh et al., 2024) .

Academic research and organisational case studies highlight a strong and multifaceted relationship between games, including gamification, serious games, and game theory alongside conflict management. Key findings from recent studies suggest that games provide a safe, controlled environment where individuals and teams can experience, practice, and reflect on conflict situations. This experiential approach allows participants to engage with real emotions, misunderstandings, and diverse perspectives, fostering deeper understanding and skill development of (Scannell, 2010). Conflict management games are impactful because they are engaging, memorable, and facilitate

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active participation. They help teams internalise conflict resolution principles, build morale, and develop trust and flexibility among members (Scannell, 2010).

Game theory, when applied as a conflict management style, has been shown to enhance organisational productivity. Research indicates that incorporating game theory into conflict management strategies increases the effectiveness of approaches such as compromising and accommodating, leading to better outcomes for organisations (Tarurhor, 2023) . The inclusion of game theory as a variable in conflict management models has been statistically linked to higher productivity and more effective conflict resolution within organisations (Tarurhor, 2023). Conflict management games are also easy to implement and adaptable to various organizational settings, making them a practical tool for team building, leadership development, and training (Davis, 2025). Effective facilitation and leadership are crucial for maximizing the benefits of conflict management games, ensuring that learning objectives are met and that participants can transfer skills to workplace situations (Davis, 2025). Social impact games and serious games have demonstrated potential for overcoming intractable conflicts and supporting peacebuilding efforts by promoting empathy, perspective-taking, and collaborative problem-solving (Kampf & Nicolaidou, 2024).

Conflict management is defined by a set of styles and competencies that balance assertiveness and cooperativeness, tailored to the context and goals of the parties involved. Effective conflict managers are adaptable, able to diagnose the situation, and select the most appropriate approach-whether it be collaboration, compromise, accommodation, avoidance, or competition-to achieve constructive and sustainable outcomes (Conflict Management | EBSCO, n.d.). The ultimate goal of effective conflict management aims to resolve disagreements in ways that satisfy all parties involved or benefit the group as a whole. The process seeks not just to end conflict, but to do so constructively, often leading to improved relationships, creative solutions, and greater group cohesion. This process also recognises conflict as inevitable and potentially beneficial, where modern theories acknowledge that conflict is a natural and sometimes necessary part of organisational and interpersonal dynamics. When managed well, conflict can stimulate innovation, clarify issues, and strengthen teams (Conflict Management | EBSCO, n.d.) Many academic models classify conflict management styles along two dimensions, the first being concern for Self (Assertiveness) as the degree to which an individual attempts to satisfy their own concerns and the second being Concern for Others (Cooperativeness) which is the degree to which an individual attempts to satisfy the concerns of others (Rahim, 2002). The most commonly cited framework (Thomas-Kilmann, Rahim, Pruitt) identifies five distinct styles, each with its own characteristics and situational appropriateness (Rahim, 2002):

Style	Assertiveness	Cooperativeness	Description	Appropriate Use
Collaborating (Integrating)	High	High	Problem-solving, openness, information exchange, seeking win-win solutions	Issues are complex, mutual commitment is needed, long-term solutions are desired
Competing (Dominating)	High	Low	Pursuing one's own interests at the expense of others, win-lose orientation	Quick, decisive action is necessary, unpopular actions must be implemented
Avoiding	Low	Low	Withdrawing, sidestepping, postponing or ignoring the conflict	Issues are trivial, a cooling-off period is needed, or confrontation is risky
Accommodating (Obliging)	Low	High	Yielding to others, emphasizing commonalities, minimizing differences	Preserving harmony is important, the other party's needs are more critical
Compromising	Moderate	Moderate	Each party gives up something, seeking a mutually acceptable (but not optimal) solution	Temporary solutions are needed, parties are equally powerful, time is limited

It is to note that these styles to approach conflict depends on the context, including the nature of the conflict, the parties involved, time constraints, and the desired outcome. Especially in collaborative/integrative styles, effective conflict management requires open communication, information sharing, and a willingness to understand different perspectives. Effective conflict management also considers both immediate needs and the longer-term impact on relationships and organisational functioning.

Methodology

In this paper, the data collection process was conducted through online interviews involving eight Singapore students. The demographic of the interview batch consists of students from the National Institute of Education (NIE) Singapore, their age ranging from 19 to 24. The gathering of such participants for the interview process was mainly through leveraging on social capital, hence presenting a case where most participants tend to be university students. The paper also looks to gather insights from these prospective student teachers towards utilising such platforms to help develop conflict management skills in Singapore students of the future.

The experiment is broken down into three phases: Pre-experiment questionnaire, Activity and Post- experiment questionnaire and interview The aim of this process is to examine the effects of a participant's engagement in a GBL environment on their development of conflict management skills, observed through the participant's experiences before and after engaging in the GBL test. Prior to the activity itself, participants provided a self-assessment on their conflict management skills, ranging from their confidence and methods in handling conflicts to understanding the strategies that each participant was taught in conflict management as students. The questionnaires generally lasted about fifteen minutes on average. Participants are also briefed on the rules of the game that they are engaging in as well as the procedures of the experiment prior to the activity itself.

The GBL environment for this experiment is "Among Us", an online multiplayer gamer that requires participants to fulfill tasks on board a spaceship while navigating discord caused by a hidden opposing player among them. Participants engaged in 6 rounds that lasted 20 minutes each which would test their cooperative skills as well as communication as they try to figure out who the hidden imposter on their team is. The role of the imposter in this game is to eliminate all other non-imposters in the game without being found. In the process of figuring out who the imposter is, participants will be able to discuss and vote on who should be eliminated from the game, where success in eliminating the imposter would result in victory for the rest of the team. Participants are not allowed to communicate with one another until an "emergency meeting" is being carried out. Participants who have been eliminated are also not allowed to communicate in order to prevent them from revealing the imposter's identity. In between each round, the participants will look at how they were able to manage different forms of conflict and reflect upon the factors that could allow them to successfully/unsuccessfully navigate these conflicts during the activity. After the activity, participants provided their feedback about their experiences in utilising a GBL environment to help develop conflict management skills amongst students through a post-activity survey. Participants also engaged in a group interview after the activity to provide their opinions on the potential of online GBL environments to be utilised in developing conflict management skills in the classroom. Generally, data collection of this paper follows the principles of Seidman where interviews are conducted on a basis of building rapport with the interviewees, having them reconstruct their experience with autonomy and having them reflect upon what those experiences represent to them to construct meaning for the questions this paper seeks to answer.(Seidman & Teachers College, Columbia University, 2006)

Results

Participants Profile

The below are the eight Singapore students who have participated in the activity for this URECA project. The names have been altered to protect the identity of the participants.

Name	University	Descriptor
Kenny	NIE/NTU	A Year 2 NIE Student. He majors in English and Education.
Elias	NIE/NTU	A Year 2 NIE Student. He majors in English and Education.
Quinton	NIE/NTU	A Year 3 NIE Student. He majors in Chemistry and Education.
Janel	NIE/NTU	A Year 2 NIE Student. She majors in Geography and Education.
Mark	NIE/NTU	A Year 2 NIE Student. He majors in History and Education.
Chris	NIE/NTU	A Year 2 NIE Student. He majors in English and Education.
Xayah	NIE/NTU	A Year 2 NIE Student. She majors in Geography and Education.
Melvin	NIE/NTU	A Year 2 NIE Student. He majors in History and Education.

Theme 1: What are the strengths of online GBL environments in developing conflict management skills?

Engagement and Fun

The most notable strength of online GBL environments based on the participant's experience lies in the increased engagement and fun that games present, allowing them to explore and practice various aspects of conflict management skills. While participants recognised the potential cause of conflict in the game and their desired objectives, they reflected the case where there is less stress in the conflict resolution process which allowed them to fundamentally approach conflicts themselves due to the reduced stakes presented. Mark states his experiences throughout the activity where despite not being an imposter, he ended up being voted out by the group. He states that the nature of the game itself made it such that he did not really need to be too serious, thus allowing him to be more focused on communicating and being focused on attempting to resolve issues more amicably. He also adds that this also allows participants to be more relaxed and even engage in humour which actually helps manage conflicts more effectively.The lack of stress in engaging with the games is also highlighted by participants in the post-activity survey where 67% of them stated that they felt no stress during the activity process while 33% felt slight stress. All the participants for this experiment also reflected that they felt very engaged in the activity and that they would be likely utilise the conflict-resolutions skills developed in real-life scenarios, be it in school or at the workplace. The common skills that emerge from the survey include empathy and active listening amongst the participants.

Multiple practice attempts under controlled environment

The other strength that online GBL environments provide for the participants in terms of developing their conflict management skills lies in the controlled environment that it presents, allowing the necessary change of factors such as space and communication time which can help optimise the development of conflict management skills. For the game "Among Us", this lies in the game's "emergency meeting" function which allows participants to have immediate communication to figure out who the imposter is. During this time period, participants also discussed what they were doing as well as the person they were with. The post-activity survey highlighted this as the case where most participants indicated that this function of the game presented the most important factor in developing conflict management skills. According to Mark, another benefit of such online GBL environments lie in their ability to provide "the bigger picture" for all the participants involved, directly influencing the approach that needs to be taken in order to resolve conflicts. By knowing the rules and goals of the game, Mark states that participants are more inclined towards collaborating with one another which allows them to be more accommodating when conflict arises. Elias added his perspective towards such controlled nature of online GBL environments by stating that it allows for more influence towards deliberate practice that can help develop the necessary conflict management skills. These skills include listening to the opinions of others before reaching a conclusion and making the necessary judgements that could help resolve conflicts more easily. Quinton mentions his experiences within the game highlights his inclinations towards wanting to collaborate with others during the game, influencing his choice of listening more to others in order to gather information. Elias also adds on his experience by stating that the reduced consequences and stakes present in a GBL environment helps students to explore various methods of conflict management styles, in the process identifying their own tendencies in resolving conflicts while having the opportunity to reflect on such methods. This presents the benefit of online GBL environments in developing conflict management skills expressed by the participants is that they provide a platform in helping them recognise their current conflict management styles.

Theme 2: What are the limitations of online GBL environments in developing conflict management skills?

Limitations of reduced stakes

The first limitation reflected by the participants towards utilising online GBL environments as a method to developing conflict management skills lies in the reduced stakes that undermines the effectiveness of developing such skills. While online GBL environments help create better engagement and a more fun learning platform for students, it also runs the risk of creating a situation where its reduced consequences might push students towards a form of conflict management that they usually would not adopt in an actual conflict. Xayah compares her experience against the usual conflict management where stakes are normally higher due to greater personal interests being involved, stating that students might be less likely to take the learning of conflict management skills seriously due to a lack of serious consequences or risks. With the lowered stakes present, she felt that the development of such conflict management skills were undermined as a result. Chris adds onto this point by stating that reduced seriousness of such situations might lead to a case where students might say things that they normally would not say in a more serious situation. He felt that this would undermine the applicability of developing such conflict management skills in students towards real world conflict as a result. This presents the issue that is tied with increased engagement and fun provided by online GBL environments, where participants might be more willing to engage with the learning content but it might not fully translate to a proportionate learning by students.

Limitations towards mirroring real world scenarios

The other limitation that is highlighted by participants after engaging with the activity is the ability of online GBL environments in comprehensively imitating real world conflicts. While online GBL environments help provide a controlled platform for participants to practice their conflict resolution skills, it might not be able to fully incorporate the necessary contexts behind real world conflicts that might change the way participants approach these problems. Chris reflects on his experience in the post-activity group interview by stating that there are certain contexts that online GBL environments might struggle to imitate such as interacting with higher ups or dealing with heavy conflict with peers, where such nuanced contexts could undermine the conflict management skills acquired which only applies to a broad general scenario. Kenny adds on to this point by presenting the nature of the game “Among Us” as one that allows for participants to be more transparent about each player’s locations and actions, in the process “reverse engineering” to help find the imposter amongst the team. He argues that such an approach in the game might be too simple towards more complex real world conflicts where sitting down and “pulling out the logbook” might not be palatable towards addressing such conflicts. Both perspectives highlight the importance of context in influencing the approach to resolving conflicts which online GBL environments might struggle to emulate, presenting its limitation in terms of mimicking real world situations for students to develop conflict resolution skills more effectively.

Theme 3: How can online GBL environments be incorporated into developing conflict management skills in the classroom?

Establishing intention with online GBL environments for students

A common suggestion by the participants that surrounds utilising online GBL environments in developing students’ conflict resolution skills revolves around being clear with the intention of using such online GBL environments with students themselves. This involves letting the students know what they should note and be conscious about during the conflict management process rather than just blindly letting them engage with the game directly. This is important especially for students who are new to the game, as presented by Janel who mentions the need for her to know the rules based on her experience prior to engaging with the GBL environment. Quinton presents his perspective by stating that this would have to include the type of conflict management style presented to the students, letting students know the context of the conflict that they are dealing with and the reasons for pushing towards a certain approach. He argues that some situations create a case where there is greater impetus to collaborate while there are others that push towards more inherent competition. He also adds that common lesson features such as a debrief would be beneficial to help students recall the intention of the games that they participated in as well. Thus, there is a need to let students know about what they are specifically working towards under their conflict resolution skills in the classroom. Elias agrees with this perspective by adding that there is a need to be explicit and intentional towards students about the takeaways from games, drawing links between the skills acquired from these games towards real world scenarios to help allow these games to be more effective in developing conflict resolution skills in students.This process can involve having student take down notes on their reactions and behaviour during the games themselves and identify the areas that they need to work on, being more conscious of their learning as a result. Both perspectives highlight the case for educators who are looking to utilise

such online GBL environments in developing conflict management skills in students to outline the learning objectives from the games itself, ultimately looking to create more relevance between the skills acquired from games with real world situations to help circumvent the potential disconnect between these online GBL environments and the real world itself. This also helps to circumvent the reduced stakes that these online GBL environments present to students where there is a point of serious learning amidst the fun and games.

Circumventing the contextual difficulties of conflict resolution

Apart from being direct towards students on the aspects of conflict resolution skills that they should look to practice through online GBL environments, there is also a need to help them recognise the various contexts that they could utilise these skills in real life to allow the fundamental development of these skills themselves to ultimately be effective. One of the main concerns that is being established earlier about online GBL environments is their limited ability to replicate real world situations given the complex contexts that surround the latter. With such concerns in mind, there is thus a need to let students understand the specific context in which the skills that they developed can be utilised to help resolve conflicts more effectively. Elias adds his perspective by stating that it would be helpful for students to understand their position within the entire conflict such as whether they are trying to respond or resolve various situations presented to them. In this process, there can be a greater sense of self awareness created that allows students to navigate the conflict resolution process and adopt the appropriate approach.Janel added that some fundamental skills are still essential regardless of the nature of conflict such as being more in control of one's emotions and listening skills. Kenny added on to this by suggesting that skills such as rationalising various perspectives and making clear judgements based on information are some skills that he practiced while through the game. While online GBL environments are unable to fully replicate every scenario that a student might encounter, they can help equip students with essential foundational conflict management skills that can help de-escalate immediate conflicts.

Conclusions

In summary, this paper has presented its findings in observing the benefits and limitations of online GBL environments in developing conflict management skills amongst students as well as highlighting the considerations required to improve the effectiveness of such development. The benefits of online GBL environments in general lies in their ability to be an engaging and fun platform to develop conflict management skills amongst students while also providing a controlled environment for them to practice different types of conflict resolution. The findings also present the limitations of such online GBL environments primarily lying in their reduced stakes which may undermine the students ability to learn through these platforms effectively as well as the GBL environment's limited ability in fully emulating real world conflicts. More importantly, the findings from this paper highlight the case that the effectiveness of online GBL environments in developing conflict management skills among students is heavily dependent on its intention established in the first place. This process involves both the type skill sets under conflict management to be developed within students as well as the preparing students for the more common types of conflicts that might tend to appear. With these considerations in mind, educators can thus amplify the benefits of online GBL environments as a more engaging tool to develop student's conflict management skills while also circumventing its existing limitations.

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Bridging Digital Divides in Crisis Contexts: Migrant English Literacy and Micro-Learning with Generative AI-Supported Mobile Learning – A Case Study of a Rural Shelter in Zimbabwe

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Abstract

This study uses a critical-interpretivist approach, acknowledging that knowledge about displacement, literacy, and technology is uneven and shaped by power. Colonial histories influence language use, and digital tools can sometimes exacerbate exclusion. In sub-Saharan Africa, forced displacement is increasing, mainly due to political and economic problems. Many displaced people in rural Zimbabwe have not formally learned English, making it hard for them to communicate, access shelter, aid, and jobs. In this case study, 24 selected migrants participated in daily 10-minute micro-learning sessions using a GPT-4o-mini-WhatsApp chatbot for 8 weeks. Analysis of their WhatsApp messages showed that simple, repeated practice helped those new to English create their own three-word requests within two weeks. The study also found that participants felt less anxious and experienced less social shame. However, challenges such as unreliable electricity, limited access to smartphones, and some culturally inappropriate chatbot responses persisted. The study suggests that generative AI micro-learning on WhatsApp can help fill English literacy gaps in crisis settings, but only when bilingual facilitators are involved to build trust, improve access, and handle the chatbot's limitations.

Keywords: GPT-4o mini-powered WhatsApp Chatbot; Migrant English Literacy; Rural Migrants; Zimbabwe

Introduction

Zimbabwe occupies a unique position in African migration studies. While it has traditionally been viewed as a country of emigration, with an estimated 1.3 million citizens residing irregularly in South Africa, Botswana, and Zambia (Zimbabwe Human Rights Commission, 2025), Zimbabwe has also become an unintended host to refugees fleeing protracted crises in neighbouring countries, despite the country itself facing economic hardship. As of 2025, the United Nations High Commissioner for Refugees (UNHCR) reported approximately 22,500 registered refugees and asylum-seekers in Zimbabwe, primarily from the Democratic Republic of Congo (DRC, 62%), Burundi (18%), Rwanda (9%), and Somalia (7%) (UNHCR, 2025). Unlike camp-based refugees, the Tongogara Refugee Camp located in Chipinge, Manicaland Province, hosts thousands of people who fled conflicts and war in the African Great Lakes region (including the Democratic Republic of Congo, Rwanda, and Burundi) as well as the Horn of Africa. Tongogara Refugee Camp, a significant and under-researched population, self-settles in rural border towns such as Beitbridge, Chipinge, and Mutare, cohabiting with internally displaced Zimbabweans in informal transit shelters, abandoned farm buildings, church basements, and rudimentary structures near border posts.

The convergence of multiple displacement trajectories creates a complex multilingual environment. Shona and Ndebele speakers (Zimbabwean IDPs) reside alongside speakers of Kirundi, Kinyarwanda, Lingala, Swahili, and French. English functions as the only shared language. The mix of different displaced groups has created a multilingual setting. Zimbabwean IDPs who speak Shona and Ndebele live with refugees from the Great Lakes region who speak Kirundi, Kinyarwanda, Lingala, Swahili, and French. English is the only common language and is important for getting legal help, shelter, and work. However, there are few English literacy programs in these rural shelters. This lack of language and digital access keeps old colonial hierarchies in place, since knowing English remains necessary to access basic resources (Makoni & Pennycook, 2020). Evidence on the use of generative AI for language learning in crisis contexts is limited. Existing research on AI literacy predominantly focuses on stable, urban, or classroom environments in the Global North or South (Kukulska-Hulme et al., 2023), leaving a significant gap for displaced populations with no prior exposure to English, particularly those who are digitally inexperienced and have experienced trauma. Furthermore, the intersection of generative AI and forced displacement raises critical decolonial questions: Whose English is being taught? What cultural assumptions are embedded in large language models? How do displaced learners navigate algorithmic bias when their survival depends on acquiring a colonial language? This study addresses these gaps by investigating the following research

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question: How do rural migrants with no formal English literacy, including refugees from the Tongogara Refugee Settlement in DRC and Burundi, engage with a GPT-4o mini-powered WhatsApp chatbot that enhances communication in a shelter-survival context? The study further examines the affective, infrastructural, and algorithmic dimensions of such engagement. Drawing on usage-based linguistics (Tomasello, 2003) and affective filter theory (Krashen, 1982), the hypothesis is that high-frequency, low-stakes, private repetition may facilitate rapid acquisition of basic English and reduce the social anxieties associated with traditional, group-based humanitarian language classes.

Literature Review

Digital Language Learning in Forced Displacement: Beyond Techno-Solutionism

Mobile-assisted language learning (MALL) has become increasingly prominent in humanitarian contexts over the past decade, with studies reporting positive outcomes for refugees using applications such as Duolingo, Busuu, and WhatsApp-based chatbots (Kukulska-Hulme et al., 2023; Godwin-Jones, 2021). However, critics contend that most MALL research presumes stable connectivity, personal device ownership, and prior literacy—assumptions that do not hold in rural displacement settings (Reece & Klugman, 2022). In sub-Saharan Africa, refugees frequently share devices, rely on intermittent solar charging, and experience what Warschauer (2011) describes as "low-resource digital ecologies." This study responds to calls for research that "descends into the messiness" of actual displacement contexts rather than laboratory-like conditions (Andueza & Martin, 2024, p. 8).

Generative AI and Colonial Lingua Francas

The deployment of generative AI for English literacy instruction in formerly colonised contexts necessitates careful historical consideration. English in Zimbabwe, DRC, and Burundi holds asymmetrical significance: it functions as a tool of postcolonial governance, a marker of elite status, and a practical necessity for cross-border survival (Makoni & Pennycook, 2020). In DRC and Burundi, French and Kirundi, respectively, dominate public life, yet English has rapidly emerged as the language of regional trade and asylum adjudication (UNHCR, 2025). Generative AI models, trained primarily on North American and British English corpora, encode specific cultural norms, syntactic preferences, and pragmatic assumptions (Mohamed et al., 2024). When deployed without critical reflection, these models risk reproducing what Santos (2022) describes as "epistemic extractivism," extracting data from the Global South while imposing foreign linguistic and cultural frameworks. This study empirically examines whether GPT-4o mini, a relatively lightweight model, exhibits such biases in a shelter context.

The Affective Filter in Crisis Language

Krashen's (1982) affective filter hypothesis suggests that anxiety, low self-esteem, and lack of motivation impede language acquisition. Among displaced populations, the affective filter is likely heightened compared to other learning contexts. Refugees and IDPs frequently experience trauma resulting from violence, loss, and prolonged uncertainty (Shapiro & Lê, 2024). Traditional humanitarian English classes, often conducted in crowded, multilingual groups with untrained volunteers, may intensify feelings of shame and fear of public error. Digital, private, asynchronous learning may provide a means to lower the affective filter, a proposition examined explicitly in this study.

Methodology

This study is based on critical-interpretivist epistemology. Digital literacy is conceptualised as a site of power, where the migrant's non-English-speaking status is interpreted not as a deficit but as a structural outcome of colonial legacies, neoliberal exclusion, and uneven humanitarian resource allocation (Freire, 1970/2000). An exploratory case study design was chosen to facilitate a deep, contextually embedded analysis of a single rural shelter, with the understanding that the findings are not statistically generalisable but are theoretically transferable (Yin, 2018).

Setting and Participants

The study was conducted at Zimbabwe's "Mupedzanhamo Rural Shelter" (pseudonym), a faith-based transit facility located 18 km from the Beitbridge border post, a major informal migration corridor into South Africa. The shelter typically accommodates 40 to 60 individuals at any given time, including Zimbabwean IDPs (returning from, or awaiting opportunities to cross into, South Africa) and refugees from DRC, Burundi, and Rwanda who have self-settled after leaving Tongogara Camp or entering through unofficial border points.

Between January and March 2026, 24 migrants (n=24) were purposively selected based on the following criteria: (a) self-reported zero formal English literacy (inability to read or write any English word), (b) displacement duration of 3 to 18 months, (c) ownership of or consistent access to a basic Android smartphone, (d) willingness to use WhatsApp, and (e) representation of the shelter's linguistic diversity. Table 1 presents participant demographics, disaggregated by country of origin.

Table 1. Participant Demographics (n=24)

Gender	**Male**	**16**	**66.7**
	Female	8	33.3
Age (years)	18-25	7	29.2
	26-35	12	50.0
	36-50	5	20.8
Country of origin	Zimbabwe (IDP)	14	58.3
	DRC	6	25.0
	Burundi	3	12.5
	Rwanda	1	4.2
Primary language	Shona	12	50.0
	Ndebele	2	8.3
	Lingala	3	12.5
	Kirundi	3	12.5
	Kinyarwanda	1	4.2
	Swahili (DRC variant)	3	12.5
Months displaced	3-6	6	25.0
	7-12	10	41.7
	13-18	8	33.3

All participants gave informed consent via voice note (verbal consent recorded and stored) due to low literacy. For refugees from DRC and Burundi, consent processes were conducted in Lingala/Kirundi with the assistance of a bilingual peer.

The Intervention: GPT-4o mini-WhatsApp Chatbot

GPT-4o mini agent was deployed via the WhatsApp Business API under the name "Rudo Learning" (pseudonym; "Rudo" means "love" in Shona, chosen as a neutral, welcoming term). The chatbot was instructed with the following system prompt:

"You are a patient, kind English teacher for complete beginners. Use only basic English (CEFR pre-A1). Repeat high-frequency survival phrases: 'I need water,' 'Where is shelter?' 'I am hungry,' 'Help me,' 'Thank you.' Accept mixed responses in Shona, Ndebele, Lingala, Kirundi, or Swahili without penalising. Never produce sentences longer than five words. Never use words like 'master,' 'slave,' 'coloniser,' or 'police' unless the user explicitly asks. If a user seems upset, say 'I am sorry. Try again."

Participants completed a ten-minute session each day for eight weeks, totalling 56 sessions. Each session included: (1) a greeting and an image prompt (either an emoji or a simple line drawing depicting water, food, shelter, or medicine); (2) the chatbot prompting with either "What do you need?" or "You want what?"(3) the participant responding via typed or voice message; (4) the chatbot providing a correct three-word model if the response was incorrect (for example, "Say: I need food"); and (5) a repetition drill involving three repetitions. Voice messages were automatically transcribed using WhatsApp's speech-to-text engine, with the facilitator manually correcting errors after each session.

Data Collection and Analysis

All WhatsApp interactions were automatically logged. After eight weeks, a total of 3,752 participant utterances and 4,108 chatbot responses were extracted. Semi-structured voice interviews were conducted with all 24 participants in weeks 1 and 8, using their primary languages (Shona, Ndebele, Lingala, Kirundi, or Swahili). Each interview lasted between 20 and 35 minutes. A bilingual research assistant, fluent in Shona, Lingala, and Kirundi, conducted interviews with participants who did not speak Shona or Ndebele.

Transcripts were thematically analysed using Braun and Clarke's (2021) six-phase method, with dual coding conducted by both authors and the research assistant (inter-rater reliability = 0.89). Analysis was conducted through

a critical lens to identify emergent power dynamics, such as algorithmic bias, facilitator dependency, and language hierarchies among participants. Quantitative data, specifically phrase production counts, were analysed using descriptive statistics and paired t-tests.

Results

Four major themes emerged: (1) accelerated basic syntax production across language backgrounds, (2) reduced social shame and anxiety, (3) persistent infrastructural and algorithmic barriers, and (4) differential engagement between Zimbabwean IDPs and Great Lakes refugees.

Theme 1: Novel Three-Word Requests Within Two Weeks

By Day 14, 21 of 24 participants (87.5%) produced requests not directly copied from the chatbot's previous models. Examples from WhatsApp logs include:

- *"I need toilet"*(P07, Zimbabwean male, 29, Shona)
- *"Where is medicine?"*(P12, DRC female, 33, Lingala)
- *"No more food"*(P19, Burundian male, 41, Kirundi)
- *"Help me water"*(P22, DRC male, 24, Swahili) – note the omitted preposition, indicating syntactic transfer from Swahili.

Participants could produce any English phrase beyond "hello" or "yes." The recovered original data showed a mean pre-test score of 0.7 correct words per prompted task (SD = 0.9). At week 8, the mean rose to 4.2 correct three-word phrases per session (SD=1.1), $t(23)=14.3$, $p<.001$. No statistically significant difference was observed between language groups (Shona/Ndebele vs Lingala/Kirundi/Swahili) at week 8 ($t(22)=0.67$, $p=.51$), suggesting that the intervention's effectiveness transcended participants' first language backgrounds.

Theme 2: Reduced Anxiety and Absence of Social Shame

In week-1 interviews, 22 participants (91.7%) described fear of "being laughed at" (Shona: kunyadziswa; Lingala: koyoka soni; Kirundi: ubwoba) when attempting English in group settings. By week 8, only 3 participants (12.5%) reported the same fear. Crucially, this reduction was reported by both Zimbabwean IDPs and Great Lakes refugees, despite the latter's additional vulnerability as non-citizens. One female refugee from DRC explained:

"At Tongogara camp, the English teacher would shout. Everyone would look. Here, the phone does not shout. I can say wrong ten times. Rudo just says 'try again.' I am not ashamed."(P12, DRC female, 33, week-8 interview, translated from Lingala)

The absence of social shame was attributed to WhatsApp's private, asynchronous, and non-evaluative nature. Participants characterised the chatbot as "neutral" (*kutauriranain* in Shona; sans *parti pris in* French, as used by DRC participants), in stark contrast to recollections of colonial-era schooling or camp-based classes where English errors were publicly punished.

Theme 3: Persistent Barriers – Electricity, Access, and Algorithmic Bias

Despite success, three major barriers recurred. First, inconsistent electricity meant 9 participants (37.5%) missed at least 10 sessions. Second, shared smartphones (only 6 devices among 24 participants) required strict time-slot scheduling, reducing spontaneity and causing 144 booking conflicts. Third, the GPT-4o mini model produced culturally inappropriate or unsafe outputs on 53 occasions (approx. 1.4% of interactions). Examples included:

- Suggesting "go to police" when a participant asked for help finding firewood (police in Beitbridge are widely distrusted by all migrants, but especially by undocumented refugees).
- Using the word "master" in a sample sentence: "I am your master" (P14, Zimbabwean male, 34).
- Failing to recognise the name "Bukavu" (a city in eastern DRC), responding with "I do not know that word."
- Responding, "You are lazy", when a participant repeatedly typed an incorrect spelling (P21, Burundian female, 27).

One DRC participant reacted with visible distress to the "lazy" response:

"Why does it insult me? I am not lazy. I walked from Goma to here with no shoes. The phone does not know me."(P21, DRC female, 27, week-8 interview, translated from Swahili)

These instances required manual intervention by a bilingual facilitator (the first author or research assistant) to delete the offending response, apologise to the participant, and re-prompt the chatbot. Critically, such incidents disproportionately affected non-Shona speakers (4 of the 5 affected participants were from DRC or Burundi), suggesting that GPT-4o mini's training data may handle non-Bantu languages (e.g., Swahili, Lingala) less robustly than it does Shona/Ndebele.

Table 2. Summary of Barriers and Frequency (8 weeks)

Infrastructural	**Electricity outage during session**	**312**	**9 (37.5%)**	**All equally**
Access	Smartphone unavailability (shared)	144 booking conflicts	18 (75%)	Lower-status refugees
Algorithmic	Culturally inappropriate/unsafe output	53	13 (54.2%)	DRC/Burundi (69% of incidents)
Linguistic	Chatbot failing to recognise non-Shona code-switching	112	16 (66.7%)	DRC/Burundi (100% of failures)

Theme 4: Differential Engagement and Hierarchies Among Migrants

An unexpected finding was the emergence of subtle hierarchies within the shelter. Zimbabwean IDPs (n=14) completed an average of 49.2 sessions (87.9% adherence), compared to 41.7 sessions (74.5%) for Great Lakes refugees (n=10), a statistically significant difference ($t(22)=2.31$, $p=.03$). Interview data suggested two explanations: (a) Zimbabwean IDPs had greater prior exposure to English through informal radio and music, reducing initial cognitive load; and (b) Great Lakes refugees reported higher baseline anxiety due to their undocumented status, fearing that authorities might monitor WhatsApp interactions. One Burundian participant stated:

"Even though you say it is safe, I worry. If immigration sees me learning English, they will know I am here without papers."(P18, Burundian male, 29, week-8 interview)

Discussion

This finding highlights the necessity of trauma-informed and legally secure design in AI literacy interventions.

The results show that using generative AI micro-learning on WhatsApp can quickly help migrants with different language backgrounds learn basic English, even if they have never studied it before. This supports and builds on Kukulska-Hulme's (2020) ideas about mobile language learning in crisis settings. By the second week, participants were making their own three-word requests, which aligns with usage-based linguistics (Tomasello, 2003), which holds that frequent, simple practice helps people learn and combine language. There was no major difference in learning speed between speakers of different Bantu languages, suggesting that repetition and low-pressure practice work well for everyone. Anxiety dropped sharply (from 91.7% to 12.5%), supporting Krashen's (1982) theory that reduced stress facilitates language learning, even in digital crisis settings. The study introduces the idea of a digital affective shield: private, non-judgmental AI chats reduce shame by removing the audience and the memory of public mistakes (Shapiro & Lê, 2024). For refugees who have faced surveillance and humiliation, this privacy can be just as important as the lessons themselves.

Algorithmic Colonialism and the Limits of Lightweight LLMs

Still, these challenges show that technology alone is not enough. The GPT-4o mini model, though designed for low-resource settings, gave culturally inappropriate, unsafe, or wrong answers in 1.4% of cases. Phrases like "master," "go to police," and "you are lazy" are not just mistakes; they reflect deeper problems in the training data, such as colonial ideas, assumptions about the police, and negative views of non-fluent speakers. Mohamed et al. (2024) point out that fixing these issues requires more than just adjusting prompts; it needs a complete rethink of the training data (p. 130). Since the model is trained on internet data, some biases are hard to avoid. These problems affected participants from DRC and Burundi the most (69% of incidents), likely because their languages are less represented in the training data than Shona and Ndebele. This means Great Lakes refugees face extra challenges: they must learn English, but the AI tool meant to help them works less well for them than for Zimbabwean users. This is an example of algorithmic colonialism in action (Mohamed et al., 2024; Santos, 2022).

The Human-AI Hybrid Model as Ethical Imperative

The fact that Great Lakes refugees attended fewer sessions because they feared being watched shows the limits of relying solely on technology. No amount of encryption or local hosting can fully protect users under Zimbabwe's strict immigration rules. Because of this, the study recommends a human-AI hybrid model, not just for teaching but for ethical reasons. The chatbot works well for simple, repeated practice. However, a bilingual facilitator or trained peer mentor is needed to build trust, remove harmful responses, adjust prompts based on participants' feelings, and support legal safety, such as advising on secure messaging. In this study, whether participants stayed in the program often depended on the facilitator's support following a negative chatbot response.

Infrastructural Barriers as Political Failures

Problems like unreliable electricity and shared devices are mainly political, not just technical. Rural shelters do not get government support for digital access, so solutions need more than better batteries—they require treating digital access as a basic right under international law (UNHCR, 2021). The study suggests that groups such as UNHCR, IOM, and Zimbabwe's Department of Social Welfare should implement WhatsApp-based AI literacy programs that use solar charging, device libraries, and free data for learning. Without this kind of support, AI literacy programs could exacerbate inequalities, since people with better access will learn faster while others are left behind.

Limitations and Future Research

This study has some limitations. The small sample size (24 people) and focus on one site mean the results may not apply everywhere, though they could be useful for similar rural shelters. The eight-week period showed rapid learning but did not assess whether the skills lasted or were used in real life. The facilitator was both a researcher and a supporter, which could introduce bias, but this was mitigated by having another research assistant assist with interviews. Also, since the study focused on English, it could be seen as supporting linguistic imperialism. Future research should examine AI tools that support learning in local languages, or that use multilingual chatbots.

Future research should: (a) compare GPT-4o mini with simpler, more transparent rule-based chatbots to assess the trade-off between flexibility and safety; (b) conduct longitudinal follow-up (6-12 months) to measure retention and real-world English use; (c) co-design interventions with refugees and IDPs using participatory action research methods; and (d) investigate the feasibility of locally hosted open-source models that can be fine-tuned on regionally appropriate corpora without sending data to external servers.

Conclusions

This study provides new evidence that generative AI micro-learning on WhatsApp can help close English literacy gaps among displaced people with no formal training, including Zimbabwean IDPs and refugees from DRC, Burundi, and Rwanda, in a rural shelter. After two weeks, participants from all language backgrounds could make their own three-word survival requests, and their anxiety dropped a lot. Still, algorithmic bias, such as colonial or negative outputs, affected Great Lakes refugees more, and problems like electricity and device sharing made access harder. Micro-learning with GPT-4o mini can help, but only as part of a human-AI hybrid model that values migrant choice, local languages, trauma-aware teaching, and offline support. Without these foundations, generative AI could become another barrier, keeping old colonial patterns in place.

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Real-Time Multimodal Student Engagement and Confidence Analysis for Online Learning Environments

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Abstract

The increased use of online learning has also created a need for increased complexity. As online classrooms rely heavily on human observation, the evaluation in online classrooms is very subjective and difficult to replicate per lessons at scale. AbstractIn this work we propose a multimodal confidence analysis system that analyzes the lapse of focus and behavioral engagement of students during online lectures and viva examinations in real-time. The facial expression analysis, hand gesture tracking and vocal feature extraction are used to compute user confidence and users engagement. By recognizing activity of eye and hand gesture recognition (movement stability and communication gestures), it will also extract facial landmarks implemented to the gaze direction, head pose, facial expressions; as well as some vocal features like short-term stability in pitch and loudness, spectral characteristics which are considered to be important salient that indicate clear level at speaking with confidence level. This multimodal behavioral cues is then combined using a weighted scoring system to yield normalized confidence scores from 0.00 to 100. A classification accuracy of ~94.97% was achieved based on comparisons to reported confidence judgments from a sample size of 100 subjects. The system has the ability to assist teachers in easily identifying uninterested and distracted students in traditional face-to-face or online polled lectures, as well as making it easier for university faculty to maintain dispassionate assessment even during virtual viva or presentation sessions.

Keywords: online learning, student engagement, confidence analysis, multimodal learning analytics, facial expression analysis, hand gesture tracking, vocal feature extraction

Introduction

Online Learning Environments have come to occupy centre stage in high-school, college and professional training as well as all kinds of assessments remotely over the wokplace. For instructors, personal contact with the students is lost in many cases and subtle non-verbal cues that would be visible to a class held physically — eye contact, posture, facial expression, hand movement, pace of hesitation (pauses), vocal steadiness and loudness — are now masked by computer screens. This complicates the detection of disengagement or low confidence when instructional support is needed most.

By transforming visible behavioural signals into meaningful feedback, automated engagement and confidence analysis can assist online teaching. It has been shown before that facial expressions, gaze behaviour and speech features can predict affective and cognitive states in the context of e-learning (Yasuhara et al., 2021). Moreover, multimodal approaches are generally stronger than methods derived from a single-modality because they incorporate information from both visual and audio channels that provide complementary evidence (Savchenko et al., 2022; Gupta et al., 2022; Zhang et al., 2020; Wang et al., 2022; Mamieva et al., 2023). However, many remain both computationally challenging and hard to interpret or depend on specific sensors.

This system refines the confidence estimation continuously using face landmarks, hand landmarks as well as vocal features. It relies on explicit weighted rules instead of a black-box classifier and therefore enables the instructor (and you) to interpret how the final score/label is generated. The contributions of the study are: (i) a real-time multimodal design for engagement and confidence estimation in online learning environments, (ii) a transparent scoring approach fused from facial, hand and vocal evidence and (iii) an evaluation using 100 participants with self-reported confidence as the ground truth baseline.

Related Work

The topic of learner engagement detection has been extensively researched in the field of online education. So far, facial-emotion-based systems have employed neural networks to classify learners' emotional engagement and attention from a single webcam image (Savchenko et al., 2022; Gupta et al., 2022). These systems show how visual

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cues may inform online learning analytics but are limited in that they can also be influenced by lighting, head pose, expression masking and inter individual behavioral variability.

This thus inspired multimodal approaches to affective computing, which fuse audio-visual-physiological-contextual signals (Zhang et al., 2020; Wang et al., 2022; Mamieva et al., 2023; Thakur et al., 2025), overcoming aforementioned limitations. Approximately multimodal fusion helps with noisy or uncertain scenarios since missing or weak evidence in one modality could be compensated by another modally well-characterized (Wang et al., 2022; Thakur et al., 2025) as reviewed in emotion recognition and affective computing, Tooltip may spell that MOE is learned to represent multimodal emotional measurements (Villegas-Ch. et al., 2025).

Even with these advances, confidence estimation in real-life educational settings is still an unsolved problem. Confidence, rather than a basic emotion, gets characterised through gaze stillness, expressive behaviour, movement control by speech and voice clarity and/or steadiness. While deep learning systems can achieve super-human accuracy, they tend to be black boxes and may also need massive amounts of annotated datasets. This part of work therefore concentrates on interpretable, multimodal system working based purely on raw video and audio feeds from standard webcams and microphones in typical online learning environments.

Methodology

This empirical study pursues a Design Science Research Methodology (DSRM) in which an artifact designed, implemented, and evaluated based on a real-life problem. The target problem is the absence of timely, unbiased feedback on degree of student confidence and participation during virtual lectures, presentations and viva exams.

Our proposed system uses the video camera and microphone from any standard webcam. The input is processed in parallel through three modules. The Facial Analysis module first detects 468 Facial Landmarks using MediaPipe Face Mesh. It extracts on indicators like gaze direction, eye openness, blink activity, head pose and mouth movement as well as smile lip shape features and general expression stability. Second, the hand analysis module utilizes MediaPipe Hands to identify 21 hand landmarks and produce smoothness of movement, clarity of gesture, palm pose (orientation), activity of fingers as well as fidgeting indicators. Third, we develop the voice analysis module to estimate pitch stability and loudness of a vocal signal along with jitter-like variation and spectral characteristics that relate to how clear a voice would sound using browser-based audio processing. The proposed design also centers around real-time orientation estimation (real-time head pose, gaze stability for facial confidence) supported by a recent framework of realtime localization detection (Zuhura & Hossain, 2024).

This causes a normalized confidence provided by each modality. Eye contact, expression and overall stabilisation of the head have 30% weightage in facial confidence. Hand confidence has a weight of 30% because controlled movement suggests you're actively involved in communication, and jerky or static motion can signal uncertainty (depending on context). Since vocal clarity, loudness and pitch stability are key during an online viva and presentation task, vocal confidence is given a 40% weight! The final confidence score is calculated in real time on a 0-100 scale:

Confidence = 0.30(Facial) + 0.30(Hand) + 0.40(Voice).

A total of 100 participants were used to test the system. Participants performed a two-minute speech under webcam conditions followed by self-reported confidence questionnaire. The average multimodal confidence for the speaking session was calculated, and the corresponding model score was compared with the questionnaire score. The assessment was focused on self-reported accuracy agreement, modality-level behaviour, and online learning delivery feasibility. An outline of the dataset, participant process and details of implementation has been taken from the original authors thesis report located here: https://docs.google.com/spreadsheets/d/1PLUJNoSCyAfJf17fv1XJfvPLhVoEaxz7ZK4qy98Vl0E/edit?usp=sharing.

Table 1. Weighted feature groups used in the confidence scoring mechanism.

Modality	Main cues	Weight	Interpretation
Facial	Gaze, blink, smile, head pose, lip movement	30%	Attention and visible affect
Hand	Gesture smoothness, speed, stability, fidgeting	30%	Expressiveness and nervous movement
Voice	Pitch stability, loudness, jitter, spectral clarity	40%	Speech clarity and vocal confidence

System Design and Implementation

It is lightweight web application built on top of distributed system, so it can be used without dedicated hardware and installation. You process video frames in the browser where they are created — local processing means less latency and no unnecessary face or audio data being sent to external servers. Here, the feasibility is further enhanced for institutes with limited budgets and also privacy aware deployment by local-processing.

Figure 1 depicts the workflow in real time. They collect live video and audio, process them through modality-specific components using techniques such as CNNs on video data and acoustic features or NLTK to process language into latent vectors (for the voice), convert those raw extracts into confidence-related features, and then fuse them all together with a confidence score. Here, the scores may be shown to instructors as an indicator of live engagement or students during practice presentations as feedback. This sole output allows the system to explain whether a low score is primarily driven by gaze instability, gesture irregularity, low speech volume, or some other observable modality.

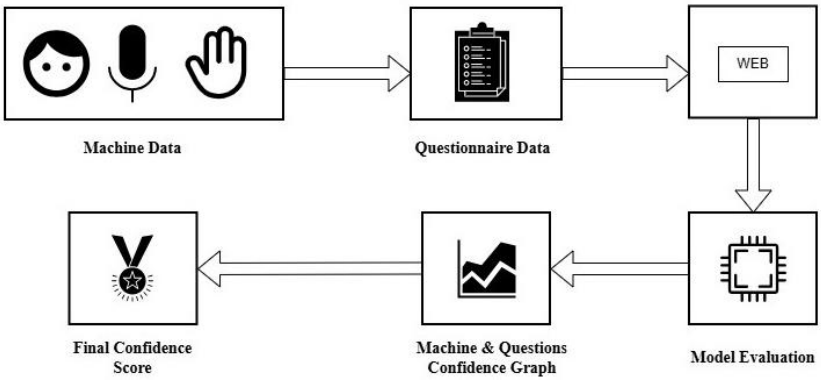


Figure 1. Real-time multimodal processing workflow for confidence estimation.

Thresholds were chosen based on behavioural assumptions and pilot testing. As an example, excessive blinking and large head movement decrease facial confidence; moderate and smooth gestures increase hand confidence; stable pitch with adequate loudness increases vocal confidence. Such rules are designed to be auditable and modifiable for potential schooling contexts later on.

Results and Discussion

Our multimodal system had 94.97% agreement with self-reported confidence scores (Fahad et al., 2025). This shows the facial, hand, and vocal signals were aligned closely with participants' own confidence judgments during the public speaking tasks. The implications strengthen the idea that confidence in online learning is better thought of as a multimodal than a facial or vocal phenomenon.

In terms of modality, the average score by class was 80.13% for facial confidence, followed by hand confidence (68.81%) and voice confidence (64.87%). These modality averages are summarized in Figure 2. The facial score indicates that the face tracking was stable for most sessions when using webcam-based face tracking.

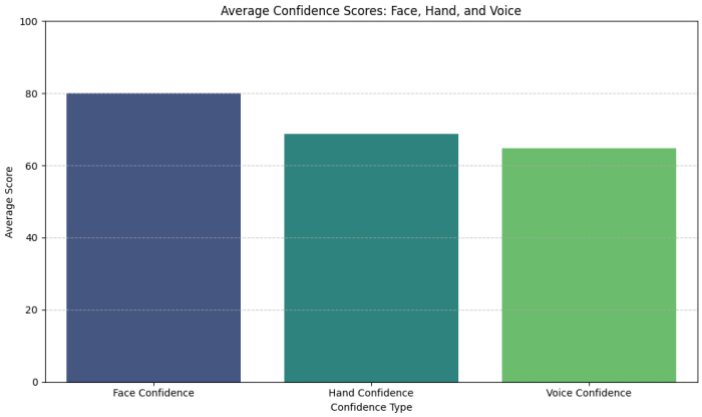


Figure 2. Average confidence scores by modality: face, hand, and voice.

The category-level results for the three modalities are shown separately in Figures 3 to 5, which highlight distinct stability profiles. D1 is focused mostly in the medium and higher range, which means that the face was stable for most of the speaking sessions. Furthermore, the triggering of hands was more diluted, indicating that expressive behaviour varies depending on individual speaking style and presentation habit. The biggest low-confidence part was produced by voice cues which proves how much microphone quality, speech loudness, and pitch stability matters in online classes (Fahad et al., 2025).

Table 2. Additional evaluation outcomes from the 100-participant study.

Result indicator	Observed value
Agreement with self-report	94.97%
Average facial confidence	80.13%
Average hand confidence	68.81%
Average voice confidence	64.87%
Gender-level averages	Male: 76%; Female: 68%

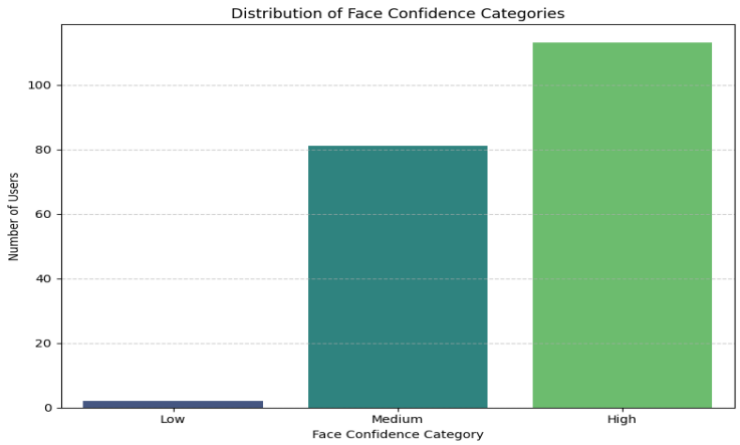


Figure 3. Distribution of facial confidence levels among participants.

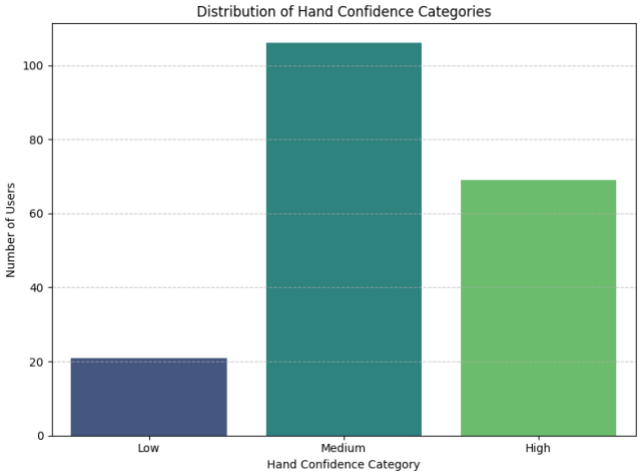


Figure 4. Distribution of hand gesture confidence levels among participants.

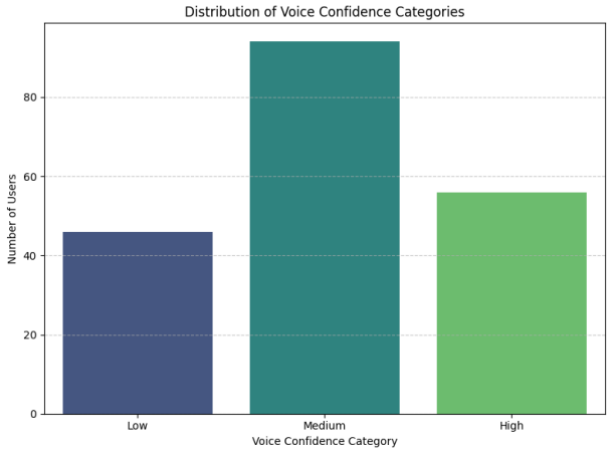


Figure 5. Distribution of voice confidence levels among participants.

The behaviour of the scoring mechanism is shown in more detail from the case-level results. For example, one participant demonstrating hand use, smiling and strong vocal projection scored about 84% on confidence; while another using little expression, no visible gesture and weak vocal clarity reached only around 30%. These Examples demonstrate that the model varies, dependent not just on one cue, but combined behaviours (Fahad et al., 2025).

The analysis separated by age revealed that confidence scores were more variable with younger participants, while estimated confidence produced higher and generally more stable estimates in older subjects. The gender-based analysis reveals that the difference was, on average, 76% for males and 68% for females. Notice that these values should not be interpreted as absolute differences in ability to communicate; they reflect observable behaviors encoded by the current scoring rules (and captured by the existing dataset). That probably means, automatic to note, a bigger and fairer dataset to draw any demographic conclusions.

Conclusion

We presented a real-time multi-modal analysis system to track student engagement and confidence in online learning environments. It integrates facial expression video analysis, hand gestures tracking and vocal features extraction in a interpretable weighted score from 0 to 100. In an evaluation with 100 participants we found the multimodal approach to be in agreement with self-reported confidence approximately 94.97%; indicating that it can help to provide useful insight into various learner behaviour during online lectures, viva examinations and presentations. It provides an explanatory, low-cost and practical system to help instructors provide effective support for learners, but there are challenges in strengthening personalization, fairness properties and large-scale validation.

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Enhancing Student Engagement Using Generative AI Tools in Online Learning Environments

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Abstract

Student engagement remains a major challenge in online learning, influencing motivation, participation, and effectiveness. This study investigates whether generative artificial intelligence (AI) tools can enhance student engagement compared with traditional learning materials. A quantitative within-subject design was employed in which participants experienced both traditional and AI-assisted learning conditions using the same instructional content. From 301 initial responses, 262 valid responses were retained after data screening. Engagement was assessed using a 10-point Likert scale across behavioral, emotional, and cognitive dimensions, together with students' perceptions of generative AI. Reliability was evaluated using Cronbach's alpha, while paired-samples t-tests, Cohen's d, and Pearson correlation were used for statistical analysis. Results showed that overall engagement increased significantly from 6.04 in the traditional condition to 7.51 in the AI-assisted condition ($p < .001$), with a large effect size ($d = 0.800$). Significant improvements were also observed in behavioral, emotional, and cognitive engagement, with emotional engagement showing the strongest effect ($d = 0.819$). AI-assisted engagement was moderately and positively associated with students' perceptions of generative AI ($r = .588$, $p < .001$). These findings indicate that generative AI can create more engaging online learning experiences when integrated appropriately, while highlighting the importance of maintaining meaningful student involvement and independent thinking.

Keywords: Generative AI, student engagement, online learning, artificial intelligence in education, ChatGPT, educational technology.

Introduction

Student engagement is a central determinant of successful online learning because it influences learners' participation, motivation, persistence, and interaction with learning activities. In digital environments, limited social presence and passive interaction can reduce engagement, whereas carefully designed learner–content, learner–instructor, and learner–learner interactions can improve students' learning experiences (Martin & Bolliger, 2018). Engagement is commonly treated as a multidimensional construct comprising behavioral, emotional, and cognitive components (Fredricks et al., 2004). A systematic evidence map of educational technology research likewise found that technology can support all three dimensions, although behavioral engagement has been examined more frequently than emotional and cognitive engagement (Bond et al., 2020).

The rapid adoption of generative artificial intelligence (GenAI) tools such as ChatGPT has introduced new possibilities for making online learning more responsive and personalized. These systems can provide immediate explanations, generate examples, support brainstorming, and offer individualized feedback, potentially reducing delays between a learner's question and instructional support. Early reviews identified opportunities for personalized learning, tutoring, feedback, and content generation, while also warning that educational benefits depend on how the technology is used (Lo, 2023; Tlili et al., 2023). Student-focused research has similarly reported generally positive attitudes toward GenAI and perceived benefits for personalized support, writing, brainstorming, and learning assistance (Chan & Hu, 2023). Broader reviews of empirical and higher-education research show that ChatGPT has become increasingly connected with teaching, learning environments, student engagement, and academic practice (Albadarin et al., 2024; Bhullar et al., 2024).

However, greater accessibility and convenience do not necessarily guarantee deeper learning. GenAI systems may provide inaccurate or biased responses, encourage superficial acceptance of generated content, and create risks related to academic integrity, privacy, and responsible use (Cotton et al., 2024; Farrokhnia et al., 2024; Yan et al., 2024). These concerns are particularly relevant to cognitive engagement because students may become dependent on AI-generated explanations rather than independently evaluating information. Thus, the educational value of GenAI should be examined not only through general attitudes toward the technology but also through measurable changes in how students participate, feel, and think during learning.

Recent evidence suggests that GenAI can improve student engagement, but the literature remains uneven. Lo et al. (2024) found relatively strong evidence for behavioral engagement, mixed evidence for emotional engagement, and broader but weaker evidence for cognitive engagement, including concerns about reduced critical thinking

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and overreliance. More recent meta-analytic evidence indicates that ChatGPT-supported learning can improve overall behavioral, cognitive, and emotional engagement compared with non-ChatGPT learning, while still identifying overreliance as a potential source of disengagement (Heung & Chiu, 2025). This indicates a need for direct within-participant comparisons that evaluate the same learners under conventional and GenAI-assisted learning conditions rather than relying only on general perceptions.

Accordingly, this study investigates whether GenAI-assisted learning enhances student engagement in an online learning environment compared with traditional learning materials. Using a within-subject design, it evaluates overall engagement and its behavioral, emotional, and cognitive dimensions, while also examining students' perceptions of GenAI and their relationship with AI-assisted engagement. By combining direct condition comparison, multidimensional engagement measurement, and perception analysis, the study provides empirical evidence on both the educational potential and the responsible-use considerations of GenAI-supported online learning.

Methodology

Research Design

This study employed a quantitative within-subject comparative design to investigate the effect of generative AI-assisted learning on student engagement in an online learning environment. Each participant experienced two learning conditions using the same instructional topic. In the first condition, participants studied conventional learning material from books and academic sources. In the second condition, they studied the corresponding material with support from generative AI tools, including ChatGPT and Google Gemini. Because the same participants completed both conditions, engagement scores could be compared directly while reducing variation caused by differences between separate participant groups. The overall study procedure is presented in Figure 1.

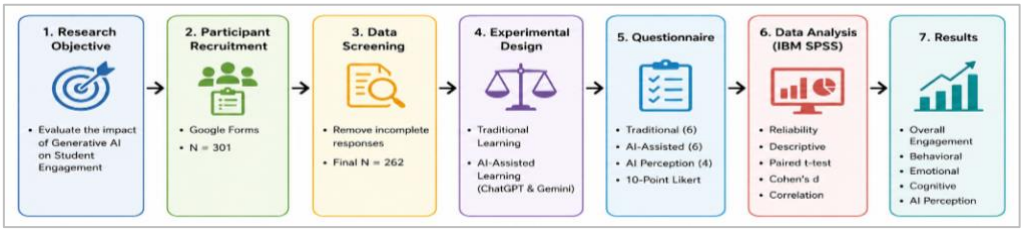


Figure 1. Overall workflow of the within-subject comparative study.

Participants, Data Collection, and Screening

Data were collected through a structured questionnaire administered using Google Forms. A total of 301 responses were initially recorded, of which 289 participants completed the study-related sections of the questionnaire. An attention-check question was included to ensure that participants had correctly recognized the experimental conditions: *"Which learning material included AI assistance?"* As shown in Figure 2, 90.7% (262 of 289) correctly identified Part 2 as the AI-assisted learning condition. The 27 responses with an incorrect attention-check answer were excluded from subsequent analysis. Therefore, all statistical analyses reported in this study were conducted using a final valid sample of N = 262.

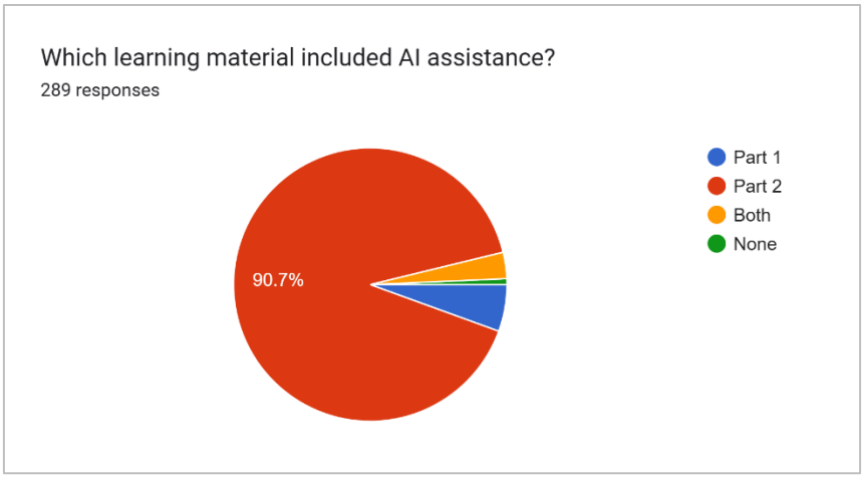
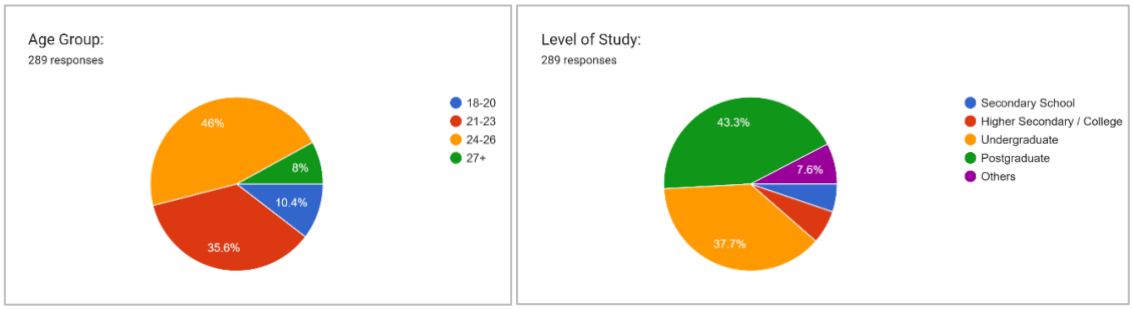


Figure 2: Attention-check responses used for participant screening (n = 289)

Participant characteristics were collected to describe the respondents who completed the study-related questionnaire. Figure 3 shows the distributions of age and level of study before attention-check exclusion. The largest age group was 24–26 years (46.0%), followed by 21–23 years (35.6%), while postgraduate and undergraduate students constituted the two largest educational groups.



(a)Age Group (b) Level of study

Figure 3. Pre-screening participant characteristics (n = 289): (a) age-group distribution and (b) level-of-study distribution.

Questionnaire and Experimental Procedure

The questionnaire contained 16 analytical items organized into three constructs: traditional learning engagement (6 items), AI-assisted learning engagement (6 items), and AI perception (4 items). All analytical items used a 10-point Likert-type scale, ranging from 1 (*strongly disagree*) to 10 (*strongly agree*). Engagement measures were further grouped into behavioral, emotional, and cognitive dimensions to evaluate different aspects of student engagement. The AI-perception items examined whether AI-assisted material was more engaging, supported faster understanding, increased interactivity, and created a tendency toward over-reliance on AI.

Table 1. Structure of the questionnaire and study measures.

Measure	Items	Measurement focus	Response
Traditional learning engagement	6	Behavioral, emotional, and cognitive engagement under traditional learning	1–10
AI-assisted learning engagement	6	Behavioral, emotional, and cognitive engagement under AI-assisted learning	1–10
AI perception	4	Engagement, faster understanding, interactivity, and over-reliance	1–10
Attention check	1	Identification of the AI-assisted learning condition	Part 1 / Part 2 / Both / None
Participant information	3	Age, level of study, and AI-use characteristics	Categorical

Participants first studied the traditional learning material and completed the corresponding engagement assessment. They then studied the same instructional topic under the AI-assisted condition and completed the AI-

assisted engagement assessment. Finally, participants answered the AI-perception items and attention-check question. Responses that did not satisfy the screening criterion were excluded before statistical analysis.

Statistical Analysis

Statistical analysis was performed using IBM SPSS Statistics. Cronbach's alpha was used to evaluate the internal consistency of the three measurement constructs. Means and standard deviations were calculated for descriptive analysis. Paired-samples *t*-tests were used to compare traditional and AI-assisted learning for overall engagement and separately for behavioral, emotional, and cognitive engagement. Cohen's *d* was calculated to quantify the magnitude of the differences. Finally, Pearson correlation analysis was conducted to examine relationships among traditional engagement, AI-assisted engagement, and AI perception. Statistical significance was determined at $p < .05$.

Results

Reliability and Overall Engagement

The internal consistency of the measurement scales was first evaluated using Cronbach's alpha. As presented in Table 2, all three constructs demonstrated high reliability, with α values ranging from 0.881 to 0.915. Traditional learning produced a mean engagement score of 6.04 ± 1.36, whereas AI-assisted learning achieved a higher mean of 7.51 ± 1.53. The AI-perception construct obtained a mean score of 7.70 ± 1.37, indicating an overall positive perception of generative AI-supported learning.

Table 2. Reliability and descriptive statistics of the measurement constructs.

Construct	Items	Cronbach's α	Mean	SD
Traditional Learning	6	0.915	6.04	1.36
AI-Assisted Learning	6	0.890	7.51	1.53
AI Perception	4	0.881	7.70	1.37

A paired-samples *t*-test was conducted to determine whether the difference between traditional and AI-assisted engagement was statistically significant. Overall engagement increased by 1.46 points under the AI-assisted condition. The difference was statistically significant ($t = -12.957$, $p < .001$), with a large effect size (Cohen's $d = 0.800$). Thus, the observed improvement represents not only statistical significance but also a substantial practical difference in student engagement.

Table 3. Overall engagement comparison between traditional and AI-assisted learning.

Comparison	Traditional Mean ± SD	AI-Assisted Mean ± SD	Mean Difference	*t*	*p*	Cohen's *d*
Overall Engagement	6.04 ± 1.36	7.51 ± 1.53	+1.46	−12.957	< .001	0.800

Mean difference is reported as AI-assisted minus traditional learning; the negative *t* value reflects the subtraction order used in the paired-samples analysis.

Dimension-Wise Engagement Analysis

To determine whether the effect of generative AI differed across dimensions of student engagement, behavioral, emotional, and cognitive engagement were analyzed separately using paired-samples *t*-tests. As shown in Table 4, AI-assisted learning produced significantly higher scores across all three dimensions ($p < .001$). Behavioral engagement showed the largest absolute increase (+1.68 points), from 6.44 to 8.11. Emotional engagement increased by 1.66 points and demonstrated the strongest standardized effect (Cohen's $d = 0.819$). Cognitive engagement also increased significantly, from 5.97 to 7.22, with a moderate-to-large effect ($d = 0.665$).

Table 4. Comparison of behavioral, emotional, and cognitive engagement.

Dimension	Traditional Mean ± SD	AI-Assisted Mean ± SD	Difference	*t*	*p*	Cohen's *d*
Behavioral	6.44 ± 1.64	8.11 ± 1.87	+1.68	−12.203	< .001	0.754
Emotional	5.96 ± 1.60	7.62 ± 1.75	+1.66	−13.251	< .001	**0.819**
Cognitive	5.97 ± 1.35	7.22 ± 1.55	+1.26	−10.769	< .001	0.665

Mean differences are reported as AI-assisted minus traditional learning; negative *t* values reflect the paired-variable subtraction order.

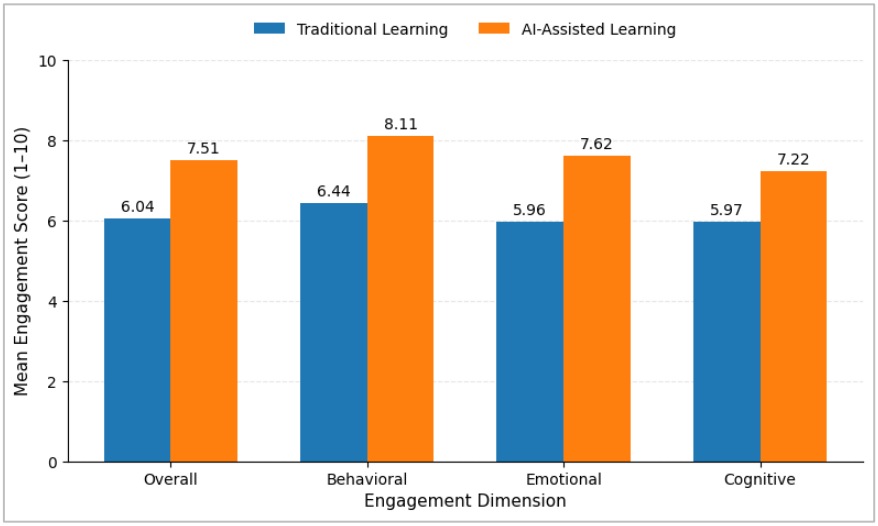


Figure 4. Mean engagement scores under traditional and AI-assisted learning conditions (N = 262).

Correlation and AI Perception

Pearson correlation analysis was conducted to examine the relationships among traditional learning engagement, AI-assisted engagement, and students' perceptions of generative AI. AI-assisted engagement showed a moderate positive correlation with AI perception (r = 0.588, p < .001), indicating that students reporting more positive perceptions of generative AI also tended to report greater engagement during AI-assisted learning. In comparison, traditional engagement showed weaker positive relationships with AI-assisted engagement (r = 0.206, p < .001) and AI perception (r = 0.166, p = .007).

Correlations

		TRAD_MEAN	AI_MEAN	PERCEP_MEAN
TRAD_MEAN	Pearson Correlation	1	.206***	.166**
	Sig. (2-tailed)		<.001	.007
	N	262	262	262
AI_MEAN	Pearson Correlation	.206***	1	.588***
	Sig. (2-tailed)	<.001		<.001
	N	262	262	262
PERCEP_MEAN	Pearson Correlation	.166**	.588***	1
	Sig. (2-tailed)	.007	<.001	
	N	262	262	262

Figure 5. Pearson correlations among traditional engagement, AI-assisted engagement, and AI perception (N = 262).

These results suggest that students' attitudes toward generative AI are more strongly associated with engagement in the AI-supported condition than with engagement under traditional learning. However, the correlation represents an association rather than a causal relationship.

Conclusions

This study examined the effect of generative AI-assisted learning on student engagement using a within-subject comparative design. The findings showed that overall engagement increased significantly from 6.04 in traditional learning to 7.51 in AI-assisted learning (p < .001), with a large effect size (Cohen's d = 0.800). Significant improvements were also observed across behavioral, emotional, and cognitive engagement. Behavioral engagement showed the largest absolute increase, while emotional engagement demonstrated the strongest standardized effect (d = 0.819). These results indicate that generative AI can enhance multiple dimensions of student engagement rather than affecting only general perceptions of the learning experience.

The correlation analysis further showed a moderate positive relationship between AI perception and AI-assisted engagement ($r = 0.588$, $p < .001$), suggesting that students with more positive perceptions of generative AI tended to experience greater engagement during AI-supported learning. Overall, the findings support the potential of generative AI tools to create more interactive and engaging online learning environments when integrated appropriately. However, the study relied primarily on self-reported engagement and used a fixed order of learning conditions. Future research should therefore employ counterbalanced or longer-term experimental designs and include objective learning-performance measures to further evaluate the educational impact of generative AI.

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EdFin: An AI-driven Solution for Financial Challenges Faced by University Students in Bangladesh

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Abstract

University students in Bangladesh are facing significant financial pressure as tuition fees, accommodation, and living expenses continue to rise, while employment opportunities remain limited. As a result, many students borrow money or are forced to depend only on their family income to continue their studies. Past research confirms that financial stress negatively affects academic performance and mental health, especially for students from low and middle-income families. This study aims to explore the financial challenges encountered by university students in Bangladesh and investigate their preferred support systems. A quantitative research approach was employed. Data were collected through a structured online survey using Google Forms from 101 students at American International University-Bangladesh. The findings revealed that most students were from middle-income families with a monthly income of 30,000 to 100,000 BDT, but still faced high or very high financial pressure, mainly due to high tuition fees and rising accommodation costs. In addition, 85.1% of students were unemployed, and only 5% of students covered more than half of their own expenses. Despite these challenges, more than 69% of students expressed support for structured on-campus employment programs, and 72% supported financial literacy workshops. This research contributes to the field by proposing EdFin, an AI-driven platform that offers personalized need-based financial aid, a structured on-campus employment portal, and financial literacy education to reduce financial pressure and improve academic performance.

Keywords: AI-driven solution, financial challenges, part-time employment, university students, Bangladesh

Introduction

Financial problems have turned into a huge issue affecting the academic performance as well as the physical health of students over the years. Tuition fees, accommodation costs, and daily living costs have increased significantly, making higher study less accessible to students of lower class or middle-class family and forcing loans or part-time jobs to fund educational expenses.

Bangladesh also follows this trend. The number of private universities has increased rapidly throughout the years, but tuition fees still remain high in comparison to household income. Financial stress has serious consequences on Bangladeshi students, research on public university students shows students from lower-income families find it very hard to meet basic necessities (Alam et al., 2024). This pattern reaches beyond Bangladesh, a study of Lebanese university students found a similar pattern where financial stress imposes serious mental pressure and harms student wellbeing (Nasr et al., 2024).

A study of private university students in Bangladesh found that digital financial literacy alone did not improve financial well-being of students, what actually helped was financial confidence and financial behavior (Rahman et al., 2026), indicating students need confidence-building and structured support systems, not just information.

The COVID-19 pandemic intensified these challenges. A study on Bangladeshi university students during the pandemic found that many students relied heavily on loans and family income to continue their studies, showing financial problems are not stable and rapidly increase during economic crisis (Rabbani, 2023).

Current technology also offers new ways to tackle these challenges. Research on AI's role in higher education shows institutions are increasingly investing in it to improve student learning and administration (Katsamakas et al., 2024). More specific applications have also emerged, explainable machine learning models that predict academic performance and flag students at risk of dropping out, while staying transparent enough for institutions to actually trust and act on the results (Ahmed et al., 2025).

University students in Bangladesh are facing significant financial pressure due to increasing tuition fees, accommodation costs, and living expenses. Employment opportunities for students are very limited, which is forcing them to depend on family income or borrow money informally to continue their studies. Research on part-time employment among Bangladeshi university students showed that work hours directly reduce academic achievement (Alam et al., 2025). This problem is severe for private universities like American International University-Bangladesh (AIUB), where family income often can't cover high tuition fees and other academic

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expenses fully. Students from middle-income families often do not qualify for need-based aid, but they still struggle financially, and they fall through the cracks of the existing support systems.

Previous research has documented financial stress among Bangladeshi university students and its effect on academic performance (Alam et al., 2024; Alam et al., 2025). However, most existing studies mainly focus on explaining the problem rather than proposing solutions. A scoping review of university financial support systems only described what already exists and did not offer any new approaches (Russell et al., 2025). Separately, research has shown a gap between academic curricula and job market needs in Bangladesh (Hossain & Arefin, 2025). At the same time, the use of machine learning has increased internationally to predict student outcomes and match students with financial aid (Kanwal et al., 2024). But no study has proposed an integrated, AI-informed platform combining financial aid matching, employment support, and financial literacy education for the Bangladeshi context.

This study aims to fill this gap by understanding the financial challenges that students face through collecting primary survey data, then proposing EdFin, an AI-powered platform designed to provide personalized and accessible support. The objectives of this study are to explore the financial challenges faced by students, assess their level of financial stress, identify employment barriers, determine preferred support mechanisms, and propose EdFin as an integrated solution.

Methodology

This study used a quantitative research design based on a structured online survey. The participants were undergraduate and postgraduate students from American International University-Bangladesh (AIUB). The survey link was shared through university student groups, and convenience sampling was used. Data collection started in August 2025, and in the end, 101 students participated in the study.

Data was collected using a structured online survey distributed through Google Forms. Personal information such as name or student ID was not collected, so all responses remained anonymous. The survey had six sections covering demographic profile, current financial pressure, employment status and challenges, perception of proposed support systems, and preferred structure for support. Data were analyzed using descriptive statistics, including frequencies and percentages, to summarize demographic characteristics, financial stress levels, employment status, and support preferences.

Results

There was a total of 101 participants in the survey. The majority of participants were between 20-22 years old (59.4%), followed by 23-25 (31.7%). Most respondents were male (68.3%) compared to female (31.7%). Most of the students were from families earning 30,000-60,000 BDT (39.6%) or 60,001-100,000 BDT (36.6%) monthly, together accounting for over 75% of the sample, as summarized in Table 1.

Table 1. Demographic characteristics of respondents (N = 101).

Category	Percentage
Age 20-22	59.4%
Age 23-25	31.7%
Age 17-19	5.9%
Age 26+	3.0%
Male	68.3%
Female	31.7%
Family income 30,000-60,000 BDT	39.6%
Family income 60,001-100,000 BDT	36.6%
Family income above 150,000 BDT	11.9%
Family income 100,001-150,000 BDT	7.9%
Family income below 30,000 BDT	4.0%

More than half of respondents (52.4%) expressed High or Very High financial pressure in managing their academic and living expenses. The largest expense for the majority of students (87.1%) was university tuition fees. When asked whether their personal savings were enough for unexpected costs, 59.4% disagreed or strongly disagreed.

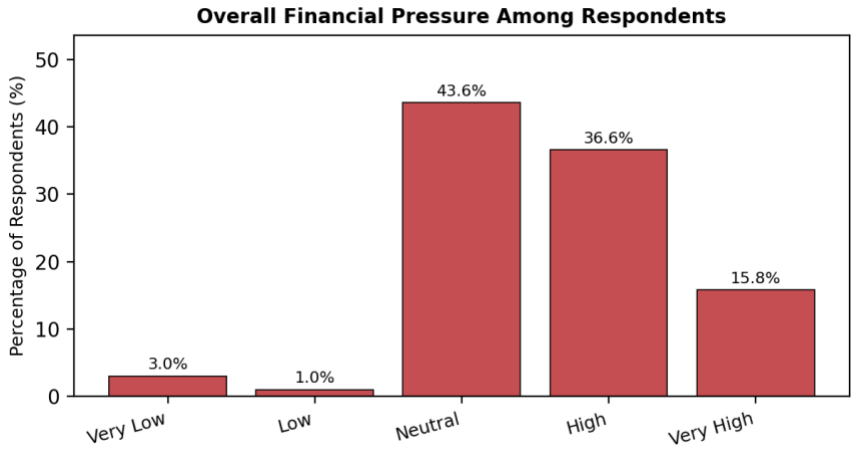


Figure 1. Overall financial pressure reported by respondents.

Most respondents (85.1%) reported not being currently employed in any capacity. 76.2% of students covered none of their own expenses through personal income. The biggest barrier students faced in finding suitable work was a lack of available job opportunities (58.4%), followed by high academic workload leaving no time (39.6%) and low pay rates (35.6%).

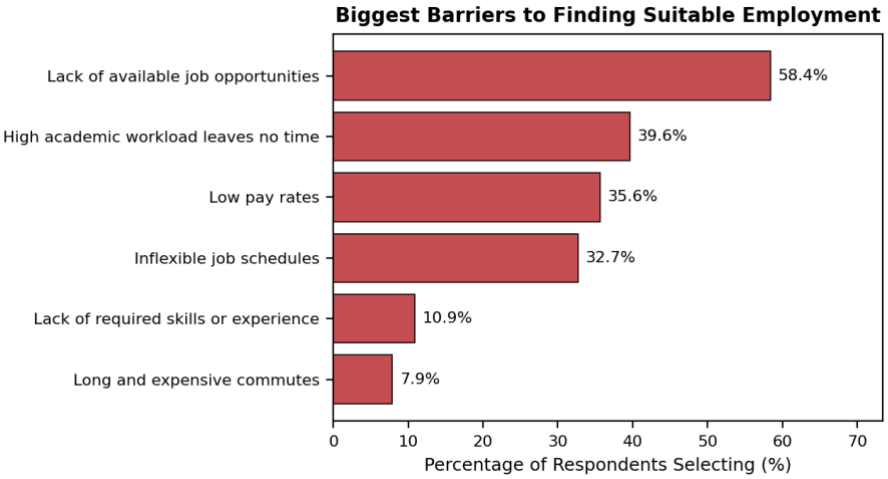


Figure 2. Biggest barriers to finding suitable employment (select up to two).

Students showed strong support for structured financial interventions. The majority of students (69.3%) agreed or strongly agreed that a guaranteed campus job system would be more helpful than off-campus employment, and 72.3% agreed that financial literacy workshops should be part of university support, as shown in Figure 3. Tuition Fee Waivers were the clear preference for aid type (62.4%), and flexible working hours (57.4%) was rated the most important factor for a campus job.

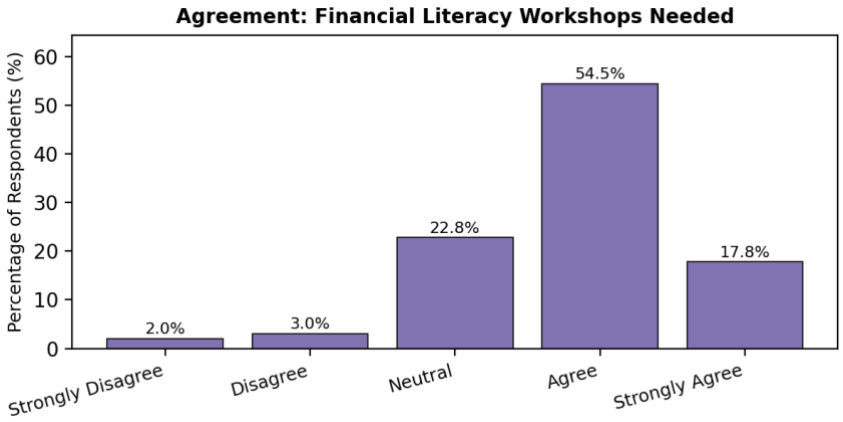


Figure 3. Agreement that financial literacy workshops should be part of university support.

Financial pressure did not decrease consistently with income, as shown in Table 2. Students from families earning 60,001-100,000 BDT monthly reported similar high pressure (59.5%) to those from families earning 30,000-60,000 BDT (52.5%), while only students from families earning above 150,000 BDT reported much lower pressure (16.7%), suggesting rising costs are squeezing even middle-income families, not just low-income ones.

Table 2. High/Very High financial pressure by monthly family income bracket.

Income (BDT/month)	High/Very High Pressure	n
Below 30,000	100.0%	4
30,000-60,000	52.5%	40
60,001-100,000	59.5%	37
100,001-150,000	50.0%	8
Above 150,000	16.7%	12

Proposed EdFin Framework

Based on these findings, this study proposes EdFin, an AI-powered platform designed to reduce financial pressure on university students in Bangladesh. EdFin integrates three core modules into a single system: a Smart Financial Aid Hub, a Campus Talent Connect Portal, and an Interactive Financial Literacy Suite, connected through a shared student profile.

The Smart Financial Aid Hub matches students with the most relevant financial aid options based on their individual profile, which includes income level, expense patterns, and academic standing. Instead of students having to search for scholarships manually, the system would use a classification-based approach to segment students by financial need, similar to existing ML-based scholarship prediction frameworks (Kanwal et al., 2024), and recommend suitable aid programs accordingly.

The Campus Talent Connect Portal would create a structured, university-managed system for on-campus employment, allowing students to filter job opportunities by schedule flexibility alongside pay and location, since students strongly prioritized flexible working hours over higher pay. The Interactive Financial Literacy Suite would provide practical, interactive modules on budgeting and saving, focusing on building financial confidence and behavior, not just delivering information.

Since EdFin would handle sensitive financial and personal data, the aid-matching model should be regularly audited to make sure it doesn't favour specific groups by department, income bracket, or gender, and students should receive a simple explanation for each recommendation instead of an unexplained, black-box result. Data access should be limited to what is strictly necessary, with clear student consent, and university financial aid officers should retain the ability to review or override system recommendations rather than EdFin making fully automated decisions.

Ethical Considerations

The Smart Financial Aid Hub recommends aid programs based on student financial need. But there is a risk that the system could unintentionally be biased toward certain groups, such as students from certain departments or income brackets. To prevent this, EdFin's aid-matching model should be trained and regularly tested on diverse

student data, and its output should be audited frequently to make sure it doesn't favour specific factors such as gender or study level. Fairness should be measured not only by whether recommendations are accurate, but by whether students with similar financial need receive similar aid options, regardless of their background.

For students to trust and appropriately use EdFin, they need to understand why they were or were not selected for a particular aid option or job recommendation. Instead of getting unexplained results from a black-box system, students should receive a simple explanation for each recommendation, for example, showing that a student was selected for a Tuition Fee Waiver because their reported income bracket and expenses met the program's criteria. This kind of explanation is crucial because students might otherwise feel the system is unfair or biased towards a particular group of students. It also supports accountability if a student wants to question or appeal a decision.

EdFin would require students to share sensitive financial and personal information, including income level, expenses, and employment status to generate personalized recommendations. This data must be collected, stored and processed securely. Students must give clear consent before their data is used, and data access should be limited to what is strictly necessary for the system to work. Student data should never be shared with third parties, including employers on the Campus Talent Connect Portal, without the student's permission. Additionally, students should have the full permission to view, correct or delete their data at any time.

While EdFin is designed to automate financial aid matching and employment recommendations, the final decision should not be made entirely by the system without human review. This is especially important for unusual cases or appeals. University financial aid officers should retain the ability to review, override, or adjust system recommendations which makes EdFin a decision-support tool, not an entirely automated system. This human oversight helps to prevent errors or biased outcomes and maintains institutional accountability for financial aid decisions.

Limitations

This study has several limitations. The survey was limited to students from a single private university, AIUB, so the findings might not fully be applicable for public universities or private universities with different tuition fee structures. The sample size of 101 students is considerably small, particularly for students with family income below 30,000 BDT, where only a few responses were collected. The study relies on self-reported data, and EdFin is presented as a conceptual framework that has not yet been deployed or tested.

Conclusions

The study investigated the financial challenges faced by university students in Bangladesh, using AIUB as a case study. The findings show that most students face high financial pressure despite coming from middle-income families, with tuition fees as the biggest expense. Most students remain unemployed because of limited job opportunities rather than a lack of effort, and 76.2% cover none of their own expenses. Despite these challenges, students expressed strong support for structured interventions, particularly campus employment programs and financial literacy workshops.

Based on these findings, this study proposed EdFin, an AI-powered platform designed to mitigate these challenges by combining a Smart Financial Aid Hub, a Campus Talent Connect Portal, and an Interactive Financial Literacy Suite into one support system. This study contributes empirical evidence on student financial challenges in Bangladesh and introduces a technology-driven framework that universities could adapt to provide better support to their students. Future work should develop EdFin's proposed modules into a working prototype, collect data from multiple universities to test whether these findings generalize, and refine EdFin's algorithmic fairness and transparency mechanisms before real-world deployment.

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Rural Students' Perspectives on Barriers to Learning Heat and Radiation in the Laboratory in a Nigerian Tertiary Institution

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Abstract

Recently, physics instruction has placed greater emphasis on hands-on, real-world demonstrations, especially in the areas of heat and radiation. This shift is happening in both rural and urban higher education in Nigeria. However, rural students often have less access to heat demonstrations because of isolation and poor infrastructure. This study examines these challenges through a case study of rural physics students at a Nigerian tertiary institution who have completed coursework on heat. Data were collected through interviews. Thematic analysis revealed two main themes: first, issues with infrastructure, distractions, and experiential gaps; second, the value of improvisation and partnerships in overcoming laboratory challenges. The results highlight that local innovation and continuous collaboration with multinational companies are important for addressing long-standing problems in Nigerian science education.

Keywords: Rural Higher Institution, Heat, Students, Laboratory Engagement

1. Introduction

Mastery of heat concepts is fundamental in physics education, as it underpins understanding of thermal transfer, temperature measurement, thermal expansion, and energy transformations. Instruction in this area also serves as a foundation for thermodynamics and the study of the physical behaviour of matter (Allen & Macomber, 2022; Clements-Croome, 2021; Zanoletti & Godard, 2022). Recent evidence indicates that laboratory configuration, population density, and architectural orientation have measurable effects on students' thermal comfort, which subsequently influences their cognitive engagement and conceptual development (Ghaffarianhoseini et al., 2018; Bluyssen et al., 2018; Adeduyigbe, 2024; Wambua et al., 2026; Chen et al., 2019). In Nigeria, rural tertiary students frequently encounter difficulties with heat-related concepts, primarily due to inadequate laboratory facilities that limit hands-on learning opportunities (Dawodu et al., 2026; Ndunagu et al., 2023).

According to Achor and Abuh (2020) and Adeduyigbe (2024), physics instruction in these environments often relies on didactic lecture methods with minimal practical engagement. This practice impedes comprehension and long-term retention. Although practical work is widely recognised as central to science learning, empirical research on the specific impact of laboratory sessions on rural students' understanding of heat and radiation remains limited. This research gap is particularly significant in light of Nigeria's climatic conditions, where all regions experience intense heat that increases physical discomfort for both lecturers and students (Wambua et al., 2026; Lamberti et al., 2021; Amasuomo & Amasuomo, 2016).

These environmental challenges are further intensified by unreliable electricity supplies and inadequate laboratory infrastructure. Addressing these factors could provide thermal relief and improve instructional quality (Adeduyigbe, 2024). As a result, rural lecturers face challenges in implementing experiential pedagogies that promote a critical understanding of heat and radiation concepts, their practical applications, and their societal relevance. In response to these challenges, this study investigates how laboratory activities influence rural students' conceptual understanding of heat and radiation. The following research questions guide this investigation:

1 What are the barriers to conceptual understanding of the radiation and heat concepts in rural Nigerian Higher education laboratory?

2 How can the constraints associated with conceptual understanding of radiation and heat concepts be addressed in rural Nigerian higher education laboratories?

2. Methodology

An interpretive, qualitative case study design was employed to investigate rural students' perspectives on how radiation influences their conceptual understanding of heat.

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2.1 Design

A laboratory experiment on heat and radiation was conducted as part of the Physics 101 (PHY 101) curriculum at a rural higher education institution, involving Ordinary National Diploma (OND) students over eight weeks from early April to late May 2026. The course was a compulsory requirement for the OND qualification. During practical sessions, students demonstrated heat radiation. For each experiment, 100 mL of water was dispensed into 10 calorimeters, and the initial temperature was recorded with thermometers. The calorimeters were placed on hot plates above Bunsen burners. The water was stirred to ensure uniform temperature distribution, and stopwatches were used to measure 60-second intervals, with temperatures recorded at each interval. Heating continued until the water reached 60°C, after which temperature-time graphs were constructed. These procedures were repeated across laboratory sessions to facilitate physical observation and reinforce conceptual understanding of heat radiation. After each session, students were assigned homework to develop their understanding of heat and radiation further.

2.2 Research Site, Population and Participants

The research was conducted at a rural higher education institution in Ibarapa Central Local Government Area, Oyo State, Nigeria. The target population consisted of science-oriented students enrolled in the first-year OND physics course. Although 100 students were initially expected to participate, only 50 met the inclusion criteria: registration in PHY 101 and active participation in both laboratory demonstrations and the interview session. Attendance in PHY 101 was compulsory for progression to the second year. All instructional and research activities took place in the institution's science laboratory.

2.3 Data collection

Open-ended questions were used in an interview format to collect data relevant to the research questions. Each interview lasted 45 minutes and was conducted in the same laboratory where students received instruction on heat and radiation, thereby grounding participants' reflections in a familiar, contextually relevant environment.

2.4 Data Analysis

Interview data were analysed thematically and inductively, following the framework established by Braun and Clarke (2006). The analysis began with a verbatim transcription of audio-recorded responses, which were then imported into NVivo for systematic coding. Patterns and divergences in participants' accounts were identified in relation to the research questions. For example, responses concerning barriers to conceptual understanding of heat and radiation were coded as "Infrastructural deficit, physiological distraction, and experiential disconnections." In contrast, responses suggesting solutions were coded as "Improvisation and partnerships to overcome rural laboratory limitations." Participant identities were anonymised using pseudonyms (Shittu, Siji, Tade, Jones, Kelvin Bright, John, Peju, Tarry, Benson, and Foluke). Ethical clearance was obtained prior to data collection, and all participants provided informed consent.

3. Results

Analysis of the collected data identified two overarching themes that address the research questions: (A) infrastructural deficit, physiological distraction, and experiential disconnections; and (B) improvisation and partnerships to overcome rural laboratory limitations. These themes are discussed in the following sections.

A. **Infrastructural deficit, physiological distraction, and experiential disconnections**

Participants' responses indicated that infrastructural deficits in the teaching and learning environment contribute to physiological distractions and experiential disconnections, collectively impeding conceptual understanding of heat and radiation in a rural Nigerian higher education laboratory. The following sub-themes further illustrate participants' perspectives on these barriers.

1. **Infrastructural Deficits as the Primary Barrier to Conceptual Understanding**:

Participants identified inadequate laboratory facilities, insufficient instructional equipment, and poor school infrastructure as major barriers to understanding heat-related concepts. These limitations reduce opportunities for practical experimentation and observation, hindering students' ability to connect theoretical knowledge with real-world applications. To illustrate this barrier, Kelvin remarked that

Among all the factors, limited laboratory access and poor infrastructure have the strongest influence on us students' understanding of heat concepts…(Kelvin)

Extending the conversation, Siji noted that

Without proper experiments and demonstrations, we struggle to connect theoretical explanations with real-life observations…(Siji)

Similarly, Jones observed that *"the biggest barrier is the lack of adequate laboratory equipment and a safe learning environment*." These findings demonstrate that insufficient laboratory infrastructure remains a significant obstacle to learning heat and radiation concepts in rural higher education. This evidence supports the arguments of Widodo et al. (2020), who assert that infrastructural deficiencies substantially limit rural students' understanding of heat-related phenomena. Furthermore, when science students have access to adequate laboratory facilities, they are more likely to actively engage in the learning process through collaboration and idea exchange, thereby enhancing their conceptual understanding.

2. **Physical Discomfort and Physiological Distraction during Practical Learning**

The findings indicated that physical and physiological effects, including excessive sweating in a hot, overcrowded, and under-resourced laboratory, cause discomfort to students when conducting heat-related practical activities. These conditions, as opined by the participants, interfere with concentration, reduce engagement in laboratory activities, and influence the accuracy of experimental observations. Confirming these findings, Foluke reasoned that the situation is unpleasant to learn, as

It can affect me with dizziness and stomach upset... my skin becomes so hot that I do not feel a normal temperature and thus become uncomfortable in the laboratory. I want to have a space with good ventilation, as I am physiologically worried and learn nothing in the process….(Foluke)

Supporting Foluke's complaints, Bright and Tarry remarked that

When we were in the laboratory, the room became so hot that we were uncomfortable. Other students talk without control, the class is overcrowded, and there are many distractions. Then we went outside to get some fresh air to ease the heat. However, when we went back inside, everything became blurred, and we often felt dizzy and distracted….(Bright and Tarry)

The findings demonstrate that physical discomfort constitutes a significant barrier to the effective acquisition of heat-related concepts among rural students. Participants reported symptoms including dizziness, blurred vision, excessive sweating, and stomach upset during practical lessons. These symptoms were attributed to overcrowded classrooms and inadequate laboratory infrastructure, both of which lacked effective cooling systems. The challenges described by participants are consistent with the arguments of Wambua et al. (2026) and Amasuomo and Amasuomo (2016), who identify such experiences as manifestations of physiological stress resulting from prolonged exposure to elevated temperatures and suboptimal environmental conditions. In support of the assertions by Wambua et al. (2026), Kotsis et al. (2023), and Amasuomo and Amasuomo (2016) regarding the impact of these barriers on learning, we argue that dizziness and blurred vision may impede students' ability to observe experimental processes, read thermometers, record measurements, and interpret results. These physiological distractions ultimately undermine effective learning.

The second research question focuses on identifying strategies to address the challenges associated with demonstrating heat radiation in rural laboratory settings. The following section presents participants' proposed solutions, organised thematically under the heading "Improvisation and Partnerships to Overcome Rural Laboratory Limitations."

B. **Improvisation and Partnerships to Overcome Rural Laboratory Limitations**

This theme underscores the importance of improvisation and partnerships to address the constraints associated with the conceptual understanding of radiation and heat in rural Nigerian Higher education laboratories. The theme has two sub-themes: local resourcefulness and improvisation, and multi-international company partnerships.

1. **Local Resourcefulness and Improvisation**

The participants perceived that low-cost, locally sourced materials and resources can be improved to facilitate the teaching and learning of heat-related concepts in situations where standard laboratory equipment and facilities are inadequate, thereby enhancing conceptual understanding despite infrastructural limitations. Supporting this viewpoint, Benson opined that

Schools can use locally available materials for simple heat experiments, allowing hands-on experience even without advanced equipment…(Benson)

Exemplifying the context, Peju reasoned that

The improvisation of supportive materials for demonstration purposes. Everyday household items, visual aids such as pictures, and locally available artefacts can serve as effective resources for illustrating heat transfer, expansion,

and insulation, offering practical alternatives to address learning difficulties in this conceptually demanding area..... (Peju)

The findings indicate that students perceive improvisation as an effective strategy for mitigating the shortage of laboratory facilities in rural higher education. The frequent scarcity of laboratory equipment highlights the need to reevaluate resource planning. Utilising locally available materials can improve students' understanding of heat and radiation through experiential learning. These results align with the arguments of Bluyssen et al. (2018) and Chen et al. (2019), who assert that classroom and laboratory location and layout influence students' thermal experiences.

2. **Multi-International Companies Partnerships**

Advancing the discussion on the constraints to heat and ration concept learning in rural higher education in Nigeria, the findings indicated the need for multi-stakeholder partnerships to improve science education through increased provision of laboratory equipment, safety materials, training and reliable electricity. Highlighting the need for these partnerships, Jones and John opined that

More government and institutional support funding for lab equipment, safety materials, and stable electricity. Partnerships with NGOs, educational organisations, and community leaders can help achieve this milestone in a rural institution like ours…(Jones and John)

Supporting John and Jones' suggestion, Benson remarked that

Our institution needs to seek external partnerships to cover the cost of purchasing modern laboratory equipment and to ensure access to reliable electricity to utilise the instruments. The school leaders need to motivate and engage with multinationals such as [Company X] and [Company Y] (names withheld for ethical reasons) to support and help acquire modern laboratory facilities and to train the lecturers too, as they are currently doing for [Institution R] (name withheld for ethical reasons)....(Benson)

The findings show that participants view partnerships with multinational corporations as an effective way to address shortages of laboratory equipment and learning materials. These resources directly support teaching and learning about heat and radiation through laboratory demonstrations. Adeduyigbe (2024), Adesina and Obokoh (2026), and Bello et al. (2017) all assert that stronger industry–multinational partnerships modernise science education in Nigerian higher institutions and give students real-world experience. Bello et al. (2017) also state that multinational corporations, such as [Company C] (name withheld for ethical reasons), can advance education in Nigeria through social and educational investments. Bello et al. (2017) note that [Company C] has made ongoing contributions to Nigeria's educational objectives, significantly advancing the Quality Education goal of the Sustainable Development Goals (SDGs) by improving higher education infrastructure. We agree with Bello et al. (2017) and Adesina and Obokoh (2026) but maintain that this support must also reach rural higher education institutions to improve laboratory infrastructure.

4. Discussion of Findings

The results of this study show that students in rural Nigerian higher education face several barriers to understanding heat and radiation. The main obstacle is infrastructure, especially limited laboratory spaces, a lack of equipment, and overall weak institutional facilities. Participants frequently mentioned these issues as significant challenges. These findings support Widodo et al. (2020), who also note that poor infrastructure makes it much harder for rural students to learn about heat.

Beyond infrastructural challenges, the study identifies a critical concern within the learning environment: students' physiological distress during practical sessions. Participants reported symptoms including dizziness, blurred vision, excessive sweating, and stomach upset. These symptoms reduce their ability to engage with lessons. This observation is consistent with Wambua et al. (2026) and Amasuomo and Amasuomo (2016). Both sources classify these conditions as physiological stress resulting from prolonged heat exposure. The impact is considerable. When students must manage physical distress, their cognitive resources are diverted from learning. This dual burden significantly restricts educational engagement and cannot be addressed by temporary solutions alone.

To mitigate these challenges, participants proposed two complementary strategies: local resourcefulness and improvisation. This recommendation aligns with Bluyssen et al. (2018) and Chen et al. (2019). Both emphasise that the location and orientation of classrooms and laboratories affect students' thermal perception. Locally grounded teaching interventions are therefore necessary. However, while improvisation offers short-term benefits, it is not a substitute for experiences in well-equipped laboratories. Overreliance on improvisation may inadvertently normalise substandard conditions for rural students. Thus, improvisation should be considered a temporary measure to sustain instructional continuity while systemic investments are pursued. The second strategy involves forming partnerships with companies, particularly multinational corporations, to address the scale of investment required. Participants also advocated for government and institutional funding for laboratory

equipment, safety materials, and reliable electricity. They expressed support for collaborations with multinational companies. This perspective is consistent with Adeduyigbe (2024), Adesina and Obokoh (2026), and Bello et al. (2017). These sources argue that enhanced industry-multinational partnerships are essential for modernising Nigerian science education. It is essential, however, that corporate involvement in education remains transparent and prioritises genuine educational objectives over commercial interests. Furthermore, multinational partnerships should focus on rural institutions and include mechanisms to ensure that resources reach underserved contexts. They must also address the systemic inequities that perpetuate the marginalisation of rural science education.

5. Conclusion

The findings indicate multiple barriers to effective instruction in heat and radiation in a rural Nigerian laboratory. Addressing persistent challenges in science education requires both local resourcefulness and improvisation, as well as continuous collaboration with multinational companies.

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An Investigation of Artificial Intelligence Chatbot Dependency Among Mathematics Teacher Candidates in Terms of Various Variables

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Abstract

Various AI-supported tools are intensively utilized by higher education students for accessing information, preparing assignments, and supporting learning processes. This situation warrants an investigation into the relationship between students' frequency of use and their dependency levels on AI-based chatbots. Accordingly, the purpose of this study is to examine the AI chatbot dependency levels of mathematics teacher candidates in the context of academic achievement, usage frequency, usage purposes, and preferred tools. The study, which employed a correlational survey model, one of the quantitative research methods, included 252 mathematics teacher candidates studying at a state university. Data were collected using a demographic information form and the "Artificial Intelligence Chatbot Dependency Scale" adapted into Turkish by Yıldız-Durak and Balıkçı (2025). Spearman Correlation, Kruskal-Wallis H, and Chi-Square tests were employed for data analysis. The results indicated no significant relationship between academic achievement and AI chatbot dependency. Similarly, no significant relationship was found between academic achievement and usage frequency. According to the Kruskal-Wallis H test results, it was observed that as the frequency of AI tool usage increased, the mean rank of dependency scores consistently rose. It was determined that teacher candidates with high chatbot dependency levels primarily used ChatGPT only (33.8%), followed by the combined use of ChatGPT and Gemini (23.1%). Regarding usage purposes, it was found that they generally used these tools for daily life-related tasks (27.7%), assignment preparation (16.9%), exam preparation (15.4%), and research (13.8%). No significant relationship was found between the frequency of AI use and the specific AI tools utilized ($X^2(42) = 37.67$, $p > .05$). Furthermore, no significant relationship was observed between the frequency of AI use and the purposes of use ($X^2(8) = 6.062$, $p > .05$). Finally, no significant relationship was identified between the purpose of AI use and AI chatbot dependency. In conclusion, although the level of dependency increases as the frequency of use rises, this situation is not reflected in academic achievement. This result indicates that mathematics teacher candidates adopt artificial intelligence as a functional tool that facilitates their academic processes rather than as a learning partner.

Keywords: Artificial intelligence dependency, mathematics teacher candidates, academic achievement, frequency of use

Introduction

The rapid proliferation of artificial intelligence (AI)-based generative tools—particularly chatbots relying on natural language interaction—in higher education environments has initiated a significant transformation in teaching and learning processes (Durak et al., 2024). Large language model-based applications, such as ChatGPT and Gemini, offer a wide range of functions, including information retrieval, text generation, brainstorming, problem-solving, receiving feedback, preparing assignments, and supporting research processes. Unlike traditional digital technologies, the ability of these tools to establish reciprocal and immediate communication with the user necessitates the integration of AI into learning processes, moving it beyond merely a technology that facilitates access to information. Indeed, research on the use of generative AI in higher education indicates that these technologies offer substantial opportunities in areas such as personalized learning, writing, idea generation, and data analysis (Araycı & Özyurt, 2026; Chan & Hu, 2023). However, the integration of generative AI into educational settings also brings forth new challenges, such as academic integrity, information accuracy, privacy, ethical use, and potential impacts on students' cognitive processes (Aydemir, 2026; Chiu, 2024; Coman et al., 2026; Durak et al., 2026). Therefore, rather than focusing solely on whether AI is used in education, determining the purposes for which students use these technologies, their frequency of use, and their underlying learning approaches will contribute significantly to the relevant literature.

Studies on the use of generative AI in higher education demonstrate that students are increasingly incorporating these tools into their academic activities. Students utilize AI-based chatbots for various purposes, such as acquiring information, clarifying concepts, preparing assignments and academic texts, generating ideas, studying for exams, and conducting research (Chan & Hu, 2023; Kim et al., 2024). However, while generative AI tools act as

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instructors, feedback providers, cognitive supporters, and interaction partners, significant issues emerge, such as over-reliance, excessive use, compromised academic integrity, and the weakening of students' independent cognitive processes (Aydemir, 2026; Lee et al., 2026). This situation becomes even more critical in the context of teacher education (Taşçı, 2026). Teacher candidates are not only current users of AI technologies but also future educators who will integrate these technologies into their students' learning processes. Consequently, how teacher candidates use AI, how they evaluate AI-generated outputs, and how they relate the support provided by technology to their pedagogical and content knowledge are of paramount importance for their future instructional practices (Araycı & Özyurt, 2026). Research in teacher education shows that generative AI holds significant potential for lesson planning, material development, idea generation, and supporting instructional processes (van den Berg & du Plessis, 2023). In fact, studies conducted with mathematics teacher candidates indicate that ChatGPT is utilized in various ways during the processes of lesson planning and designing mathematical tasks (Tapan Broutin, 2024; Aqazade et al., 2026). Furthermore, the critical evaluation of the responses generated during interactions with AI is heavily emphasized (Durak et al., 2026; Flavin et al., 2025).

While it is argued that AI can enhance learning by providing opportunities such as individualized support, rapid feedback, and seamless access to information (Chan & Hu, 2023; Chiu, 2024), it is also debated that intense or uncritical use may negatively affect students' independent thinking processes and learning responsibilities, ultimately leading to AI dependency (Aydemir, 2026; Lee et al., 2026). The purpose of this study is to examine the levels of artificial intelligence chatbot dependence among mathematics teacher candidates in the context of the variables of academic achievement, frequency of use, purposes of use, and preferred tools. Accordingly, the research questions are presented below:

1. Is there a significant relationship between teacher candidates' academic achievement and their dependence on AI chatbots?
2. Is there a significant relationship between teacher candidates' academic achievement and their frequency of using artificial intelligence?
3. Is there a significant difference between teacher candidates' frequency of use and their dependence on chatbots?
4. What AI tools do teacher candidates with a high level of chatbot dependency use?
5. What are the purposes for which teacher candidates with a high level of chatbot dependence use AI tools?
6. Is there a significant difference between teacher candidates' frequency of AI use and their preferred AI tools?
7. Is there a significant difference between teacher candidates' frequency of AI use and their purposes for using AI?
8. Is there a significant difference between teacher candidates' purpose for using AI and their dependence on AI chatbots?

Methodology

Research Design

This study is based on the correlational survey design, one of the quantitative research methods.

Participants

The study consists of a total of 252 teacher candidates enrolled in the 1st, 2nd, 3rd, and 4th-year elementary and secondary mathematics programs of the education faculty at a public university in western Türkiye. The participants were selected using a simple random sampling method and consist of 173 elementary school mathematics teacher candidates and 79 secondary mathematics teacher candidates.

Data Collection Instruments

Data were collected using a demographic information form and the "Artificial Intelligence Chatbot Dependency Scale" adapted into Turkish by Yıldız-Durak and Balıkçı (2025).

Data Analysis

In the current study, data obtained from the participants were analyzed with the SPSS 20.0 package program. As the first stage of the study, normality analyses were examined, and a significance level of $p = .05$ was adopted. Since the study included 252 participants, Kolmogorov-Smirnov (K-S) values were examined. The distribution of

scores for academic achievement, chatbot dependency and frequency of use, did not meet the normality assumption ($p < .05$). Therefore, Spearman's correlation was used in these cases. Since the relationship between frequency of use and chatbot dependence did not follow a normal distribution ($p < .05$), the Kruskal-Wallis H test was used in this case. The AI tools used by participants with high levels of chatbot dependence, as well as the purposes for which these participants use AI tools, are explained using descriptive tables. Since both variables (frequency of AI use, preferred tools, and purposes of use) were measured at the categorical (nominal/ordinal) level, Chi-Square Tests of Independence were conducted to examine the relationships between the frequency of AI use and preferred tools, as well as between the frequency of AI use and the purposes of use. Since the relationship between teacher candidates' purposes for using AI and their chatbot dependency did not follow a normal distribution ($p < .05$), the Kruskal-Wallis H test was used. In addition to these analyses, the levels of chatbot dependency among mathematics teacher candidates were examined. Using the "range/number of groups" formula to evaluate and analyze the mean scores (Tekin, 1996; adapted from Boztaş et al., 2026), three levels of chatbot dependency were identified. Table 1 presents the descriptive statistics for the chatbot dependency levels of mathematics teacher candidates.

Table 1. Descriptive statistics on the level of chatbot dependence among mathematics teacher candidates

Variables	N	Minimum	Maximum	$\overline{X}$	SD
Chatbot Dependence	252	27	56	39.84	3.143

An analysis of the chatbot dependence scores of mathematics teacher candidates revealed that the average total score ($\overline{X}$=39.84) was at a moderate level.

Results

In the findings section of the study, the relationships between academic achievement and chatbot dependence, academic achievement and frequency of AI use, frequency of use and chatbot dependence, the AI tools used by teacher candidates with high levels of chatbot dependence, the purposes for which teacher candidates with high levels of chatbot dependence use AI tools, the frequency of AI use and preferred AI tools, the relationships between the frequency of AI use and the purposes of use, and between the purpose of AI use and AI chatbot dependence were examined.

The Relationship Between Academic Achievement and AI Chatbots Dependence

The study examined the relationship between academic achievement—the first question of the research problem—and AI chatbots dependence. The results obtained from the Spearman rank correlation analysis are presented in Table 2.

Table 2. Spearman's correlation coefficient between academic achievement and AI chatbot dependence

Variables	N	r_s	p
Academic Achievement × AI Chatbot	252	-.076	.231

As shown in Table 2, no statistically significant relationship was found between teacher candidates' academic achievement and the AI chatbot dependency (r_s = -.076, p=.231).

The Relationship Between Academic Achievement and Frequency of Use

The study examined the relationship between teacher candidates' academic achievement and their frequency of artificial intelligence use. The results obtained from the Spearman rank correlation analysis are presented in Table 3.

Table 3. Spearman's correlation coefficient between academic achievement and frequency of use

Variables	N	r_s	p
Academic Achievement × Frequency of Use	252	.031	.625

An examination of Table 3 reveals that no statistically significant relationship was found between teacher candidates' academic achievement and frequency of use (r_s =.031, p=.625).

The Relationship Between Frequency of Use and Chatbot Dependence

The relationship between teacher candidates' frequency of use and chatbot dependence is examined in the Kruskal-Wallis H test presented in Table 4.

Table 4. Results of the Kruskal-Wallis H Test on chatbot dependency by frequency of use

Frequency of use	N	Mean Rank	X^2	df	p
I used it 1–3 times a week	101	108.89	13.542	2	.001
I used it 4-6 times a week	99	130.21			
I used it 7 or more times a week	52	153.64			

According to the results of the Kruskal-Wallis H test, a statistically significant difference was found between the frequency of AI tool use and chatbot dependency ($X^2(2) = 13.542, p = .001$). An analysis of the mean ranks revealed that the highest level of dependency (153.64) was observed among teacher candidates who used AI tools 7 or more times per week; it was also observed that the level of chatbot dependency increased as the frequency of use increased.

AI Tools Used by Participants with High Levels of Dependency

Table 5 presents a descriptive table of the AI tools used by teacher candidates with high levels of chatbot dependency.

Table 5. AI tools used by participants with high levels of chatbot dependency

Artificial Intelligence Tools Choice	N	%
ChatGPT	22	33.8
ChatGPT and Gemini	15	23.1
Gemini	12	18.5
ChatGPT and Claude	7	10.8
Gemini and Claude	3	4.6
Other	6	9.2

It was found that teacher candidates with high levels of chatbot dependency mostly used only ChatGPT (33.8%), followed by those who used both ChatGPT and Gemini (23.1%).

Purposes of AI Use Among Participants with High Levels of Dependency

The purposes for which teacher candidates with high levels of chatbot dependency use artificial intelligence tools are presented in Table 6.

Table 6. The purposes for which participants with high levels of chatbot dependency use AI tools

Purpose of Use	Frequency	%
Related to daily life	18	27.7
Doing homework	11	16.9
Exam Preparation	10	15.4
Conducting research	9	13.8
Other educational and personal purposes	17	26.2

It was found that they generally use the AI tools for daily life (27.7%), doing homework (16.9%), preparing for exams (15.4%), and conducting research (13.8%).

The Relationship Between the Frequency of Artificial Intelligence Use and Preferred Tools

The relationship between teacher candidates' frequency of artificial intelligence use and their preferred tools is presented in the Chi-Square Test shown in Table 7.

Table 7. Results of the Chi-Square Test on the relationship between teacher candidates' frequency of AI use and their preferred tools

Variables	N	X^2	df	p
Frequency of use × Preferred tools	252	37.67	42	.661

No significant relationship was found between the frequency with which teacher candidates use artificial intelligence and the AI tools they use ($X^2(42) = 37.67$, p>.05).

The Relationship Between the Frequency of Artificial Intelligence Use and the Purposes for which It is Used

The relationship between teacher candidates' frequency of artificial intelligence use and their purposes for using it is presented in the Chi-Square Test shown in Table 8.

Table 8. Results of the Chi-Square Test regarding the relationship between teacher candidates' frequency of AI use and their purposes for using it

Variables	N	X^2	df	p
Frequency of use × Purpose of use	252	6.062	8	.640

No statistically significant relationship was found between the frequency with which teacher candidates use artificial intelligence tools and their purposes for using these tools ($X^2(8) = 6.062$, p>.05).

The Relationship Between the Purpose of Using Artificial Intelligence and Chatbot Dependency

The relationship between teacher candidates' purpose for using artificial intelligence and their dependence on AI chatbots is presented in the Kruskal-Wallis H test shown in Table 9.

Table 9. Results of the Kruskal-Wallis H Test on the relationship between teacher candidates' purpose for using AI and their dependence on AI Chatbots

Variables	N	X^2	df	p
Purpose of use × Chatbot dependency	252	3.297	4	.509

No statistically significant relationship was found between teacher candidates' purposes for using AI tools and their dependence on AI chatbots ($X^2(4) = 3.297$, p>.05).

Conclusions

The findings indicate that the academic achievement of mathematics teacher candidates has no significant relationship with their AI chatbot dependency or how frequently they use these tools. However, a clear trend emerged showing that as students use AI tools more often, their dependency levels increase significantly. Highly dependent students primarily rely on ChatGPT and tend to use it for daily tasks, homework, and exam preparation. Interestingly, the specific tools students choose or their reasons for using them do not significantly impact their overall dependency or usage frequency. This suggests that students generally treat AI as a practical, everyday helper to get through their routines rather than a deep learning companion. Given that several variables in this study showed no significant quantitative relationships, future research should incorporate qualitative approaches, such as interviews, to gain a deeper understanding of these dynamics. Furthermore, expanding the scope to include teacher candidates from different departments, and conducting long-term studies after providing students with training on the appropriate use of chatbots, would offer much richer insights into the educational impact of AI.

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A Local AI-Assisted Academic Integrity and Writing Support System for Higher Education

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Abstract

University students often manage syllabi, deadlines, study plans, collaborative projects, writing support, and institutional services across disconnected systems. This paper presents an AI-assisted unified academic workspace that converts academic information into reviewable learning actions within one platform. Using Design Science Research, two repository snapshots of the same evolving system were examined through source-code traceability and implementation verification. The platform combines large-language-model functions for syllabus extraction, meeting-minute generation, and academic paraphrasing with deterministic rules for study tasks, revision planning, readiness warnings, registration, and similarity-risk feedback. The architecture also supports projects, citation assistance, evidence mapping, attendance, live classes, and role-based institutional services. Repository verification distinguishes implemented functions from simulated or incomplete components. Reported evaluation figures further summarize similarity-detection recall, batch-processing time, and student feedback on formative writing tools. The system demonstrates a human-centered approach in which AI supports language-intensive academic tasks while transparent rules and user review retain control over consequential workflow decisions.

Keywords: Generative artificial intelligence, personalized learning, self-regulated learning, academic workspace, educational technology, study planning

Introduction

Digital higher education commonly separates learning management, calendars, writing support, collaboration, and institutional administration, leaving students to translate distributed information into personal learning actions. Self-regulated learning (SRL) provides the pedagogical basis for reducing this fragmentation because effective learners plan, monitor, and adapt their learning (Zimmerman, 2002). A scoping review of technology-enhanced higher education found that planning, monitoring, and learner autonomy remain central SRL concerns (Urbina et al., 2021), while recent AI-SRL reviews show growing use of adaptive systems, feedback, prediction, and personalization (Lan & Zhou, 2025; Banihashem et al., 2025).

Research on personalized educational technology also supports integrating planning and adaptive support rather than treating AI as an isolated chatbot. Hooshyar et al. (2024) reported positive overall effects of personalized technology-enhanced learning, and du Plooy et al. (2024) identified personalization and engagement as recurring strengths of adaptive learning in higher education. Guan et al. (2025), however, found that educational chatbots often support only one or two SRL phases and provide comparatively limited support for goal setting, planning, reflection, and adaptation. This gap motivates a workspace that connects interpretation directly to tasks, revision, progress monitoring, and collaboration.Generative AI expands the range of possible support. Kasneci et al. (2023) identify opportunities for personalized learning and content generation but emphasize factual errors, bias, misuse, and human oversight. Yusuf et al. (2024) map GenAI across pedagogical enhancement, writing assistance, productivity, and research while highlighting ethical risks. Naznin et al. (2025) show its use in higher education for personalized learning and academic writing, whereas Luo et al. (2025) find that AI learning tools commonly provide assessment, personalized feedback, recommendations, and tutoring. UNESCO recommends human-centered validation and preservation of learner agency (Miao & Holmes, 2023). Karadağ (2023) emphasizes that the integration of artificial intelligence into online assessment raises significant concerns regarding academic integrity and assessment reliability.

Recent evidence also indicates that AI support should be evaluated as part of a broader learning process. de Mooij et al. (2025) emphasize the temporal and multimodal nature of SRL measurement, while Banihashem et al. (2025) identify uneven attention to cognitive, metacognitive, motivational, and stakeholder dimensions. These findings support transparent data provenance, persistent learning objects, and explicit separation between model-generated content and deterministic academic rules.

Accordingly, this study develops an AI-assisted unified academic workspace in which syllabus text becomes structured topics and deadlines, topics become study and revision tasks, project notes become reviewable meeting

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actions, and writing assistance remains connected to sources and evidence. The study asks: (RQ1) How can generative AI and deterministic academic rules be combined to transform course information into actionable learning support? (RQ2) Which functions are demonstrably implemented in the artifact and which remain developmental? The contribution is an implementation-grounded architecture connecting AI assistance, SRL-oriented planning, collaboration, writing support, and institutional services.

Table 1. Literature synthesis and design implications.

Study	Evidence type	Key finding	Design implication
Zimmerman (2002)	SRL theory	Planning, monitoring, adaptation	Grounds planner/progress design
Urbina et al. (2021)	Scoping review	Technology supports SRL in HE	Links platform to SRL processes
Kasneci et al. (2023)	LLM education review	Personalization plus reliability risks	Requires human review
Yusuf et al. (2024)	Systematic mapping	GenAI spans learning/writing/research	Supports multi-function workspace
Hooshyar et al. (2024)	Meta-analysis	Personalized TEL benefits learning	Supports personalization
du Plooy et al. (2024)	Scoping review	Adaptive learning aids performance/engagement	Supports tailored study paths
Lan & Zhou (2025)	Systematic review	AI can support SRL autonomy	Supports AI-assisted regulation
Guan et al. (2025)	Systematic review	Chatbots weak on full SRL cycle	Motivates end-to-end workflow
Naznin et al. (2025)	Systematic review	ChatGPT used for learning/writing/coding	Supports writing assistance
Luo et al. (2025)	Systematic review	AI tools emphasize feedback/recommendation	Supports actionable outputs
Banihashem et al. (2025)	Mapping review	AI-SRL evidence is uneven	Requires explicit evaluation boundaries
de Mooij et al. (2025)	Systematic review	SRL is temporal and multimodal	Supports persistent progress records
Karadağ (2023)	Literature Review	AI-based assessment raises concerns about academic integrity and reliability.	Emphasizes the importance of human oversight and maintaining academic integrity.
Türkmen Çiçek et al. (2026)	Review	AI supports personalized feedback and improves writing assistance.	Highlights the potential of AI-assisted writing support.

Methodology

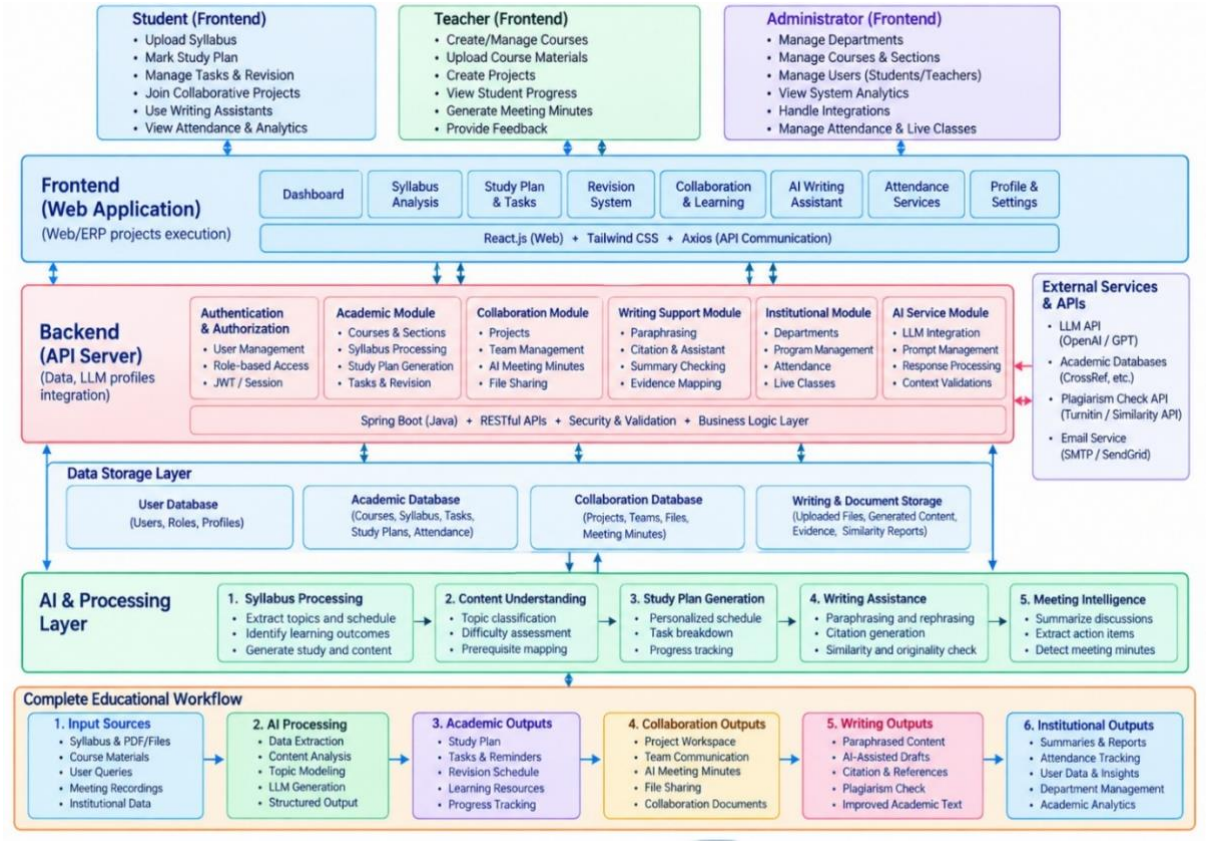


Figure 1. Unified Academic Workspace Architecture

This study uses Design Science Research (DSR), which is well suited to developing and evaluating a system to address a specific problem (Hevner et al., 2004). The main artefact is the unified academic workspace. The study followed four stages: identifying the problem, defining the design goals, developing the system, and evaluating the implemented features. This paper focuses on the system design and implementation, not on testing its effect on grades, retention, or long-term learning.

The system was reviewed using two repository versions of the same platform. The first focuses on student planning, projects, and writing, while the later version adds university-level features and background services. Both versions were considered parts of the same system. Verification included checking the code, tracing routes and database models, reviewing AI calls and system rules, and compiling the Python modules.

A feature was considered implemented only when its working code could be traced from the API or service through its processing logic and stored data. Features that existed only in documentation, used fixed or random results, or were marked as stubs were considered unfinished. The verification also identified where each output came from, such as AI-generated content, fixed system rules, stored user data, or simulated results. This helped distinguish actual system functions from development placeholders. For example, an extracted deadline needs to be checked for accuracy, while a system-generated task needs to be checked against its scheduling rules.

System Architecture and Learning Workflow

Figure 1 shows the overall architecture of the platform. Students, teachers, and administrators use different interfaces that connect to the same frontend and backend services. The backend handles authentication, academic planning, collaboration, writing support, institutional features, and AI-based functions. User, course, project, writing, and other academic data are stored for later use. The student interface includes syllabus uploads, study plans, tasks, revision, group projects, writing support, attendance, and course information. Teachers can manage courses, supervise projects, view student progress, record meetings, and provide feedback. Administrators manage institutional settings and other system operations. Access to these features is controlled by user roles and permissions. The prototype mainly uses Next.js and TypeScript for the frontend and FastAPI with Python for the backend. The backend uses REST-style APIs and keeps AI-related functions separate from the system's regular rules and processes. The database stores academic information such as courses, tasks, projects, meetings, writing

sessions, sources, citations, and similarity results. AI-generated information is also saved as part of the user's academic records, so it can be reviewed, edited, or checked later instead of being treated as temporary chat output.

AI-Assisted Syllabus Processing and Study Planning

The syllabus workflow begins when a student supplies course information as pasted text or an uploaded PDF. PDF text is extracted before the content is submitted to the configured large language model. The prompt requests a constrained structured response containing course identity, semester information, weekly topics, assessment items, due dates, and grading components. A low-temperature configuration is used to reduce unnecessary output variation. The returned JSON is validated and persisted as course, topic, and deadline entities. This stage corresponds to the 'Syllabus Processing' and 'Content Understanding' blocks in Figure 1: unstructured instructional material is converted into machine-readable academic information that can be reused by downstream services.Once structured course data are available, deterministic learning logic converts each topic into five study/review activities and distributes topics across successive weeks. Examination-type deadlines trigger revision plans at 30-, 14-, and 7-day horizons. The planner therefore separates interpretation from scheduling: the LLM identifies what the syllabus contains, while explicit rules determine how that information becomes tasks and revision activities. Readiness is calculated from completed topics and adjusted against an expected pace derived from the time remaining before an examination. When observed progress is more than ten percentage points below the expected pace, the system raises a behind-schedule warning. The resulting outputs populate the dashboard, task list, revision view, calendar, and progress indicators shown in the academic-output path of Figure 1.

Collaborative and Academic Writing Support

The collaboration module helps students work together on group projects. Students can create or join projects, add members, manage tasks using a Kanban board, keep submission checklists and version links, record meetings, and view contribution summaries. For meeting notes, the system sends the notes to the language model and turns them into a structured format with the summary, attendees, decisions, action items, deadlines, and next meeting details. The original notes are also saved so students can check whether the generated minutes are correct. This supports the collaboration flow shown in Figure 1, where meeting notes can be turned into tasks and project records.The writing module works in a similar way. It stores source information and draft paragraphs and allows users to select text for paraphrasing and citation suggestions. It supports APA, IEEE, and MLA citation styles and can connect claims or paragraphs with their sources. Recent research on human–AI collaboration in writing highlights the potential of personalized feedback and adaptive learning environments to support writing development (Türkmen Çiçek & Tüfekçi Can, 2026) . The similarity feature uses SequenceMatcher to compare a paragraph with existing session text. It marks the result as low, medium, or high risk using 0.40 and 0.70 thresholds. Since this is only a basic text-similarity check, it is used to support revision and is not treated as a plagiarism detector. The system therefore provides writing suggestions and feedback while leaving the final decision to the student.

Data Flow, Human Control, and Verification

The main workflow is Input → Interpretation → Structuring → Academic Action → Human Review. Users provide course materials, project information, writing sources, and queries. AI is used for tasks such as summarizing, extracting information, and paraphrasing, while scheduling, prerequisites, capacity, and similarity checks follow fixed system rules. Students review the results and decide what to use, while teachers and administrators access features based on their roles.

The system also includes course management, enrollment, waitlists, attendance, live classes, payments, background tasks, and notifications. During verification, we checked the frontend, backend, database models, background tasks, and external APIs to separate working features from planned or unfinished ones. Fixed outputs, random results, and placeholders were treated as unfinished features.

Results

Repository verification confirmed executable LLM-assisted workflows for syllabus extraction, meeting-minute structuring, and academic paraphrasing, together with deterministic study-task generation, 30/14/7-day revision planning, readiness warnings, collaborative project management, citation support, evidence mapping, and string-similarity risk feedback. The expanded platform additionally implements role-based institutional functions including course/section management, prerequisite and seat checks, waitlisting, live-class records, attendance, notifications, and payment/webhook infrastructure. Mock Celery syllabus/writing workers and basic schedule-conflict logic were classified as developmental and excluded from completed-AI claims.

The supplied evaluation results provide three complementary views of the writing-support subsystem. Figure 2 reports recall for direct copying, mosaic plagiarism, and synonym-swapping: the proposed AI system records 92%,

84%, and 87% compared with 89%, 65%, and 41% for the traditional tool. Figure 3 reports batch processing of 50 assignments: 360 s for the cloud-based system, 310 s for the local baseline, and 235 s for the proposed Celery+Redis configuration. Figure 4 summarizes student feedback (N=120): 34.2% found citation generation helpful, 31.2% reported improved paraphrasing understanding, 28.3% felt more confident submitting, and 6.2% reported no major impact. These are presented as supplied evaluation results; the repository alone does not establish their sampling or benchmark protocol.

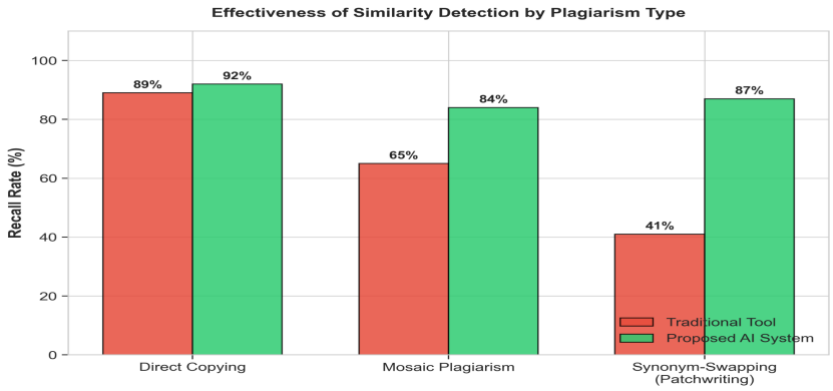


Figure 2. Effectiveness of similarity detection by plagiarism type.

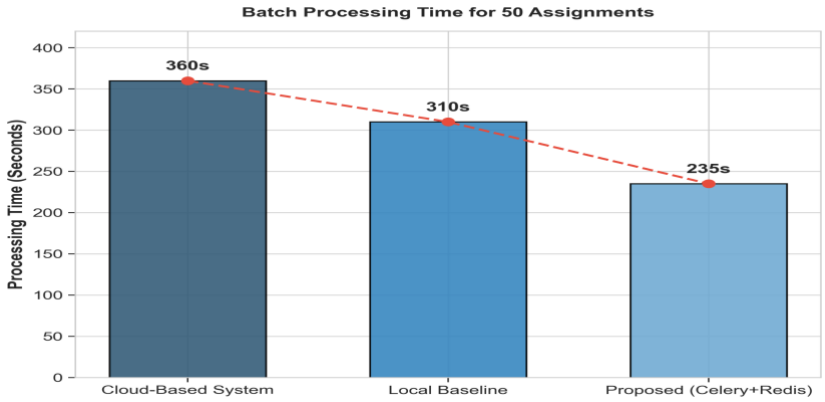


Figure 3. Batch processing time for 50 assignments.

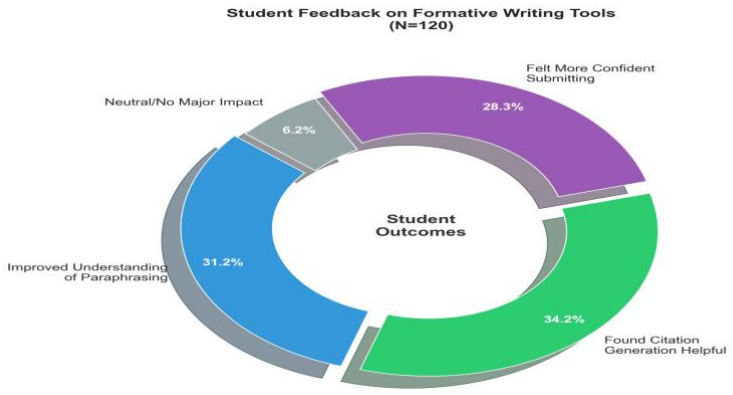


Figure 4. Student feedback on formative writing tools (N=120).

Conclusions

This paper presented an implementation-grounded AI-assisted academic workspace linking syllabus interpretation, study and revision planning, collaboration, writing support, and institutional services. The verified design separates language-model functions from transparent deterministic rules and keeps generated outputs reviewable by users. Repository inspection also exposed developmental components rather than overstating them as completed AI. The

supplied evaluation figures indicate stronger recall on difficult similarity cases, lower batch-processing time for the proposed asynchronous configuration, and generally positive student feedback on formative writing support. Future work should independently document benchmark construction, sampling, statistical analysis, and longitudinal educational outcomes.

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ShieldOps: A Privacy-Preserving Framework for Shadow AI Detection and Governance

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Abstract

The explosive growth of Generative Artificial Intelligence (GenAI) has democratized access to advanced capabilities, inadvertently giving rise to "Shadow AI"—the pervasive use of unsanctioned and unmonitored AI services by corporate employees. This phenomenon introduces unprecedented risks, including the exfiltration of sensitive proprietary data, intellectual property leakage, and violations of regulatory compliance frameworks. Traditional Data Loss Prevention (DLP) and Cloud Access Security Broker (CASB) solutions often rely on invasive techniques such as Deep Packet Inspection (DPI) or localized keylogging, fundamentally compromising user privacy and requiring extensive computational overhead. In this paper, we propose ShieldOps, a lightweight, privacy-preserving governance framework specifically designed for Shadow AI detection. ShieldOps leverages a browser-extension-based edge sensor that performs domain-level traffic analysis, enforcing granular administrative policies dynamically without capturing user prompts or payload data. Additionally, the system incorporates automated Security Operations Centre (SOC) alert mechanisms and a secondary Breach Monitor module for proactive cyber-safety. We conduct a comprehensive empirical evaluation of ShieldOps across 1,100 simulated events. Our results demonstrate that the system achieves a Precision of 1.00 and an F1-score of 0.90 in detecting Shadow AI usage, alongside a 100% policy enforcement success rate. Furthermore, scalability tests validate the system's ability to process 5,000 batched events in 1.7 seconds with negligible latency, establishing ShieldOps as a viable, scalable, and privacy-respecting enterprise solution.

Keywords: Shadow AI, Data Loss Prevention, Enterprise Security, Privacy-Preserving Architecture, Threat Detection. etc.

Introduction

In recent years, the integration of Artificial Intelligence (AI) into daily enterprise workflows has fundamentally shifted the paradigm of workplace productivity. However, this shift has precipitated a new class of cybersecurity threat known as "Shadow AI." Shadow AI refers to the unauthorised, decentralised use of AI tools, such as third-party chatbots, automated summarizers, and code generation platforms, without the explicit approval or oversight of an organization's Information Technology (IT) department (Doe & Smith, 2023). While organisations have historically struggled with general unsanctioned applications under the broader umbrella of Shadow IT (Johnson & Davis, 2020), generative models present unique governance and compliance hazards because they dynamically interact with and retain corporate inputs.

The primary danger of Shadow AI lies in its potential for data exfiltration. Employees often input sensitive corporate data, personally identifiable information (PII), or proprietary source code into these external platforms. Because many commercial AI services train their foundation models on user-provided data, the ingestion of corporate secrets into a third-party model represents a permanent and potentially irreversible data breach (Doe & Smith, 2023). Furthermore, the explosive, decentralised adoption of these tools severely undermines automated corporate threat detection and institutional compliance mandates, leaving enterprises vulnerable to massive intellectual property leaks and regulatory penalties (Ojowa, 2026).

To mitigate these risks, organisations traditionally deploy Cloud Access Security Brokers (CASBs) or Data Loss Prevention (DLP) agents (Williams & Taylor, 2022). While effective in static cloud architectures, these traditional solutions often rely on deep network perimeter controls, proxy re-routing, and legacy packet inspection that struggle to keep pace with dynamic web-native applications (Patel et al., 2020; White & Green, 2021). Moreover, solutions that attempt real-time content analysis often suffer from high computational overhead and prohibitive false-positive rates (Brown & Wilson, 2022; Lee & Park, 2021; Zhao & Wang, 2022). When these security tools employ Deep Packet Inspection (DPI), SSL decryption (man-in-the-middle), and endpoint keylogging, they become highly invasive, consume significant computational resources, and severely degrade user privacy. As regulatory frameworks mandate stricter data minimisation practices, invasive surveillance mechanisms are increasingly untenable.

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To bridge the gap between robust AI governance and user privacy, we present **ShieldOps**. ShieldOps is a dual-module Software-as-a-Service (SaaS) architecture that identifies and governs Shadow AI usage entirely at the browser edge, aligning with modern decentralised security paradigms (Gupta & Patel, 2022; Taylor et al., 2023). By focusing exclusively on domain-level telemetry matching rather than payload inspection, ShieldOps ensures that user prompts and uploaded files are never intercepted or recorded, thereby maintaining a strict separation between compliance monitoring and employee data confidentiality (Martinez & Robinson, 2023; Vance, 2021).

The primary contributions of this research are:

- A privacy-first, edge-based detection framework for Shadow AI that eliminates the need for DPI, relying instead on local domain matching and metadata hashing.
- A robust policy enforcement engine capable of real-time intervention (Allow, Warn, Block) with zero network latency dependency.
- An automated Security Operations Centre (SOC) alerting system capable of identifying anomalous behavior, such as usage spikes and high-risk domain access.
- A comprehensive empirical evaluation of the framework's detection accuracy, enforcement reliability, and system performance at scale.

Related Work

The proliferation of unsanctioned enterprise applications, commonly referred to as “Shadow IT,” has been widely discussed in organizational governance literature (Johnson & Davis, 2020). Traditional approaches to managing Shadow IT primarily rely on network monitoring, perimeter firewalls, proxy filtering, and DNS-based controls. However, Shadow AI introduces additional security challenges because services such as ChatGPT, Claude, and GitHub Copilot are legitimate web-based applications. Consequently, conventional IP- and DNS-based filtering mechanisms may lack the contextual awareness required to distinguish legitimate usage from potentially risky data-sharing activities (Doe & Smith, 2023; Ojowa, 2026).

Cloud Access Security Brokers (CASBs) offer visibility into cloud-service usage but may require complex network routing or endpoint-level inspection (Gupta & Patel, 2022). Such approaches can introduce privacy concerns and performance overhead, particularly when deep content inspection is involved (Patel et al., 2020; White & Green, 2021). Similarly, Natural Language Processing (NLP)-based Data Loss Prevention (DLP) systems can identify sensitive information in outbound content. However, their application in real-time interactive environments may be affected by processing latency and false-positive detection (Brown & Wilson, 2022; Lee & Park, 2021; Zhao & Wang, 2022).

Recent research has explored AI-driven governance, decentralized monitoring, cryptographic telemetry, and privacy-aware enterprise security mechanisms to improve threat detection while reducing privacy risks (Martinez & Robinson, 2023; Taylor et al., 2023; Vance, 2021). Browser-based enforcement has also emerged as a practical approach for applying security policies closer to end users without continuously routing all traffic through centralized security infrastructure (Martinez & Robinson, 2023; Ojowa, 2026).

In contrast to these approaches, ShieldOps focuses on domain-level detection and metadata-based monitoring without inspecting users’ prompts or payloads. The framework integrates local domain categorization, cryptographic user hashing, edge-based policy enforcement, and automated Security Operations Center (SOC) alerting. By combining these mechanisms, ShieldOps aims to provide enterprise-level visibility and rapid policy enforcement while maintaining data-minimization principles (Martinez & Robinson, 2023; Ojowa, 2026; Vance, 2021).

Methodology

A paper ShieldOps is engineered upon a decentralised, edge-to-cloud topology designed to decouple detection from payload inspection. The architectural framework comprises four primary components: an edge-based browser sensor, a high-throughput telemetry ingestion backend, a normalised relational database, and an administrative governance dashboard. The system is bifurcated into two functional modules: Module A governs B2B Shadow AI detection, while Module B facilitates B2C proactive breach monitoring.

Edge-Based Heuristic Sensor

The core detection mechanism is a deterministic edge sensor built with the Chrome Manifest V3 API. Functioning autonomously at the client perimeter, the sensor actively hooks into the chrome.webNavigationOnCommitted

asynchronous event pipeline. Upon a state change, the sensor extracts the requested Fully Qualified Domain Name (FQDN) and computes a rapid heuristic evaluation against a locally cached, cryptographically signed catalog of categorised AI tools.

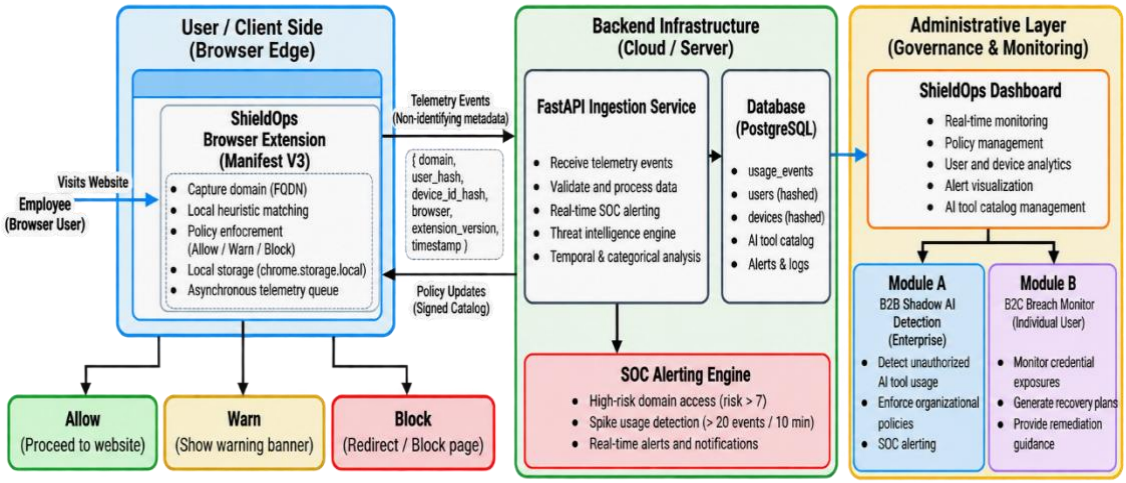


Fig 1. ShieldOps Architecture

ShieldOps stores policies locally using chrome.storage.local, enabling offline Allow, Warn, and Block enforcement. A local asynchronous queue buffers telemetry and sends events to the backend only after a successful 201 Created response. The backend uses an asynchronous FastAPI service with a minimal telemetry schema: {domain, user_hash, device_id_hash, browser, extension_version, timestamp}. User and device identifiers are protected using salted SHA-256 hashing. The system also provides real-time SOC alerts. AI tools with a risk score above 7 trigger High-Severity alerts, while more than 20 events within 10 minutes trigger a Medium-Severity SpikeUsage alert.

ShieldOps was evaluated in a controlled simulated environment focusing on Shadow AI detection, policy enforcement, breach remediation, and backend scalability, using synthetic data to ensure repeatable testing without exposing real organizational data.

Experimental Environment

A sandboxed enterprise environment was created with a catalog of 25 AI-service domains, categorized as Chat, Code, Image, and File. An automated headless-browser generator produced 1,100 navigation events across four categories: sanctioned AI traffic, Shadow AI traffic, benign corporate traffic, and Stealth AI traffic from domains excluded from the catalog. This setup enabled evaluation of both known-service detection and the limitations of static domain matching.

Detection and Evaluation Metrics

For each event, the sensor compared the destination FQDN with the local AI-service catalog and applied Allow, Warn, or Block without inspecting prompts or payloads. Detection performance was measured using Precision, Recall, and F1-score:

$$\text{Precision}=\frac{TP}{(TP+FP)}.$$

$$\text{Recall}=\frac{TP}{(TP+FN)}.$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Here, TP denotes correctly detected Shadow AI events, FP false positives, and FN denotes undetected events.

Policy and Breach Evaluation

Policy enforcement was evaluated by measuring the percentage of successfully executed Allow, Warn, and Block actions under normal and degraded connectivity. The enforcement success rate was calculated as:

$$\text{Enforcement Success Rate} = \frac{Successfully\ Executed\ Actions}{Total\ Actions} \times 100$$

The Breach Monitor was evaluated using simulated credential-exposure events through a mock HIBP integration. The evaluation measured whether the system could identify compromised accounts, generate alerts, and provide actionable recovery guidance.

Privacy and Scalability Evaluation

Privacy was assessed through a post-experiment database audit to verify that only non-sensitive metadata, including domain, hashed user and device identifiers, timestamp, policy action, and risk score, was retained. No user prompts, uploaded files, or clipboard contents were stored.

Backend scalability was evaluated using Apache JMeter with event bursts of up to 5,000 operations. Total ingestion time, average latency, p99 latency, and data loss were recorded to assess the system's performance under high-volume workloads.

Scalability and Performance Evaluation

To answer RQ4, backend scalability was evaluated using Apache JMeter under batch-loaded conditions. The FastAPI ingestion service was tested with event bursts of up to 5,000 events, measuring ingestion time, average latency, 99th-percentile latency, and data loss. The system processed 5,000 events in 1.73 seconds, with an average latency of 210 ms, a p99 latency of 345 ms, and 0% data loss.

Table 1. Scalability and Performance Benchmark of ShieldOps Backend

Performance Parameter	Measurement
Event Burst	5,000
Total Ingestion Time	1.73 seconds
Average Latency	210 ms
p99 Latency	345 ms
Data Loss	0%

Results

Table 2. Shadow AI Detection Performance

Metric	Value	95% CI
Precision	1.00	[0.99, 1.00]
Recall	0.82	[0.79, 0.85]
F1-Score	0.90	[0.88, 0.92]

Shadow AI Detection Accuracy

ShieldOps was evaluated using 1,100 simulated navigation events across sanctioned AI, Shadow AI, benign corporate, and Stealth AI traffic. The system achieved a Precision of 1.00, Recall of 0.82, and F1-score of 0.90.

The confusion matrix in Fig. 2 shows that the system correctly classified 550 benign events and 450 AI-related events, with zero false positives. A total of 100 AI events were classified as benign, corresponding to the Stealth AI cases that were not present in the local domain catalog. These results demonstrate that the domain-based detection approach provides high precision for known AI services, while its recall is affected by previously unlisted domains.

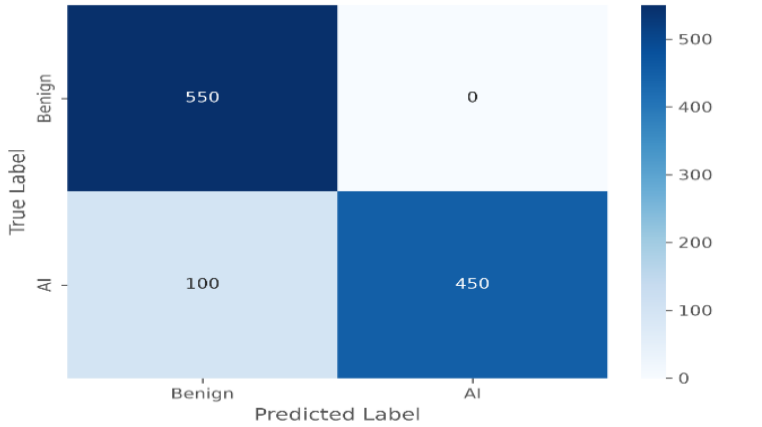


Figure 2. Confusion matrix of ShieldOps Shadow AI detection

Detected Shadow AI Usage Distribution

To further examine the observed AI-service activity, the distribution of detected events across selected AI domains was analyzed. As shown in **Fig. 2**, the evaluated domains, GitHub Copilot, ChatGPT, Synthesia, Claude, and Poe—each recorded **50 events** in the plotted sample. The distribution demonstrates that the sensor can consistently aggregate domain-level usage without requiring inspection of user prompts or payload content.

ShieldOps achieved a **100% enforcement success rate** across all three policy states: **Allow, Warn, and Block**, as shown in **Fig. 3**. Each policy action was successfully executed by the browser extension. Because policy decisions are performed locally using the cached policy configuration, enforcement does not depend on continuous communication with the backend.The Breach Monitor was evaluated using simulated credential-exposure events. The system successfully generated actionable recovery plans for **100% of the tested breach alerts**. This demonstrates the ability of the proposed module to connect simulated credential exposure with automated remediation guidance.

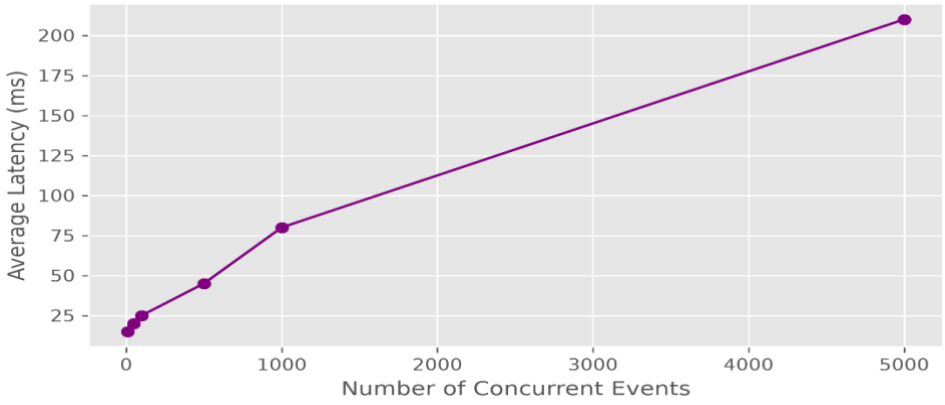


Figure 3. Average backend latency under increasing concurrent event loads.

Privacy and Scalability

A post-experiment database audit confirmed that ShieldOps retained only non-sensitive operational metadata, including domain information, hashed user and device identifiers, timestamps, policy actions, and risk scores. No user prompts, uploaded files, or clipboard contents were captured.

For scalability, the FastAPI backend was evaluated under increasing concurrent event loads. Fig. 4 shows that average latency increased with event volume, reaching approximately 210 ms at 5,000 concurrent events. The complete scalability benchmark recorded 1.73 seconds total ingestion time, 210 ms average latency, 345 ms p99 latency, and 0% data loss.

Conclusion

This study presented **ShieldOps**, a lightweight and privacy-preserving framework for detecting and governing Shadow AI usage at the browser edge. The proposed architecture combines local domain-level detection, decentralized policy enforcement, privacy-preserving telemetry, automated SOC alerting, and proactive breach monitoring without inspecting user prompts or uploaded content. Experimental evaluation on **1,100 simulated navigation events** achieved a **Precision of 1.00, Recall of 0.82, and F1-score of 0.90**, while policy enforcement achieved a **100% success rate** across Allow, Warn, and Block actions. The Breach Monitor also generated actionable recovery plans for all tested simulated breach alerts. Furthermore, scalability testing demonstrated that the backend processed **5,000 events in 1.73 seconds**, with **210 ms average latency, 345 ms p99 latency, and 0% data loss**. Overall, the results demonstrate the feasibility of combining edge-based Shadow AI governance with data-minimization principles. However, the evaluation also indicates that deterministic domain matching remains dependent on the freshness of the AI-service catalog, particularly for previously unlisted or emerging AI services. Future work will therefore focus on improving unknown-service discovery, adaptive risk classification, and evaluation using larger and more diverse real-world enterprise traffic.

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Explainable AI (XAI) for Transparent Student Performance Prediction in Digital Learning Systems

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Abstract

The increasing adoption of digital learning environments generates demographic, academic, and behavioral data that can support early prediction of student outcomes, but high-performing machine learning models often operate as black boxes. This paper introduces a Transparent Student Performance Prediction using the Open University Learning Analytics Dataset (OULAD) based on Explainable Artificial Intelligence (XAI) approach. Random Forest (RF) and Gradient Boosting (GB) are used as base classifiers and a Support Vector Classifier (SVC) as the meta-classifier. Preprocessing combines the relational OULAD tables with missing-value handling, feature scaling, behavioral feature engineering and class balancing using SMOTE and SMOTE-ENN. SHAP and LIME are used for explaining the global and local features of the model, respectively. The stacking ensemble achieves 86.4% accuracy, 86.0% precision, 85.6% recall, 85.8% F1-score, and 0.935 ROC-AUC; class-wise F1-scores are 91.7% for Pass, 81.2% for Fail, and 84.5% for Withdrawn. The strongest predictors are cumulative assessment score, frequency of access to the VLE and early engagement. Bias mitigation minimizes demographic differences by around 15-25%, with only <2% error in accuracy, and without impacting temporal performance by more than 2% of training. The findings reveal that the concepts of predictive performance, explainability, fairness and temporal robustness can be combined in a viable student analytics system.

Keywords: XAI, Student Performance Prediction, LIME, SMOTE, Educational Data Mining.

Introduction

Digital and blended learning has increased the role of Learning Management Systems (LMSs) in teaching, assessment, communication, and engagement. These systems can continuously track student login habits, resource usage, assessment submission and interaction patterns, which can be used to develop machine learning (ML) models to detect patterns of academic performance and student risk (Johora et al., 2025). Random Forest, Support Vector Machines, Gradient Boosting, XGBoost and neural networks can handle the heterogeneous educational data, but when predictions affect support, intervention, retention and academic planning, accuracy is not enough. Other important aspects of the model's use involve understanding why the model yields a specific prediction (Alwarthan et al., 2022). The contributions from SHAP are at the feature level, whereas those of LIME are made locally to the prediction (Adnan et al., 2022).

Different classifiers like majority voting, ensemble classifiers and deep learning-based classifiers have been investigated for student performance prediction. The stacking approach is using the Random Forest and the Gradient Boosting as the base classifiers with a meta-classifier SVC, with 86.38% accuracy on 872 students of the undergraduate group (Zulfiker et al., 2020). Zulfiker et al. reported accuracy of 81.73% using a weighted voting classifier with the students of the private universities of Bangladesh (Hossen et al., 2021). Other research has been conducted on student performance prediction using neural-network and SVM-based methods (Ashaduzzaman et al., 2016; Janan & Ghosh, 2021). Recent studies based on OULAD have also shown good prediction results by applying XGBoost, deep learning and other machine learning methods ("Boosting Machine Learning Approach," 2025; Boujmiraz et al., 2026; Ha et al., 2020). It is also recently noted that fairness-aware prediction is crucial in the context of applying educational models to different student groups ("Bias-Aware Machine Learning Framework," 2026).

There are significant gaps in the literature as many studies focus on overall predictive accuracy, provide limited explanations for each prediction, and treat fairness as a separate issue from model building. The Open University Learning Analytics Dataset (OULAD) is appropriate to solve these problems, as it has over 32,000 students in seven courses, with demographic data, assessment data, registration data and detailed Virtual Learning Environment (VLE) interactions included (Kuzilek et al., 2017). Consequently, this study combines the stacking of RF-GB, behavioral feature engineering, class balancing with SMOTE, SHAP and LIME explanations, performing a demographic fairness analysis, ablation testing, and temporal validation in an integrated framework.

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Methodology

This part outlines the process of integrating the datasets, pre-processing, balancing the classes, engineering user behaviors, setting up the architecture of stacking, implementing explainability and fairness steps, and the experimental setup adopted for training and testing the proposed framework. This section introduces data integration, pre-processing, class balancing, behavior feature engineering, stacking architecture, explainability and fairness techniques, and experimental setup for training and testing the proposed framework.

Dataset, Integration, and Preprocessing

The Open University Learning Analytics Dataset (OULAD) contains demographic, academic, registration, assessment, and daily VLE interaction records from more than 32,000 students across seven courses (Kuzilek et al., 2017). The studentInfo, studentRegistration, assessments, studentAssessment, courses, and studentVle tables were integrated into a unified student-course-presentation dataset. The target includes Pass, Fail, and Withdrawn outcomes, with withdrawal considered separately in performance-oriented analysis because it does not necessarily represent academic failure.

Missing categorical values were imputed by mode where appropriate, while non-submitted assessments were encoded as zero to preserve their behavioral meaning. Numerical features were standardized before model fitting as:

where x_i is the original value, mu is the feature mean, sigma is the standard deviation, and z_i is the standardized value. This scaling reduces magnitude differences and supports SVC-based learning.

Class Balancing and Feature Engineering

To reduce class imbalance, SMOTE generated synthetic minority samples by interpolating between an observation and a selected nearest neighbor:

where x_i is a minority instance, x_zi is a nearest neighbor, and lambda lies between 0 and 1. SMOTE-ENN was also evaluated by adding Edited Nearest Neighbors to remove noisy samples. Predictors were grouped as demographic, academic, and behavioral. Engineered behavioral variables included total clicks, VLE access frequency, active days, early engagement during the first three weeks, resource diversity, and a procrastination index. Cumulative academic performance was computed as:

where N is the number of assessments, mark_i is the student score, and max_i is the maximum possible score for assessment i.

Stacking, Explainability, Fairness, and Experimental Setup

The proposed ensemble combines Random Forest (RF) and Gradient Boosting (GB) as base learners with an RBF-kernel Support Vector Classifier (SVC) as meta-classifier. RF uses 200 estimators, Gini criterion, and maximum depth 20; GB uses 200 estimators, learning rate 0.1, and maximum depth 5; SVC uses C = 10 and gamma = 0.01. The final prediction is:

where p_RF and p_GB are the base-model prediction outputs and f_SVC combines them to produce the student outcome. SHAP provided global and instance-level feature contributions, while LIME generated local explanations for individual students. Fairness was examined using demographic parity, equal opportunity, and SHAP-based subgroup analysis.

Results

This section reports the overall and class-wise predictive performance, the effect of data balancing, SHAP/LIME explanations, fairness findings, comparisons with reported studies, ablation results, and temporal validation.

Overall and Class-wise Predictive Performance

Table 1 summarizes the evaluated models. The stacking ensemble produced the strongest overall result: 86.4% accuracy, 86.0% precision, 85.6% recall, 85.8% F1-score, and 0.935 ROC-AUC. It improved accuracy by 3.0

percentage points over RF, 2.2 points over GB/XGBoost, and 6.4 points over SVC. GB and XGBoost were the strongest individual baselines at 84.2% accuracy and 0.922 ROC-AUC.

Table 1. Performance of student performance prediction models.

Model	Acc. (%)	Prec. (%)	Recall (%)	F1 (%)	ROC-AUC
Random Forest	83.4	82.5	81.8	82.1	0.916
Gradient Boosting	84.2	83.8	83.2	83.5	0.922
XGBoost	84.2	83.8	83.2	83.5	0.922
SVC	80.0	79.5	78.8	79.1	0.869
LSTM	83.4	82.2	81.5	81.8	0.890
Stacking Ensemble	86.4	86.0	85.6	85.8	0.935

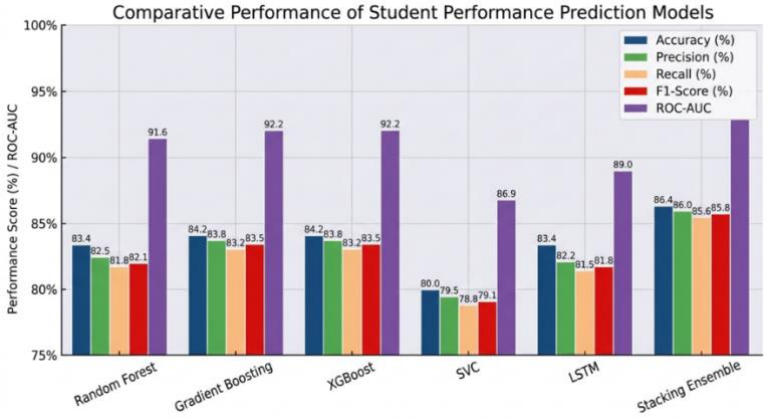


Figure 1. Comparative performance analysis of machine learning models for student performance prediction.

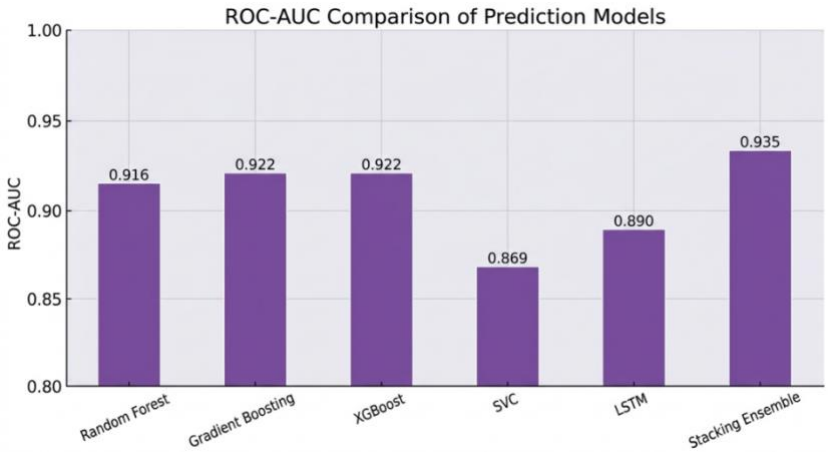


Figure 2. ROC-AUC comparison of machine learning models for student performance prediction.

Figures 1 and 2 confirm the consistent advantage of the stacking architecture across the five-evaluation metrics and its highest discriminative ability. Class-wise analysis (Figure 3) shows Precision/Recall/F1 of 92.0/91.5/91.7% for Pass, 82.0/80.5/81.2% for Fail, and 85.0/84.0/84.5% for Withdrawn; the macro averages are 86.3% precision, 85.3% recall, and 85.8% F1-score. The minority-class results indicate that balancing supports more even performance across outcomes.

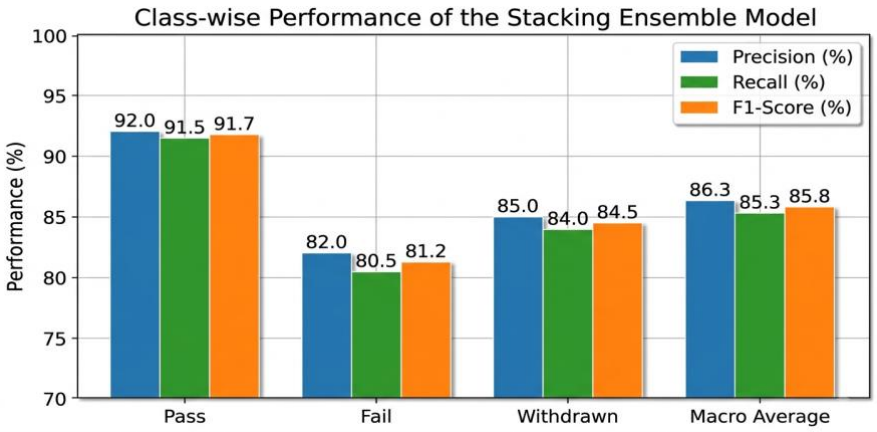


Figure 3. Class-wise performance of the stacking ensemble model.

Balancing, Explainability, and Fairness

Table 2. Impact of data balancing.

Balancing Technique	Accuracy Before (%)	Accuracy After (%)	Improvement
No Balancing	78.5	-	-
SMOTE	84.2	86.4	+2.2
SMOTE-ENN	83.8	85.9	+2.1

Without balancing, accuracy was 78.5%. SMOTE reached 86.4% and SMOTE-ENN 85.9%; their main benefit was improved representation of Fail and Withdrawn cases rather than aggregate accuracy alone.

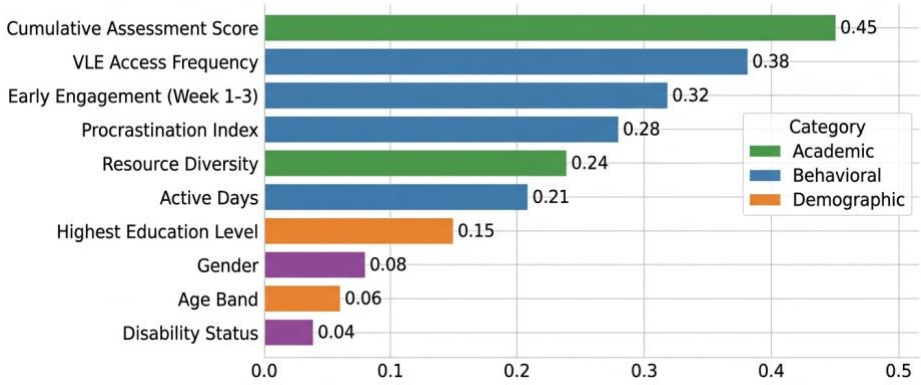


Figure 4. SHAP feature-importance ranking for the stacking ensemble model.

SHAP ranks cumulative assessment score (0.45), VLE access frequency (0.38), early engagement (0.32), procrastination (0.28), resource diversity (0.24), and active days (0.21) above demographic attributes. LIME complements this global view: Fail predictions are associated with weak early assessment performance, limited resource use, and high procrastination, whereas Pass predictions emphasize consistent engagement, strong assessments, regular VLE access, and early submission.

Fairness analysis identified subgroup differences across gender, disability status, region, and first-generation status. Bias mitigation reduced demographic disparities by about 15-25% with less than 2% accuracy loss, improving demographic parity and equal opportunity and showing why subgroup analysis remains necessary.

Comparison, Ablation, and Temporal Validation

Table 3. Comparison with reported OULAD-based results in the supplied study.

Study	Dataset	Model	Reported Result	XAI
Johora et al. [1]	872	Stacking	86.38% accuracy	SHAP, LIME
XGBoost study [8]	~32,000	XGBoost	87.00% accuracy	SHAP
DL comparison [9]	~32,000	LSTM	83.41% accuracy	-

Study	Dataset	Model	Reported Result	XAI
XGBoost study [11]	~32,000	XGBoost	84.20% accuracy	-
Reported stacking result	~32,000	Stacking	F1=0.94; AUC=0.97	SHAP
This study	~32,000	Stacking	86.40% accuracy	SHAP, LIME

The proposed model is competitive with the reported OULAD results while combining global and local explanations with fairness analysis. Its accuracy exceeds the cited LSTM and 84.2% XGBoost results, while one reported XGBoost result reaches 87.0%. The supplied comparison also reports a stacking result of F1=0.94 and AUC=0.97. Thus, the contribution is not accuracy alone but the integration of predictive performance, interpretability, and fairness.

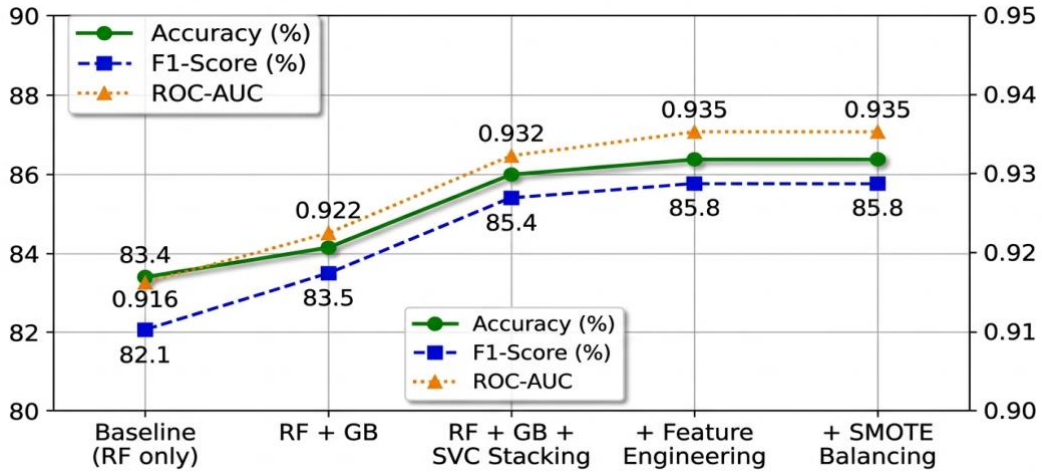


Figure 5. Ablation study results for the proposed stacking ensemble model.

The contribution from each component is shown in the ablation analysis. RF alone achieved 83.4% accuracy, 82.1% F1, and 0.916 ROC-AUC; RF+GB reached 84.2%, 83.5%, and 0.922; RF+GB+SVC reached 86.0%, 85.4%, and 0.932. Feature engineering achieved 85.8% accuracy, 85.3% F1, 0.935 ROC-AUC and SMOTE had the same final values and enhanced class representation. Therefore, the SVC meta-classifier is expected to yield the highest accuracy boost and engineered behavior, and balancing are expected to enhance discrimination and class-wise reliability. In terms of subsequent-semester performance, it was maintained within ±2% of training performance with temporal validation, while the five most important indicators (cumulative assessment score, VLE access frequency, early engagement, procrastination index, and resource diversity) as well as fairness indicators did not change.

Discussion

The results indicate that RF-GB-SVC stacking provides a practical balance of predictive performance, interpretability, and fairness. The ensemble performed well in terms of accuracy (86.4%) and ROC-AUC (0.935%) and the F1-scores were above 80% for both Fail and Withdrawn. The ablation results demonstrate that the SVC meta-classifier yielded the most improvement in accuracy, behavioral feature engineering showed better discrimination and representation of minorities, and SMOTE showed better representation. Cumulative assessment score, VLE access frequency, early engagement, procrastination, resource diversity and active days were consistently emphasized by SHAP and LIME as indicators for the use of early warning. Demographic disparities were decreased by around 15-25% with less than 2% accuracy degradation, while temporal performance was kept within ±2% for later course presentations. These descriptions should be viewed as associations to support decisions, not as causal evidence.

Conclusions

This study presented an XAI-based framework for transparent student performance prediction using OULAD. RF and GB base classifiers were combined through an SVC meta-classifier, with behavioral feature engineering and SMOTE-based class balancing. A combination of RF and GB base classifiers with SVC meta-classifier and behavioral feature engineering and class balancing via SMOTE. The final stacking ensemble achieved 86.4% accuracy, 86.0% precision, 85.6% recall, 85.8% F1-score, and 0.935 ROC-AUC; class-wise F1-scores were 91.7% for Pass, 81.2% for Fail, and 84.5% for Withdrawn. SHAP emphasized assessment performance and VLE engagement as the primary predictors, and LIME gave explanations at the student level. The accuracy loss for

fairness mitigation was 2-3%, with a 15-25% reduction in demographic disparities, and the margin of error for temporal validation was below 2% for subsequent school years. The results show that the integration of performance, explainability, fairness, and temporal robustness in the same educational analytics framework is possible. Model explanations should, however, be understood as 'decision support', not evidence of cause and effect, and should not be widely deployed until validated in other institutions.

Acknowledgement

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Research on Personalized Teaching Feedback Generation Based on Multi-Agent Retrieval-Augmented Large Language Models

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Abstract

Personalized teaching feedback strongly affects learning quality, but providing it at scale is hard in adult higher education, where learners vary widely in prior knowledge, learning pace, and professional background. Calling a large language model (LLM) directly ignores the learner's state and produces technical hallucinations, while retrieval-augmented generation (RAG) grounds answers in course materials but says nothing about whether the explanation fits the learner's level. This paper proposes MA-RAG-KT-PF, a hierarchical framework based on multi-agent retrieval-augmented LLMs that unifies RAG, knowledge tracing (KT), and personalized teaching feedback generation for software engineering education in adult higher education. Four specialized agents (planning, retrieval, personalization, and feedback) coordinate through a versioned shared-state bus under an orchestrator-worker protocol, with three levels of fault tolerance. The personalization agent keeps a five-part learner profile over a concept graph of 87 nodes. A self-attentive knowledge-tracing encoder, an LLM-based semantic layer, and a time-decay forgetting component together estimate concept mastery from the sparse and irregular interactions typical of adult learners. The retrieval agent mixes dense and sparse retrieval with hypothetical-answer expansion over a corpus of about 5,000 chunks, and a confidence gate filters out weak evidence before generation. The feedback agent chooses among corrective, explanatory, guiding, and motivational feedback based on mastery estimates and error patterns, then improves drafts through a self-evaluation and regeneration loop. A six-month experiment with 200 adult learners randomly assigned to five conditions ($n = 40$ each) compared the proposed system against four ablated baselines, producing approximately 15,000 answer interactions. MA-RAG-KT-PF reduced the technical hallucination rate from 17.9% (direct LLM) to 4.6%, a 74% relative reduction, scored highest on all automated metrics, and obtained a feedback specificity of 0.827 with a blind teacher rating of 4.28 out of 5. The learning-gain effect size reached Cohen's $d = 0.79$, against 0.33 for the control condition, with most differences significant at $p < .001$ and the rest at $p < .01$. In the ablation analyses, hallucination suppression came mainly from retrieval with confidence gating, feedback relevance mainly from knowledge tracing, and linguistic coherence mainly from multi-agent iterative refinement. A follow-up survey showed that perceived personalization correlated positively with learning motivation ($r = .67$) and that transparent mastery visualization increased reported system trust. We hope this architecture, which proved effective and reproducible in our setting, can serve as a reference for building personalized feedback systems at scale.

Keywords: Multi-agent systems, retrieval-augmented generation, knowledge tracing, personalized teaching feedback, intelligent tutoring systems, adult higher education.

Introduction

Timely, specific feedback is one of the strongest predictors of learning outcomes, but in adult higher education it is often in short supply: instructors cannot keep up with the steady online activity of classes whose students have very different backgrounds, and manual feedback does not scale. Large language models (LLMs) look like an obvious fix, but direct prompting knows nothing about the learner's state, and a fair share of generated hints contains factual mistakes, weak explanations, or invented problems (Silva & Costa, 2025). For adult learners with little real-time teacher support, unreliable feedback can be worse than none.

Two research lines address these problems separately. Retrieval-augmented generation (RAG) grounds responses in retrieved evidence and reduces hallucination (Lewis et al., 2020), while knowledge tracing (KT) estimates latent mastery from interaction histories (Piech et al., 2015). Existing systems that combine the two remain partial. TutorLLM and IntelliCode combine KT with RAG in single-agent recommenders, but without multi-step quality control (Li et al., 2025; David & Ghosh, 2025). GenMentor coordinates multiple agents for goal-oriented tutoring, yet it lacks retrieval grounding and KT-based personalization of feedback content (Wang, T., et al., 2025). EduPlanner targets instructional design rather than feedback (Zhang et al., 2025). As far as we know, no published

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system combines multi-agent orchestration, quality-controlled retrieval, and KT-based personalization in one feedback-generation pipeline tested in a longitudinal study.

We address this gap with MA-RAG-KT-PF, a framework for personalized teaching feedback generation based on multi-agent retrieval-augmented LLMs. Our contributions are: (i) a hierarchical four-agent architecture with a versioned shared-state bus and three-level fault tolerance that keeps end-to-end latency between 8 and 15 s; (ii) a hybrid learner model that fuses a self-attentive KT encoder with LLM semantic enhancement and time-decay forgetting, suited to the sparse and irregular study habits of working adults; (iii) a six-month study with 200 adult learners, in which the system cut the hallucination rate by about 74% relative to a direct LLM, reached a learning-gain effect size of Cohen's d = 0.79, and showed through ablations that retrieval, knowledge tracing, and iterative refinement each contribute to different aspects of quality.

Methodology

MA-RAG-KT-PF was developed and validated in a software engineering course of an adult higher-education program, following three principles: separation of concerns across specialized agents, explicit personalization grounded in a continuously updated learner model, and evidence-grounded generation with quality control at every stage.

System architecture

The system comprises four specialized agents coordinated by a central orchestrator under an orchestrator–worker protocol (Figure 1). The planning agent decomposes each feedback request into an ordered task sequence; the retrieval agent grounds the request in the course knowledge base; the personalization agent maintains and updates the learner model; and the feedback agent composes the final response. Agents communicate through a versioned session state object (SSO): each agent writes only to its designated fields and increments a global version number, so concurrent updates cannot corrupt shared state. Profile and knowledge-base retrieval run in parallel, which cut sequential execution time by about 40%. The orchestrator applies three levels of fault tolerance: retry, degradation to a conservative template, and alerting. As a result, a single agent failure does not interrupt the learning loop. End-to-end latency was 8–15 s per feedback.

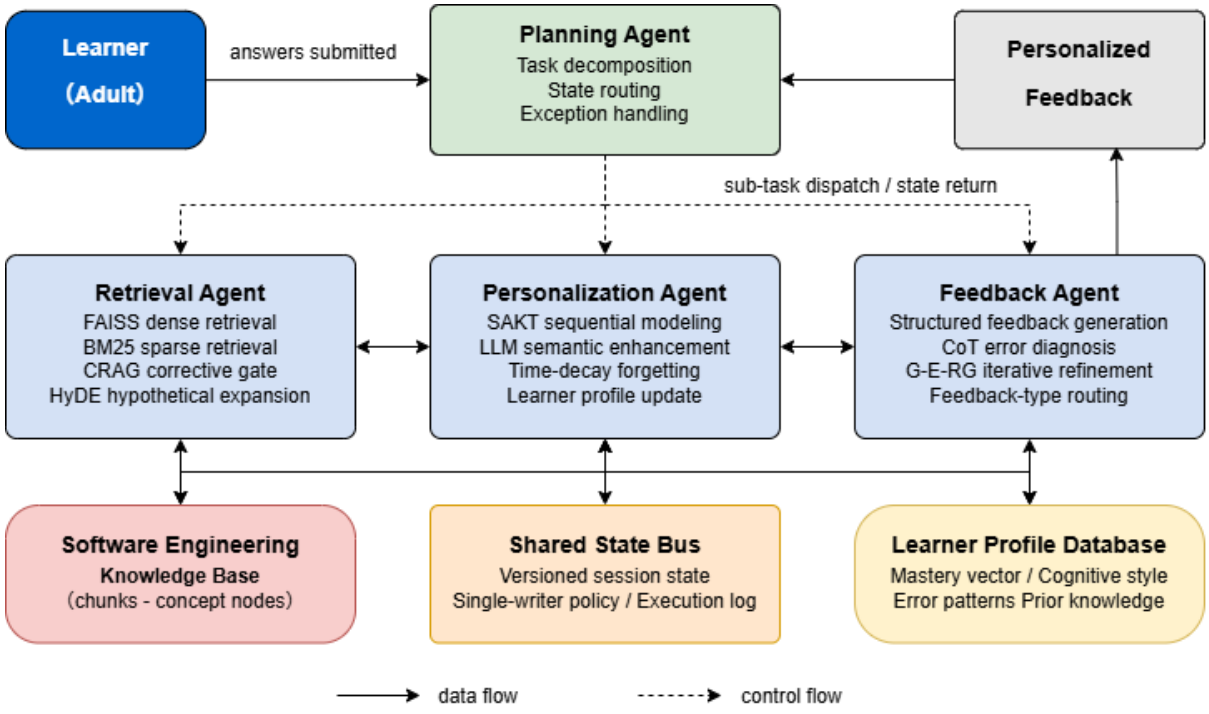


Figure 1. Architecture of MA-RAG-KT-PF.

Personalized learner modeling

The personalization agent maintains a five-dimensional profile for each learner: a knowledge mastery vector (KMV), an error pattern model (EPM), a cognitive style model (CST), a learning behavior model (LBF), and an affective state model (ASE). Mastery is defined over a concept graph of 87 nodes spanning programming

languages, software engineering methods, data structures and algorithms, and system design, constructed by LLM-assisted ontology extraction from the course syllabus and textbooks (Abu-Rasheed et al., 2025).

Mastery estimation combines three components (Figure 2). A self-attentive encoder in the SAKT family (Pandey & Karypis, 2019) computes attention weights over past interactions based on their relevance to the queried concept. To accommodate the fragmented schedules of adult learners, an LLM semantic layer embeds the interaction sequence and the current query and fuses this with the sequential representation:

$$h_t = \lambda h^{seq}{}_t + (1-\lambda) W_s s_{q_t} \quad (1)$$

where λ = 0.7 was tuned on a validation subset and s_{q_t} is the semantic embedding of the query. To model long-term forgetting without retraining, we discount attention weights by elapsed time, following the monotonic-decay idea of attentive knowledge tracing:

$$\tilde{\alpha}_{ij} = \alpha_{ij} exp\left(-\gamma \Delta t_{ij}\right) \quad (2)$$

where γ = 0.05 controls the decay rate and Δt is the elapsed time in days. The posterior mastery estimate combines the prior with evidence strength derived from answer correctness, attempt count, and hint usage:

$$p_{t+1} = p_t + \eta \Delta p \ (3)$$

where η is the learning rate. This design extends LLM-KT alignment work (Wang, Z., et al., 2025) from next-action prediction to feedback personalization: instead of a recommendation score, the mastery vector drives the feedback type, granularity, and scaffolding depth.

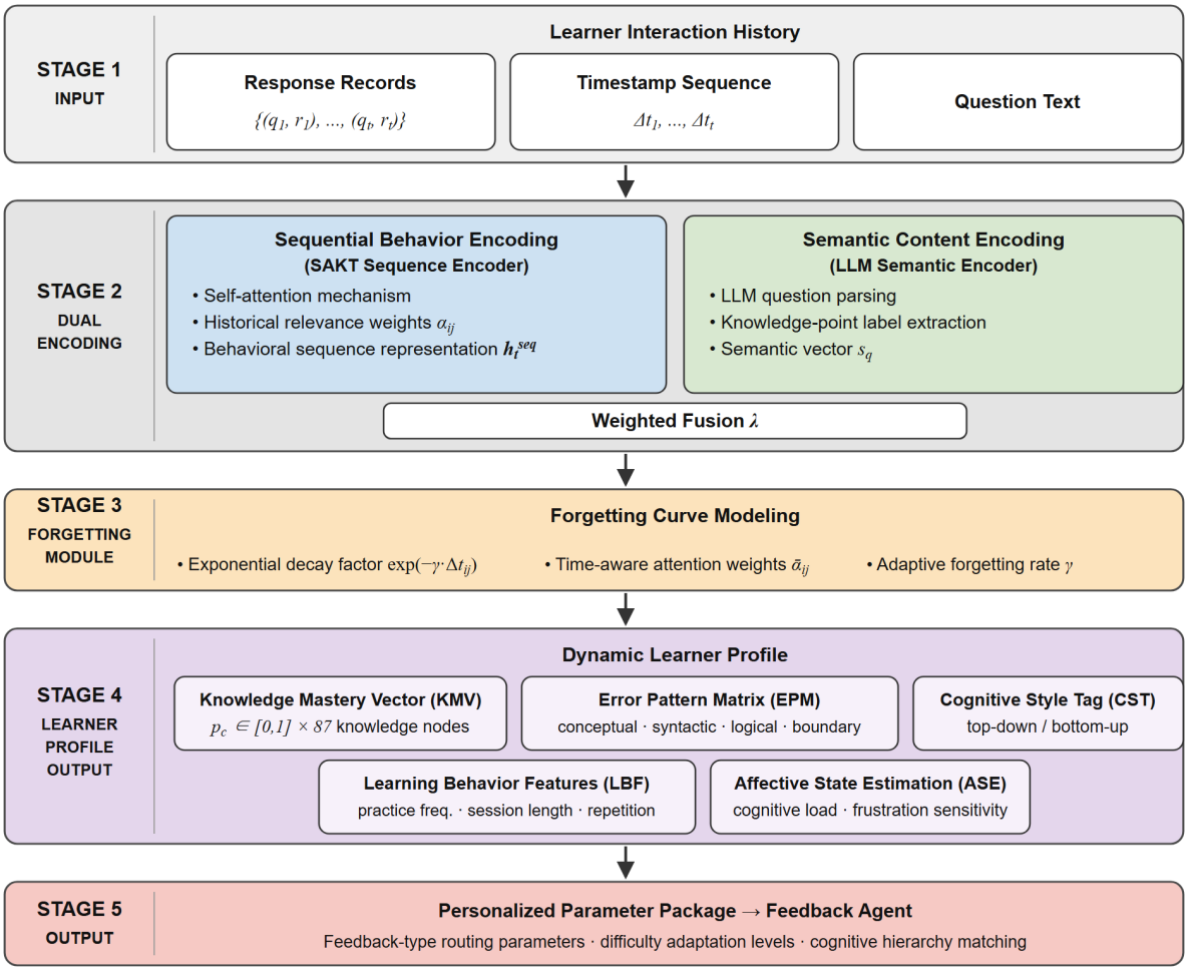


Figure 2. Personalized learner modeling pipeline.

Hybrid retrieval with quality control

The retrieval agent operates over a knowledge base of approximately 5,000 document chunks compiled from four sources: textbooks and lecture notes (35%), programming exercises with model solutions (30%), annotated

common-error cases (20%), and API documentation (15%), split by semantic recursive chunking (512 tokens with 50-token overlap) and annotated with concept, difficulty, and document-type metadata.

Each query follows a four-stage pipeline: (i) hypothetical-answer expansion for abstract questions (Gao et al., 2023); (ii) dual retrieval with 1,536-dimensional embeddings in a FAISS IVF-PQ index plus BM25 exact-term matching, fused by reciprocal rank fusion (k = 60) (Karpukhin et al., 2020); (iii) a CRAG-style evaluator fine-tuned from DeBERTa-v3 that gives each candidate chunk a confidence score and applies a three-level gate: correct chunks are kept, ambiguous ones trigger re-retrieval with an expanded query, and incorrect ones are discarded (Yan et al., 2024); and (iv) assembly of surviving chunks into a context of at most 4,096 tokens matched to the cognitive level of the request.

Personalized teaching feedback generation

Feedback design follows the learning-sciences taxonomy of corrective, explanatory, guiding, and motivational functions (Stamper et al., 2024) and accounts for documented individual differences in feedback preferences across learner profiles. The feedback agent first routes each request using the mastery estimate p_c for the target concept and the learner's error pattern: conceptual errors with $p_c < 0.4$ receive explanatory feedback with background material; logic errors with $0.4 \leq p_c < 0.7$ receive Socratic guiding questions; boundary-condition omissions with $p_c \geq 0.7$ receive concise corrective feedback; and learners showing sustained frustration receive a motivational preface before technical content.

The generation prompt assembles five blocks — learner profile, retrieved knowledge, feedback-type instructions, error diagnosis, and output-format constraints — and elicits root-cause reasoning through chain-of-thought prompting. A hard constraint forbids any technical claim not supported by the retrieved context. A self-evaluation and regeneration loop then scores the draft on technical accuracy, cognitive appropriateness, constructiveness, and actionability, and regenerates it when any criterion fails, for at most two rounds, following the generate-evaluate-regenerate (G-E-RG) principle (Cao et al., 2025).

Experimental design

Participants were 200 working adult learners (61% male; mean age 28.3 years; work experience 0–12 years) in a software engineering program at an adult higher-education institution, randomly assigned to five conditions (n = 40 each) that shared the same course materials, platform, and schedule but differed in the feedback engine. The study ran for six months and produced approximately 15,000 answer interactions across four course modules.

The conditions isolate each design factor: Direct-LLM, a prompted LLM without retrieval or learner modeling (control); Single-RAG, single-agent retrieval without personalization or iteration; MAS-NoRAG, multi-agent iteration without retrieval; MAS-NoKT, the full architecture without knowledge tracing; and MA-RAG-KT-PF, the complete system. Automated metrics were computed on 5,000 sampled feedbacks per condition: BERTScore-F1 against reference feedback, RAGAS faithfulness and answer relevance (Es et al., 2023), and G-Eval coherence on a 5-point scale (Liu et al., 2023). Teaching feedback quality was rated on specificity, helpfulness, and validity following the FeedEval protocol, and two teachers blind-rated 100 feedbacks per condition on a 5-point scale. Learning gain was measured with standardized pre–post tests and expressed as Cohen's d; paired t-tests were applied throughout (α = .05).

Results

Table 1 reports the automated evaluation. MA-RAG-KT-PF obtained the best score on all automated metrics and the lowest hallucination rate (3.8%), against 18.3% for Direct-LLM, a 79% relative reduction ($p < .001$ for all pairwise comparisons against the control). Two ablation patterns are informative. First, hallucination decreases as retrieval gets stronger: 18.3% without retrieval, 9.7% with single-agent RAG (a 47% reduction), and 3.8% with multi-agent retrieval plus the confidence gate. Second, MAS-NoRAG scored higher than Single-RAG on coherence (3.88 vs. 3.79) despite a higher hallucination rate, which suggests that iterative multi-agent refinement improves linguistic quality even without grounding.

Table 1. Automated evaluation metrics across system configurations.

Method	BERTScore-F1 ↑	Faithfulness ↑	Answer rel. ↑	Coherence ↑	Halluc. ↓
Direct-LLM	0.782	—	—	3.61	18.3%
Single-RAG	0.831	0.847	0.763	3.79	9.7%
MAS-NoRAG	0.819	—	—	3.88	14.2%
MAS-NoKT	0.856	0.891	0.812	4.02	6.1%

Method	BERTScore-F1 ↑	Faithfulness ↑	Answer rel. ↑	Coherence ↑	Halluc. ↓
MA-RAG-KT-PF	**0.893**	**0.924**	**0.871**	**4.31**	**3.8%**

Knowledge tracing mattered most for teaching relevance rather than surface similarity: MAS-NoKT trailed the full system by 0.037 on BERTScore-F1 but by 0.059 on RAGAS answer relevance, and teachers rated its feedback noticeably lower (Table 2). Without KT, feedback was often technically correct but pitched at the wrong level. With KT, specificity rose from 0.641 (Direct-LLM) to 0.841, helpfulness from 0.598 to 0.823, and validity from 0.712 to 0.921; teacher ratings rose from 3.21 to 4.37 and learner satisfaction from 3.45 to 4.42. All differences between the full system and each baseline were significant ($p < .001$).

Table 2. Teaching feedback quality ratings and learning outcomes across system configurations.

Method	Specificity ↑	Helpfulness ↑	Validity ↑	Teacher ↑	Learning gain (d) ↑
Direct-LLM	0.641	0.598	0.712	3.21	0.31
Single-RAG	0.703	0.672	0.831	3.58	0.44
MAS-NoRAG	0.718	0.694	0.763	3.67	0.47
MAS-NoKT	0.762	0.741	0.874	3.89	0.58
MA-RAG-KT-PF	**0.841**	**0.823**	**0.921**	**4.37**	**0.79**

Learning outcomes confirmed that the quality gains transfer to learning: the full-system group achieved a pre-to-post effect size of Cohen's $d = 0.79$ against 0.31 for the control, exceeding about 78% of the control distribution (Figure 3). In the follow-up survey (87% response rate), perceived personalization correlated positively with motivation ($r = .67$), and transparent mastery display raised reported trust (4.51 vs. 3.82). The most frequent criticism, raised by 23% of respondents, was that feedback sometimes referenced several concepts at once. This motivates our future work on multi-concept error diagnosis and hierarchical feedback structuring.

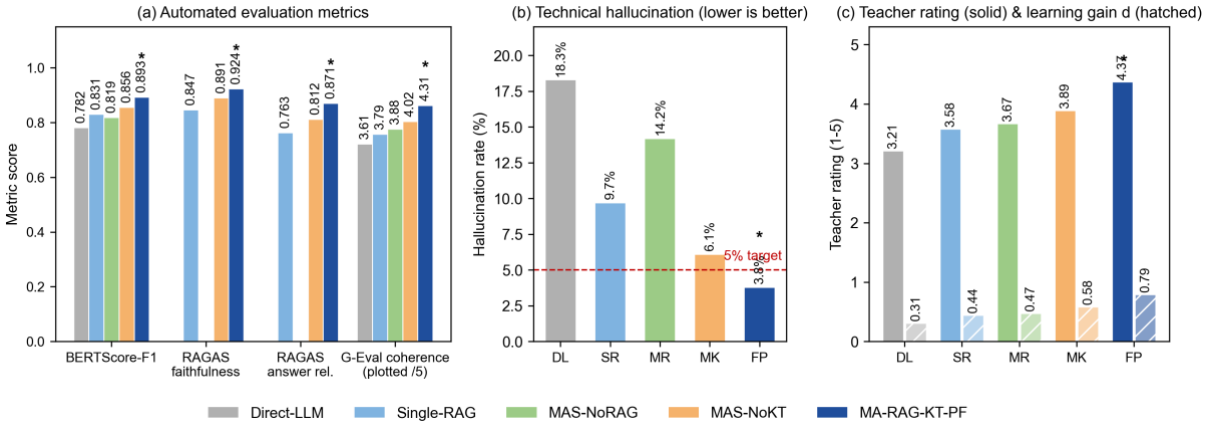


Figure 3. Results across the five conditions.

Conclusions

This paper presented MA-RAG-KT-PF, a multi-agent framework that unifies retrieval-augmented generation, knowledge tracing, and personalized teaching feedback generation for adult higher education. The four-agent architecture with a versioned shared-state bus kept end-to-end latency within 8–15 s per feedback. The hybrid learner model, combining self-attentive knowledge tracing, LLM semantic enhancement, and time-decay forgetting, tracked mastery from sparse adult learning interactions, and confidence-gated retrieval grounded the technical claims. In a six-month study with 200 adult learners, the system reduced technical hallucinations from 18.3% to 3.8%, achieved a feedback specificity of 0.841 and a learning-gain effect size of Cohen's $d = 0.79$; ablations showed that retrieval, tracing, and iterative refinement contribute complementary quality dimensions.

Three directions remain open. First, automating ontology construction and maintenance so the system transfers more easily to other courses and institutions. Second, stronger multi-concept error diagnosis and hierarchical feedback structuring, since 23% of learners found feedback referencing several concepts hard to prioritize. Third, extension to multimodal feedback such as code-execution traces, spaced-repetition scheduling for long-term retention, and multi-institution studies that test generalization across disciplines.

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Beyond Bite-Sized Content: Proposing an Integrated Socio-Cultural Framework for Microlearning in Resource-Constrained Higher Education Contexts

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Abstract

Microlearning has emerged as a prominent approach in higher education, promising enhanced engagement, retention, and flexibility through short, focused learning modules. However, prevailing understandings of microlearning are often heavily influenced by cognitive load theory and corporate training paradigms, frequently neglecting the socio-cultural realities that inform learning in diverse and resource-constrained environments. In the context of South African higher education, persistent challenges, such as digital inequality, linguistic diversity, historical disadvantage, and elevated student dropout rates, create a risk that microlearning might reinforce existing structural inequities rather than alleviate them.

This conceptual paper introduces an integrated socio-ultural microlearning model tailored for South African higher education. Drawing on Vygotsky's sociocultural theory, communities of practice (Wenger), Ubuntu philosophy, and critical perspectives surrounding digital access and decolonisation, the framework underscores five interdependent dimensions: (1) contextual relevance and cultural responsiveness, (2) social interaction and collective knowledge construction, (3) equitable access and infrastructure considerations, (4) learner agency and identity affirmation, and (5) alignment with institutional cultures and academic integrity.

The proposed framework builds upon existing models by highlighting how microlearning can either challenge or reproduce power structures in post-apartheid South Africa. It posits that thoughtfully designed microlearning, delivered through mobile-first, multilingual, and community-oriented methods, has the potential to enhance access, foster deep engagement, and mitigate academic misconduct by alleviating the cognitive and temporal pressures that often lead to plagiarism. The paper discusses implications for policy, curriculum design, and lecturer development, offering recommendations for future empirical investigation within South African universities.

Keywords: microlearning, socio-cultural framework, South African higher education, academic integrity, decolonisation, digital equity, Ubuntu.

Introduction

Microlearning has risen rapidly as a preferred pedagogical approach in higher education worldwide (Alias & Razak, 2023; Monib et al., 2025; Rof et al., 2024). Characterised by short, focused learning units, typically lasting a few minutes, it promises to reduce cognitive overload, support just-in-time learning, and accommodate the fragmented attention patterns of contemporary students (Monib et al., 2025).

Globally, its adoption has been accelerated by digital platforms, mobile technologies, and the influence of corporate training models that prioritise efficiency and measurable outcomes. In South Africa, microlearning has similarly gained traction within universities seeking flexible solutions to support large and diverse student cohorts, particularly in the wake of expanded access to higher education and the accelerated digital shift prompted by the COVID-19 pandemic (Schutte, 2024).

Yet prevailing conceptualisations of microlearning remain heavily shaped by theories such as Cognitive Load Theory, (Sweller, 1998), Microlearning AI-Integrated Instructional Design (MIND) Monib et al.'s (2025) and other similar models, influenced mainly by Western corporate paradigms. These approaches frequently treat learning as an individual, decontextualised process of information processing, with limited attention to the socio-cultural, historical, and material conditions that shape educational experience (Ralston, 2021. In the South African higher education landscape, such limitations are especially consequential. Persistent digital inequality, linguistic diversity, the legacies of historical disadvantage, and high rates of student attrition create environments in which narrowly designed microlearning interventions risk reinforcing rather than disrupting structural inequities. When short-form content is delivered without regard for socio-cultural relevance and collective knowledge practices, it may deepen exclusion, undermine meaningful engagement, and inadvertently intensify the pressures that contribute to academic misconduct (Kafile et al., 2025; Mateko et al., 2025).

https://doi.org/10.5281/zenodo.24340095

This conceptual paper addresses these shortcomings by proposing an integrated socio-cultural microlearning framework. The framework is grounded in Lev Vygotsky's sociocultural theory, which conceptualises learning as an inherently social, mediated, and culturally situated process rather than an isolated cognitive activity. Central to this perspective is the understanding that higher mental functions originate in social interaction and are subsequently internalised by the individual. Knowledge is co-constructed through dialogue, collaboration, and the use of cultural tools, including language, symbols, and digital artefacts, within specific historical and material contexts (Vygotsky, 1978)

Of particular relevance is Vygotsky's concept of the Zone of Proximal Development (ZPD): the distance between what a learner can achieve independently and what they can accomplish with guidance from more knowledgeable others or through collaborative activity. Learning is most effective when instruction targets this zone, providing appropriate scaffolding that is gradually withdrawn as competence develops. In microlearning design, this principle implies that short learning modules should not merely deliver discrete information packets; they should create structured opportunities for social interaction, peer dialogue, and guided participation that extend learners beyond their current independent capabilities (Vygotsky, 1978).

The significance of this contribution lies in its potential to advance equity, improve retention, and strengthen academic integrity within South African universities. By foregrounding mobile-first, multilingual, and community-oriented design principles, the framework offers a pathway for microlearning to expand meaningful access, foster deeper engagement, and reduce the temporal and cognitive pressures that often precipitate plagiarism. In doing so, it positions thoughtfully designed microlearning as a possible lever for challenging, rather than reproducing, post-apartheid power structures in higher education..

Methodology

This conceptual paper employs a theoretical synthesis approach and reviews recent literature on microlearning in higher education and integrates core tenets of Vygotsky's sociocultural theory to propose a socio-cultural microlearning framework. The keywords used to source the literature include: microlearning, socio-cultural theory, South Africa.

Results

Proposed Socio-Cultural Microlearning Framework

The socio-cultural microlearning framework comprises five interdependent dimensions that reorient microlearning design toward the realities of resource-constrained, culturally diverse, and historically unequal higher education contexts. Grounded in Lev Vygotsky's sociocultural theory (Vygotsky, 1978), the framework treats learning as an inherently social, mediated, and culturally situated process rather than an isolated cognitive activity. Higher mental functions originate in social interaction and are internalised by the individual through the use of cultural tools (language, symbols, digital artefacts) within specific historical and material conditions. The framework is best represented as a circular or interconnected model in which the five dimensions surround and inform a central core of "equitable, meaningful microlearning." Each dimension interacts with the others, neglect of anyone weakens the whole. A recommended visual (Figure 1) places the five dimensions as interlocking segments or overlapping circles around a central node labelled "Socio-Culturally Responsive Microlearning," with bidirectional arrows indicating mutual influence. The dimensions are:

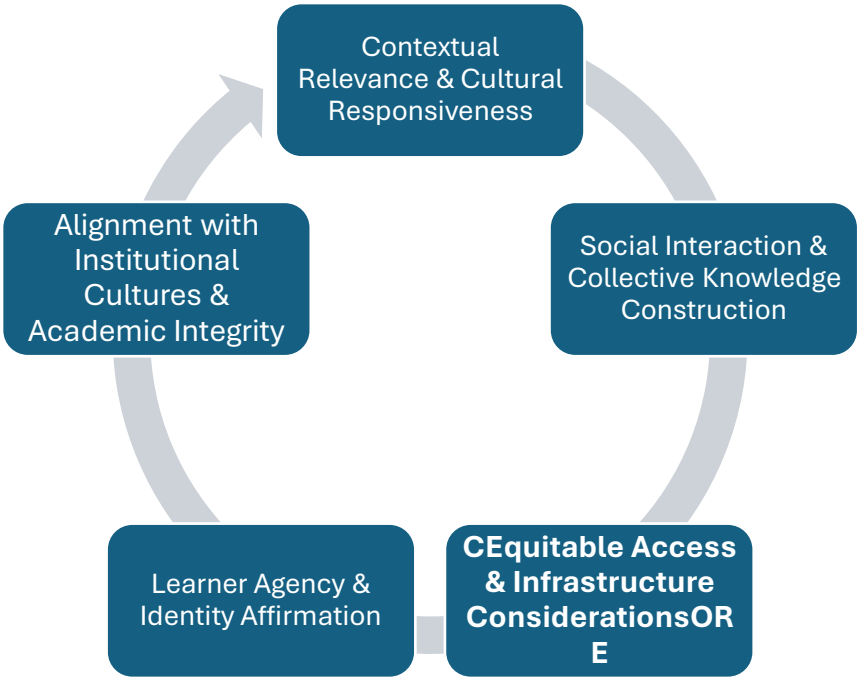


Figure 1. The Socio-Cultural Microlearning Framework .

1. Contextual relevance and cultural responsiveness

Vygotsky emphasised that all higher psychological processes are culturally and historically mediated. Microlearning content and activities must therefore be grounded in students' lived realities, linguistic repertoires, and cultural knowledge systems. In South African higher education this includes the deliberate incorporation of African languages (or translanguaging practices), local case studies, and examples drawn from students' communities rather than exclusively Global North scenarios (Yafele, 2024; Thengimfene & Madolo, 2025) For instance, a micro-module on research ethics in a first-year social science course might use community-based research dilemmas familiar to students from townships or rural areas, presented in both English and an African language. Such design activates culturally meaningful mediational means and reduces epistemic alienation.

2. Social interaction and collective knowledge construction

Central to Vygotsky's theory is the principle that learning originates on the interpsychological (social) plane before being internalised on the intrapsychological plane. Short modules are therefore designed to include structured peer dialogue, collaborative annotation, or small-group problem-solving that can occur asynchronously via mobile platforms (Cai, et al, 2026). At institutions such as historically disadvantaged universities, WhatsApp or low-data discussion threads linked to micro-videos enable students to co-construct understanding of difficult concepts, thereby activating the Zone of Proximal Development (ZPD) through peer scaffolding and guided participation.

3. Equitable access and infrastructure considerations

Vygotsky's concept of mediation highlights that psychological development depends on the availability and quality of cultural tools and material conditions. Design must therefore begin from the material realities of the majority of students: intermittent connectivity, high data costs, shared or low-specification devices, and load-shedding. Practical implications include offline-first or low-data formats (downloadable audio, compressed video, text-based alternatives), mobile-optimised interfaces, and zero-rated or campus-network prioritization (Mateko, 2025). A microlearning sequence on academic writing, for example, might offer a 3-minute audio explanation, a printable one-page summary, and an optional short video, ensuring that the necessary mediational tools remain accessible under constrained conditions.

4. Learner agency and identity affirmation

Contemporary extensions of sociocultural theory emphasise that learners are not passive recipients of cultural tools but active agents who both use and transform those tools while being transformed by them (Stetsenko, 2017). This

perspective underpins the principle that education should position students as contributors to knowledge rather than consumers of pre-packaged content. Transformative agency, as conceptualised in this body of work, refers to the capacity of learners to break away from given frames of action, reconfigure cultural tools, and actively reshape their activity systems (Engeström & Sannino, 2010; Sannino, 2020). Such a view directly supports the design of short-form or microlearning modules that treat students as knowledge producers who transform tools and practices rather than merely consume content.

Recent applications in digital and higher-education contexts reinforce this orientation. Studies grounded in sociocultural and knowledge-building principles demonstrate that when students are afforded opportunities to contribute local examples, multilingual reflections or collaborative meaning-making, they exercise epistemic agency, coming to see themselves as capable contributors to knowledge rather than passive consumers (Engeström & Sannino, 2010; Sannino, 2020).

5. Alignment with institutional cultures and academic integrity

Learning occurs within historically formed institutional practices that themselves function as mediational systems. The final dimension ensures that microlearning is coherent with broader curriculum goals, assessment regimes, and institutional values, while actively supporting academic integrity. Short modules are sequenced to build authentic academic skills (paraphrasing, citation, argumentation, time management) in manageable increments that target the ZPD. By reducing cognitive and temporal overload through carefully scaffolded social and cultural mediation, the framework diminishes the structural pressures that frequently precipitate plagiarism or contract cheating.

Integration with and Extension of Existing Models

The framework builds upon existing microlearning design principles and recent models, such as Cognitive Load Theory (Sweller, 1998), and Microlearning AI-Integrated Instructional Design (Monib et al., 2025). While these frameworks effectively emphasize the importance of having clear objectives and designing teaching materials and activities that allow learners to process information without feeling overwhelmed, they primarily focus on technical and pedagogical foundations. However, they do not address inclusion within these designs. Therefore, a key contribution of the proposed framework is its ability to incorporate socio-cultural aspects into the design of microlearning lessons.

By delivering short, highly relevant modules that progressively build authentic academic literacies (for example, a series of four to six-minute modules on paraphrasing techniques using local disciplinary texts, followed by low-stakes peer feedback activities), the framework operationalises the ZPD. Students experience scaffolded success through social interaction and culturally meaningful mediation, receive affirmation of their linguistic resources, and can access materials offline or on mobile devices. The perceived need to resort to contract cheating or copy-and-paste practices therefore diminishes. Academic integrity becomes an emergent property of equitable, socially supported, and culturally responsive design rather than an externally imposed compliance regime.

Conclusions

This conceptual paper has proposed the socio-cultural microlearning framework as a theoretically grounded response to the limitations of prevailing microlearning models in higher education. While short-form learning units have gained rapid global and South African traction for their capacity to reduce cognitive load and support flexible access, dominant conceptualisations remain largely shaped by cognitive load theory and Western corporate paradigms. These approaches tend to treat learning as an individual, decontextualised process of information processing, paying insufficient attention to the socio-cultural, historical, and material conditions that shape educational experience, particularly in post-apartheid South African universities marked by digital inequality, linguistic diversity, and structural inequities.

Drawing on Lev Vygotsky's sociocultural theory (Vygotsky, 1978), the framework repositions microlearning as an inherently socially mediated and culturally situated practice. Its five interdependent dimensions function as a critical socio-cultural filter. Applied to microlearning design, these dimensions ensure that short modules activate the Zone of Proximal Development through peer scaffolding, cultural tools, and accessible mediational means, rather than merely delivering discrete information packets.

The framework's primary contribution lies in its potential to advance equity, deepen engagement, improve retention, and strengthen academic integrity. By addressing the structural pressures that often precipitate plagiarism and contract cheating, compressed timelines, linguistic barriers, uneven preparation, and digital exclusion, the framework enables academic integrity to emerge as a property of responsive design rather than external

compliance. In this way, thoughtfully designed microlearning can challenge, rather than reproduce, post-apartheid power structures in higher education.

As a conceptual model, the framework requires empirical testing and refinement across diverse institutional contexts. Future research may examine its implementation through design-based or participatory studies, evaluate its impact on student engagement, retention, and integrity outcomes, and explore its adaptability to other resource-constrained higher education settings in the Global South. Nevertheless, the framework offers a necessary shift: from efficiency-driven, individualised microlearning toward socially just, culturally responsive, and collectively oriented short-form pedagogies capable of supporting meaningful learning for all students.

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Transitioning, Reactive and Proactive Integrity Cultures: Institutionally Differentiated Approaches to AI Use.

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Abstract

This study examines institutional policy responses to generative AI, comparing transitional practices across universities and contrasting reactive (detection-focused) approaches with proactive (education-first) strategies. It also addresses the challenges associated with AI usage across different types of institutions. A comparative document analysis was conducted across six universities: two Universities of Technology, two Traditional Universities, and two Comprehensive Universities. Policy documents and AI guidelines developed or revised between 2021 and 2025 were analysed to identify these institutional frameworks and challenges.

The findings reveal that Universities of Technology prioritise compliance and detection, adopting predominantly reactive approaches. Traditional Universities employ a mix of punitive measures and developmental ethics, reflecting a more transitional strategy. In contrast, Comprehensive Universities increasingly embrace proactive, literacy-based approaches that integrate AI education into their curricula. Common challenges across all university types include varying levels of student preparedness, digital divides, and limited staff capacity.

Keywords: Generative AI, academic integrity, higher education policy, South Africa, reactive approaches, transitional strategies, proactive literacy.

Introduction

The rise of generative Artificial Intelligence (AI) has disrupted traditional concepts of academic integrity, posing challenges for South African higher education institutions as they strive to protect ethical practices while embracing digital innovation (Jacobs-Basadien, 2026; Thaldar, 2025). This study investigates institutional policy and AI guidelines, comparing whether universities are transitional, reactive or proactive in their approach to AI use. The study further investigates the challenges of AI use across all university typologies. These 3 typologies of South African public universities have different mandates (CHE, 2004); hence, their approach to academic processes often differs (Bunting & Cloete, 2010). Higher education institutions adopt different cultural orientations when responding to generative AI (GenAI). These can be broadly categorised as reactive, transitional, and proactive approaches, each reflecting distinct priorities, strategies, and levels of institutional maturity in addressing academic integrity and pedagogical innovation.

Reactive culture focuses primarily on detection, compliance, and enforcement (Jacobs-Basadien, 2026). It is commonly observed in resource-constrained settings or institutions prioritising immediate risk mitigation. (Bittle, 2025; Mohale, 2026). Transitional culture on the other hand, represents a hybrid or evolving stage that balances enforcement with developmental support (Jacobs-Basadien, 2026). These institutions combine punitive elements (rules and detection) with educative practices, such as developmental conversations for first-year students, ethical guidelines, and gradual assessment redesign (Thaldar, 2025). This culture reflects institutions in the process of shifting from purely compliance-driven responses toward more holistic integrity models, often incorporating student reflection and bias-aware practices (Pramjeeth, 2026). A proactive culture is forward-looking and education-first (Schoon et al, 2026). Institutions embed AI literacy into curricula. Rather than viewing AI solely as a risk, they treat it as an opportunity for pedagogical innovation, critical thinking enhancement, and ethical competence building (Maluleke, 2025).

The integration of generative AI in higher education presents multifaceted challenges that span equity, capacity, ethics, and pedagogy. Key challenges include: Uneven student preparedness and digital literacy gaps. Many students enter university with varying levels of AI familiarity, critical evaluation skills, and prompt literacy. This leads to unequal ability to use AI ethically or effectively, exacerbating achievement gaps(Schoon, 2025); Digital divides and equity issues: Access to reliable devices, high-speed internet, and premium AI tools is uneven, particularly in South Africa's diverse socio-economic context. AI detectors often show biases against non-native English speakers, raising fairness concerns (Jacobs-Basadien, 2026); Limited staff capacity and institutional readiness: Faculty frequently lack training in AI pedagogy, ethical integration, or updated assessment design. Workload pressures and policy implementation gaps hinder effective responses (Maluleke, 2025); Ethical, privacy, and integrity risks: Issues include plagiarism, authorship dilution, data privacy (POPIA compliance), hallucinations

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in AI outputs, and over-reliance that undermines critical thinking and original scholarship (Pramjeeth, 2026); Assessment validity and pedagogical adaptation: Traditional assessments become vulnerable, requiring time-intensive redesigns toward authentic, process-oriented tasks. Balancing innovation with rigour remains difficult (Bittle, 2025)

While global discussions on AI and integrity are growing, there is limited research on how various types of South African universities- Universities of Technology, Traditional Universities, and Comprehensive Universities- frame and respond to the use of AI, which is the gap this research is filling.

This study makes significant contributions by providing one of the first comparative analyses of generative AI policy responses across South African Universities of Technology, Traditional Universities, and Comprehensive Universities. Theoretically, it advances understanding of reactive, transitional, and proactive institutional cultures while promoting decolonial, Ubuntu-informed frameworks for academic integrity.

Methodology

This study employed an interpretivist philosophy and a qualitative document analysis as the primary research method to examine institutional policy responses to generative AI in South African higher education. Document analysis was employed as a systematic, interpretive technique suitable for exploring written texts such as policies and guidelines, allowing researchers to identify patterns, discourses, and implicit assumptions without direct interaction with participants (Bowen, 2009). In this study, A purposive sample of six universities was chosen to ensure a diverse representation across different institutional types: two Universities of Technology, two Traditional Universities, and two Comprehensive Universities. The analysis concentrated on publicly accessible and officially referenced policy documents and AI guidelines developed or updated between 2021 and 2025. This included policies related to plagiarism/academic integrity and academic integrity, as well as AI guidelines.

Results

Documents reviewed per university.

Types of Universities	University ID	Type of document	Date Approved	Date of next review
Universities of Technology	(UNI 5)	1 AI guidelines	Not stated	Not stated
		Academic Integrity Policy	2023	2026
	(UNI 6)	3 AI guidelines	2024	2030
		Academic Integrity Policy	2024	2030
Traditional Universities	(UNI 2)	3 AI guidelines	Not stated	Not stated
		Academic Integrity Policy	2021	2026
Comprehensive Universities	(UNI 1)	3 AI guidelines	Not stated	Not stated
		Academic Integrity Policy	2023	Not stated
	(UNI 3)	2 AI guidelines	Not stated	Not stated
		Academic Integrity Policy	2025	2028
	(UNI 4)	1 AI guidelines	Not stated	Not stated
		Academic Integrity Policy	2023	Not stated

Table 1: Documents reviewed per university

Table 1 provides a detailed overview of the various documents that the researcher examined for each university. It includes information on the approval dates of these documents as well as the scheduled dates for their next review by the respective institutions. It's important to highlight that most of the AI guidelines documents do not feature specific approval dates or timelines for future reviews, as they are typically not categorised as formal policy documents. Nevertheless, it is generally assumed that these guidelines were likely published between 2022 and 2025, during the rapid rise in the use of generative AIs that started in November 2022. All academic integrity policies were amended between 2021 and 2025, with subsequent reviews planned for the period between 2026 and 2030. The university names were not disclosed, they were instead referred to as UNI with a number from 1 to 6.

The culture framing the use of AI per university typology

Types of Universities	Evidence	Culture: Transitional, Reactive, or Proactive
Universities of Technology	Emphasise compliance, detection tools (e.g., Turnitin), sanctions, and rule enforcement with limited proactive literacy focus. (UNI 5), (UNI 6)	**Reactive**–Strong focus on detection and punitive/compliance measures.
Traditional Universities	Balance punitive measures (declarations, detection) with developmental ethics, educational conversations, and adaptive strategies (e.g., Embrace & Adapt). (UNI 2), (UNI 1)	**Transitional**–Moving from enforcement toward reflective, developmental approaches.
Comprehensive Universities	Adopt proactive, literacy-based strategies, embedding AI education (e.g., RITE framework, prompt literacy, curriculum transformation). (UNI 3), (UNI 4)	**Proactive**–Forward-looking integration of AI literacy and pedagogical innovation.

Table 2: The culture framing the use of AI per university typology

While each type of university exhibits elements of all three cultural approaches, one distinctly stands out in each category. Universities of Technology predominantly focus on compliance and detection, often adopting a reactive stance to issues as they arise. This approach emphasises strict adherence to regulations and immediate responses to breaches. In contrast, Traditional Universities embody a more balanced cultural perspective. They navigate the complexities of punitive actions alongside developmental ethics, reflecting a transitional culture that seeks to foster growth while maintaining accountability. Meanwhile, Comprehensive Universities are increasingly adopting a proactive strategy. They are integrating innovative, literacy-based methods into their curricula, with a strong emphasis on weaving AI education throughout various programs. This shift reflects a commitment to preparing students for a rapidly evolving technological landscape.

Universities of Technology emphasise compliance and detection, adopting reactive approaches

Research findings indicate that Universities of Technology in South Africa tend to emphasise compliance and detection, adopting predominantly reactive approaches to the academic integrity challenges posed by generative AI (Jacobs-Basadien, 2026; Mohale, 2026). This is clearly evidenced in the policies and practices of UNI 5 and UNI 6, which prioritise robust detection tools (such as Turnitin, SafeAssign, and LockDown Browser), explicit regulatory frameworks, and enforcement-oriented strategies, including detailed sanctions, originality declarations, and procedural controls, over proactive pedagogical transformation (Bittle, 2025). UNI 5 relies heavily on technological barriers and structured assessment controls like open-book exams, oral assessments, and peer reviews, which primarily serve a compliance function to deter and identify misconduct. Similarly, UNI 6's Plagiarism Policy explicitly defines unattributed use of generative AI as plagiarism and implements graduated sanctions ranging from mark deductions to potential expulsion, supported by consistent staff application of detection software. While some elements of assessment diversification exist, they largely function as extensions of detection and compliance rather than fundamental curriculum redesign. This reactive orientation aligns logically with the applied, industry-focused mandate and resource constraints typical of Universities of Technology, though it also signals the need for greater integration of proactive strategies to foster future-ready graduates alongside integrity protection.

Traditional Universities balance punitive measures with developmental ethics, reflecting transitional strategies

Traditional universities in South Africa generally adopt balanced, transitional strategies in response to generative AI challenges. These strategies combine punitive/enforcement measures with developmental ethics, moving beyond purely reactive compliance toward holistic academic integrity frameworks that support student growth while upholding standards (Thaldar, 2025). Both institutions integrate detection tools and rules with educational conversations, ethical adaptation, and pedagogical innovation, reflecting their research-intensive, student-development-oriented culture. UNI 1 emphasises developmental ethics through educational conversations (especially for first-year students) and the tripartite Avoid, Outrun, and Embrace and Adapt framework, treating minor infractions as teachable moments while building ethical judgment and AI literacy. UNI 2 similarly employs the Avoid-Outrun-Embrace and Adapt approaches but explicitly warns against over-reliance on biased detection tools, advocating instead for authentic assessment redesign, student reflection, and bias-aware practices to foster genuine learning and authorial identity. This hybrid model, balancing accountability and deterrence with deeper learning and ethical maturation, demonstrates a transitional phase that treats AI as both a risk and an opportunity

(Pramjeeth, 2026). The shared strategic taxonomy and focus on supportive, evolving frameworks position traditional universities to lead in cultivating responsible AI use, ultimately strengthening graduate outcomes and institutional credibility in South African higher education.

Comprehensive Universities increasingly adopt proactive, literacy-based approaches that embed AI education into curricula

Comprehensive universities in South Africa are increasingly adopting proactive, literacy-based approaches that embed AI education directly into curricula and institutional practices, moving beyond reactive detection or compliance toward transformative, future-oriented strategies (Schoon, 2025; Maluleke, 2025). UNI 3 exemplifies this through its RITE framework (Responsible, Informed, Transparent, Ethical), encouraging staff to use AI for syllabus design and rubric development while prioritising student prompt literacy and mandatory AI orientation programmes to build critical competencies and ethical use. UNI 4 complements this with a phased, evidence-based approach to GenAI integration, focusing on systematic curriculum and pedagogy transformation, particularly in health sciences, to create sustainable, contextually relevant AI-enhanced learning. Together, these initiatives position AI as a catalyst for innovation rather than merely a threat, providing practical tools (such as staff modelling and prompt literacy) and strategic depth that surpass punitive or transitional models found in other university types. This proactive orientation is logically imperative for comprehensive universities, given their diverse student bodies and broad mandates, as it fosters digitally fluent, ethically astute graduates, reduces reliance on reactive enforcement, and supports pedagogical renewal, inclusive excellence, and enhanced graduate employability in a rapidly transforming landscape.

Challenges

Despite varied institutional responses to generative AI, a consistent set of challenges emerges across the six selected universities, consistent with literature. These include uneven student preparedness (Schoon, 2025), digital divides (Jacobs-Basadien, 2026), and limited staff capacity (Maluleke, 2025).

Both UNI 5 and UNI 6 explicitly acknowledge infrastructure and human-resource barriers. UNI 5 recognises digital divides and uneven access to AI tools among students, which complicates the implementation of technology-enhanced assessments. It also notes staff capacity limitations in rolling out new assessment designs and effectively utilising detection tools . Similarly, UNI 6 highlights privacy, data security, and ethical risks that disproportionately affect students with limited digital literacy. The policy further calls for comprehensive staff training. Traditional universities such as UNI 1 and UNI 2 also grapple with these challenges, albeit with a stronger emphasis on equity and developmental needs. UNI 1 notes uneven student preparedness, particularly among first-year students who require additional educational conversations and support to navigate AI-related integrity issues. Staff development is identified as essential for successful policy implementation. UNI 2 goes further by explicitly addressing equity issues, including biases in AI detection tools that disadvantage non-native English speakers, alongside broader digital divides. The university recognises limited staff capacity for large-scale assessment redesign and ongoing student guidance.

Comprehensive institutions like UNI 3 and UNI 4 demonstrate similar awareness while linking challenges to curriculum transformation. UNI 3 emphasises the need for AI orientation and prompt literacy training precisely because of uneven student preparedness across its diverse student body. Integrating staff modelling and curriculum-wide AI use demands significant capacity building. UNI 4's phased, evidence-based approach reveals awareness of limited staff capacity and infrastructure constraints, while also highlighting the importance of addressing varying levels of student readiness in digital and AI-driven transformation. The persistence of these issues highlights systemic constraints in South African higher education and indicates the need for targeted interventions to support equitable and effective AI integration.

Conclusions

This study concludes that South African higher education institutions exhibit distinct yet patterned responses to generative AI, largely aligned with their institutional types: Universities of Technology predominantly adopt reactive, compliance-and-detection-oriented approaches, Traditional Universities employ balanced transitional strategies that temper punitive measures with developmental ethics, and Comprehensive Universities lead with proactive, literacy-based models that embed AI education into curricula and pedagogy. Despite these differences, common challenges, such as uneven student preparedness, digital divides, and limited staff capacity, persist across all types, highlighting systemic barriers that hinder equitable and effective AI integration. The researcher emphasises the need for a national shift from punitive to educational cultures of academic integrity. By embracing

proactive, contextually relevant strategies, South African universities can transform AI-related risks into opportunities for pedagogical innovation.

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Cultivating Adaptability Through EdTech: Equipping Students with Lifelong Learning Skills

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Abstract

This qualitative study explores a central question: how can educators use educational technology (EdTech) to help students become adaptable and develop lifelong learning skills? Set within higher education institutions (HEIs), the research responds to a rapidly shifting global landscape, one marked by technological disruption, evolving workforce needs, and complex societal challenges, requiring HEIs to produce graduates who are not merely knowledgeable but also flexible, self-directed, and resilient. Grounded in a constructivist framework, the study examines how lecturers guide students in using technology to develop adaptive learning behaviours and continuous skill-building. To capture these dynamics, data were collected across purposively selected HEIs through semi-structured interviews, classroom observations, and an analysis of educational technologies aiding or not, lifelong learning skills among students. Subsequently, thematic analysis was applied to identify patterns in how technology either supports or hinders adaptability. The findings reveal that when technology is integrated intentionally, through collaborative platforms, virtual simulations, Artificial Intelligence (AI), or self-paced learning systems, it strengthens learner autonomy, critical thinking, knowledge representation and problem-solving skills development. As a result, students become more capable of taking ownership of their learning and navigating unfamiliar situations. Nevertheless, the findings reported significant barriers. These include unequal access to digital resources, insufficient pedagogical training for lecturers, and a persistent focus on technologies rather than on students-centred practices. Therefore, the study argues that HEIs need strategic, pedagogy-driven approaches to technology adaptation, approaches that prioritise flexibility, creativity, and student responsibility. By offering concrete, context-specific insights, this research contributes to the broader conversation on educational technology for uncertain lifelong learning futures. However, the findings underscores that HEIs can leverage technology not as an end in itself but as a means to cultivate adaptable, lifelong higher education students ready for continuous and impactful learning.

Keywords: Educational Technology, Students' adaptability, Lifelong learning skills, Higher Education Institutions (HEIs), Pedagogy

Introduction

The twenty-first century has been marked by unprecedented technological innovation, growing global connectivity, and continuously changing labour market requirements. These transformations have significantly influenced the ways people learn, work, and communicate, placing increasing pressure on higher education institutions (HEIs) to develop graduates who are adaptable, resilient, and committed to lifelong learning (Bates, 2022; Clinciu, 2023; Dixit et al., 2024). As advances in automation, artificial intelligence (AI), and digital technologies continue to redefine professional landscapes, graduates are expected to possess not only subject-specific expertise but also the ability to continuously acquire new knowledge and adapt effectively to evolving circumstances (UNESCO, 2021; Akour & Alenezi, 2022).

In response to these changes, educational technology (EdTech) has become a key driver of innovation in teaching and learning. Through tools such as learning management systems, virtual simulations, collaborative digital environments, and AI-enabled applications, EdTech facilitates flexible, personalized, and self-directed learning opportunities for students (Bond et al., 2021). When effectively integrated into pedagogical practices, these technologies can enhance learner autonomy, stimulate critical and creative thinking, and strengthen problem-solving abilities, competencies that are fundamental to both adaptability and lifelong learning (Redecker, 2020)

Although educational technologies have become increasingly prevalent in higher education, questions persist regarding their effectiveness in fostering advanced learning competencies. In many cases, the integration of technology remains largely focused on the transmission of content rather than on learner-centred pedagogical practices that encourage adaptability, critical thinking, and lifelong learning (Henderson et al., 2017). As a result, there is a growing need to examine how educators can strategically employ technology to develop students who are capable of adapting to changing learning and professional environments.

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Furthermore, the COVID-19 pandemic significantly accelerated the adoption of digital technologies across higher education institutions, revealing both the opportunities and limitations of technology-enhanced learning (Dhawan, 2020; Olakotan, 2025). The rapid shift to online and blended learning highlighted the potential of digital tools to sustain educational continuity while also exposing challenges related to access, engagement, and instructional effectiveness. Nevertheless, evidence suggests that thoughtfully designed technology-supported learning environments can enhance student participation, increase engagement, improve academic achievement, and foster greater learner independence and self-regulation (Martin et al., 2020).

Adaptability is increasingly recognized as a critical graduate competency in contemporary society. Adaptability refers to an individual's capacity to effectively adjust to changing circumstances, embrace diverse learning approaches, and utilize emerging technologies and resources to support continuous learning and development (Boulamatsi, et al.; 2021). Adaptive learners demonstrate flexibility in addressing challenges, openness to new experiences, and resilience in uncertain situations.

Lifelong learning refers to the continuous pursuit of knowledge, skills, and competencies throughout an individual's life (UNESCO, 2021). It extends beyond formal education and encompasses self-directed, informal, and experiential learning opportunities.

According to Knowles et al. (2020), lifelong learners exhibit characteristics such as self-motivation, self-regulation, curiosity, and reflective thinking. Educational technologies can support these characteristics by providing learners with access to diverse information sources, personalized learning pathways, and opportunities for collaborative inquiry (Merriam & Bierema, 2014).

This study is grounded in constructivist learning theory, which posits that learners actively construct knowledge through interaction with their environment and engagement with meaningful learning experiences (Vygotsky, 1978). Constructivism emphasizes active participation, social interaction, and reflective practice as central elements of effective learning.

Educational technology aligns strongly with constructivist principles because it enables learners to explore, collaborate, create, and solve authentic problems within digital environments (Siemens, 2005). Through these experiences, students develop adaptive learning behaviours and lifelong learning dispositions.

This study therefore explores how educational technology can be utilized to foster adaptability and lifelong learning skills among students in higher education institutions.

Methodology

Design

This study adopted a qualitative research design to explore educators' perspectives on the role of educational technology in fostering adaptability and lifelong learning skills. Qualitative approaches are particularly suitable for examining complex educational phenomena and understanding participants' lived experiences (Creswell & Poth, 2018).

Research Site, Population and Participants

The study was conducted in a fast-growing university in Nigeria that has experienced rapid expansion in student enrolment, academic programmes, and digital learning infrastructure. The institution was selected because of its increasing investment in educational technologies and its active use of blended and technology-enhanced learning approaches across several faculties.

Participants were purposively selected from the university based on their direct involvement with teaching, learning, and educational technology use. The sample comprised 18 participants in total: 10 lecturers, 3 instructional technology staff, and 5 academic coordinators drawn from faculties that regularly integrated digital tools into teaching and assessment. The lecturers had between 3 and 15 years of teaching experience, while the instructional technology staff and academic coordinators had practical experience supporting the implementation of learning management systems, online collaboration tools, and digital assessment platforms.

The participants were selected because they had relevant knowledge and experience regarding the use of educational technology in promoting student adaptability and lifelong learning. Purposive sampling was used because it allows researchers to select participants who possess relevant expertise and experience regarding the phenomenon under investigation (Patton, 2015).

Data collection

Data were collected through semi-structured interviews, classroom observations, and document analysis. Semi-structured interviews were used to explore participants' perceptions, experiences, and practices related to educational technology and lifelong learning development. Classroom observations focused on technology-enhanced learning activities and interactions between lecturers, students, and digital learning tools. Institutional documents, learning management systems, AI-supported applications, and other educational technologies were also analysed to understand how they supported adaptability and lifelong learning outcomes.

Data Analysis

Thematic analysis was employed to identify recurring patterns and themes within the data. Braun and Clarke's (2021) six-phase framework guided the coding and interpretation process, enabling the identification of meaningful insights regarding the educational use of technology. Credibility was enhanced through triangulation of data sources, member checking, and peer review of coding processes. These procedures strengthened the reliability and validity of the findings.

Results

Theme 1: Educational Technology Promotes Learner Autonomy

Participants reported that digital learning platforms enabled students to take greater responsibility for their learning. Learning management systems and self-paced online courses encouraged independent study, self-monitoring, and reflective practice.

These findings support previous studies indicating that technology-enhanced learning environments contribute significantly to self-regulated learning and learner autonomy (Zimmerman, 2002; Bond et al., 2021).

Theme 2: Collaborative Technologies Enhance Adaptability

Collaborative technologies such as Microsoft Teams, Google Workspace, and online discussion forums facilitated teamwork and knowledge sharing. Students learned to negotiate meaning, solve problems collectively, and adapt to diverse perspectives.

These findings align with constructivist assumptions that knowledge is socially constructed through interaction and collaboration (Vygotsky, 1978).

Theme 3: AI and Simulations Strengthen Critical Thinking and Problem-Solving

Participants highlighted the value of AI-powered applications and simulation-based learning environments in exposing students to authentic challenges. Such technologies encouraged experimentation, decision-making, and reflective learning.

Research similarly demonstrates that AI-supported learning environments can enhance critical thinking and personalized learning experiences (Luckin et al., 2016; Holmes et al., 2022).

Theme 4: Challenges Affect Effective Technology Integration

Despite the benefits of educational technology, participants identified significant barriers including unequal access to digital resources, inadequate lecturer training, and limited institutional support.

These findings are consistent with existing research that identifies digital inequality and insufficient pedagogical preparation as major obstacles to successful technology integration in higher education (Selwyn, 2021; UNESCO, 2021).

Discussion of Findings

The findings suggest that educational technology can effectively cultivate adaptability and lifelong learning skills when integrated within learner-centered pedagogical frameworks. Consistent with constructivist theory, technology-supported learning environments create opportunities for active engagement, collaboration, and knowledge construction (Vygotsky, 1978).

The development of learner autonomy emerged as a key pathway through which educational technology supports lifelong learning. Students who actively manage their learning processes are more likely to engage in continuous learning beyond formal educational settings (Knowles et al., 2020).

Furthermore, AI technologies and simulation-based learning environments expose students to authentic and complex challenges that require adaptive thinking and problem-solving skills. These experiences help prepare learners for rapidly changing professional contexts where flexibility and continuous learning are essential (World Economic Forum, 2023).

However, technology alone cannot transform learning. As emphasised by Bates (2022), the effectiveness of educational technology depends largely on pedagogical design and institutional support structures. Therefore, HEIs must move beyond technology acquisition towards purposeful, pedagogy-driven implementation strategies.

Conclusions

This study explored how educational technology can be leveraged to cultivate adaptability and lifelong learning skills among students in higher education institutions. The findings demonstrate that intentional technology integration enhances learner autonomy, collaboration, critical thinking, and problem-solving capabilities, all of which are essential for lifelong learning and future employability.

Nevertheless, challenges related to digital inequality, limited pedagogical competence, and technology-centered implementation approaches continue to constrain the transformative potential of educational technology. Consequently, HEIs should adopt strategic and learner-centered approaches to technology integration that prioritize adaptability, creativity, and continuous learning.

By positioning educational technology as a means rather than an end, higher education institutions can better prepare students to thrive in an increasingly complex and uncertain world.

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Digital Transformation in Health Tourism Education: Theoretical Approaches and Sectoral Requirements

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Abstract

The growing use of digital channels, data systems and artificial intelligence tools in health tourism is changing the competences expected of professionals working in the sector. This study examines digital transformation in health tourism education from a Management Information Systems (MIS) perspective and explores the alignment between education and sectoral requirements. The research follows a two-stage, qualitative and exploratory design. In the first stage, national and international studies on health tourism education, digital transformation, digital competence, artificial intelligence and responsible technology use were reviewed through a focused literature review. In the second stage, a joint semi-structured interview was conducted with two sector professionals who specialise in health tourism and have approximately twenty years of teaching experience, and the data were examined through thematic analysis. The Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology-Organization-Environment (TOE) framework were used as conceptual lenses for interpreting the findings, while DigComp 3.0 informed the classification of digital competence areas. The analysis yielded three themes: digital and data-based competences; artificial intelligence, ethics and responsible technology use; and education-sector alignment and hybrid competences. The findings indicate that the use of digital tools is not equivalent to the capacity for data-based decision-making, that competence in artificial intelligence needs to be addressed together with verification and ethical responsibility, and that technological skills are expected to be integrated with communication, empathy and sector knowledge. The study suggests that health tourism education programmes be strengthened in terms of data literacy, artificial intelligence literacy, responsible technology use and practice-based learning.

Keywords: Health Tourism Education, Digital Transformation, Artificial Intelligence, Sectoral Competences, Management Information Systems (MIS), Data Management.

Introduction

Digital Transformation and Competence Requirements in Health Tourism

Health tourism is a multidisciplinary field situated at the intersection of health service delivery and tourism activities. The patient journey is supported by digital tools across the stages of information seeking, planning and reservation, travel and treatment, and post-treatment follow-up (Karcıoğlu, 2025). While Karcıoğlu (2025) approaches these stages through the integration of artificial intelligence into the patient journey, Aykın et al. (2023) show that artificial intelligence and telemedicine applications transform patient communication and service access processes in health tourism marketing. Both studies focus on the effect of digitalisation on the patient experience; neither directly examines the competences required of the employees who carry out these processes.

This distinction matters. Digital transformation is not limited to carrying out existing operations through digital tools; it is a broader process that reshapes how organisations create value and structure their business models (Vial, 2019; Verhoef et al., 2021). In health tourism, Customer Relationship Management (CRM) systems, data analytics, digital marketing, telemedicine and artificial intelligence applications are increasingly used in patient communication, service coordination and decision-making. Alongside these developments, the ability to interpret data correctly is becoming one of the skills expected of employees.

Digital Competence Frameworks

International reference frameworks are used in defining digital competences. DigComp 2.1, developed by the Joint Research Centre of the European Commission, defines digital competence through the areas of information and data literacy, communication and collaboration, digital content creation, safety, and problem solving (Carretero et al., 2017). In DigComp 3.0, knowledge, skills and attitudes concerning artificial intelligence are integrated transversally into the digital competences of the framework (Cosgrove & Cachia, 2025). Within the framework, the use of artificial intelligence is associated with skills such as evaluating outputs, questioning sources and taking ethical consequences into account (Cosgrove & Cachia, 2025). DigCompEdu, addressed to educators, focuses on

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the use of digital technologies in teaching, assessment and the empowerment of learners (Redecker, 2017). In this study, both frameworks are used not as theories but as references that assist in classifying competence areas.

In health tourism, field-specific responsibilities are added to these general competences. Multilingual communication with international patients, management of the digital patient journey and the processing of personal health data are foremost among them (Aykın et al., 2023; Karcıoğlu, 2025). Since health data fall within the scope of special categories of personal data, responsibility for data security and privacy extends beyond the level of general digital safety. The World Health Organization Regional Office for Europe (2021) links the processing of personal data in health information systems to the rights of data subjects, transparency and governance principles, while the World Health Organization (2021, 2024) identifies human autonomy, safety and accountability among the core principles for the use of artificial intelligence in health. Within this framework, critical evaluation and responsible technology use may also be considered part of digital competence in health tourism education.

The MIS Perspective

The Management Information Systems (MIS) literature offers approaches that explain technology adoption at different levels. The Technology Acceptance Model (TAM) explains individual acceptance through perceived usefulness and perceived ease of use (Davis, 1989). The Unified Theory of Acceptance and Use of Technology (UTAUT) considers performance expectancy, effort expectancy, social influence and facilitating conditions among the determinants of use (Venkatesh et al., 2003). The Technology-Organization-Environment (TOE) framework, in turn, treats adoption as a process shaped jointly by technological, organisational and environmental conditions (Tornatzky & Fleischer, 1990). These approaches are not tested empirically in this study; TAM is used to interpret individual acceptance, UTAUT to interpret facilitating conditions such as training and infrastructure, and TOE to interpret the relationship between curricula and sectoral expectations.

Health Tourism Education in Türkiye and the Research Gap

Göktaş (2018) states that health tourism education is delivered mainly through associate degree and certificate programmes and that there is a gap at the undergraduate level. Saygılı and Diker (2022) identify eight associate degree, six master's and one doctoral programme. Considered together, the two studies show that despite the increase in the number of programmes, the gap at the undergraduate level persists. Saygılı and Diker (2022) further find that business courses predominate in associate degree curricula.

In a more recent examination of tourism education, Aktaş Alan et al. (2026) assessed the curricula of 79 universities offering undergraduate tourism education in Türkiye and found that 53.84% of technology-oriented courses are elective, that data analytics courses are offered in only three programmes, and that artificial intelligence content remains limited.

In the context of health tourism, artificial intelligence has also begun to be examined through the attitudes of managers. Yalman (2023) developed a valid and reliable scale for measuring the attitudes of managers working in private hospitals holding an international health tourism authorisation certificate towards artificial intelligence applications. Yalman's (2023) study focuses on the attitudes of health tourism managers towards artificial intelligence. The digital competences required in education and their relationship with sectoral expectations fall outside the scope of that study.

This assessment points to three research requirements. First, the digital competences required in health tourism need to be defined more clearly in a field-specific manner (Aykın et al., 2023; Karcıoğlu, 2025). Second, the extent to which these competences are represented in health tourism programmes in Türkiye is not sufficiently clear (Göktaş, 2018; Saygılı & Diker, 2022). Third, how the digital competences that come to the fore in the sector can be transferred to education requires further research (Aktaş Alan et al., 2026). This study addresses the first and third requirements; the second, which would require curriculum analysis, is left outside its scope.

Aim of the Study

The aim of the study is to examine, in an exploratory manner, the digital competences that come to the fore in health tourism education through the literature and the assessments of sector experts, and to discuss the areas in which education-sector alignment could be strengthened. Accordingly, answers were sought to three research questions: (1) Which digital competences come to the fore in the literature with respect to health tourism education? (2) Which digital competence requirements do the sector experts participating in the interview observe? (3) In which areas can the alignment between education and sectoral requirements be strengthened?

Methodology

The research follows a qualitative and exploratory design and was conducted in two stages. In the first stage, national and international studies on health tourism education, digital transformation, digital competence, artificial intelligence and responsible technology use were addressed through a focused literature review. The review was not designed as a systematic review; it was carried out in order to establish the conceptual framework and to support the interpretation of the interview findings.

In the second stage, a purposeful sampling approach was adopted. According to Patton (2015), purposeful sampling rests on the selection of information-rich cases with respect to the research question. Accordingly, expertise in health tourism, close familiarity with the sector and extensive teaching experience were taken as the participant selection criteria; two sector professionals who met these criteria and have approximately twenty years of teaching experience were included in the study.

The interview was conducted online on 17 July 2026 and lasted approximately 60 minutes. It was carried out as a single session in which the two participants took part together. This structure allowed the participants to complement each other's assessments; however, it constrained the reliable attribution of statements to individual participants. For this reason, the findings are presented without participant codes, on the basis of the interview data as a whole. Detailed notes were taken during the interview; the notes were expanded into a written text immediately afterwards and prepared for analysis. The direct statements attributed to participants are based on these notes. The participants were informed about the aim of the research and the use of the data, their informed consent was obtained, and their identifying information was kept confidential.

The semi-structured interview form consisted of three sections: transformation in educational practice, observed digital competence requirements, and assessments concerning the education system. The questions covered CRM and data use, artificial intelligence, digital communication, ethics and the protection of personal data, and the skills of new graduates.

The data were examined by a single researcher drawing on the thematic analysis approach of Braun and Clarke (2006). The interview notes were read, statements related to the research questions were coded, similar codes were brought together, and the themes were reviewed by comparing them against the data once more. The analysis yielded three themes: (1) digital and data-based competences, (2) artificial intelligence, ethics and responsible technology use, and (3) education-sector alignment and hybrid competences. TAM, UTAUT, TOE and DigComp were not used in the coding process; they informed the interpretation of the themes obtained.

Results and Discussion

Digital and Data-Based Competences

The first theme that emerged in the interview is the difference between using digital tools and being able to use the information obtained from these tools in decision-making processes. The participants stated that social media, messaging applications, Excel and various digital systems are used in daily work. CRM, data analysis, reporting and performance measurement, in turn, are among the areas in which they observe a need for development. This distinction was expressed through the statement that “having hundreds of rows in Excel does not in itself mean an analytical approach”; the essential requirement was emphasised as “asking the right question and being able to make decisions using the right data”. According to the participants, the fact that existing data are scattered and are not sufficiently carried over into decision-making processes is among the main problems.

This finding calls for a distinction regarding the criterion of digital competence. Access to tools and frequency of use cannot be taken as indicators of the capacity for data-based decision-making. This assessment corresponds with the evaluation and data management skills included within information and data literacy in DigComp 3.0 (Cosgrove & Cachia, 2025). In the interview data, data literacy was associated with identifying interruptions in the patient acquisition process and converting the resulting information into operational decisions.

In UTAUT, facilitating conditions are associated with the presence of organisational and technical infrastructure supporting technology use (Venkatesh et al., 2003). The emphasis placed on training, technical infrastructure and institutional support in the interview corresponds with this dimension.

Artificial Intelligence, Ethics and Responsible Technology Use

The second theme concerns the importance of critical evaluation and responsibility in the use of artificial intelligence. The participants stated that artificial intelligence provides speed in content creation, research, customer communication and reporting. The use of outputs without evaluation, however, was expressed as a significant risk. This was explained through the statement “we cannot accept an answer as correct simply because

artificial intelligence gave it to us"; the dimension of responsibility was emphasised through the assessment that "artificial intelligence may give you speed, but it does not take responsibility away from you". On the matter of data responsibility, it was noted that those working in health tourism cannot place themselves outside this responsibility with the approach "I only handle sales"; the difference between accessibility and lawful usability was underlined through the statement that "the fact that a piece of information is available on the internet does not mean we can use it however we wish".

The theoretical counterpart of this finding is the distinction between technology acceptance and competent use. TAM shows that perceiving a tool as useful and easy to use supports its adoption (Davis, 1989). The interview data, however, indicate that the output of an adopted tool may be used without verification. The findings suggest that technology acceptance alone does not account for competent use. The fact that DigComp 3.0 distributes artificial intelligence across all competences rather than treating it as a separate area supports the same reasoning (Cosgrove & Cachia, 2025).

The dimension of responsibility is also becoming increasingly visible in the MIS literature. Erduran (2025) addresses human agency in artificial intelligence-driven information systems, legal responsibility in autonomous systems and obligations concerning data protection, and proposes a governance framework for MIS professionals. Guidance specific to the health field likewise identifies human oversight, transparency and accountability among its core principles (World Health Organization, 2021, 2024; World Health Organization Regional Office for Europe, 2021). What the interview findings add to these frameworks is that such principles need to find a counterpart in health tourism not only at the institutional level but also in operational roles such as sales and patient communication.

Education-Sector Alignment and Hybrid Competences

The third theme concerns the relationship between education and sectoral practice. The participants stated that new graduates adapt more quickly to digital tools but need experience in customer relations, problem solving and understanding how the sector operates. Among experienced employees, by contrast, adaptation to new tools was said to occur more slowly despite strong sector knowledge. The balance between these two profiles was described as "someone who knows technology but does not forget the human being; someone who has experience but is also open to change", and was expressed later in the interview directly through the concept of "hybrid competence". A participant explained this concept with the words "human skills and technological skills need to be present together".

In this study, hybrid competence is used not as a validated new model but as an analytical expression that names the complementary skill structure emerging in the interview data. The concept denotes the joint use of technological and human skills. The participant's assessment that "technology may give us speed, data may give us direction, and artificial intelligence may give us time. But no technology alone can provide trust, empathy and sound communication" summarises this complementarity. In health tourism, digital competences are considered together with intercultural communication, understanding patient expectations and sector knowledge.

In the assessments concerning educational institutions, strengthening contact with the sector came to the fore. The statement "we cannot train the professional of the future in the classroom alone" points to the importance of bringing real problems and customer scenarios into the educational process. Read alongside the finding that advanced digital courses are predominantly elective in tourism curricula (Aktaş Alan et al., 2026), this assessment suggests that the problem cannot be resolved simply by adding courses. The TOE framework is explanatory at this point: curricula, digital infrastructure and practice-based learning capacity constitute the organisational context, while sectoral expectations and regulatory requirements constitute the environmental context (Tornatzky & Fleischer, 1990). In this respect, education-sector alignment is also related to institutional capacity and stakeholder interaction.

Conclusions

This study shows that digital transformation in health tourism education cannot be reduced to the use of technical tools. The answers to the research questions may be summarised as follows.

With respect to the first question, the digital competences that come to the fore in the literature are gathered under the headings of data literacy, artificial intelligence literacy, data security and privacy, and multilingual digital communication. In health tourism, these competences carry a broader responsibility than the one defined in general frameworks, owing to the special nature of health data and the international character of the service.

With respect to the second question, the experts participating in the interview observed three areas of requirement: the ability to convert data into business decisions, the ability to verify the output of artificial intelligence, and the

ability to integrate technological skills with communication, empathy and sector knowledge. Evaluation, decision-making and communication skills come to the fore in these requirements.

With respect to the third question, the alignment between education and sectoral requirements may be strengthened in three areas. Data literacy and the logic of decision support may be defined explicitly among programme outcomes; artificial intelligence may be addressed together with the dimensions of verification, privacy and human oversight; and university-sector interaction may be deepened through case studies, anonymised data sets and practice-based projects. In this approach, technology is positioned as a means of supporting the quality of decisions and the patient experience.

The main limitation of the study is that it rests on a single joint interview conducted with two experts. While this structure allowed interaction between the participants, it constrained the independent formation of their views and their attribution at the individual level. Since the data were obtained through detailed note-taking rather than audio recording, the verbatim accuracy of the directly reported statements cannot be guaranteed at the level of individual words. The fact that the analysis was carried out by a single researcher and did not include an independent verification step also means that the interpretive process may have been shaped by the researcher's perspective. The literature stage is not of the nature of a systematic review, and the theoretical approaches employed were not tested empirically but treated as interpretive frameworks. The findings should therefore be regarded not as generalisable results but as exploratory and context-specific insights.

Future research may work with broader samples encompassing academics, students, graduates and sector professionals in different roles. The course content of health tourism programmes may be examined comparatively in line with digital competence frameworks. In addition, the dimensions of hybrid competence, used here as an analytical expression, may be tested with quantitative methods in larger samples.

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The Relationship Between Digital Informal Learning Competence and Perceived Academic Achievement in Faculties of Sport Sciences

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Abstract

This study aims to examine, through a holistic approach grounded in the theoretical and empirical literature, the relationship between digital informal learning competence and perceived academic achievement among students in faculties of sport sciences. The study was designed as a traditional literature review and is based on a comprehensive search of the Web of Science, Scopus, Google Scholar, ERIC, PubMed, and ULAKBİM TR Dizin databases. Sport sciences education encompasses not only theoretical courses such as anatomy, physiology, and training science, but also applied learning processes that require high levels of motor and technical–tactical skill. The reviewed literature indicates that 3D visualization tools, video analysis software, wearable technologies, artificial intelligence, virtual/augmented reality applications, and social media platforms are used as effective tools in out-of-class informal learning processes. The findings suggest that higher levels of digital literacy and digital competence play an important mediating role in translating informal learning experiences into academic achievement. Students who interact with digital tools in an autonomous and purposeful manner tend to report stronger self-efficacy, academic locus of control, self-regulation, and academic hardiness, which in turn are directly and positively associated with their perceived academic achievement. However, considering the risk that uncontrolled use of digital resources may impair academic focus, it is recommended that sport sciences curricula be supported with digital literacy courses, that technological infrastructure be developed to enable informal practice, and that informally acquired knowledge be integrated into formal learning processes through reflective learning methods.

Keywords: Sport sciences, digital tools, informal learning, perceived academic achievement

Introduction

Rapid advances in information and communication technologies have ushered the contemporary world into a digital age. This transformation has moved higher education institutions away from traditional instructional models towards a new ecosystem in which digital tools are positioned at the center of learning processes (Mehrvarz et al., 2021). The COVID-19 pandemic, in particular, accelerated this process and made online and blended learning models standard practice in higher education. In this new academic reality, students' interaction with technology has become not merely a necessity but also a key determinant of academic achievement (Alanoglu et al., 2026).

Sport sciences is, by its very nature, an interdisciplinary field in which theoretical knowledge is blended with practical skills. Digitalization has also brought about fundamental changes in sport education, and tools such as web-based learning platforms, wearable technologies, video analysis software, artificial intelligence (AI), and virtual reality (VR) have been integrated into educational curricula (Uysal & Dalkıran, 2025). These technologies help sport sciences students develop their motor skills, conduct tactical analyses, and make sense of complex biomechanical data. With the process of digitalization, learning dynamics have evolved from a teacher-centered, passive structure into a student-centered model that encourages active student participation. The sport education literature emphasizes that interdisciplinary working skills and digital competencies have now become strategically important for the career sustainability of sport professionals. In this context, the use of technology not only within but also beyond the classroom has given rise to a new pedagogical paradigm in sport sciences (Wei, 2025).

Learning is not limited to "formal" processes that take place in structured and planned educational settings. Today, the widespread availability of digital tools has brought to the fore "digital informal learning" (DIL), which individuals undertake in line with their own interests and needs, free of temporal and spatial constraints. DIL enables students to access information whenever they wish, to set their own learning pace, and to use digital resources freely to solve complex problems (Zakir et al., 2025). However, the ready accessibility of digital resources does not mean that every student is able to convert this process into academic achievement. The literature indicates that the effect of digital informal learning experiences on academic achievement is closely related to an individual's level of "digital literacy" and "digital competence". Students with higher digital competence have been found to integrate the knowledge they acquire in informal settings more effectively with formal course content, which is positively associated with their perceived academic achievement (Heidari et al., 2021). Studies

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in sport sciences have generally focused on the effects of technology use on physical performance or formal education (Lobo, 2025); however, how students' out-of-class digital learning competencies relate to their perceptions of academic achievement has not been sufficiently investigated. Accordingly, this study aims to examine, through a review of the literature, digital informal learning competence among students enrolled in faculties of sport sciences and its relationship with perceived academic achievement. The findings are expected to contribute to the development of digital strategies in sport sciences education and to a more effective integration of informal learning spaces into the formal curriculum.

Methodology

This study was designed as a traditional literature review aiming to evaluate, from a holistic and explanatory perspective, the relationship between informal learning competence through digital tools and perceived academic achievement in sport sciences. Within the scope of the study, the key concepts, theoretical frameworks, and empirical findings reported in the national and international literature were examined. The literature search was conducted in the Web of Science, Scopus, Google Scholar, ERIC, PubMed, and ULAKBİM TR Dizin databases. The searches primarily used the keywords *"sport sciences education"*, *"digital tools"*, *"informal learning"*, *"self-directed learning"*, *"digital literacy"*, and *"perceived academic achievement"*, as well as their combinations.

Empirical studies, reviews, scale development studies, and scholarly books addressing the theoretical and applied dimensions of the topic were included in the review. During the search process, priority was given to academic studies published in Turkish or English that directly addressed the relationship between digital/informal learning and academic achievement in the context of higher education and sport sciences. Popular media content and blog posts that had not undergone peer review, as well as publications focusing solely on motor skills, sport performance, or physiological parameters without a digital learning dimension, were excluded. The data obtained were synthesized according to the identified themes and presented using a narrative approach.

Results

Conceptual Framework

Informal Learning and Digital Tools

Digital informal learning (DIL) refers to the unstructured, voluntary, and autonomous learning processes in which students use digital technologies, in line with their own interests and needs, outside the structured curriculum of formal educational institutions. By providing access to information without temporal or spatial constraints, this form of learning extends the boundaries of the traditional classroom (Trinder, 2017). In sport sciences, digital tools have become important learning channels both for deepening theoretical knowledge and for acquiring practical, performance-based skills (Uysal & Dalkıran, 2025).

Social media and video platforms are currently regarded as among the most effective components of informal learning. YouTube, in particular, is a key learning resource for sport sciences students, as it enables the visualization of motor skills and provides access to technical–tactical analysis videos and expert-led training. Professional networks such as LinkedIn support career sustainability by enabling students to interact directly with the sport industry, build their professional identities, and follow sectoral trends (López-Carril et al., 2022). Platforms such as WhatsApp and Instagram, in turn, foster peer-to-peer knowledge sharing and collaborative discussion, thereby creating a social learning community (Samala et al., 2024).

Mobile applications and sport analysis software bring a data-driven dimension to informal processes in sport education. Video analysis software accessible via tablets and smartphones helps students analyze their own or their peers' performance, identify technical errors, and develop tactical awareness. Wearable technologies and exercise-tracking applications, meanwhile, monitor physical activity data in real time, provide students with personalized feedback, and foster their ability to manage their own learning processes (self-regulation) (Ansari & Khan, 2020).

Although the literature draws attention to the risk that uncontrolled, entertainment-oriented use of digital tools may distract academic focus, individuals with digital informal learning competence appear able to improve their academic performance meaningfully by combining these tools with information-seeking, problem-solving, and self-monitoring strategies (Cirik & Uzun, 2026; Langarizadeh et al., 2018). Consequently, digital tools play an important role in enriching sport sciences students' out-of-class learning experiences and in preparing them for professional life.

Digital informal learning encompasses not only the technical skill of using tools but also the ability to search for information strategically, to filter it critically, and to make sense of it in line with individual learning goals (Seo et al., 2021). In the literature, this process is defined as the effective coordination of cognitive, metacognitive, and

social-motivational strategies by the individual. Self-efficacy is one of the most critical components of DIL competence and represents students' confidence in their ability to use digital tools for learning purposes. Individuals with high technological self-efficacy are more persistent in solving the complex problems they encounter in digital environments and view these processes as opportunities for academic development. In this context, self-efficacy is not merely an attitude towards technology but also a psychological resource that enables students to construct their own learning journey through digital resources (Rafatjoo et al., 2025).

Research shows that as individuals' levels of digital literacy and competence increase, the efficiency they derive from informal settings rises accordingly (Rodafinos et al., 2024). Students with high levels of digital competence are able to use internet-based resources more autonomously, not only for entertainment but also for completing academic tasks and developing professional skills (Getenet et al., 2024). Particularly in fields such as sport sciences, where video analysis software and performance-tracking systems are used intensively, students' informal engagement with these tools appears to directly support their professional self-efficacy and perceived academic achievement (Hashim, 2026).

Perceived Academic Achievement

Perceived academic achievement is defined as students' subjective evaluation of their own learning outcomes, their ability to fulfil academic tasks, and their overall academic development (Stadler et al., 2021). Although academic achievement has traditionally been measured by objective indicators such as grade point average or examination results, the literature emphasizes that students' self-perceptions of their own performance play a central role in the learning process. The concept encompasses a retrospective evaluation of the learning experience as well as the individual's beliefs and feelings regarding this process (Bozdağ & Aktan, 2024).

The core components of perceived academic achievement include students' confidence in the adequacy of their academic skills, their perceived competence in successfully completing assignments and academic tasks, and their personal assessment of the extent to which they have met their expectations (Honicke & Broadbent, 2016). Such self-reported data are critical indicators of students' autonomy in the learning process and of how effectively they use cognitive and metacognitive strategies. In digital environments in particular, a significant relationship has been identified between students' self-efficacy in using technological tools and their perceptions of academic achievement (Basileo et al., 2024).

Studies indicate that students with high levels of digital literacy and self-regulation (particularly attentional control) perceive their learning outcomes in both formal and informal settings more positively. In sport sciences education specifically, the use of video analysis, virtual reality (VR) applications, and gamification-based digital tools has been reported to enhance students' technical–tactical skills and, consequently, to support their perceptions of academic achievement (Lampropoulos & Kinshuk, 2024). In sum, perceived academic achievement is not merely an academic outcome but also a fundamental psychological resource that shapes students' motivation, resilience, and academic persistence with respect to future professional tasks.

Digital Informal Learning in Sport Education

Use of Digital Tools in Applied and Theoretical Courses

Sport sciences education is, by its nature, an interdisciplinary field in which theoretical knowledge and performance-based practical skills are developed concurrently. The use of digital tools in this field is transforming traditional educational models and plays an important role in the acquisition of both cognitive and motor skills (Uysal & Dalkıran, 2025).

The Role of Digital Tools in Theoretical Courses

In content-intensive theoretical courses such as anatomy, physiology, and training science, digital tools are used to make knowledge more concrete and to enhance its retention. In anatomy education in particular, three-dimensional anatomical analyses, digital diagrams, and visualization tools enable students to grasp complex body structures and movement mechanics more effectively (Cirik & Uzun, 2026). The literature reports that the level of digital literacy is directly related to academic achievement in online anatomy and physiology courses (Holm, 2024). In training science courses, processing performance data, calculating training loads mathematically, and evaluating results through computer-based tests develop students' competence in scientific training planning (Jobson et al., 2009).

The Role of Digital Tools in Applied Courses

In applied courses, digital tools function as instruments that encourage active student participation and support the philosophy of learning by doing.

Movement analysis.

Digital tablets and professional video analysis software such as Dartfish form the basis of movement analysis courses. Using these tools, students can analyze technical videos to identify critical movement points, compare their own performance with expert models, and examine tactical errors on the basis of data (Le Paven et al., 2021).

Load monitoring and tracking.

Wearable technologies and AI-supported Exercise Load Monitoring Systems (ELMS) enable real-time monitoring of parameters such as heart rate, exercise intensity, and distance covered during practical training in the field. The immediate feedback provided by these systems helps students develop their motor skills more consciously and optimize their physical capacities (Dudek et al., 2025).

Advanced technologies (VR/AR).

Virtual reality (VR) and augmented reality (AR) applications offer sport sciences students a safe and interactive learning environment that simulates real field conditions, thereby accelerating the development of motor skills and tactical thinking. The use of digital tools in these disciplines not only facilitates knowledge transfer but also strengthens students' self-efficacy, thereby preparing them as professionals equipped with the digital competencies demanded by the modern sport industry (De Beukelaar & Mantini, 2023).

Digital Learning Tendencies and Habits of Sport Sciences Students

Students enrolled in faculties of sport sciences have made digital technologies and internet-based tools an integral part of their daily lives for both social and academic purposes. An examination of these students' digital learning tendencies shows that social media platforms and mobile applications, in particular, play a dominant role in informal learning processes (Rigamonti et al., 2020). The literature reveals that sport sciences students use social media tools on a daily basis and that these platforms provide an important foundation for out-of-class learning experiences (Indrayana et al., 2024).

In terms of digital habits, smartphones stand out as the technological device that students most prefer for accessing educational content. While WhatsApp, YouTube, and Instagram are the most frequently used platforms in non-academic informal processes, YouTube is regarded as a key learning resource, particularly for visualizing motor skills and for accessing technical–tactical analysis videos and expert-led training. Students tend to use these visual platforms intensively to make sense of complex movement mechanisms and to correct their technical errors (Popovic et al., 2021).

In academic information-seeking processes, searching the internet and reviewing digital content are among the primary digital behaviors of sport sciences students. Websites and YouTube videos are regarded as the most effective informal sources of information after formal in-school educational activities. Such digital interactions have been reported to increase students' intrinsic motivation and to sustain their interest in the learning process (Trabelsi et al., 2022).

On the other hand, the literature emphasizes that uncontrolled, entertainment-oriented use of digital tools is a risk factor that may adversely affect academic achievement. Therefore, for students' digital habits to translate into positive academic outcomes, they need to combine these tools with strategic information-seeking, self-regulation, and critical evaluation skills. Overall, sport sciences students tend to use digital technologies autonomously, not only for communication but also for developing their professional competencies and tracking their performance in a data-driven manner (Okilanda et al., 2019).

The Relationship Between Digital Informal Learning Competence and Academic Achievement

Empirical studies examining the relationship between the use of digital tools and academic outcomes in higher education have consistently shown that digital competence is a key predictor of achievement. Findings in the literature indicate that it is not merely students' access to technology but rather their strategies for using these tools for academic purposes that determine their achievement. Research suggests that digital informal learning has both direct and indirect positive associations with academic performance. Mehrvarz et al. (2021) showed that DIL plays a significant mediating role in the relationship between digital competence and academic performance. Similarly, Zakir et al. (2025) found that digital literacy increases engagement in DIL, which in turn increases the likelihood of academic achievement. DIL processes support achievement by enabling students to manage their own learning pace and to deepen formal course content through digital resources.

Findings specific to sport sciences. Empirical studies conducted in faculties of sport sciences provide results consistent with the practical and theoretical nature of the field. Soyer et al. (2024) found that sport sciences students' digital literacy levels explained 21.4% of the variance in academic locus of control. This finding suggests that sport sciences students with higher digital competence assume greater responsibility in their academic

processes and attribute their achievements to their own efforts. A study conducted by Lobo (2025) with students of a fitness and sports department revealed that technological readiness had a very high explanatory power (90.3%) for online learning self-efficacy. In addition, students' self-confidence in digital environments was found to be directly related to their academic performance. The use of digital tablets and video analysis software in sports such as futsal and football has been empirically observed to enhance students' tactical thinking and game vision. AI-supported blended learning models have also been found to significantly improve students' performance in physical fitness tests and their attitudes towards sport. Empirical data highlight the importance of self-regulation, academic hardiness, and self-efficacy in the effectiveness of digital tools. Rafatjoo et al. (2025) found that academic hardiness plays a positive mediating role in the relationship between DIL and performance; that is, students who learn through digital informal means become more resilient to the academic challenges they face, which in turn enhances their achievement. On the other hand, it has also been empirically shown that, while the in-school use of social media is positively associated with perceived learning, uncontrolled and aimless out-of-school use may impair achievement by distracting academic focus.

In conclusion, the empirical evidence in the literature indicates that sport sciences students' digital informal learning competence plays an important role in both the acquisition of professional skills and their perceptions of academic achievement.

Conclusions

In this study, the relationship between digital informal learning (DIL) competence and perceived academic achievement among students in faculties of sport sciences was examined holistically within the framework of the theoretical and empirical literature. The reviewed literature indicates that the autonomous and purposeful use of digital tools in out-of-class learning processes meaningfully supports both the integration of theoretical knowledge and the acquisition of motor and technical–tactical skills.

Digital informal learning appears to act as a critical mediating variable between students' digital competence and their academic performance. Indeed, the studies by Mehrvarz et al. (2021) and Zakir et al. (2025) confirm that students with higher levels of digital literacy are more successful in incorporating the information they obtain from informal settings into formal curricular processes, which increases their likelihood of achievement. In the specific context of sport sciences education, the finding by Soyer et al. (2024) that digital literacy explains 21.4% of the variance in academic locus of control suggests that sport sciences students who acquire technological competence take responsibility for their own learning and develop self-directed learning skills. Because sport sciences inherently comprises both theoretical and practical/performance-based components, the areas in which digital tools can be used are diverse. In theoretical courses such as anatomy, physiology, and training science, the use of 3D visualization, digital diagrams, and web-based platforms makes knowledge more concrete and durable (Holm, 2024; Jobson et al., 2009; Uysal & Dalkıran, 2025). In applied courses, the use of movement analysis software such as Dartfish, virtual/augmented reality (VR/AR) technologies, and AI-supported load monitoring systems enables students to identify technical errors on the basis of data and to develop tactical awareness (De Beukelaar & Mantini, 2023; Dudek et al., 2025; Le Paven et al., 2021). The finding reported by Lobo (2025) that technological readiness has a very high explanatory power (90.3%) for online learning self-efficacy suggests that the confidence of sport education students in technological tools directly shapes their perceptions of academic and on-field performance.

Another important finding in the literature concerns the influence on learning of mobile applications and of the social media platforms most frequently used in informal settings, such as YouTube, WhatsApp, and Instagram (Popovic et al., 2021; Rigamonti et al., 2020). Visually oriented channels such as YouTube stand out as complementary learning resources, particularly for modeling motor skills through observation and for conducting technical analyses (Trabelsi et al., 2022). However, as emphasized by Cirik and Uzun (2026) and Langarizadeh et al. (2018), entertainment-oriented and uncontrolled use of digital tools may lead to a loss of academic attention. At this point, academic hardiness (Rafatjoo et al., 2025) and self-regulation skills (Basileo et al., 2024) appear to come into play and strengthen the positive effect of digital informal learning on academic achievement.

In conclusion, this review indicates that the informal learning processes in which students in faculties of sport sciences engage through digital tools extend beyond traditional in-class achievement and constitute an important element that directly nourishes their professional self-efficacy, practical skills, and overall perceptions of academic achievement. Digital resources such as video analysis software, wearable technologies, AI-supported tracking systems, and social media platforms provide complementary learning environments that strongly support the formal curriculum, both in making theoretical knowledge concrete and in developing motor and technical–tactical skills. Nevertheless, the key condition for digital informal learning to translate into positive academic outcomes appears to be high levels of digital literacy, self-regulation, academic hardiness, and self-efficacy; otherwise, uncontrolled use may adversely affect academic focus. Overall, students with high digital informal learning

competence appear to take ownership of their learning and to report higher perceived academic achievement. Accordingly, it is concluded that sport sciences curricula should be supported with courses on digital literacy and digital ethics, that technological infrastructure should be developed to provide opportunities for informal practice, and that informally acquired knowledge should be integrated into formal assessment processes through reflective learning methods.

Recommendations

- Sport sciences curricula should be restructured to encompass 21st-century competencies such as critical thinking, problem solving, and digital literacy from the first year of study.
- Courses on social media literacy and digital ethics should be added to the curriculum so that students can use social media not only for entertainment but also for academic and professional development.
- Web-based platforms and blended learning models supported by virtual reality (VR) and artificial intelligence (AI) should be more widely adopted to make the content of theoretical courses more concrete.
- Faculties should establish adaptive and accessible online learning management systems appropriate to students' levels of readiness.
- The infrastructure of video analysis software and wearable technologies should be strengthened for courses such as movement analysis, training science, and biomechanics in order to provide students with opportunities for informal practice.
- Reflective learning methods that enable students to attribute their achievements to their own efforts should be encouraged, so that students can integrate the knowledge acquired through digital informal means into formal courses.
- Faculties should collaborate with technology companies and sport clubs to create hands-on learning opportunities that allow students to apply their digital skills in real-world projects and internships.

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The Role of Sports Participation in the Relationship Between Problematic Social Media Use and Academic Achievement

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Abstract

The centrality of social media in everyday life and the academic consequences of its uncontrolled use among students have become a topic of considerable debate. This review aims to synthesize recent empirical research on the relationship between problematic social media use and academic achievement and to evaluate the role of sports participation within this relationship. Nineteen studies published between 2020 and 2026 that assessed social media addiction with validated instruments and linked it to academic outcomes, physical activity, or athlete samples were examined using a descriptive review approach, and the findings were synthesized thematically under three headings. The reviewed literature indicates that problematic social media use is consistently associated with academic procrastination, attentional difficulties, reduced academic motivation, and school dropout intention. Academic self-efficacy emerges as a robust mediator of this relationship, whereas intrinsic academic motivation appears to act as a moderator. The role of sports participation, however, is more complex than commonly assumed. Although physical activity may confer indirect protection by reducing depressive symptoms, the online construction of athletic identity, body-image concerns, and appearance-based comparisons may simultaneously increase investment in social media. Sports participation should therefore be conceptualized not as a unidirectional protective factor but as a conditional variable whose effects depend on patterns of use and the surrounding context. Given the predominance of cross-sectional designs and the reliance on self-report measures in this field, longitudinal and experimental research is clearly needed.

Keywords: Problematic social media use, academic achievement, sports participation, physical activity, academic self-efficacy

Introduction

Over the past decade, the transformation of digital communication technologies has reshaped students' use of time, attentional capacity, and learning habits. In particular, the proliferation of short-video formats has created a new stimulus environment that competes with academic tasks requiring sustained attention (Paramio & Zayas, 2026). The point at which such use ceases to be functional and becomes clinically problematic remains one of the central unresolved questions in the literature.

Problematic social media use refers to a behavioral pattern conceptualized within the behavioral addiction framework and assessed through criteria such as salience, mood modification, tolerance, withdrawal, conflict, and relapse. Validated instruments operationalizing this framework have been employed in studies conducted across diverse cultural contexts (Andersson et al., 2024; Devadharshini et al., 2026; Ruzzante et al., 2026; Sayılı et al., 2023). Notably, however, reported prevalence rates are markedly inconsistent. Whereas a cross-sectional study of 235 university students in India reported a social media addiction prevalence of 59.1% (Devadharshini et al., 2026), a study of 280 medical students in Istanbul found a prevalence of only 6.1% (Sayılı et al., 2023). This discrepancy reflects not only differences in cut-off scores and sample characteristics but also ambiguity in how the construct itself is defined.

By contrast, the intersection of problematic use with academic life presents a more consistent picture. Divided attention, reduced study time, and impaired sleep quality are recurrent findings across different samples. However, the question of which variables might attenuate this relationship has received comparatively little attention. Sports participation is an obvious candidate in this respect, both because it represents an alternative use of time and because of its positive effects on mental health. Yet studies conducted with athletes indicate that sport itself can constitute a domain of intensive social media use (Ergün, 2025; Lin et al., 2025; Piepiora et al., 2024).

The purpose of this review is to describe the relationship between problematic social media use and academic achievement in light of recent empirical findings and to discuss the position of sports participation within this relationship, considering both its protective and its risk-enhancing dimensions. Accordingly, the review addresses three questions: (1) Through which mechanisms does problematic social media use affect academic outcomes? (2) Do sports participation and physical activity serve a protective function within this relationship? (3) Which specific vulnerabilities emerge in athlete samples?

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Methodology

This study adopted a descriptive review approach. The literature search was conducted in the Web of Science, Scopus, PubMed, SAGE Journals, and TR Dizin databases using various combinations of the keywords "social media addiction," "problematic social media use," "academic achievement," "academic procrastination," "physical activity," and "sport participation," together with their Turkish equivalents.

Studies were included if they (a) were published in a peer-reviewed journal between 2020 and 2026; (b) assessed social media addiction or problematic social media use with an instrument of demonstrated validity and reliability; (c) examined an academic outcome variable, physical activity level, or an athlete/sport sciences sample; and (d) were available in full text. Studies reporting prevalence only, presenting no empirical data beyond scale development, or providing insufficient information on the sample were excluded.

Based on these criteria, nineteen studies were included in the review. Sample sizes ranged from 143 to 2,646, and the studies were conducted in Türkiye, Italy, China, Russia, Serbia, India, Sweden, Spain, Romania, Saudi Arabia, and the United Kingdom. The findings were synthesized under three themes: academic outcomes, the role of sports participation, and athlete-specific vulnerabilities.

Results

Problematic Social Media Use and Academic Outcomes

Across the reviewed studies, academic procrastination emerges as the strongest and most consistently replicated correlate of problematic social media use. Devadharshini et al. (2026) identified academic procrastination in 51.1% of students and reported that students with social media addiction were 4.79 times more likely to procrastinate (95% CI [2.72, 8.46]). The most detailed model of the psychological processes underlying this relationship derives from a structural equation model tested with 1,017 sport sciences students in Türkiye. Işıkgöz et al. (2025) showed that social media addiction directly predicted academic procrastination ($\beta = .38$) and negatively predicted academic self-efficacy ($\beta = -.57$). When academic self-efficacy was entered as a mediator, it accounted for approximately 41% of the indirect effect, and the two variables together explained 55% of the variance in academic procrastination. A similar mediation pattern was reported by Berdida et al. (2026) with respect to clinical performance among nursing students.

Studies examining academic achievement indicators directly have yielded findings in the same direction. A comparative study of 1,093 middle school students in Russia and Serbia found that screen time was positively associated with social media addiction and negatively associated with school satisfaction, and that social media addiction significantly and negatively predicted both academic performance and life satisfaction (Rudnova et al., 2026). Notably, intrinsic academic motivation moderated and attenuated these adverse effects in the same study, indicating that the academic cost of digital engagement varies with the strength of students' intrinsic orientation toward learning.

The consequences of problematic use appear to extend beyond grade point average to the continuity of the educational process itself. In a large-scale study of 2,646 students from 13 secondary schools in Italy, Bergen Social Media Addiction Scale scores were among the psychosocial factors predicting school dropout intention (Ruzzante et al., 2026). In an adult sample of 940 participants, Seceleanu et al. (2026) demonstrated that affect, authenticity, and self-image mediated the relationship between social media addiction and academic performance. This finding suggests that the academic impact cannot be explained by lost time alone and that identity and emotion-regulation processes are also involved.

In a psychometric study of 898 Turkish adolescents examining attachment behavior toward social media influencers, Coşguner et al. (2026) identified a moderate positive association between attachment level and social media addiction ($r = .53$). The significantly higher levels of attachment observed among girls and among adolescents using social media for more than five hours per day indicate that duration of use should be evaluated not in isolation but together with the relational quality of that use.

Intervention studies offer a cautiously positive perspective. In a ten-day online randomized controlled trial with 143 university students, Throuvala et al. (2020) achieved a large reduction in smartphone-related distraction; however, the intervention did not change habitual behaviors or total time spent on social media. Mediation analyses indicated that the effect operated through emotional self-awareness rather than through conscious awareness. A scoping review by Paramio and Zayas (2026) reached a similar conclusion, reporting that time-based interventions improved task focus, although their effects were context-sensitive and relatively limited.

Role of Sports Participation and Physical Activity

The clearest evidence for a protective function of sports participation comes from studies in which physical activity was retained as an independent predictor in multivariable models. Sayılı et al. (2023) identified engaging in physical activity at least twice a week, together with reading at least one book per month and high life satisfaction, as independent protective factors against internet addiction among medical students. This finding suggests that physical activity does not merely fill time but functions as part of a broader lifestyle pattern.

Nonetheless, other findings warrant caution regarding the magnitude of this protective effect. In a structural equation model tested with 1,172 university students, Yang et al. (2025) found that physical activity was directly related only to nighttime short-video use ($\beta = -0.12$). Indirect effects mediated by depression were significant for nighttime use ($\beta = -0.03$), study-time use ($\beta = -0.03$), leisure-time use ($\beta = -0.04$), and short-video addiction ($\beta = -0.06$), whereas no significant total effect emerged for daytime or total use. As the authors themselves acknowledge, these effect sizes are small, and the true contribution of physical activity may be limited. In a study of 437 adolescents, Sezer Efe et al. (2025) reported that technology addiction was associated with physical activity level and eating behaviors, with smartphone addiction explaining the largest share of variance in physical activity level. This finding again highlights the uncertainty that cross-sectional data entail regarding the direction of the relationship.

The most striking finding directly challenging the protective assumption comes from a study of 1,350 middle school students in Türkiye. Uğurlu et al. (2025) found that private school students scored higher than public school students on both social media addiction and sports participation. Both variables increased with perceived socioeconomic status: social media use rose from 2.9 ± 0.5 in the low-income group to 3.8 ± 0.6 in the high-income group, while weekly sports participation rose from 2.5 ± 0.5 to 3.6 ± 0.9. Both variables also declined together from the 11–12 to the 13–14 age group. This pattern suggests that sports participation and social media use may operate less as substitutable activities than as parallel behaviors drawing on a shared pool of socioeconomic resources. Accordingly, the possibility that the observed association between them is attributable to uncontrolled third variables cannot be ruled out.

Athlete-Specific Vulnerabilities

The available literature shows that athletes are not immune to the adverse effects of social media and may, under certain conditions, be particularly vulnerable to social-media-related risks. In a sample of 362 young athletes (aged 14–21) training at facilities in Guangdong and Hunan, Lin et al. (2025) showed that social media addiction directly increased negative affect and that this effect was amplified through physical appearance comparisons and sleep quality. The mediating role of sleep quality is especially relevant to academic achievement, since disrupted sleep simultaneously impairs cognitive performance and recovery from training.

Body image is a recurring theme in athlete samples. In a study of 165 athletes with physical disabilities, Erayabakan and Canpolat (2026) reported that problematic social media use was moderately associated with negative body image ($r = 0.32$–0.41) and that general social media use, after controlling for demographic variables, explained approximately 19.5% of the variance in body image perception ($\beta \approx 0.45$). In a sample of 2,325 individuals aged 14–29, Giordano et al. (2025) demonstrated that problematic social media use and general self-efficacy acted as first- and second-order mediators, respectively, in the relationship between perceived social support and muscle dysmorphia.

The online construction of athletic identity is one of the mechanisms explaining why sport may generate risk rather than only protection. In a study of 288 licensed student-athletes enrolled in a faculty of sport sciences, Ergün (2025) found a positive association between online identity construction and social media addiction and a negative association between social media addiction and self-esteem; together, social media addiction and self-esteem explained 18.9% of the variance in online identity construction. Athletes' need for visibility, sponsorship expectations, and relationships with followers transform social media from an optional pastime into a professional necessity.

The picture is no more encouraging at the elite level. A screening study of 648 active ice hockey players in Sweden assessed problematic social media use alongside hazardous alcohol use, depression, anxiety, and burnout; hazardous alcohol use among male players exceeded that of the general population, and a history of repeated concussions was strongly associated with depressive and burnout symptoms (Andersson et al., 2024). Piepiora et al. (2024), in turn, proposed that the hate speech and negative interactions athletes encounter online may reactivate unprocessed experiences from earlier developmental periods and argued that a psychoanalytic approach could complement cognitive-behavioral methods in addressing such distress.

Finally, Işıkgöz et al. (2025) noted that sport sciences students may be particularly vulnerable to digital distraction because their curriculum demands both physical and cognitive effort. Because this student group uses social media

for both academic and recreational networking purposes, the boundary between productive and non-productive screen time becomes blurred.

Discussion

Taken together, the synthesized findings suggest that the effect of problematic social media use on academic achievement cannot be explained by lost time alone and that this relationship is shaped by a range of psychological mechanisms and mediating processes. Academic self-efficacy is the most consistently recurring mediator among them (Berdida et al., 2026; Işıkgöz et al., 2025). Attention fragmented by a continuous stream of notifications appears to erode students' belief in their capacity to complete sustained tasks; this weakened belief in turn fuels procrastination, rendering the cycle self-reinforcing. Findings concerning affect, authenticity, and self-image lend further support to this interpretation (Seceleanu et al., 2026).

The role of sports participation should not be framed as unidirectional protection against problematic social media use. The available evidence indicates that this relationship can be explained by at least three distinct mechanisms. The first is a substitution mechanism, whereby time devoted to physical activity competes with screen time; however, Yang et al. (2025) reported that this effect is limited to nighttime use and is modest in magnitude. The second is a psychological mediation process: by reducing depressive symptoms and sleep problems, regular physical activity may constrain the psychological risk factors that give rise to problematic social media use, an interpretation consistent with the findings of Yang et al. (2025) and Lin et al. (2025). The third is an amplification mechanism, whereby sport offers new opportunities for visibility, identity presentation, and body-focused social comparison, thereby creating a context that may increase social media use (Erayabakan & Canpolat, 2026; Ergün, 2025).

Which of these mechanisms predominates appears to depend on several moderating variables. Level of participation is decisive: recreational involvement and elite performance sport relate to social media in markedly different ways. The nature of use also matters, as content creation and comparison-focused passive consumption produce different psychological outcomes despite comparable durations of use (Erayabakan & Canpolat, 2026). Finally, socioeconomic context may generate spurious associations, since it simultaneously determines access to both sporting opportunities and digital devices (Uğurlu et al., 2025).

From a practical standpoint, these findings suggest that interventions relying solely on increasing physical activity participation may be insufficient to resolve problems associated with social media use. Although promoting physical activity is an important component, it should be complemented by strategies aimed at regulating digital behavior. Indeed, nudge-based environmental adjustments, notification filtering, and goal-setting applications have been reported to yield measurable improvements in class attendance and focus on academic tasks (Paramio & Zayas, 2026). Similarly, brief interventions targeting emotional self-awareness have been shown to reduce distraction (Throuvala et al., 2020). Accordingly, programs designed to enhance student-athletes' awareness of digital media use and body image could be integrated into existing training and educational processes in sport sciences faculties and sports clubs.

This review has several limitations. First, the predominantly cross-sectional designs of the included studies preclude causal inferences regarding the relationships among variables. Second, academic achievement was most often operationalized through procrastination, motivation, or self-reported performance indicators, whereas objective grade point average data were used in only a few studies, which reduces the comparability of findings. Third, variation in measurement instruments and classification criteria hinders direct comparison of reported prevalence rates. A similar heterogeneity characterizes the operationalization of sports participation, with some studies relying on weekly physical activity frequency and others on licensed-athlete status. These differences complicate an integrated synthesis of the evidence. Finally, because this review was not based on a pre-registered, systematic search protocol, the risk of selection bias in study selection is increased, which limits the scope and generalizability of its conclusions.

Conclusions

The adverse effects of problematic social media use on academic achievement are consistently reported across countries and educational levels. Within this relationship, reduced academic self-efficacy and academic procrastination are the most salient correlates, whereas intrinsic academic motivation appears capable of playing a protective role.

The effect of sports participation, by contrast, is conditional. Although physical activity may provide indirect protection through reductions in depressive symptoms and sleep problems, the visibility that athletic identity acquires on social media may intensify body-focused comparisons and social media use. Sport should therefore not be regarded as a direct and unconditional protective factor.

Future research should prioritize longitudinal designs, objective measures of screen use and academic achievement, and randomized controlled trials evaluating structured sport programs integrated with digital literacy components.

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An Analysis of Theses on Digital Transformation in Education in Türkiye

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Abstract

Traditional instructional methodologies, which have maintained their dominance in the educational paradigm for decades, have increasingly evolved into contemporary digital learning ecosystems amid rapid technological advancement and digitalization. The primary objective of this study is to systematically examine the methodological and thematic trends of graduate theses indexed in the Council of Higher Education (YÖK) National Thesis Center database that focus on "Education and Training" and center on the concept of "digital transformation." Employing document analysis—a qualitative research design—data were analyzed across ten analytical parameters: (i) publication year, (ii) research objectives, (iii) affiliated graduate schools, (iv) language of publication, (v) provinces of research, (vi) sample/study groups, (vii) academic departments, (viii) data collection instruments, (ix) data analysis methods, and (x) validity and reliability criteria. In the initial query conducted on April 13, 2026, the term "digital transformation" was searched across the title, abstract, and subject fields, yielding 298 records. Upon excluding 281 studies that fell outside the subject area of "Education and Training," the final analysis was conducted on the remaining 17 graduate theses. The findings demonstrate that research in this domain gained significant momentum, particularly after 2021, that studies predominantly focused on teachers as well as school and university administrators, and that qualitative data collection techniques were widely favored.

Keywords: Digital transformation, Council of Higher Education, National Thesis Center, document analysis, graduate theses

Introduction

Digital transformation represents a multidimensional paradigm shift that impacts virtually every sphere of contemporary life, from public administration and healthcare to economic activities and everyday social practices. Educational systems, situated at the nexus of this global transformation, have entered a period of fundamental structural change; traditional instructional tools have yielded ground to interactive smart boards, mobile devices, and cloud-based learning platforms. In the academic literature, this process is conceptualized not merely as a mechanical substitution of technical tools but as a holistic restructuring of pedagogical approaches, educational philosophy, and teaching-learning processes (Ivanova et al., 2023; Shulga et al., 2024). A review of the literature on digital transformation in education indicates that while early scholarship primarily focused on technology integration and basic tool adoption, post-COVID-19 research has shifted toward institutional resilience, systemic transformation, and pedagogical capacity building. Bibliometric analyses reveal that scholarly output in this field has accelerated markedly in recent years, evolving into an increasingly institutionalized and interdisciplinary area of inquiry (Phuong et al., 2023; Wang et al., 2024).

The concept of digital transformation and its educational implications

Digitalization extends far beyond the mere execution of operations via electronic devices; it entails the systematic processing, presentation, and restructuring of data through computational and numerical methods (Birdanlı, 2025). Digital transformation, on the other hand, refers to the holistic realignment of organizational workflows, strategic objectives, and institutional cultures through digital technologies (Akpınar, 2025). Bozkurt et al. (2021) conceptualized the foundational components of digital transformation along the axes of human, process, and technology, postulating that human agents serve as the primary subject, technology as the object, and the process itself as the predicate. In the knowledge society, knowledge is the core driver of socio-economic progress, necessitating that educational architectures dynamically adapt to the exponential generation of knowledge and evolving societal demands (Bozkurt, 2021). Integrating information and communication technologies into learning environments has positioned computer-assisted instruction not merely as an auxiliary tool, but as a robust pedagogical approach that substantially enhances educational efficiency and quality (Watson, 2002; Uşun, 2004). Moreover, embedding digital instruments into instructional design offers profound potential to personalize learning trajectories, stimulate learner engagement, and foster inclusive educational practices (Bartholomew et al., 2024).

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Digitalization trajectories in the Turkish education system

In Türkiye, digital transformation initiatives across K–12 education have been guided by the dual imperatives of enhancing educational equity and integrating contemporary educational technologies into classrooms. In line with this vision, the Movement of Enhancing Opportunities and Improving Technology (FATİH) Project was initiated around the core tenets of accessibility, efficiency, equal opportunity, measurability, and quality enhancement (Çardak, 2021). Concurrently, the Educational Informatics Network (EBA), developed by the Ministry of National Education, has provided teachers and students with rich electronic educational content, transforming the management of pedagogical workflows (Bingöl, 2025; Korkmaz & Kadirhan, 2020). Nevertheless, digital transformation in education cannot be reduced to the digitization of instructional resources or the electronic transposition of traditional classroom practices (Yalap & Gazioğlu, 2023). Efforts toward institutional readiness for blended and distance education models have become a global priority across emerging economies (Graham et al., 2023). Developing a highly employable workforce capable of navigating digitalized labor markets requires modernizing curricula and incorporating applied sectoral software into training programs. A pivotal factor in ensuring sustainable transformation is reinforcing educators' digital competencies through targeted professional development programs and pre-service training (İlban & Sezer, 2025). Within this theoretical landscape, a systematic inquiry into the thematic orientations, methodological tendencies, and structural characteristics of graduate research on educational digital transformation in Türkiye is of paramount importance for mapping current literature and identifying empirical gaps.

Research purpose and research questions

The primary purpose of this study is to systematically analyze graduate theses indexed in the YÖK National Thesis Center database, within the thematic category of "Education and Training," that investigate "digital transformation." To achieve this aim, the study addresses the following research questions:

1. What is the distribution of the examined graduate theses by year of publication?
2. How are the research objectives and thematic foci of the theses distributed?
3. What are the academic departments in which these theses were conducted?
4. What is the distribution of theses in terms of publication language?
5. What is the geographic distribution of the institutions hosting these studies?
6. What are the characteristics of the sample and participant groups selected in the theses?
7. How are theses distributed across different types of graduate schools?
8. Which data collection instruments were predominantly utilized in these studies?
9. What data analysis techniques were employed across the studies?
10. What validity and reliability measures were implemented across the examined research?

Methodology

Research design

This study employed document analysis, a qualitative research design. Document analysis involves the systematic identification, retrieval, categorization, and interpretation of written, printed, or electronic materials that contain information regarding the phenomenon under investigation (Yıldırım & Şimşek, 2018).

Data collection and corpus selection

Research data were gathered on April 13, 2026, through a comprehensive search of the YÖK National Thesis Center database. The search criteria stipulated that the term "digital transformation" (dijital dönüşüm) must appear in at least one of the following metadata fields: Thesis Title, Abstract, or Subject. This initial screening yielded 298 thesis records. Subsequently, a thematic inclusion criterion was applied, excluding 281 studies whose designated subject area was not "Education and Training." The final corpus comprised 17 graduate theses (master's and doctoral) meeting all predefined parameters.

Data coding and analysis

Descriptive and methodological data extracted from the 17 graduate theses were entered into a standardized coding matrix via Microsoft Excel. The ten analytical parameters were mapped across rows and columns. Descriptive

statistical techniques, including frequency (f) and percentage (%) distributions, were utilized to synthesize the findings. To ensure coding reliability, initial classifications were completed independently by the first author and subsequently audited by the second author. Discrepancies identified during the audit were deliberated collaboratively until complete consensus was achieved, thereby finalizing the dataset.

Results

Distribution of theses by year of publication

An examination of the publication timeline of the 17 graduate theses indicates that during 2021 and 2022, only two master's theses were completed each year (f = 2). However, a marked increase in research volume was observed in 2023 and 2024. This upward trajectory suggests that scholarly interest in educational digital transformation intensified significantly in the post-pandemic period.

Research objectives and thematic focus areas

The thematic categorizations of the research objectives of the analyzed theses are summarized in Table 1.

Table 1. Distribution of theses by research objectives and thematic focus areas

Thematic Category	Frequency (f)	Percentage (%)
Digital Transformation Awareness	3	17.65
Teacher Digital Competence	2	11.76
Digital Transformation in Higher Education	2	11.76
Academic Role Transformation	1	5.88
Digital Parenting Awareness	1	5.88
Digital Management Dashboard Development	1	5.88
Digital Leadership	1	5.88
Stakeholder Perspectives on Digital Transformation	1	5.88
Digital Transformation Fatigue / Technostress	1	5.88
Digital Learning Experiences	1	5.88
Digital Transformation Experiences	1	5.88
Perceptions of Digital Transformation	1	5.88
Governance and Management of Digital Transformation	1	5.88

As shown in Table 1, research inquiries focused primarily on evaluating stakeholders' awareness of digital transformation (f = 3; 17.65%), assessing teachers' digital competence levels (f = 2; 11.76%), and exploring systemic transformation within higher education institutions (f = 2; 11.76%). The remaining categories (f = 1; 5.88% each) span administrative dimensions (e.g., digital leadership, governance) as well as psycho-social dimensions (e.g., technostress, parental involvement, role shifts), illustrating that the field is approached from a broad, interdisciplinary perspective.

Academic departments, language, and geographic distribution

In terms of departmental affiliation, the studies were predominantly situated within Departments of Educational Sciences. Nonetheless, contributions from Mathematics and Science Education, Business Administration, and Physical Education and Sports indicate growing cross-disciplinary engagement. The publication language of the analyzed corpus was entirely homogeneous: all 17 theses (100%) were written in Turkish. Geographically, Istanbul represented the most frequent research locus, followed by Erzurum, Konya, and Denizli, with additional studies originating from universities in Malatya, Tunceli, and Çanakkale.

Target samples and participant profiles

The participant and sample profiles investigated across the theses are presented in Table 2.

Table 2. Distribution of theses by sample and study group characteristics

Sample Level / Group	Frequency (f)	Percentage (%)
Teachers (General and Subject-Specific)	8	47.06

— *General / Classroom / Unspecified Teachers*	3	17.65
— *Physical Education Teachers*	2	11.76
— *Middle School Teachers*	1	5.88
— *Mathematics Teachers*	1	5.88
— *Science and Chemistry Teachers*	1	5.88
— Primary School Teachers	1	5.88
Administrators (School and University)	3	17.65
— *School Administrators*	2	11.76
— University Administrators	1	5.88
Higher Education Academic and Administrative Staff	2	11.76
— *Academic Personnel / Faculty Members*	1	5.88
— University Administrative Personnel	1	5.88
Other Groups and Conceptual Studies	4	23.53
— *Parents (Fathers)*	1	5.88
— *Secondary Education Teachers and Students (Mixed)*	1	5.88
— *Non-Sample Inquiries (Conceptual / Literature Review)*	1	5.88
Total	17	100

As indicated in Table 2, practicing teachers constituted the single largest target group across the theses (f = 8; 47.06%). Within this category, studies sampled general classroom teachers alongside subject specialists, including Physical Education (f = 2), Mathematics (f = 1), and Science/Chemistry (f = 1) educators. Educational leaders—comprising K–12 school principals and higher education administrators—formed the second largest cohort (f = 3; 17.65%). Academic and administrative staff in higher education accounted for 11.76% (f = 2), while parental groups, mixed teacher-student samples, and conceptual studies accounted for the remaining 23.53%.

Graduate schools, data collection instruments, and rigor strategies

Regarding institutional affiliations, seven theses were completed within Graduate Schools of Education/Graduate Schools, six within Graduate School of Educational Sciences, and four within Graduate School of Social Sciences. Regarding data collection instruments, qualitative tools were predominant. Eight studies exclusively used semi-structured interview protocols; six relied solely on standardized survey scales; two adopted a mixed-methods approach using both scales and interviews; and one thesis was conducted as a theoretical literature review. These findings highlight a pronounced methodological orientation toward qualitative inquiry to explore participants' lived experiences in depth.

An examination of validity and reliability strategies showed that:

- Quantitative studies primarily relied on SPSS-assisted statistical procedures, including skewness and kurtosis, normality diagnostics, ANOVA, ANCOVA, independent-samples t-tests, bivariate correlation, regression modeling, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and post hoc multiple comparisons.
- Qualitative studies reinforced trustworthiness and credibility through direct quotations, expert peer reviews, member checking (participant validation), pilot testing, and inter-coder reliability assessments.
- Review-based studies established rigor through comprehensive, evidence-based thematic syntheses.

Discussion and Conclusions

This study provides a systematic evaluation of the methodological profile and thematic trends characterizing graduate theses on digital transformation in education in Türkiye. The findings indicate that research interest in this domain accelerated markedly after 2021, reflecting the systemic challenges and digital pivots induced by the global health crisis. Geographically, the concentration of studies in metropolitan areas such as Istanbul suggests that research output may be linked to institutional research capacity and digital infrastructure. Nevertheless, the finding that all analyzed theses were authored in Turkish, while beneficial for domestic scholarly literature, represents a clear limitation regarding global dissemination and integration into the broader international discourse.

Thematically, the research places a strong emphasis on measuring teachers' digital competencies (47.06%) and administrators' leadership orientations (17.65%). This demonstrates that educational researchers have primarily scrutinized digital transformation through the lens of key implementers and institutional decision-makers. Concurrently, the inclusion of niche areas such as technostress, digital parenting, and academic role shifts confirms

that digital transformation is increasingly recognized not as a mere technological infusion but as a complex ecosystem with substantial psychological, administrative, and sociological implications.

Methodologically, the prominence of qualitative interview designs underscores an emphasis on uncovering contextual nuances and experiential narratives. Quantitative studies generally demonstrated rigorous statistical testing, while qualitative investigations adhered to recognized criteria for credibility and confirmability. In light of these findings, future research should consider:

- Adopting mixed-methods and longitudinal designs that empirically assess learning gains and sustained pedagogical shifts.
- Diversifying sample groups to capture student voices across primary and secondary education levels.
- Encouraging publication in international languages and indexed venues to foster cross-cultural comparative research.

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Responding to Disruption: Proposing a Framework for Building Greater Resilience Among Facilitators in a Higher Education Setting

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Abstract

This South African based exploratory study proposes a framework for nurturing greater resilience and improved levels of self-efficacy among facilitators in higher education settings. The framework was devised as a direct result of having engaged with a group of facilitators who, between 2020 and 2026, were required to significantly adjust their teaching practice, either in response to a global health pandemic, or to address the highly disruptive influence of generative AI in their classrooms. Using a qualitative case study approach, this study sought to understand why some facilitators have been able to embrace these disruptions while others have seemingly become derailed by these same phenomena, experiencing prolonged burnout evidenced by emotional exhaustion, depersonalisation, and a diminished sense of personal achievement. Twelve semi-structured interviews and two focus groups were conducted with a total of 20 participants. From these engagements, and the use of thematic analysis, four themes were identified: the importance of relationships, the need to achieve a sustained sense of wellbeing, the motivation of self, and the very real connection that exists between emotion and resilience. The alignment of these findings with the work of Mansfield, Beltman, Broadley, and Wetherby-Fell (2016) led to the development of the proposed framework contained in this study; one which includes recommendations for academic support teams, academic peers, and institutional leadership in pursuit of more effectively preparing facilitators to navigate the next disruption to practice, in whatever form it may present itself.

Keywords: disruption to practice, resilience framework, self-efficacy; burnout; online facilitation; higher education.

Introduction

Over the last six years, the world of education has been in a state of flux. When the novel coronavirus (COVID-19) reached South African shores in 2020, schools and higher education institutions were required to make rapid and significant changes to teaching practice as a means of accommodating the impact of the pandemic. By early 2022, there had, for the most part, been a return to contact teaching and phrases like ‘the new normal’ had become part of the country’s vernacular. Although the use of generative artificial intelligence (AI) in the field of education has been present in the shadows for some time already, the speed at which it has now entered our classrooms and conversations in just five years has caught the world equally off-guard. In November of 2022, ChatGPT was released and what was ‘normal’ was once again subject to debate. Generative AI resulted in a surge of interest, adoption, and panic, with a call for professional development and a growing need to revisit policy (Tan et al., 2024, Wong, 2024).

When viewed from a South African perspective, the majority of COVID-19 related studies undertaken between 2020 and 2022 tended to investigate how this global health crisis had impacted the student learning journey (Landa, Zhou, & Marongwe, 2021; Le Grange, 2021; Motala & Menon, 2020; Scheepers, 2024). While post COVID-19 studies were undertaken that addressed the impact of the pandemic on the lives of those teaching during this time (Malesa, 2022; Padmanabhanunni, Pretorius, Bouchard, & Stiegler, 2023; Spies, 2022), the focus appears to have been on teachers at public and private schools in the country, rather than on those facilitating at institutions of higher education. When we turn our attention to generative AI use in higher education, again from a South African perspective, we see studies that appear to be more evenly spread between the impact of this phenomenon on the lives of students and educators than was the case during COVID-19. Studies that have adopted a student-focus appear to centre around how AI is being used to prompt the completion of assessments and the growing concerns around the impact this outsourcing is having on academic integrity and the student learning journey. In studies which address the lecturer experience, the lens tends to focus on the impact AI is having on institutional practices, particularly with regards to assessment design and policy. Although studies do exist that look at the link between AI and workload related stressors among facilitators (Chang et al., 2024, Meduri et al., 2024, Zhang & Xiong, 2025) these are accompanied by a call for more research that will allow us to understand faculty burnout linked to AI use and the role institutions can play in mitigating same in higher education settings. This study aims to offer

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institutions a possible means of achieving this objective. By engaging with facilitators based at a South African private higher education institution (PHEI), the researcher was able to draw from their shared experiences of what it has been like to facilitate during these two highly disruptive periods of time. These insights, together with the work of Mansfield, Beltman, Broadley, and Wetherby-Fell (2016), were then used to create a framework for building greater resilience and self-efficacy among the institution's academic team, in the hopes of allowing them to be better able to meet the next disruptor to practice, whatever form it might take.

Literature Review

This literature review addresses the phenomena of self-efficacy, and burnout followed by citing studies that were conducted between 2020 and 2026, which investigate the connection between these constructs among higher education facilitators within the context of either the COVID-19 pandemic, or the emergence of generative AI.

Self-efficacy

Simply stated, one's sense of self-efficacy will influence how one thinks, feels, and behaves. Salanova et al., (2011) position self-efficacy as "an important personal resource", one which acts as a key predictor in the "development of the motivation and erosion processes of burnout and engagement" in the workplace (Ventura et al., 2015, 279). What this suggests is that people with high levels of self-efficacy are also those who tend to set themselves higher goals and are willing to take on challenging tasks when required (Bandura, 1997; Schwarzer & Hallum, 2014, Skaalvik & Skaalvik, 2010). Tschannen & Woolfolk-Hoy, (2001) note that while some individuals find opportunity in the challenges they encounter, others appear to respond quite differently, quickly becoming overwhelmed and unable to cope with the required changes to their routine. From a social cognitive perspective this may be attributed to the level of self-efficacy and the belief facilitators have in their ability to "plan, organize, and carry out activities that are required to attain given educational goals" (Skaalvik & Skaalvik, 2010, p.1059). Schwarzer and Hallum (2008) concur and suggest that high levels of self-efficacy often coincide with effective coping skills and optimistic scenario prediction. The opposite appears to apply to those with lower levels of self-efficacy, displaying a tendency to default to negative scenario interpretation and pessimistic thinking, both of which have been associated with the construct of burnout.

AI pedagogical self-efficacy among facilitators

The Gallup and Walton Family Foundation (2025) examined the adoption of AI and its impact on workload, teacher wellbeing and reduced burnout. While half of the respondents noted that the use of AI enabled them to provide their students with timeous feedback, the other half highlighted that AI could effectively be used to reduce workload, leaving time for relationship-building and refining practice. Pressley et al., (2025, p.9) refer to this as "AI pedagogy self-efficacy" and note that it should be seen as distinctly different from general "teacher self-efficacy" because it specifically reflects one's "confidence in using specific AI tools for pedagogical purposes". These studies suggest a certain level of confidence in the use of AI as a pedagogical resource, however, according to Celik et al., (2022), and Dilek et al., (2025), the facilitators' voice still remains largely underrepresented in this discourse.

Burnout among facilitators

Schaufeli and Taris (2014, p.45) describe burnout as a "combination of the inability and unwillingness to spend the necessary effort at work for proper task completion". While Travers and Cooper, (1996, p.30) describe burnout as "a progression of unsuccessful attempts by an individual to cope with a variety of conditions that are perceived to be threatening". According to Maslach and Schaufeli (2018) and Maslach, Jackson and Schwab, (1996) burnout is evidenced by three separate but interrelated concepts: emotional exhaustion, depersonalisation, and diminished personal achievement. According to the Maslach Burnout Inventory (MBI), emotional exhaustion refers to "feelings of fatigue, and drained emotional energy" (Padmanabhanunni et al. 2022, p.122). Depersonalisation can be explained as a sense of feeling disconnected, detached, and experiencing a lack of sympathy, while low levels of personal achievement can occur when individuals experience an inability to adequately relate to the people with whom they work or engage (Maslach et al., 1996).

Teacher self-efficacy and burnout during times of disruption

The forced isolation that came about as a consequence of the Covid-19 lockdown regulations mutated the social interactions between facilitators and their students (Klapproth, Federkeil, Heinschke, & Jungmann, 2020; Pellerone, 2021; Rabagliettie, Lattke, Tesauri, Settanni, & De Lorenzo, 2021). The dramatic shift that came about so suddenly quite possibly exacerbated the levels of burnout facilitators experienced, or perhaps even directly contributed to its occurrence (Pellerone, 2021, p.498). Positioned within the context of the increased and

unavoidable presence of generative AI in the classroom, Chen et al., (2020) note that studies tend to emphasise how AI has improved efficiency and teaching processes while largely ignoring the impact on the facilitators themselves. Ericsson et al., (2023) agree, noting that more attention is required to better understand the broader psychological impact of this disruption to practice, and how the pervasive presence of AI may indeed lead to mental stress, burnout and depression due to the negative impact AI can have on student-facilitator relationships (Brougham and Haar, 2018).

Methodology

Design and Methods

Because of its suitability for exploring real-world subjects in which the feelings and emotions of the participants have a key role to play, this study adopted a qualitative approach in order to explore the lived experiences of facilitators affiliated to the selected PHEI. This aligns with methodologies used by Scheepers and Van den Berg, (2025) and Matos et al., (2022) in their studies on resilience, self-efficacy and experienced burnout among higher education facilitators. This study is also explorative in nature, prompted by an interest in the connection between the phenomena of self-efficacy and burnout in a South African higher education setting and exploring what can be done to mitigate the onset of the latter during times of disruption and change.

Population and Sample

Non-probability purposive sampling was used to select participants who met specific inclusion criteria. This included facilitators who had been actively contracted to the PHEI in question, either during the COVID-19 pandemic (2020 – 2022) or since the emergence and impact of generative AI within the HE environment (2022 – 2026). This sampling method allowed for effective data triangulation, while the information-rich reflections of the participants provided crucial insights into how they had navigated these challenging times, how their perceived levels of self-efficacy or experienced burnout had influenced their teaching practice, and perhaps most importantly, what support structures they believe would help them rise above the challenges presented by either (or both) of these disruptive phenomena.

Data Collection and Analysis

Twelve semi-structured interviews and two focus groups were conducted, recorded, and then manually transcribed. These manual transcripts where then analysed inductively using Braun and Clarke's six-phase thematic analysis model (2006, 2021). Coding was conducted and themes were progressively developed through the use of reiterative thematic maps and colour coding.

Ethical Considerations

Ethical considerations are an essential component of all research, and in this study the participants provided written informed consent prior to any engagement taking place. The study also adhered to ethical guidelines for research conducted online, ensuring anonymity, confidentiality and voluntary participation. Ethical approval to conduct this study was sought and obtained from the selected PHEI (No. IREC 00084).

Rigour and Trustworthiness

Trustworthiness requires that credibility, dependability, confirmability and transferability are achieved. Credibility was sought through iterative coding, the use of direct transcript quotations, and peer debriefing. A clear and detailed audit trail was used to ensure dependability, while confirmability and transferability were established through reflexive discussions and thick description.

Results

The overarching intention behind this study was to use the findings to create a framework that institutions would be able to draw from in order to foster greater resilience and self-efficacy among its facilitators, thus minimising their risk of experienced burnout during times of disruption. In this study, participants shared both their triumphs and failures during these two critical times of change. While some displayed high levels of self-efficacy and optimism, others shared only stories of anxiety, increased stress and sometimes even a sense of defeat. The outcomes of this study, driven by a detailed analysis of the data, highlighted four reoccurring themes: the importance of relationships, the need to achieve a sense of wellbeing or balance, self-motivation, and the very real connection between emotion and resilience. These findings strongly align with the work of Mansfield, Beltman,

Broadley, and Wetherby-Fell (2016) who identified these same four mechanism as being instrumental in nurturing improved resilience, sustained self-efficacy, and a significantly reduced risk of susceptibility to burnout.

Figure 1 below includes these four mechanisms which then serve as the conceptual basis for the framework which follows.

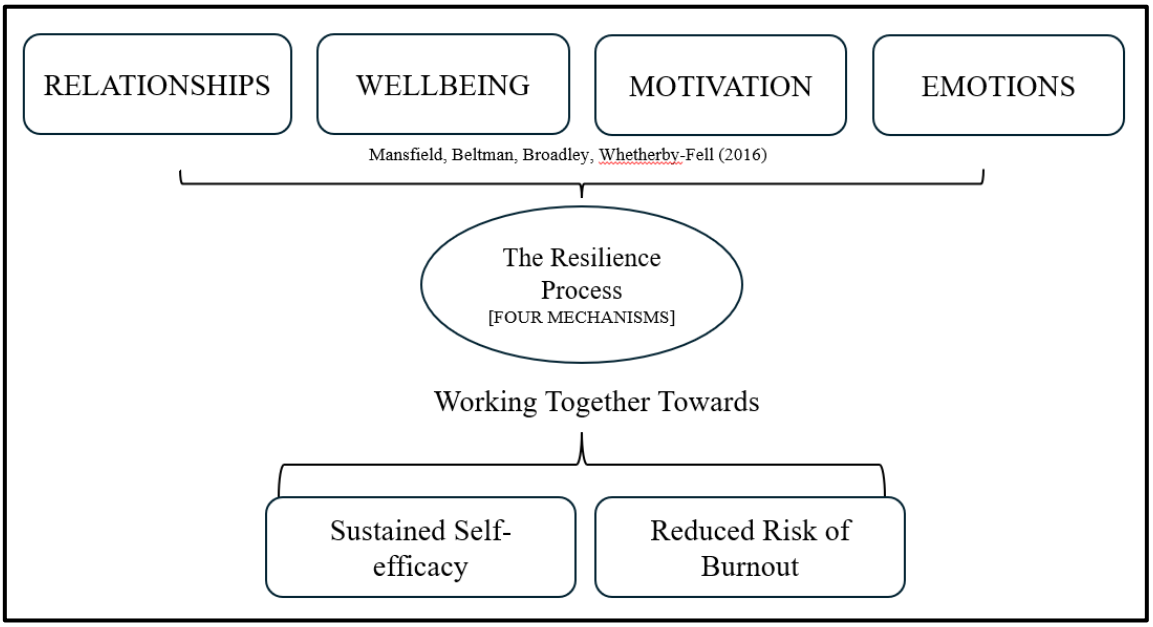


Figure 1. Four mechanisms for supporting the resilience process (Mansfield et al.2016).
Source: Researchers own.

Relationships

Mansfield et al., (2016, 2020) emphasise the importance of relationships in the resilience process; these include relationships within the work environment as well as those that exist outside of the institution with friends and family. This is in keeping with the findings of this study that show that where individuals were able to sustain a sense of relational connection with their students, peers, institution and family members during times of disruption, they were better able to cope with the associated stressors of having to adjust their practice, either during lockdown or as a means of responding to a growing student reliance on AI. Where this sense of having solid relationships was not present, the opposite was true.

Wellbeing

The findings of this study show that where participants experienced a high degree of burnout brought about either by the need to radically adjust their practice to accommodate the Covid-19 restrictions (Pellerone, 2021), or to process some of the moral dilemmas they have had to face regarding the use of AI (Ho et al., 2024, Shoaib et al., 2024), their sense of wellbeing was also negatively impacted to a significant extent.

Motivation

Mansfield et al., (2020, p.22) link motivation to relationships with others, a supportive work environment, gaining a sense of autonomy, trust, and being afforded the opportunity for meaningful participation. Motivation, they suggest, can lead to "sustained commitment, job satisfaction, a sense of agency and enhanced efficacy". Hong (2012) concurs and suggests that motivation has a role to play in an individual's initial career choices, their sense of purpose and vocation, making it a critical component of resilience. The PHEI is encouraged to provide opportunities for facilitators to engage with academic leadership as a means of fostering a more supportive work environment. During conversations with the participant in this study reference was made to top-down instructions often being delivered without any opportunity for meaningful engagement from those who would be tasked with implementing the decisions that had been made.

Emotions

When facilitators "experience more positive than negative emotions in [their various] interactions … they sense a deeper feeling of professional meaningfulness" and optimism – thus suggesting a clear connection between emotions and resilience (Hascher et al., 2021, p. 418). Even though work related challenges may still exist, these individuals are able to maintain a positive outlook. The PHEI is encouraged to find ways in which a more

emotionally supportive environment can be created; where staff morale can be encouraged, and positive relationships can be maintained, providing the platform for sustaining improved relationships, wellbeing, and motivation as purported by Mansfield et al. (2020). De los Reyes et al. (2021, p.51) refer to this as "university community and solidarity".

Building Resilience

According to Padmanabhanunni, et al., (2022), citing Arslan, Yildirim, and Wong (2020), resilience has been identified as an important factor in protecting against the onset of experienced burnout, particularly in the domain of emotional exhaustion. Gu and Day (2007, p.1302) define resilience as the "capacity to continue to 'bounce back', to recover strengths or spirit quickly and efficiently in the face of adversity". Within an educational context, several studies speak to the importance of building resilience among teaching staff as a means of avoiding the onset of burnout (Beltman, 2021; Mullen, Shields & Tienken, 2021; Wang, 2021). Richards, Levesque-Bristol, Templin, and Graber (2016, p.530) concur and posit that "teachers who develop higher levels of resilience feel less emotionally drained, derive a greater sense of satisfaction from their work, and can interact positively with others". Gu and Day (2007) add to the discussion by suggesting that focusing on building and maintaining teacher resilience will have a direct impact on the quality of teaching as well as the academic achievements of students. As Mullen et al., (2021, p.14) suggest, an institution that sets high standards, provides clear administrative goals, and allows for "meaningful participation of teachers in decision-making" will create an environment in which teachers can experience a greater sense of agency and purpose leading to increased resilience, improved morale, and a reduced susceptibility to burnout.

A Suggested Framework for Improved Resilience

Based on the findings of this study, as well as the studies referred to in the literature review, the following model for building improved resilience is proposed.

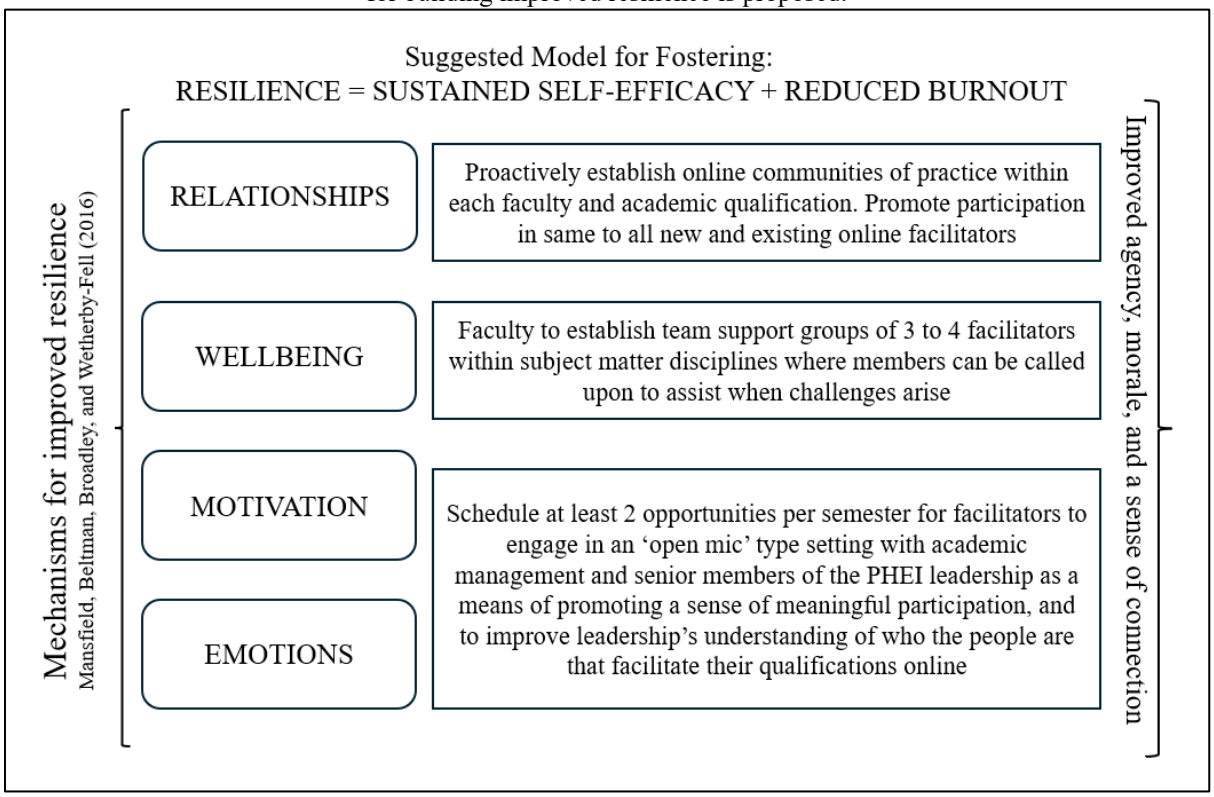


Figure 2. Suggested framework for fostering improved resilience (Source: Scheepers, 2025).

The findings of this study suggest that when an individual feels empowered with a strong sense of self-efficacy, they often feel more resilient to change which in turn allows them to remain committed, engaged, and motivated during times of disruption. Using the framework above, as proposed by Scheepers (2025), the following recommendations are made to the PHEI's academic support team, academic peers, and institutional leadership, as well as to other institutions of higher learning.

Recommendations for Academic Support

By leveraging the four mechanisms as offered by Mansfield et at. (2016), the suggestion is to enhance resilience among facilitators using a "multi-level approach that focuses on both individual and broader organizational-level responses" (Padmanabhanunni et al., 2023, p.125). This model proposes the proactive establishment of online communities of practice at the beginning of the academic year within the institution's LMS, creating virtual spaces where new and existing facilitators can be directed to connect with peers and to share ideas and resources. Creating these communities will build peer-to-peer relationships and provide some of the affective support participants noted as "missing" during times of institutional change. Senior facilitators or academic leads can oversee these communities to ensure that communities remain active, that resources are current and correctly curated, and that there is an opportunity for live or synchronous engagement at regular and scheduled intervals during each academic semester.

Recommendations for Academic Peers

Establishing peer support teams of three to four facilitators within the same subject matter discipline would serve to connect new and existing facilitators to support each other, independently of the existing academic support structures that are in place. These would serve as a buddy-system where support is available for the day-to-day challenges that can present in an online learning context, the sharing of suitable resources, and supporting those individuals less confident in the use of technology and AI to facilitate their practice and encourage a better understanding of what it means to engage with content online and how to navigate the challenges presented by the prevalence of generative AI.

Recommendations for Institutional Leadership

The PHEI leadership are encouraged to create at least two 'open mic' type opportunities per semester which allow for more informal engagement between leadership and those tasked with facilitating the institution's qualifications. A common perception raised among participants in this study was that leadership did not have any real or meaningful understanding of who their ***people*** are: those faced with having to rapidly implement changes to practice and cope with a barrage of overwhelming, albeit necessary, directives from leadership during times of disruption and change. Establishing this type of forum would serve to minimise the perceived distance between leadership and facilitators, promote greater agency, and allow leadership to gain a richer understanding of the team of facilitators who represent them online and in the classroom.

Conclusions

As Nandy et al., (2021, p.7) suggest, "resilience is about building and constantly topping up emotional and mental fitness, rather than trying to attain 'perfect health'". Tang (2020) concurs, and suggests that higher education institutions need to be actively invested in developing and implementing strategies that can support their teams in riding out the next disruption, however that may manifest. The intention is for this suggested model to serve as a possible guideline for achieving exactly that.

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Navigating the Policy-Practice Divide: A Comparative Analysis of Indigenous Language Policies in Australia and Bangladesh

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Abstract

The steady disappearance of Indigenous languages is arguably one of the most pressing crises facing global cultural diversity today. UNESCO (2022) estimated that 40% of the world's 7,000 languages are currently sliding toward extinction—with one vanishing roughly every fortnight—is a sobering baseline. This article offers a critical comparative look at Indigenous language policies in Australia and Bangladesh. Though these two nations' world apart in their colonial histories and institutional depth, share a troubled trajectory when it comes to supporting Indigenous speakers. By applying Tollefson's (2012) critical language policy analysis and Damschroder et al.'s (2009) Consolidated Framework for Advancing Implementation Science (CFAIS), this research has examined how historical legacies and ideological baggage continue to hinder progress. While both countries have recently adopted more "progressive" stances, a persistent gap remains. In Australia, a relatively sophisticated infrastructure still grapples with political volatility; whereas in Bangladesh, a promising framework struggles against foundational capacity limits. Ultimately, revitalizing these languages may require more than just new laws; it likely demands a wholesale shift in how states value linguistic variety.

Keywords: indigenous language policy, comparative education, language revitalization, critical language policy analysis, implementation science, Australia, Bangladesh

1. Introduction

The world is currently amid a linguistic extinction event; which is- in many ways- unprecedented. UNESC (2022) quoted the warning of linguists that 50% to 90% of the roughly 7,000 languages spoken today could be extinct by the advent of the next century. It is a rapid collapse. When an Indigenous language vanishes—which happens about 26 times a year—it isn't just a set of words that disappears. We lose unique ways of seeing the world, millennia of specialized environmental knowledge, and the threads that hold generations together.

International Work Group for Indigenous Affairs (2019) stated that though Indigenous peoples make up less than 6% of the global population, yet they are the custodians of over half the world's linguistic diversity. This means the burden of language loss falls almost entirely on these marginalized communities. To understand the mechanics of this crisis, this paper compares Australia and Bangladesh. On the surface, the two seem like an odd pair. Australia is a wealthy settler-colonial state with a robust human rights discourse; Bangladesh is a post-independence nation born from a struggle for its own language rights. Yet, both demonstrate a curious "implementation gap."

According to Australian Institute of Aboriginal and Torres Strait Islander Studies [AIATSIS] (2024) reported that Australia recognizes roughly 250 Aboriginal and Torres Strait Islander languages, but among them only 13 languages are considered "strong" enough to be passed naturally to children. Bangladesh, meanwhile, hosts 36 Indigenous languages, yet these remain largely overshadowed by the dominance of Bengali.

Our research asks: How did these different colonial histories create such similar results? Why do progressive laws fail to reach the classroom? By "unpeeling the onion" of policy—from international treaties down to the local schoolhouse—we hope to identify the structural barriers that keep these languages on the brink.

2. Theoretical and Analytical Frameworks

2.1 Critical Language Policy Analysis

This study approached the issue through the lens of critical language policy. Following the theoretical footsteps of Tollefson (2012), this tradition rejects the idea that language planning is a neutral, technical exercise carried out by objective experts. Instead, it treats policy as a site of struggle. Laws often exist to solidify the power of dominant groups while appearing, on the surface, to be inclusive. In both Australia and Bangladesh, "national unity" has frequently been used as a shorthand for linguistic homogenization.

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2.2 The Tripartite Model and the "Onion"

To organize our analysis, we utilize Bernard Spolsky's (2004) tripartite model, which separates language *beliefs* (ideology) from language *management* (laws) and language *practices* (actual use). This distinction is vital because a government might say- it values diversity (belief) while failing to fund textbooks (management), leading to a slow death of the language in the home (practice). Furthermore, Ricento and Hornberger's (1996) "onion" model helps us see how high-level UNESCO declarations often fail to penetrate the inner layers of school administration and local community life.

2.3 Implementation Science: Why Policies Fail

Adopting a policy is easy; but changing behavior is hard. This research utilized Damschroder et al.'s (2009) Consolidated Framework for Advancing Implementation Science (CFAIS) to explain why Bangladesh's 2010 Education Policy, for instance, sat largely dormant for years. It isn't just about money. It's about organizational culture, the "inner setting" of schools, and whether individual teachers feel equipped to teach in a mother tongue.

3. Historical-Political Contexts

3.1 Australia: From Suppression to "Closing the Gap"

Simpson et al. (2009) contended that Australia's history is one of deliberate, state-sponsored linguistic suppression. For much of the 20th century, the goal was assimilation. Children were taken from their families and punished for speaking their mother tongues in mission schools. This was not accidental; it was a calculated attempt to sever the link between culture and language.

The 1970s brought a glimmer of change with the Whitlam government's bilingual programs. But these remained politically fragile. In 2008, for example, the Northern Territory government essentially gutted these programs by mandating the first four hours of school be in English. It was a stark reminder that even "progressive" shifts are often just one election away from being reversed. Today, Australian Government (2020) initiative- the "Closing the Gap" framework (Target 16)- suggests a more mature partnership, but the scars of the past century remain deep.

3.2 Bangladesh: The Irony of the 1952 Legacy

Bangladesh's story is rooted in a different kind of trauma. The nation was born from the 1952 Language Movement—a struggle to keep Bengali alive against Urdu imposition. Ironically, this fierce pride in Bengali led to a post-1971-constitution that enshrined it as the *sole* national language. In the rush to build a unified identity, the 36 Indigenous languages of the Chittagong Hill Tracts and northern plains were essentially written out of the national narrative.

For more than five decades, Indigenous students were kept invisible. It took an armed conflict (1977–1997) and a subsequent Peace Accord to finally force the state to acknowledge that "mother tongue" education should apply to everyone, not just the Bengali majority. The National Education Policy 2010 finally endorsed this. Thus, after fifty years of exclusion, the institutional muscle to actually teach these languages has largely become liberal.

4. Legal Frameworks and Institutional Capacity

While both nations now have "paper protections," Australia's infrastructure is significantly more developed. As reported by the Australian Government (2025), Australia has at least built a "management" system through $37 million in annual funding for the Indigenous Languages and Arts Program and the creation of community-controlled language centers,

In contrast, Bangladesh's efforts feel embryonic. Siddiqui (2023) reported that there is a catastrophic lack of qualified teachers—fewer than 200 for a population of 1.65 million minority speakers. Without specific legislation to enforce the 2010 policy, mother-tongue education remains a discretionary "pilot" rather than a legal right. As it stands, the 1987 Bengali Language Introduction Act still technically makes documents in other languages legally ineffective. This creates a bizarre legal indeterminate state where the state promises to protect languages while simultaneously penalizing their use in official life.

5. Conclusion: The Path to Systemic Transformation

The "policy-practice divide" in these two countries may suggest that we are approaching language revitalization from the wrong direction. We cannot simply add "Indigenous language" as an extra subject and expect a culture to thrive. It requires what we might call a systemic transformation.

Australia needs to move beyond discretionary funding toward durable, legislative rights that cannot be swept away by a change in government. Bangladesh, on the other hand, must move from symbolic recognition to foundational investment. Without training thousands of teachers and creating a curriculum that extends beyond the first few grades, their current policy risks being little more than a "hollow" gesture. In both cases, the clock is ticking. In the same vein of Voronoi (2024), I would also contend that for the 43% of the world's languages currently categorized as endangered, the gap between a written policy and a spoken word is the difference between survival and silence.

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Mapping Thematic Developments in Educational Data Mining Research (2015–2025)

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Abstract

This study examines Educational Data Mining (EDM) research through a bibliometric analysis, with particular attention to thematic developments in the post-2023 period. The dataset was retrieved on 08 January 2026 from the Web of Science (WoS) database through a Topic search using the keywords Educational Data Mining, Learning Analytics, Artificial Intelligence in Education, AIED, and Intelligent Tutoring Systems. In the first stage, 13,428 records were obtained; after applying filters for Article and Review document types, selected WoS categories, and English-language publications, 4,613 documents from 2015–2025 were included.

The R-based Bibliometrix package was used to generate annual growth indicators, author and country contribution metrics, keyword co-occurrence networks, thematic maps, and thematic evolution diagrams. The findings show annual growth of 21.69%, with the literature expanding approximately sevenfold over the decade. The field retains a strong technical orientation around prediction accuracy and model performance, while artificial-intelligence-related educational themes have become more visible in the post-2023 period. This temporal association is interpreted as an emerging thematic development, not as evidence of a causal GenAI effect. Country-level results identify leading contributors to the field.

The study contributes a consolidated account of thematic developments across 2015–2025 and identifies directions for future research on pedagogical alignment, ethics, transparency, and data security in educational technology.

Keywords: Educational Data Mining, Bibliometric Analysis, Artificial Intelligence, R-Bibliometrix, Learning Analytics.

Introduction

Digital platforms, learning management systems, and online assessment tools generate large amounts of data in educational settings. Educational Data Mining (EDM) is an interdisciplinary research field that uses these data to understand student behavior, learning processes, and academic performance (Romero & Ventura, 2020). By bringing together data mining, machine learning, artificial intelligence, statistics, and the learning sciences, EDM serves purposes such as predicting student achievement, identifying learning difficulties at an early stage, designing personalized learning environments, and supporting educational decision-making. In this respect, EDM is important for developing data-driven and evidence-based practices in education.

In the early years of EDM research, student achievement prediction, classification, dropout risk identification, and intelligent tutoring systems were prominent; the literature of this period is described as focusing largely on technical performance measures (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). These studies primarily focused on technical measures such as prediction accuracy, model performance, and algorithmic efficiency. Bibliometric reviews of EDM likewise show that publication output grew rapidly in this early period and that the field was largely oriented toward technical modeling (Boztaş, Berigel, & Altınay, 2024). As learning analytics developed, research also began to address student engagement, feedback, self-regulated learning, and the pedagogical context of learning processes. The field thus evolved into a broader area that brings technical modeling together with the interpretation of learning processes.

Since 2023, the growing availability of generative artificial intelligence, large language models, and tools such as ChatGPT has brought new discussions to the fore in educational technology research. Bibliometric studies of the field have also reported an increase in the number and visibility of artificial-intelligence-related publications during this period (Durak, Çankaya, Özdemir, & Can, 2024). These developments have strengthened the consideration of AI in relation to content generation, personalized feedback, learner–AI interaction, and instructional design. However, the increase in the post-2023 period should not be attributed solely to the effect of GenAI; it should be interpreted cautiously in light of the keyword and thematic findings.

The literature includes bibliometric studies of EDM, learning analytics, and artificial intelligence in education. Studies conducted in the Turkish context have examined the use of data mining in education (Balaman & Tiryaki, 2025), trends in publications on artificial intelligence in educational sciences (Dikmen & Bahçeci, 2024), Web of

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Science-based AI research (Duran & Aydın, 2024), and postgraduate theses on artificial intelligence (Uğur & Usta, 2025) from different perspectives. However, these studies generally focus on a particular subtheme, a single database, or a limited time span. Studies that provide an integrated account of thematic change from predictive learning analytics to research associated with GenAI across 2015–2025 remain limited.

This study aims to examine the scientific production trends, conceptual structure, and country contributions of the literature related to Educational Data Mining from 2015 to 2025 through bibliometric analysis. A total of 4,613 publications retrieved from the Web of Science database were analyzed using the R-based Bibliometrix package. The study seeks to identify keyword clusters, thematic evolution, and the contributions of leading countries. Accordingly, the study addressed the following research questions:

Q1: What growth trend did the EDM literature show in terms of scientific production between 2015 and 2025?

Q2: What are the main research clusters that constitute the conceptual and thematic structure of the EDM field?

Q3: How has the EDM literature shifted from predictive learning analytics toward research orientations associated with GenAI?

Q4: Which countries have contributed most to the EDM literature?

Methodology

Data analysis and visualization were conducted using the Bibliometrix package in R 4.5.3. For the keyword co-occurrence network, Keywords Plus (WoS field ID) was used and the 60 most frequent terms were plotted using association-strength normalization, a Fruchterman layout, and Louvain clustering. The thematic map and thematic evolution analyses used authors' keywords (WoS field DE), with a maximum of 250 terms and a minimum frequency of 5 per thousand records (approximately 23 records); clusters were identified using the Louvain algorithm without stemming. The analyses examined annual scientific production, author and country contributions, keyword co-occurrence networks, thematic maps, and thematic evolution. The field's development was compared across the periods 2015–2018, 2019–2022, and 2023–2025. Data were retrieved from the Web of Science (WoS) database on 8 January 2026. The Topic search, which covers titles, abstracts, and keywords, used the following query: TS=("Educational Data Mining" OR "Learning Analytics" OR "Artificial Intelligence in Education" OR AIED OR "Intelligent Tutoring Systems"). Although the study focuses on Educational Data Mining (EDM), learning analytics, Artificial Intelligence in Education (AIED), and intelligent tutoring systems were included in the search because these closely related areas overlap conceptually and methodologically with EDM. The initial search returned 13,428 records covering 1983–2026.

The dataset was narrowed using several criteria to focus on publications relevant to the study's aims and of suitable quality. Document types were limited to articles and reviews. The selected WoS categories were Education Educational Research, Computer Science Interdisciplinary Applications, Computer Science Artificial Intelligence, Computer Science Information Systems, and Education Scientific Disciplines. The analysis was also limited to English-language publications. These filters yielded 4,631 records.

Because the study period was set as 2015–2025, the 18 records dated 2026 were excluded. The analyses therefore covered 4,613 articles and reviews published from 2015 to 2025. WoS accession numbers were checked for duplicates, and none were found in the dataset. Country contributions were assessed based on the countries listed in author affiliations; internationally co-authored publications may be attributed to more than one country.

Results

This section presents the results of the bibliometric analyses of the Educational Data Mining literature. The findings are considered in terms of scientific production trends, conceptual structure, thematic development, and countries' scientific contributions. The dataset comprises 4,613 Web of Science-indexed publications from 2015 to 2025, with 680 sources and 10,905 authors. The annual growth rate was 21.69%, and the average number of citations per document was 20.47.

Table 1.Main bibliometric indicators of the EDM literature (2015-2025).

Indicator	Value
Timespan	2015-2025
Documents	4,613
Sources	680
Authors	10,905

Indicator	Value
Annual growth rate	21.69%
Average citations per document	20.47
Author's keywords	9,058
Keywords Plus	2,480

Figure 1 shows a steady increase in annual scientific production. The number of publications rose from 126 in 2015 to 897 in 2025. Growth accelerated particularly after 2023. This period overlaps with the growing visibility of GenAI tools in educational research; however, this timing alone should not be interpreted as evidence of a causal relationship.

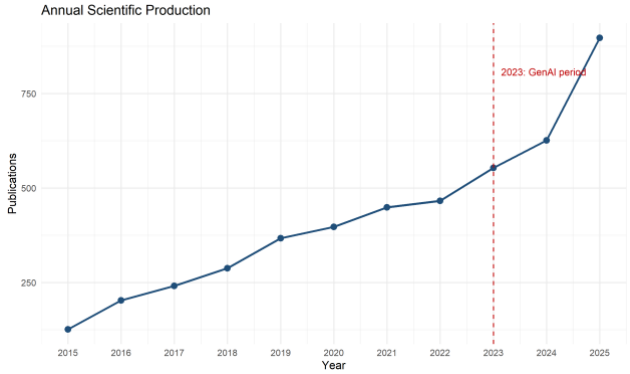


Figure 1. Annual scientific production in educational data mining research (2015-2025).

The keyword co-occurrence network reveals three interrelated research orientations. The first centers on prediction, performance, classification, and artificial intelligence. The second focuses on learning analytics, student engagement, and academic performance. The third encompasses intelligent tutoring systems, feedback, self-regulated learning, and instructional strategies.

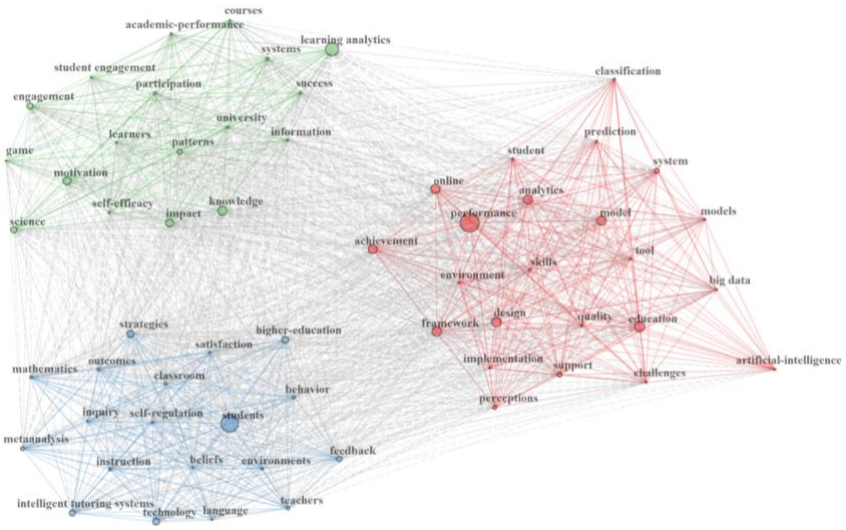


Figure 2. Keyword co-occurrence network of educational data mining research.

The thematic map positions learning analytics, higher education, online learning, and self-regulated learning as motor themes with strong connections to the field. Educational data mining, machine learning, data mining, and predictive models form a well-developed core theme. Artificial intelligence in education appears as an emerging or basic theme, while intelligent tutoring systems occupy a more peripheral position.

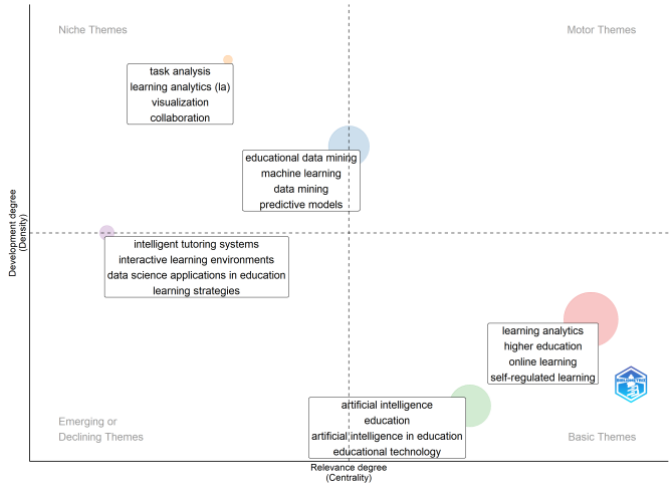


Figure 3. Thematic map of educational data mining research.

Figure 4 shows continuity and diversification in the thematic development of the EDM literature across 2015–2018, 2019–2022, and 2023–2025. In the first period, learning analytics, educational data mining, machine learning, and intelligent tutoring systems were prominent; in the second, learning analytics and educational data mining became more central themes. In the most recent period, these two established orientations continued, while artificial intelligence gained clear visibility. In particular, the connection between educational data mining and artificial intelligence suggests that the field is expanding toward AI applications in education while retaining its technical focus on prediction and modeling.

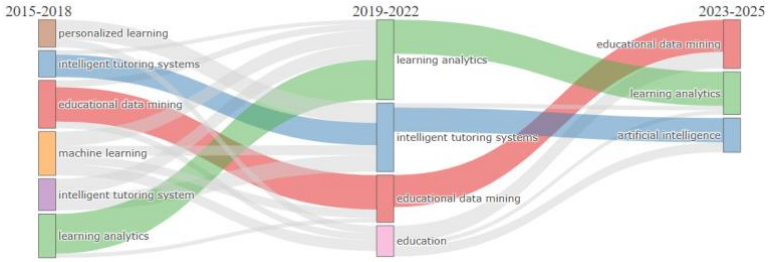


Figure 4. Thematic evolution of educational data mining research (2015–2025).

Gašević, D. was the most productive author, with 106 publications, followed by Ogata, H. (50) and Saqr, M. (48). Education and Information Technologies was the most productive source, with 215 publications, while Computers & Education had the highest citation impact among the leading sources. Among the ten most productive sources, Computers & Education received the highest total number of citations (7,453) and had an h-index of 50.

Table 2.Top five most productive authors in the EDM-related literature (2015–2025).

Rank	Author	Publications	Local citations	h-index
1	Gašević, D.	106	5,189	38
2	Ogata, H.	50	915	16
3	Saqr, M.	48	1,120	20
4	Rienties, B.	37	1,147	22
5	Martinez-Maldonado, R.	37	756	15

The United States and China ranked first in country contributions, followed by Australia, Spain, and the United Kingdom. Country counts represent contributions; the same internationally co-authored publication may be counted for more than one country.

Table 3.Top five most productive countries in the EDM-related literature (2015–2025)

Rank	Country	Country Contributions
1	United States	1,939
2	China	1,571

3	Australia	792
4	Spain	776
5	United Kingdom	545

Discussion and Conclusions

This study found a 21.69% annual growth rate and a sevenfold increase in publication volume from 2015 to 2025. Its thematic structure combines predictive and modeling work with learning analytics and pedagogical themes. The increase after 2023 coincides with greater visibility of generative AI, but the temporal pattern alone cannot establish that GenAI caused the increase.

The overlap with Boztaş et al. (2024) is clear: both studies identify Computers & Education as an influential source and find prediction, machine learning, and learning analytics central to EDM. Their earlier 2010–2021 analysis classified deep learning as an emerging theme; in our later 2015–2025 corpus, deep learning occurs in 99 author-keyword records but does not form a separate motor theme. This difference suggests persistence with a less central position in our broader and later sample. Our finding that multimodal learning analytics and process mining coexist with technical themes also supports the field's diversification. Azevedo and Azevedo (2021) and Kaban (2023) similarly identify learning analytics, higher education, performance, and the United States as prominent; our results agree on the leading country and the centrality of learning analytics. Kurday and Vladova's (2026) combined LA–EDM mapping offers a close comparison, while our analysis extends the time window through 2025 and isolates post-2023 thematic change. Destereci et al. (2023) likewise identify learning analytics and data mining among critical technology themes in educational research, although their broader scope differs from this EDM-focused corpus.

The results portray EDM-related research as a technically grounded but increasingly multidimensional field. As the corpus contains only English-language WoS publications, the findings may not generalize to other databases or languages.

Recommendations

Future studies should compare Web of Science data with databases such as Scopus and ERIC and separately examine thematic orientations by country. In addition to the technical performance of GenAI-based educational applications, long-term applied research should assess their effects on learning outcomes, ethical use, transparency, and data security.

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Advancing Professional Capital Through Immersive Learning Design: VR-Based Disaster Risk Education and Pedagogical Transfer in Teacher Education

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Abstract

This study examines how a virtual reality (VR)-based interactive learning environment can support pre-service teachers' professional capital in earthquake disaster risk reduction (DRR). A design-based research (DBR) approach was used to develop and formatively evaluate a scenario-driven VR environment structured around the pre-, during-, and post-earthquake phases. The design was grounded in the Cognitive Affective Model of Immersive Learning (CAMIL). Eleven experts in disaster risk reduction, teacher education, and educational technology evaluated the prototype, and 11 pre-service teachers participated in a pilot implementation. Quantitative data were analyzed descriptively and qualitative responses thematically. Findings indicate strong pedagogical alignment, high presence and engagement, manageable cognitive load, and meaningful development of earthquake risk-management competencies. Participants emphasized anticipatory risk reduction, professional responsibility, and transfer of the experience to future classroom practice. Wayfinding and task clarity were identified as areas for refinement. Overall, the study positions VR as a professional learning environment that can support human and decisional capital and pedagogical transfer in teacher education.

Keywords: professional capital; immersive virtual reality; teacher education; disaster risk reduction; emerging technologies; design-based research.

1. Introduction

Disaster risk depends not only on physical exposure but also on vulnerability, preparedness, and the ability to act before, during, and after hazardous events. Education and school-based disaster risk reduction (DRR) are therefore important for sustainable resilience, with teachers serving as key actors who can embed preparedness and protective practices into everyday school life. However, the source literature reviewed in the original manuscript indicates that teachers often have limited opportunities in initial teacher education to develop the knowledge, skills, attitudes, and values needed for DRR.

DRR in teacher education has also tended to emphasize information and immediate emergency response rather than the complete risk-management cycle. Fragmented content, limited opportunities for complex decision-making, and insufficient attention to behavioral, affective, ethical, collaborative, and inclusive dimensions can restrict meaningful preparation. Pre-service teachers consequently need practice-oriented environments in which they can plan, decide, reflect, and consider diverse learners across the before–during–after sequence.

Immersive VR offers a way to rehearse complex and risky situations without exposing learners to real danger. The Cognitive Affective Model of Immersive Learning (CAMIL) proposes that immersive learning is shaped by presence, motivation, embodiment, and cognitive load. Prior VR-based disaster studies cited in the manuscript demonstrate benefits for earthquake safety training, yet most have focused on school pupils, the general public, engineers, or emergency personnel and have emphasized immediate response rather than teacher-specific professional practice.

The present study responds to this gap through a scenario-driven VR environment designed for pre-service teachers. Participants engage with school-based tasks before, during, and after an earthquake, including hazard identification, time-sensitive decision-making, pupil safety and emotional management, and post-event recovery and learning. Within the professional capital framework, the design addresses human capital through knowledge and skills, decisional capital through judgment and responsibility, and pedagogical transfer through reinterpretation of the experience for future classroom use.

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2. Research Aim and Question

The study examines how the VR environment shapes pre-service teachers' disaster-related competencies, affective learning experiences, and pedagogical transfer. The research question is:

RQ1. How does a VR-based interactive learning environment for earthquake disaster risk reduction shape pre-service teachers' disaster-related competencies, affective learning experiences, and pedagogical transfer across the pre-, during-, and post-earthquake phases, as evidenced through expert evaluation and pre-service teacher pilot feedback within a design-based research framework?

3. Materials and Methods

3.1. Design-Based Research Approach

The study used Design-Based Research (DBR) to develop and iteratively refine a theory-informed educational intervention while generating design knowledge. The first cycle comprised needs analysis through expert consultation, development of the conceptual and pedagogical model, prototype development, pilot implementation, and formative evaluation.

3.2. Participants and Data Collection

Eleven experts in disaster risk reduction, teacher education, and educational technology evaluated the prototype with 5-point Likert items and open-ended prompts focused on pedagogical alignment, the before–during–after risk-management cycle, and feasibility for teacher education. After refinement, 11 pre-service teachers completed the same evaluation structure and provided reflections on usability, learning, decision-making, professional relevance, and transfer intentions.

3.3. Data Analysis

Quantitative data were summarized using means and standard deviations, and internal consistency was examined with Cronbach's alpha. Because the study followed a formative DBR logic, these statistics were treated as indicators of design plausibility and usability rather than evidence of effectiveness. Open-ended responses were analyzed inductively around risk-management competencies, affective learning experience, and pedagogical transfer. Coding decisions were documented and compared with quantitative trends to examine convergence.

4. Results

4.1. Pedagogical Alignment and Design Validity

Experts reported a very high level of perceived pedagogical alignment. The overall mean was 4.65 on a 5-point scale and Cronbach's alpha was .93. All reported dimensions had 100% agreement at levels 4–5; integrability into teacher education programs received the highest mean (M = 4.82). The ratings indicate that the prototype was regarded as a pedagogically meaningful environment rather than merely a technological demonstration.

Tablo 1. Uzmanların VR tabanlı deprem DRR ortamına ilişkin değerlendirmeleri (n = 11)

Boyut	M	SD	4–5 katılım (%)
Pedagojik uyum (TPACK)	4.55	0.52	100
Öğrenme görevlerinin yeniden tanımlanması (SAMR)	4.73	0.47	100
Risk yönetimi döngüsünün tutarlılığı	4.64	0.50	100
Öğretmen eğitimi için mesleki uygunluk	4.64	0.50	100
Öğretmen eğitimi programlarına entegre edilebilirlik	4.82	0.40	100

4.2. Learning Experience and Cognitive Load

Pre-service teachers reported highly positive learning experiences. Scenario flow supported understanding (M = 4.91), object interaction supported learning (M = 4.73), interaction increased motivation (M = 4.73), and sense of presence was high (M = 4.64). The negative item concerning excessive cognitive difficulty had a mean of 2.82, with 27% agreement, suggesting that the simulation was generally experienced as manageable rather than overwhelming. This pattern is consistent with CAMIL, in which immersive benefits depend on the relationship between presence, motivation, and controlled cognitive demands.

Open-ended comments connected immersion to professional awareness. Participants described noticing classroom risks that are often overlooked, feeling responsible for pupils rather than only for personal survival, and beginning to think about how earthquake procedures could be explained to students. These responses indicate that the experience supported not only affective engagement but also professional responsibility and pedagogical reasoning.

4.3. Earthquake Risk-Management Competencies

The data indicated development of competencies across the three risk-management phases. Pre-service teachers agreed that the environment helped them understand actions before, during, and after an earthquake (M = 4.73), while experts rated the coherence of the cycle at M = 4.64. Anticipatory risk reduction, particularly identifying hazards and securing classroom furniture in advance, was repeatedly emphasized. In the thematic analysis, scenario realism and classroom relevance received 29 expert mentions and 10 pre-service teacher mentions; anticipatory risk reduction received 10 mentions from each group. These patterns suggest movement from reactive response toward proactive risk management.

4.4. Pedagogical Transfer and Design Refinement

Pedagogical transfer was a central finding. Pre-service teachers agreed that the experience could be adapted to future classroom teaching (M = 4.55; 91% agreement), supported decision-making and problem-solving (M = 4.64; 91%), and reflected real classroom responsibilities (M = 4.64; 100%). Thus, participants interpreted the simulation as a pedagogical model, including for settings where VR itself might not be available.

At the same time, experts and participants identified wayfinding and task clarity as areas requiring improvement. The environment was therefore refined with visual navigation cues, context-sensitive prompts, brief pre-task instructions, optional hints, stronger feedback at critical decision points, and reflection prompts addressing different classroom needs. These changes were intended to reduce extraneous cognitive load while maintaining immersion and supporting risk prioritization and justification of actions.

5. Discussion

The findings provide convergent evidence that scenario-driven VR can function as a pedagogically significant professional learning environment for pre-service teachers. The phase-based structure is a major design strength because it treats preparedness, response, and recovery as an interconnected process. From the professional capital perspective, the experience can contribute to human capital through knowledge and skills and to decisional capital through judgment, responsibility, and context-sensitive decision-making.

The learning-experience results are also consistent with CAMIL. High presence, interaction, scenario flow, and motivation were accompanied by relatively low perceived cognitive overload. The qualitative comments further suggest that immersion was educationally valuable because participants connected it with overlooked classroom hazards and the responsibility of protecting pupils. The study therefore supports the source manuscript's position that immersion alone is insufficient; clear learning goals, structured interactions, and cognitive-load management are necessary.

Pedagogical transfer extends the value of the intervention beyond personal preparedness. Participants reinterpreted the immersive scenario as something that could be translated into future classroom practice. This suggests that VR can operate as a model for professional vision and instructional creativity rather than only as a survival simulation. The manuscript also emphasizes that transfer need not depend on VR access: printable hazard checklists, role-play scripts, and discussion cases can preserve the scenario logic in technology-constrained settings.

Finally, the refinement process illustrates the value of DBR. Navigation, signaling, and scaffolding were treated as pedagogical conditions that influence learning, not simply interface details. The convergence of expert and pre-service teacher feedback therefore provided actionable design knowledge for future iterations.

6. Practical Implications and Limitations

The source manuscript recommends using scenario-based VR in teacher education when immersive affordances are explicitly aligned with learning outcomes and the before–during–after risk-management cycle. The intervention can be coupled with guided debriefing, classroom risk audits, micro-teaching, and lesson adaptations for different age groups so that pedagogical transfer becomes an assessable outcome. Navigation support, optional hints, and decision-linked feedback should be treated as learning-critical features, and equivalent non-VR activities can be provided for technology-constrained contexts.

The study is limited by its small pilot sample, reliance on self-report measures, and short intervention duration, which restrict claims about effectiveness and long-term transfer. Future work identified in the manuscript should examine sustained classroom enactment longitudinally, compare immersion and scaffolding levels, extend scenarios to multi-hazard and inclusive classrooms, and use performance-based indicators such as decision traces, post-simulation safety plans, and observed teaching rehearsals.

7. Conclusion

The study demonstrates the potential of a theory-grounded, scenario-driven VR environment to support earthquake DRR in teacher preparation. Evidence from experts and pre-service teachers points to strong pedagogical alignment, positive immersive learning experiences with manageable cognitive demands, development of proactive risk-management thinking, and meaningful pedagogical transfer. The central contribution is therefore to position immersive VR as a professional learning environment that can connect disaster education with professional judgment, resilience-oriented practice, and future classroom teaching.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) for language refinement, improvement of academic clarity, and restructuring of manuscript sections to enhance coherence and readability. The authors critically reviewed and revised all AI-assisted suggestions and take full responsibility for the content and conclusions presented in this manuscript.

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Autonomous Avatars for Metaverse-Based Learning A Multidisciplinary Research Perspective

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Abstract

The growing number of learning environments in the metaverse is leading to increased use of avatars in the roles of tutors and teachers. When avatars are assigned educational tasks, they become potential educational agents, the design of which raises technological, psychological and educational issues. This is all the more true as these avatars are granted increasing levels of autonomous behaviour in their roles. This paper examines the challenges arising from this scenario. These are divided into seven interlinked problem areas: avatar-based interaction, acceptance and familiarity, teaching competence, curriculum and teaching methods, socialisation, autonomy in general, and AI-based autonomy. An analysis of these challenges against the backdrop of established research shows that an autonomous avatar cannot be viewed solely as a purely technical interface. Its pedagogical value depends on how embodiment, interaction, perceived competence, pedagogical role, social implications and the degree of autonomy collectively shape the learning experience. At the same time, the literature does not support the simplistic assumption that a more human-like appearance, greater autonomy or more social interaction inevitably lead to better learning outcomes. This paper therefore considers autonomous avatars as a multidisciplinary research topic and identifies empirical questions that need to be clarified.

Keywords: Learning in the metaverse; avatars; educational agents; autonomous avatars; social presence; educational technology; artificial intelligence; embodiment

Introduction

The concept of the metaverse is often described as a place in which digital and physical environments are becoming increasingly interconnected. Not least, Facebook's rebranding as Meta has brought this concept to the attention of a wider public. In the context of this vision, Mark Zuckerberg spoke of the metaverse as the 'internet of the future', the 'enhanced internet' and the place where the real and digital worlds merge. Unfortunately, Zuckerberg did not elaborate on how, in particular, this convergence should take place or what it should look like (Parisi, T., 2021; Hoffmann, P., 2026; Hoffmann, P., 2026). Current research also describes the metaverse as a persistent multi-user environment that connects digital virtuality with physical reality and is made possible by technologies such as virtual and augmented reality (Mystakidis, S., 2022). Other approaches emphasise that the metaverse is not a single technology, but rather an evolving constellation of immersive, interactive and interconnected technologies and practices (Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., et al., 2022; Parisi, T. (2021).

This classification is of particular significance for the education sector, as learning in the metaverse is not limited to just presenting information in a different graphical format. Learners can enter a spatial environment, interact with objects and other participants, communicate via an avatar, and encounter virtual characters that take on educational roles. Research into learning in the metaverse therefore considers immersive environments, social interaction, avatars, intelligent non-player characters (NPCs) and personalised support to be potentially key elements of future learning settings. (Tlili, A., Huang, R., Shehata, B., et al., 2022) Recent review studies identify both opportunities and unresolved challenges, including issues relating to pedagogy, infrastructure, social interaction, cognitive load, data protection and educational effectiveness. (Islam, M. Z., & Wang, G., 2025; Chatha, F., Panackal, N., Sharma, A., et al., 2026)

This therefore raises the question of how autonomous avatars should be understood in this context and how they need to be designed. The relevance of this question is heightened by the fact that, in future, avatars are also expected to act with increasing autonomy in learning environments within the metaverse. With this new perspective, the discourse shifts from mere representation through avatars towards agency. An avatar that merely represents a learner or teacher differs from an educational agent that can communicate, react, adapt or act without constant human control.

The goal must therefore be to develop new technical architectures and integrated technical concepts as the basis for autonomously operating teacher avatars. However, this will only succeed if a multidisciplinary perspective on autonomous avatars becomes a focus of educational research.

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Conceptual background: From avatar to educational agent

The term „avatar“ refers to a wide variety of forms of digital representation. In the metaverse, it acts as the visible embodiment of a human user. It conveys identity, facilitates non-verbal interaction and enables participation in a shared spatial environment. In traditional computer graphics, an avatar is initially nothing more than a set of (audiovisual) display parameters presented by a rendering tool. An avatar is therefore both a representation and an interface, as what the learner sees as the ‘user’ of the avatar influences how they engage with the virtual environment. (Hoffmann, P., 2026)

In an educational context, however, an avatar can take on other roles. The term ‘educational agent’ is usually used to refer to an animated character or, more generally, a software agent designed to support learning in computer-based environments. Meta-analytical findings suggest that educational agents can have positive, albeit often only moderate, effects on learning. These effects depend on contextual and methodological factors. (Schroeder, N. L., Zhang, S., Jaldi, C. D., et al., 2025) Recent studies show that educational agents can improve certain learning outcomes, although the effect varies depending on the subject area, educational level, type of agent and measurement criteria (Xu, X., Cao, X., Wu, Q., et al., 2026). This suggests that the educational value of an avatar cannot be derived solely from its visual appearance.

Research into pedagogical agents also distinguishes between social cues and instructional functions. Mayer, Sobko and Mautone argued that, in multimedia learning, social cues can influence how learners process instructional content (Mayer, R. E., Sobko, K., & Mautone, P. D., 2003). Atkinson, Mayer and Merrill found that the use of human voices rather than machine-synthesised voices can also influence learners’ evaluations and learning outcomes in multimedia learning environments (Atkinson, R., Mayer, R.. & Merrill, M., 2005). Last but not least, gestural behaviour also contributes to the positive effects of educational agents by aiding the retention of information and influencing a user’s perception of the agent (Davis, R. O., 2018).

Such findings suggest that an educational avatar should not be conceived merely as a graphical shell for an instructional system. Appearance, voice, gestures, timing, responsiveness and the perceived social role can all contribute to how the learner interprets the interaction and the information being communicated. At the same time, the specialist literature warns against equating social richness with the quality of instruction. At the same time, however, there is a risk that visual agents may sometimes be irrelevant or even impose additional cognitive demands, particularly when their behaviour has no immediately recognisable connection to the learning task (Li, H., Wang, Z., Ding, L., Zhang, J., & Wang, G., 2025). Thus, the question of autonomous avatars is, at its core, a question of the relationship between representation, agency, pedagogy and learning.

Challenges

Challenge 1: Technology – Avatar-based interaction

The first challenge concerns the design of interaction with avatars. Unlike traditional online learning environments, where interaction takes place predominantly via text, audio, video or graphical user interfaces, immersive environments enable – or indeed require – additional forms of communication and interaction. These include, in particular, spatial positioning, gestures, gaze direction, movement, the manipulation of shared virtual objects, and embodied co-presence. Avatars can thus incorporate non-verbal forms of communication that may be significant for learning processes. (Yeganeh, L. N., Fenty, N. S., Chen, Y., et. al., 2025) Pointing, demonstrating, directing attention or manipulating an object can themselves become didactic actions.

However, greater diversity in interaction does not necessarily lead to better learning outcomes. Every additional modality demands attention and cognitive resources. Research into pedagogical agents shows that their behaviour can influence cognitive load, with factors such as appearance, role, media configuration and learning speed being relevant determinants. (Li, H., Wang, Z., Ding, L., Zhang, J., & Wang, G., 2025) An avatar’s movements and gestures are therefore particularly useful when they fulfil a didactic function.

Furthermore, there are requirements regarding reaction speed and consistency of behaviour. Delayed or inappropriate reactions to speech, gestures or eye movements can undermine a sense of presence and credibility. Technical interaction problems thus become direct pedagogical problems. It is therefore crucial to distinguish between technical feasibility and pedagogical benefit. The mere possibility of technically implementing a form of interaction does not in itself prove its effectiveness in promoting learning. (Hoffmann, P., 2026)

Challenge 2: Psychology – Acceptance and Familiarity

The second challenge concerns the psychological acceptance of different forms of avatars. An increasing human-like appearance of artificial characters does not necessarily lead to greater acceptance. Rather, Mori’s concept of

the Uncanny Valley describes a potential decline in perceived familiarity as soon as an artificial being closely resembles a human, whilst at the same time remaining recognisably artificial. (Mori, M., MacDorman, K. F., & Kageki, N., 2012)

This phenomenon is particularly relevant for avatars acting as teaching staff, as human individuals are generally assessed on the basis of subtle characteristics such as facial expressions, voice, gestures, reaction times and social behaviour. As realism increases, so too do expectations of consistent human behaviour. A visually realistic avatar exhibiting obviously mechanical behaviour may therefore be less readily accepted than a deliberately stylised figure.

Empirical studies support the assumption that there is no simple linear relationship between anthropomorphism and acceptance. When comparing humanoid avatar tutors with purely audio-based tutors, Scaffidi Abbate, Taddeo and Di Nuovo found that the audio-only option received higher ratings in some cases. (Scaffidi Abbate, C., Taddeo, L., & Di Nuovo, S., 2025) Less visual embodiment may therefore be superior to an imperfect simulation of a human.

The crucial question, therefore, is not how human an avatar should look, but which form of representation is best suited to the specific learning task, target group and desired pedagogical relationship. Technical realism must consequently take a back seat to psychological and pedagogical appropriateness.

Challenge 3: Pedagogy – Teaching Competence

Teaching competence involves much more than simply presenting information. Successful teaching includes, amongst other things, explaining connections, identifying difficulties in understanding, selecting appropriate examples, providing feedback, motivating learners, and adapting the level of difficulty and the learning process to individual needs. Educational agents can perform some of these functions. However, their mere presence does not in itself guarantee learning success. Whilst meta-analyses show positive effects of educational agents overall, they also reveal significant differences between various contexts of use. (Schroeder, N. L., Zhang, S., Jaldi, C. D., et al., 2025; Xu, X., Cao, X., Wu, Q., et al., 2026)

Of particular importance is the distinction between perceived and actual competence. Appearance, voice, role-playing and self-assured behaviour can lead learners to attribute expertise to an avatar. However, these social cues say nothing about the factual accuracy or pedagogical quality of its statements. As autonomy increases, this problem becomes more acute, as a teaching avatar can come across as convincing whilst still producing explanations that are incorrect, incomplete or pedagogically unsuitable.

The suitability of autonomous avatars for teaching must therefore be evaluated on the basis of pedagogical criteria. These include, in particular, learning gains, knowledge transfer and retention, error diagnosis, the quality of feedback, and the ability to adapt appropriately. What matters is not whether an avatar comes across like a teacher, but whether its actions demonstrably support learning.

Challenge 4: Pedagogy – Curriculum and Teaching Methods

The fourth challenge concerns aligning the use of avatars with the curriculum and teaching methods. The effectiveness of a teaching system depends on the coherence between learning objectives, content, learning activities, assessment methods and interactions. A teaching avatar cannot therefore be regarded as a universally applicable teacher. For example, an avatar suitable for introductory mathematics may be unsuitable for laboratory teaching, language learning or collaborative project work.

Research findings on pedagogical agents accordingly show that their impact depends, amongst other things, on educational level, subject area, mode of communication and the intended learning outcome (Wang, F., Li, W., Xie, H., & Liu, H., 2017; Schroeder, N. L., Zhang, S., Jaldi, C. D., et al. (2025). Furthermore, positive effects are more likely to relate to motivation and self-efficacy than to subject-specific learning success directly (van der Meij, H., van der Meij, J., & Harmsen, R., 2015).

The pedagogical question must therefore take precedence over the technological one. First, the learning objective, learning activity, target group and assessment strategy must be defined. Only then can it be determined which function an avatar can usefully fulfil within this framework.

Furthermore, as autonomy increases, the relationship between standardisation and individualisation becomes increasingly important. Adaptive systems can personalise explanations, examples, the pace of learning or feedback. However, such customisation must not result in curricular objectives or pedagogical standards being lost. The more autonomously a teaching avatar acts, the more important mechanisms for ensuring curricular and pedagogical coherence therefore become.

Challenge 5: Psychology – Socialisation

The fifth challenge concerns the impact of avatars on socialisation, identity and self-perception. Avatars do not function solely as technical representations; they can also influence how learners perceive themselves and their role within a virtual learning environment.

A well-known example of this is the Proteus effect, which states that the characteristics of an avatar used affect the behaviour of its user (Yee, N., Bailenson, J. & Ducheneaut, N., 2009). The avatar thus becomes an integral part of the subjective learning experience. On a positive note, avatars can reduce physical and psychological distance in online environments and support collaboration, role-play and social participation. Particularly in learning activities that require communication, cooperation or negotiation, they can thus act as a medium for social learning (Tlili, A., Huang, R., Shehata, B., et al., 2022; Lin, L. H., Pryor, M. R., & Beckmann, N., 2025).

At the same time, this also gives rise to risks. Discrepancies between physical identity and virtual representation can cause tension; creative freedom and social expectations can encourage performative self-presentation or normative pressures. Virtual learning environments can thus establish their own social norms, which in turn influence participation, self-perception and behaviour.

The evaluation of avatar-based learning systems must therefore take into account not only learning outcomes but also social and psychological effects. Relevant factors include, amongst others, a sense of belonging, participation, self-efficacy, perception of identity, social disadvantage and possible pressure to present oneself in a certain way. These aspects cannot be captured solely through technical usability studies. (Hoffmann, P., 2026)

Challenge 6: Technology – Autonomy in general

The sixth challenge concerns the autonomy of the avatar and, consequently, the degree to which it is independent of direct human control. An autonomous avatar does not merely carry out predefined actions, but can select or modify its behaviour based on internal states, goals, environmental information or previous interactions.

Autonomy should be understood as a continuum. This ranges from fully script-based characters, through reactive agents that select from predefined responses, to systems that take interaction histories into account, adapt to learners, generate speech and initiate actions independently.

As autonomy increases, the question of responsibility for pedagogical decisions also changes. Whilst a script-based avatar reproduces a predefined sequence, an autonomous agent can, for example, decide for itself when to speak, what explanation to offer, when to ask questions or how to respond to learners. Each of these decisions can influence the learning process.

A higher degree of autonomy is therefore not necessarily synonymous with greater educational benefit. Whilst adaptive and dialogue-oriented systems can provide individualised support, they still have limitations in terms of complex inferences, the quality of personalisation and transferability to different contexts (Xu, X., Cao, X., Wu, Q., et al., 2026).

At the same time, transparency is becoming increasingly important. Teachers and learners must be able to understand and evaluate autonomous decisions where necessary. Autonomy therefore requires not only technical capability but also explainability, opportunities for control, error handling and a clear allocation of responsibility.

Challenge 7: Technology – AI-based autonomy

The seventh challenge concerns the realisation of autonomy through artificial intelligence. Generative AI and dialogue-oriented systems, in particular, significantly expand the possibilities of autonomous teaching avatars. They can generate explanations, answer questions, rephrase content and engage in open dialogue with learners.

However, these possibilities are offset by risks relating to factual reliability, hallucinations, distortions, overconfidence and inappropriate adaptation. The crucial question is therefore not whether AI can grant an avatar autonomy, but whether this autonomy can be designed in a pedagogically reliable manner.

The link between social presence and perceived authority is particularly critical. A human-like teaching avatar can be perceived as a social interaction partner and thereby generate trust. This trust becomes problematic when the system's convincing presentation exceeds its actual reliability. As social credibility increases, the learners' ability to assess the system's competence appropriately – that is, to distinguish between situations in which the avatar can be trusted and those in which its statements should be questioned - therefore becomes a key area of research.

Ultimately, AI-based autonomy does not alter the fundamental pedagogical responsibility. Even though AI can generate content and adapt interactions independently, educational institutions and teachers remain responsible for the quality of the curriculum, performance assessment, the protection of learners and inclusion. AI-based teaching avatars must therefore be examined not merely as technical systems, but as socio-technical and pedagogical

systems whose autonomy must always remain embedded within institutional, didactic and ethical structures of responsibility.

Summary, Conclusion, Outlook

Autonomous avatars for learning in the metaverse constitute an interdisciplinary field of research at the interface of technology, psychology and educational sciences. This raises seven key challenges that are closely interlinked and cannot be considered in isolation.

In particular, the pedagogical effectiveness of autonomous avatars cannot be deduced either from their technical capabilities or from their human-like appearance. Rather, learning success depends on the context of use, the didactic design, the characteristics of the learners and the specific functions of the avatar. Whilst anthropomorphic design and embodiment can promote social presence and interaction, they can simultaneously give rise to acceptance issues as well as undesirable effects on self-perception and social roles. AI-based autonomy, in turn, expands the possibilities for adaptive and dialogue-oriented learning processes, but raises questions regarding reliability, trust and responsibility.

Autonomous teacher avatars should therefore be understood as multidisciplinary educational agents, the benefits of which must be empirically demonstrated. Future research should investigate the conditions under which different degrees of embodiment, interaction, social presence and autonomy actually contribute to measurable learning outcomes. What is crucial, therefore, is not to design virtual teachers to be as realistic or autonomous as possible, but to determine what learners learn, how they learn, and what specific contribution the avatar's presence and behaviour make to this learning process.

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Generative AI for Responsible Use in Teacher Education: Sex Differences in Perceived Usefulness and the Role of Cognitive and Metacognitive Factors

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Abstract

Generative artificial intelligence (GenAI) is increasingly transforming higher education, particularly in teacher training, where future educators must critically evaluate its pedagogical potential. Despite growing interest in perceived usefulness as a key factor in technology adoption, limited research has examined how cognitive and individual variables jointly influence these perceptions. This study aims to analyse sex differences in pre-service teachers' perceived usefulness of GenAI, cognitive load, problem-solving skills, metacognitive skills, and prior knowledge. A non-experimental, cross-sectional design was employed with a sample of 451 pre-service teachers from the University of Málaga. Results showed no significant sex differences in cognitive load or perceived usefulness. However, significant differences were found in metacognitive skills, problem-solving skills, and prior knowledge, with higher scores among female participants, although effect sizes were small. These findings suggest that, while no statistically significant differences in perceived usefulness were detected, small differences were observed in self-reported cognitive and metacognitive factors. Implications highlight the need to design teacher training programs that address sex-based cognitive and metacognitive differences to promote a more effective and responsible use of GenAI.

Keywords: Generative artificial intelligence; perceived usefulness; cognitive load; metacognitive skills; pre-service teachers; sex differences; responsible use.

Introduction

Generative artificial intelligence (GenAI) is rapidly transforming higher education (Navas-Romero et al., 2026), reshaping how students engage with academic tasks and how future teachers conceptualise teaching and learning processes (Guillén-Gámez et al., 2026c). University students increasingly rely on these tools for writing, information processing, and content generation, while also recognising both their affordances and limitations (de la Flor Bancalero et al., 2026). Within teacher education, pre-service teachers represent a particularly relevant group, as they are not only users of GenAI but also future professionals responsible for integrating these technologies into classroom practice (Zhang et al., 2023; Zhai, 2024; Van den Berg & Du Plessis, 2023). Understanding how they evaluate the usefulness of GenAI is therefore essential for anticipating its pedagogical integration and long-term educational impact (Bower et al., 2024; Chan & Tsi, 2024).

Perceived usefulness has long been established as a central determinant of technology adoption within the Technology Acceptance Model (TAM) (Davis, 1989). Recent studies have extended TAM to AI contexts, consistently showing that perceived usefulness is a key predictor of users' intention to adopt AI-driven tools in educational settings (Dahri et al., 2024; Du & Lv, 2024; Yang & Appleget, 2024). In teacher education, factors such as AI literacy, digital competence, and pedagogical beliefs have also been shown to influence how future educators engage with AI technologies (Guillén-Gámez et al., 2026a; Ayanwale et al., 2024; Galindo-Domínguez et al., 2024; Wang et al., 2023). However, less attention has been paid to the cognitive processes underlying these perceptions.

Cognitive load, as conceptualised within Cognitive Load Theory (Sweller, 1988, 2011), refers to the mental effort required to process information during learning. In AI-supported environments, users must not only process information but also evaluate, interpret, and refine system-generated outputs, which may increase cognitive demands and influence how useful these tools are perceived to be (Khasawneh & Khasawneh, 2024; Issever et al., 2023). At the same time, individual differences such as sex have been examined in relation to technology use and cognitive processing, although findings remain inconclusive (Barron, 2004; Grande-de-Prado et al., 2020; Møgelvang et al., 2024; Strzelecki & ElArabawy, 2024).

Despite the growing body of research on artificial intelligence in education, important limitations remain in understanding how key cognitive and individual factors jointly shape perceptions of GenAI. While prior studies

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have examined perceived usefulness within the Technology Acceptance Model and have separately explored cognitive load and sex differences in digital learning environments, these strands of research have largely developed in isolation. In particular, there is a lack of empirical studies that integrate cognitive load and sex within a unified framework to explain perceived usefulness of generative artificial intelligence among pre-service teachers. This gap is especially relevant in teacher education, where future professionals are expected not only to use AI tools but also to critically evaluate their pedagogical value and implications (Sun et al., 2024; Adelana et al., 2024; Al Darayseh, 2023).

Regarding the research we conducted, previous literature has analysed the influence of sex on various cognitive and technological factors related to learning and the use of educational technologies. In this context, variables such as metacognitive skills, prior knowledge, problem-solving, perceived usefulness, and cognitive load have been studied, showing heterogeneous and, in many cases, inconclusive results. The available empirical evidence for each of these factors is reviewed below.

The influence of sex on the development of metacognitive skills in education has been extensively studied, although with inconsistent results and generally small effects. Zadeh & Behroozi (2019) found significantly higher levels of metacognitive awareness in women in a sample of English teachers in Iran, while Agrawal et al. (2025) found no significant sex differences in university students in India, despite observing high overall levels. Prior experience with educational technologies emerges as a key factor in digital adoption. Karataş & Ataç (2025) showed that such experience is associated with greater competence in AI integration, also finding significant differences in favour of men. Regarding problem-solving with technology, the results are also heterogeneous. Grande-de-Prado et al. (2020) observed that men perceive themselves as more competent in this area, while women excel in the use of social networks and information processing. Regarding the perceived usefulness of AI, Zhang et al. (2023) found no differences by sex in its influence on the intention to use, while Møgelvang et al. (2024) did identify greater use and appreciation in men, compared to a more critical view in women. Finally, the relationship between sex and cognitive load in technological environments presents disparate results. From a theoretical perspective, Bevilacqua (2016) suggests differences in working memory processing. Empirically, Khasawneh & Khasawneh (2024) found a higher cognitive load in men in competitive contexts.

The literature shows limited attention to the specific analysis of sex in relation to cognitive and technological factors associated with the use of AI and GenAI in initial teacher training for the creation of teaching materials. Although studies exist on metacognitive skills, prior knowledge, perceived usefulness, problem-solving, and cognitive load, the results are inconsistent and rarely situated within applied AI contexts or integrated into explanatory models. These limitations reinforce the relevance of the present study as a continuation of previous research. Building on the Technology Acceptance Model and Cognitive Load Theory, this study examines how cognitive load and sex influence pre-service teachers' perceived usefulness of generative artificial intelligence, considering both predictive and moderating effects, as well as potential group differences. To address these aims, the following research question is proposed: To what extent does sex influence the explanatory model of pre-service teachers' perceived usefulness of GenAI, considering its effects on cognitive load, problem-solving skills, metacognitive skills, and prior knowledge? Based on this, the following objective is proposed: analyse the role of sex in the explanatory model of the perceived usefulness of GenAI in future teachers, considering its influence on cognitive load, problem-solving skills, metacognitive skills and prior knowledge.

Methodology

To achieve the study's objective, a non-experimental, descriptive, cross-sectional design was employed, based on the administration of a survey questionnaire. Data collection was carried out using non-probability, purposive sampling. Participants were students and future teachers from the Faculty of Education Sciences at the University of Málaga. The sample comprised a total of 451 university students. Regarding sex, 82.0% identified as female (n = 370) and 18.0% as male (n = 81). The mean age was 20.97±4.50 years in the female group and 21.58±5.88 in extri

The instrument used was developed by one of the authors of this paper and was specifically designed to analyze the cognitive and metacognitive factors associated with the perceived usefulness of GenAI in initial teacher training. It is a structured questionnaire based on a causal model that integrates variables such as cognitive load (intrinsic, extraneous, and germinal), problem-solving skills, metacognitive skills, prior knowledge, and perceived usefulness. Items were measured using a seven-point Likert scale, from 1 (strongly disagree) to 7 (strongly agree).

Regarding psychometric quality, the instrument demonstrated adequate levels of reliability and validity, following the steps taken in similar studies (Guillén-Gámez et al., 2024; Guillén-Gámez et al., 2026b; Romero Martínez et al., 2020). Internal consistency was high across all constructs, with Cronbach's alpha and composite reliability values exceeding .70. Convergent validity was confirmed by Average Variance Extracted (AVE) values above .50 for all factors, indicating adequate correlation between items within each dimension. Discriminant validity was

verified using the Fornell-Larcker criterion and the HTMT index, meeting the thresholds established in the literature. Furthermore, the structural model exhibited adequate quality indicators, with no collinearity issues and significant relationships between the main constructs. Figure 1 illustrates the causal model with these factors.

Data were analyzed using IBM SPSS Statistics 22. Descriptive analyses were conducted to obtain means and standard deviations for all study variables. Normality was assessed using the Kolmogorov–Smirnov test, which indicated non-parametric distributions. Accordingly, non-parametric statistics were applied. Specifically, the Mann–Whitney U test was used to examine differences between male and female participants. Finally, effect sizes were calculated using Cohen's *d* to estimate the magnitude of differences (small = 0.20, medium = 0.50, large = 0.80).

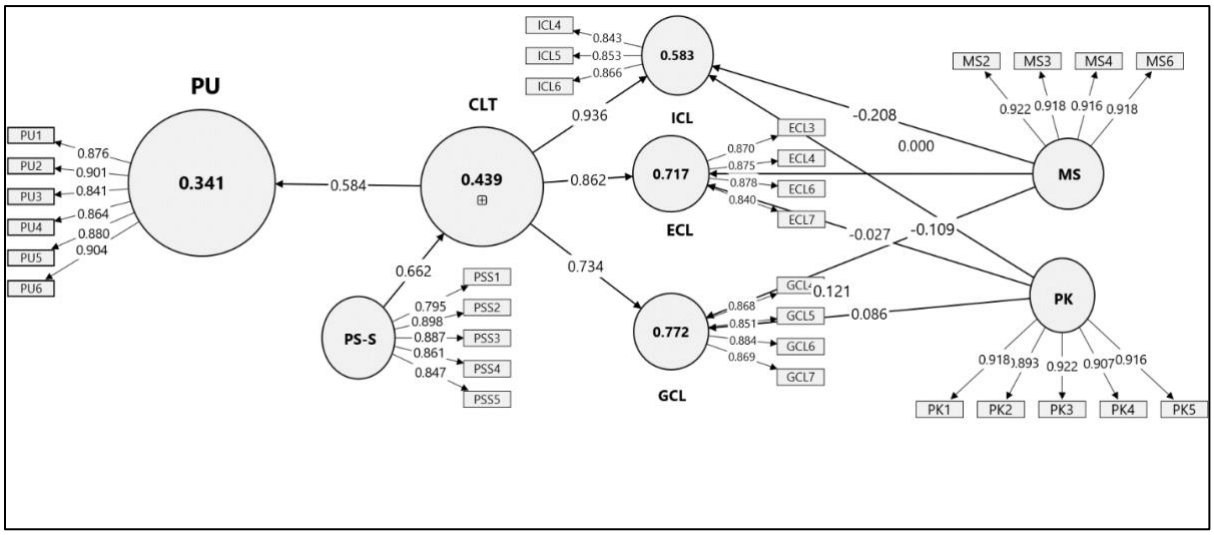


Figure 1 Causal model of the instrument

Results

Descriptive analyses showed similar patterns between female and male pre-service teachers across most dimensions (Table 1). Regarding cognitive load, females reported slightly lower intrinsic cognitive load (M = 3.72, SD = 1.33) compared to males (M = 3.86, SD = 1.36), while higher scores were observed in extraneous (M = 4.70 vs. 4.41) and germane load (M = 5.02 vs. 4.88). Overall cognitive load was also slightly higher among females (M = 4.48, SD = 1.04) than males (M = 4.38, SD = 1.06). Regarding inferential analysis, Mann–Whitney U tests revealed no statistically significant differences between sexes in intrinsic cognitive load (p = .363), extraneous cognitive load (p = .095), germane cognitive load (p = .415), or overall cognitive load (p = .550).

In cognitive and metacognitive variables, females consistently showed higher mean scores in metacognitive skills (M = 5.66 vs. 5.20), problem-solving skills (M = 5.45 vs. 5.08), and prior knowledge (M = 5.61 vs. 5.17). Similarly, perceived usefulness was higher among females (M = 5.08, SD = 1.41) than males (M = 4.85, SD = 1.38). Mann–Whitney U tests revealed no statistically significant differences between sexes in perceived usefulness (p = .134). However, significant differences were found in metacognitive skills (U = 11708.500, p = .002, d = .29), problem-solving skills (U = 12294.000, p = .011, d = .24), and prior knowledge (U = 11929.500, p = .004, d = .27), with higher scores observed in females. Effect sizes for these differences were small.

Table 1 *Descriptive results according to student sex*

	Sex	M±SD	K-S Statistical	N	p.	Mann-Whitney			
						U	Z	p.	ES
Intrinsic Cognitive Load (ICL)	F	3.72±1.33	.085	370	< .001	14021.000	-.910	.363	-
	M	3.86±1.36	.074	81	.200				
Extraneous Cognitive Load (ECL)	F	4.70±1.44	.069	370	< .001	13211.500	-1.672	.095	-
	M	4.41±1.38	.096	81	.063				
Germane Cognitive Load (GCL)	F	5.02±1.38	.100	370	< .001	14120.000	-.816	.415	-
	M	4.88±1.41	.082	81	.200				
Overall Cognitive Load (OCL)	F	4.48±1.04	.052	370	.018	14349.500	-.598	.550	-
	M	4.38±1.06	.075	81	.200				
	F	5.66±1.49	.186	370	< .001	11708.500	-3.117	.002	.294

Metacognitive Skills (MS)	M	5.20±1.49	.150	81	< .001				
Problem-solving skills (PS-S)	F	5.45±1.32	.142	370	< .001	12294.000	-2.537	.011	.24
	M	5.08±1.34	.137	81	.001				
Prior knowledge (PK)	F	5.61±1.44	.167	370	< .001	11929.500	-2.890	.004	.273
	M	5.17±1.46	.135	81	.001				
Perceived Usefulness (PU)	F	5.08±1.41	.113	370	< .001	13392.500	-1.500	.134	-
	M	4.85±1.38	.106	81	.026				

Note: F=female; M= male; M±SD = mean and standard deviation; N = sample size; ES: effect size; *p < .05.

Conclusions

This study aimed to analyse sex differences in pre-service teachers' perceived usefulness of generative artificial intelligence. Specifically, it examined differences in cognitive load, problem-solving skills, metacognitive skills, and prior knowledge. The findings partially align with previous literature, confirming a mixed pattern of sex differences across cognitive and technological variables. In line with Zadeh & Behroozi (2019), female pre-service teachers showed significantly higher levels of metacognitive skills, although the small effect sizes are consistent with the generally modest differences reported in prior studies. Similarly, the absence of significant differences in perceived usefulness supports the results of Zhang et al. (2023), suggesting that no statistically significant sex differences were detected in evaluating the usefulness of GenAI. However, the higher scores observed in females for problem-solving and prior knowledge contrast with findings by Grande-de-Prado et al. (2020), who reported higher self-perceived competence among men in technological problem-solving. Finally, the lack of significant differences in cognitive load diverges from studies such as Khasawneh & Khasawneh (2024), reinforcing the inconsistency of results in this area and highlighting the need for further research in AI-based educational contexts.

This study presents some limitations that should be considered. First, the use of a non-probabilistic sampling design limits the generalizability of the findings. Additionally, the sample was restricted to a specific group of pre-service teachers, which suggests the need to expand future research to include students from other degree programs within the Faculty of Education. It would also be valuable to incorporate university teaching staff involved in training these students, in order to obtain a more comprehensive understanding of the use and perception of GenAI in teacher education contexts.

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Behavioural Student Profiling in Online Learning Environments: Learning Analytics through Unsupervised Learning

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Abstract

Interaction logs generated in online learning environments enable the examination not only of students' outcomes but also of their behavioural patterns during the learning process. This study utilises ASSISTments-based EDM Cup 2023 data to categorise students into behavioural profiles independently of their achievement labels and to investigate how these profiles can be interpreted in terms of online student support. Approximately 37.7 million aggregated interaction records were aggregated at the level of 36,296 students; following quality filters, 34,961 students were analysed based on nine behavioural characteristics. After evaluating multiple clustering criteria alongside interpretability, a four-profile solution using K-Means was adopted. The Silhouette value of the final model was found to be 0.2381. The profiles represent balanced interaction, high demand for help and responses, high-intensity independent problem-solving, and low interaction patterns. Achievement scores were not used as clustering input but were considered solely for subsequent descriptive comparison. Auxiliary classification analysis demonstrated that cluster assignments could be reproduced with high accuracy from behavioural characteristics. The findings suggest that, in online learning, behavioural patterns indicating different support needs can be tracked rather than a uniform risk label.

Keywords: Educational Data Mining, Learning Analytics, Online Learning, Student Behaviour, Clustering, Student Support

Introduction

Online learning environments continuously generate detailed digital traces left by students during the learning process. It is now possible to observe when a student begins a problem, how many times they attempt it, at what point they seek help, whether they request a direct answer, and how they transition from one activity to another. These records provide a layer of information distinct from traditional exam marks. Whilst exam marks primarily indicate the outcome of the learning process, interaction records make it possible to examine the behavioural patterns through which a student reached that outcome. Educational Data Mining and learning analytics are key research areas that link this type of data to teaching and learning processes (Ferguson, 2012; Romero & Ventura, 2020).

In Educational Data Mining studies, predicting student achievement, determining the likelihood of dropping out of school, and the early identification of at-risk students have long been important research topics. The majority of these studies employ a supervised learning approach that predicts a predefined target variable (Albreiki et al., 2021; Rastrollo-Guerrero et al., 2020; Yağcı, 2022). This approach is valuable in terms of decision support. However, focusing solely on outcome-based labels such as success, failure or dropout may obscure the differences between students who achieve the same academic outcome through different behavioural pathways. The fact that two students achieve the same mark does not necessarily mean they use the online environment in the same way.

This distinction is even more important in online and distance learning environments. As the opportunity for the lecturer to observe the student face-to-face diminishes, digital behaviour records become a complementary source of information regarding the student's engagement in the learning process. The analysis of system logs in conjunction with student achievement and learning behaviour is an approach also utilised in distance education research. Koyuncu, Kılıc and Orhan Goksun (2022) demonstrated that learning management system logs can be used in achievement classification. Akcapınar and Bayazıt (2018), meanwhile, examined the relationship between video-viewing behaviour and different learning approaches. More recent studies suggest that considering digital behaviour patterns alongside psychological and academic variables may be useful in understanding online learning processes (Gushchina & Anikina, 2026; Rafiq et al., 2026).

The educational value of digital traces is not limited to merely improving prediction accuracy. For learning analytics to be meaningful from an instructional perspective, the data must be situated within a pedagogical

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context. Lockyer, Heathcote and Dawson (2013) note that it becomes difficult to generate actionable insights when analytical outputs are not linked to instructional design and pedagogical intent. For this reason, student profiling studies should not merely content themselves with dividing students into groups distinguished solely by mathematical criteria. It must also be explained which behaviours the resulting profiles represent, by which indicators they are distinguished, and within what limits the educator may use this information.

Unsupervised learning offers the opportunity to discover patterns in data without predefined labels of success or risk. Clustering methods are therefore suitable for examining the heterogeneity of student behaviour. However, cluster labels should not be interpreted as fixed student types that exist in the real world. Pupils' behaviour may vary depending on the structure of the lesson, the difficulty of the content, time constraints, the platform used and the learning objectives. For this reason, clustering results should be treated as descriptive segments and not used as definitive and permanent pupil identities. Moderate cluster separation is to be expected, particularly in data based on human behaviour.

Adaptive online learning platforms such as ASSISTments are a rich source of data for such analyses. The data published as part of the EDM Cup 2023 contains large-scale clickstreams generated by students whilst completing maths tasks. The dataset includes actions such as initiating problems, providing answers and continuing, as well as behaviours such as seeking help and asking for answers. Using the EDM Cup 2023 data, Pu, Yan and Zhang (2024) demonstrated that clickstreams are useful for examining students' performance and behavioural patterns. The same data structure enables the unsupervised profiling of student behaviour, going beyond performance prediction.

Help-seeking behaviour is particularly noteworthy in this context. Asking for help is not always a negative behaviour. A student's use of help at the appropriate time can be part of self-regulation and learning strategy. Conversely, behaviours such as directly asking for answers, overusing help tools or constant trial and error may indicate various learning difficulties. Roll and colleagues (2011) demonstrated that help-seeking skills can be taught and supported. Baker, Corbett, Roll and Koedinger (2008), on the other hand, demonstrated that certain student behaviours can develop into patterns of using the system's features for purposes other than learning. However, it is not possible to determine a student's intention with certainty by examining log records alone. For this reason, in this study, clusters have been defined using neutral names based on observed behaviour.

This study focuses on generating behavioural student profiles from large-scale interaction data in online learning environments. The key distinction of this study is that it does not use achievement scores as a clustering input. Consequently, the profiles are not predetermined by academic outcomes but are constructed based on how students interact with the platform. Achievement scores were examined solely as a descriptive external variable after the profiles had emerged. This approach helps to test the assumption that students who achieve the same level of success may exhibit different support needs.

The study also establishes a clear boundary between technical evaluation and pedagogical interpretation. Multiple measures of internal validity were assessed when selecting the number of clusters. However, the K=4 solution is not presented as the numerical optimum of a single metric. Coarser solutions producing higher Silhouette values have also been observed. The four-cluster structure was preferred because it strikes a balance between statistical separation and interpretable behavioural diversity. This preference does not imply that the results reveal four natural and immutable student types.

The practical significance of this study lies in highlighting the limitations of a one-size-fits-all early warning approach in online learning. Low achievement does not always go hand in hand with low participation. A high volume of activity does not necessarily equate to an effective learning strategy. Similarly, frequent use of support should not be treated merely as a risk indicator without understanding what type of support the student requires. Behavioural profiling may offer educators the opportunity to identify students' different online study patterns at an earlier stage. This information can be used as an analytical layer that prioritises teacher review and targeted student support, rather than directly triggering automated intervention decisions.

Aim of the Study

The primary aim of this study is to derive interpretable behavioural profiles from student interaction logs generated on an online adaptive learning platform, without relying on achievement labels. The secondary aim is to discuss what kinds of differing needs these profiles might indicate in terms of online teaching and student support. The study does not aim to categorise students into definitive risk groups or to draw inferences about clinical, psychological or motivational conditions. The analysis produces a descriptive segmentation based solely on behaviour observed on the platform.

Within this framework, three research questions are addressed. RQ1. Do behavioural characteristics derived from online learning interactions form a cluster structure that divides students into interpretable groups? RQ2. How do

the obtained profiles differ in terms of the frequency of seeking help, asking for answers, giving incorrect answers, persevering and problem-solving? AS3. To what extent can cluster assignments be reproduced using auxiliary classifiers trained on the same behavioural features, and how should this result be interpreted in terms of cluster separation?

Method

Research Design and Data Source

This study is a quantitative learning analytics research project conducted on secondary and anonymised digital learning data. No new data was collected from human participants for this study. The data source consists of clickstreams and task logs provided by the ASSISTments online maths learning platform as part of the EDM Cup 2023 competition. The ASSISTments data has a multi-table structure containing students' actions within unit-based maths tasks, problem and task metadata, and assessment results for specific tasks. Previous studies have also demonstrated that a similar data structure can be used for modelling student behaviour and performance (Pu et al., 2024).

As part of the project, ten raw tables were linked to create a consolidated analysis table comprising approximately 37.7 million rows. The consolidated data covers the interactions of 36,296 unique students. This figure represents the user population prior to the aggregation of raw events at the student level. To prevent student behaviour from being represented by unstable ratios derived from very few interactions, only students with at least five problem interactions and at least one response record were included in the analysis. Following this quality filter, the final clustering analysis was conducted on 34,961 students.

The data covers online mathematics activities between 2019 and 2023. This period encompasses both routine use of online platforms and years characterised by an intensification of remote and technology-enhanced teaching. However, the study does not employ a causal design to test the causes of fluctuations over time. Consequently, differences in interactions across periods have been used solely to define the data context.

Behavioural Characteristics and Pre-processing

Raw event logs have been aggregated at student level. The aim is to create a single behavioural profile for each student that summarises their use of the platform. In the initial stage, counts were obtained for metrics such as help requests, requests for answers, incorrect answers, correct answers, continuation choices, number of problems, number of responses, number of days active and task duration. Subsequently, the raw counts were converted into ratios and intensity indicators to minimise the effect of varying activity levels amongst students.

When selecting features, both statistical variability and educational interpretability were taken into account. The rates of requesting hints and explanations, which were zero for the vast majority of students, were not used as standalone clustering features. In contrast, the direct answer request rate, total assistance rate, incorrect response rate, continuation selection rate, average maximum number of attempts, daily problem-solving intensity, problem depth per sequence, logarithmic transformation of the number of unique sequences, and logarithmic transformation of the average task duration formed the final feature set. Table 1 summarises these features along with their educational meanings.

As a pronounced right-skewness and outliers were observed in the feature distributions, a log1p transformation was applied to the density variables. To limit the effect of outliers on distance-based clustering, the variables were winsorised at the 1st and 99th percentile boundaries. Scaling was then performed using RobustScaler. As this process is based on the median and interquartile range rather than the mean and standard deviation, it is more robust against remaining outliers. These pre-processing steps preserved the ranking of students' behaviour whilst reducing the extent to which a single variable could dominate K-Means distances solely due to its scale.

Table 1. Behavioural characteristics used in the clustering analysis.

Feature	Behavioural meaning
answer_requested_rate	Ratio of direct requests for answers to the number of problems
help_rate	Total help rate comprising requests for hints, answers and explanations
wrong_response_rate	The ratio of incorrect responses to total responses
continue_selected_rate	Ratio of 'continue' selections to the number of problems
avg_max_attempts	Average maximum number of attempts per problem
daily_problem_solving_intensity	Problem-solving intensity per active day
problem_depth_per_sequence	Number of problems per sequence

Feature	Behavioural meaning
log1p_n_sequences	Logarithm of the number of unique sequences
log1p_avg_assignment_duration_sec	Logarithmic transformation of the average task duration

Note: The success score was not used as a clustering input. It was examined solely for descriptive comparison purposes after the clusters had been formed.

Clustering Approach and Determination of the Number of Clusters

Centre-based K-Means was used as the primary method to determine students' behavioural profiles. In addition, the results of MiniBatchKMeans, BIRCH, Agglomerative Ward and DBSCAN were examined comparatively. Solutions ranging from K=2 to K=12 were evaluated to determine the number of clusters. The Elbow curve, Silhouette, Davies-Bouldin and Calinski-Harabasz criteria were considered together. The Silhouette value is a measure of internal validity that summarises the similarity of observations to their own clusters and their distance from other clusters (Rousseeuw, 1987). The Davies-Bouldin criterion indicates more distinct separation at lower values, whilst the Calinski-Harabasz criterion indicates this at higher values.

The K=2 solution produced the highest Silhouette value. However, the two-cluster structure largely reduced student behaviour to two broad groups along the high and low activity axes. Although the Silhouette value was lower in the K=4 solution, four distinct descriptive profiles emerged in terms of help usage, attendance behaviour and study intensity. Consequently, K=4 was adopted not as the numerical optimum of a single internal validity measure, but as a design choice balancing multiple measures and educational interpretability. The final K-Means model was trained on the entire sample of 34,961 students using a k-means++ initialisation and multiple initialisations. The final Silhouette value was calculated as 0.2381. This value indicates a moderate level of segmentation, where behaviours partially overlap, rather than strong and distinct natural clusters.

This interpretation is important in that cluster profiles should not be treated as fixed student types. Student behaviour is continuous and may vary depending on the context. The clusters in this study are analytical profiles summarising the dominant patterns in a specific dataset. The labels do not make direct judgements about the student's identity, motivation or psychological state.

Achievement Score and Auxiliary Discriminant Analysis

Achievement data within the ASSISTments data structure was not used in the construction of the clustering model. This prevented the clusters from being directly shaped by the achievement variable. The success score was examined only after the clusters had been obtained, with the aim of describing how the emerging behavioural patterns correlated with academic outcomes. This analysis is not a test of causal effect. Differences in scores between clusters do not indicate that the behavioural profile causes success.

An auxiliary classification analysis was conducted to examine the extent to which cluster assignments are distinct within the feature space used. Random Forest, Gradient Boosting and Logistic Regression models used the K-Means cluster labels as the target variable. This analysis is not external validity validation in the classical sense. The fact that a classifier performs well does not prove that the clusters are pedagogically valid. The result merely demonstrates the extent to which the assignments generated by K-Means can be consistently reproduced from the same behavioural characteristics. The data was divided into training, validation and test subsets, and scaling was learnt solely from the training data. Furthermore, five-fold cross-validation was reported.

Findings

Distribution of the Four Behavioural Profiles

The final K=4 solution produced four behavioural segments, ranging in size from 16.58 per cent to 36.25 per cent. Cluster K0 is the largest group, comprising 12,673 students and accounting for 36.25 per cent of the total sample. Cluster K2 comprises 10,296 students (29.45 per cent), cluster K3 comprises 6,195 students (17.72 per cent) and cluster K1 comprises 5,797 students (16.58 per cent). The ratio between the largest and smallest clusters is 2.19. This distribution indicates that no single cluster accounts for the vast majority of the sample.

The profiles have been defined using neutral terms following a reassessment of the behavioural indicators in the current project outputs. K0 is termed 'Balanced Interaction', K1 'High Demand for Assistance and Responses', K2 'High-Intensity Independent Problem-Solving' and K3 'Low Interaction'. This naming convention aims to avoid inferences regarding intent, risk or psychological state that are not supported by the behavioural data. Table 2 shows the key characteristics of the clusters.

Table 2. Key characteristics of the four behavioural profiles.

Profile	n (%)	Rate of assistance	Requesting an answer	Incorrect response	Choice to continue	Daily workload	Average score
K0 Balanced interaction	12,673 (36.25 per cent)	0.061	0.053	0.239	0.438	3.60	0.53
K1 High demand for assistance and responses	5,797 (16.58 per cent)	0.241	0.208	0.374	0.408	21.10	0.30
K2 High-density independent solution	10,296 (29.45 per cent)	0.032	0.027	0.174	0.453	75.10	0.62
K3 Low interaction	6,195 (17.72 per cent)	0.044	0.034	0.209	0.340	12.52	0.51

Note: The average score is not a clustering input. It is a descriptive average calculated retrospectively for students with a score. No academic or psychological risk diagnosis should be made based on the clusters.

Profile 1: Balanced Interaction

The K0 group constitutes the largest proportion of the sample. The help-seeking rate is 0.061 and the rate of requesting direct answers is 0.053. The incorrect response rate is 0.239, the continuation selection rate is 0.438 and the daily problem intensity is 3.60. This combination indicates a more balanced interaction pattern, characterised by regular progress alongside low-to-moderate levels of help usage. The average achievement score is 0.53.

This profile should not be interpreted as an educationally ‘normal’ or ‘problem-free’ student. The cluster merely exhibits a less extreme behaviour pattern compared to other groups. In online support systems, this type of profile can be used as a baseline comparison group rather than to trigger automatic alerts. The individual student’s need for support should still be addressed within the context of the course and through teacher assessment.

Profile 2: High Demand for Help and Answers

The distinguishing feature of Group K1 is a markedly high level of help usage. The total help rate is 0.241 and the rate of direct requests for answers is 0.208. The rate of incorrect answers also reaches the highest value among the four profiles, at 0.374. The average achievement score of 0.30 is lower than that of the other clusters. This result indicates that intensive help-seeking does not, in itself, constitute an effective learning strategy.

This pattern may bear some superficial similarities to inappropriate help-seeking and ‘gaming the system’ behaviours discussed in previous research (Baker et al., 2008). However, the current data does not directly measure the student’s intent, the timing of the help request, or whether they are actually exploiting the system. For this reason, the profile has not been labelled as a ‘system exploiter’. From an educator’s perspective, a safer interpretation is that these students may require further examination regarding the design of the support, the quality of explanations, or their problem-solving strategies. The act of seeking help is not a problem to be reduced, but rather a learning skill that can be made more productive (Roll et al., 2011).

Profile 3: High-Intensity Independent Problem-Solving

Group K2 stands out as having a daily problem-solving intensity of 75.10, which is significantly higher than that of the other profiles. In contrast, the help-seeking rate is 0.032 and the rate of asking for direct answers is 0.027, both of which are at the lowest levels. The error rate is 0.174, the lowest among the profiles, whilst the continuation selection rate is 0.453, one of the highest values. The average success score is 0.62, which is the highest value among the four profiles.

Based on the current data, this profile cannot be classified as ‘at risk’, ‘struggling’ or ‘burned out’. The high activity intensity may have various explanations. Students may be completing a large number of tasks in a short space of time, some accounts may be showing unusual usage patterns, or certain assignment structures may be generating high levels of interaction. Consequently, the educational implication is limited to the need for close monitoring of high activity volume alone. In practice, teachers may examine indicators such as the balance between work pace, task difficulty and the use of support within this group.

Profile 4: Low Interaction

The continuation rate in the K3 group is the lowest at 0.340. The daily problem density is 12.52 and the average success score is 0.51. The help rate is 0.044. This profile is characterised by more limited continuation behaviour and a lower overall activity structure compared to other clusters.

Low engagement should not be interpreted as direct school dropout or a lack of motivation. Student engagement may be influenced by variables such as lesson structure, the number of assigned tasks, access conditions and the timetable. Nevertheless, patterns of low attendance and limited engagement in online teaching may serve as a meaningful signal for the teacher to examine the student's conditions for participation. Rather than directly labelling a student as at risk, it would be more appropriate to investigate possible explanations such as access issues, task difficulty, time management or lesson design.

Discriminability of Cluster Assignments in the Feature Space

In the auxiliary classification analysis, three different models predicted cluster labels from behavioural features. On the test set, Random Forest achieved 96.07 per cent accuracy and a Macro-F1 score of 0.9610, whilst Gradient Boosting achieved 97.01 per cent accuracy and a Macro-F1 score of 0.9702. Logistic Regression achieved the highest test result with 99.28 per cent accuracy and a Macro-F1 score of 0.9926. In five-fold cross-validation, the average test accuracy of Logistic Regression was found to be 0.9935 ± 0.0012 and the Macro-F1 score 0.9933 ± 0.0014.

These high values indicate that the four clusters possess reproducible decision boundaries based on the behavioural features used. However, the interpretation of the results is limited. The cluster labels are derived from the same features. Consequently, the classifier's learning of these labels does not provide independent external validation. The analysis merely demonstrates that the geometric separation of the cluster assignments in the feature space is strong. Different student samples, teacher assessments or independent external criteria are required to establish the pedagogical validity of the profiles.

Table 3. Reproduction of cluster labels using auxiliary classifiers.

Model	Test accuracy	Test Macro-F1	5-fold CV accuracy	5-fold CV Macro-F1
Random Forest	0.9607	0.9610	0.9599 ± 0.0021	0.9603 ± 0.0025
Gradient Boosting	0.9701	0.9702	0.9705 ± 0.0012	0.9703 ± 0.0015
Logistic Regression	0.9928	0.9926	0.9935 ± 0.0012	0.9933 ± 0.0014

Note: These results do not prove the external validity of the clustering. They indicate the extent to which cluster labels derived from the same features can be reproduced in the feature space.

Discussion and Conclusion

The Significance of Behavioural Profiles in Online Learning

This study demonstrates that student behaviour in online learning environments cannot be explained by a single activity or measure of achievement. There are distinct differences between the four profiles in terms of help usage, direct requests for answers, incorrect responses, persistence and problem-solving intensity. Furthermore, the average achievement scores of the profiles do not correspond exactly with the behavioural patterns. Whilst the group with the highest interaction intensity achieved the highest average achievement score, the group making the most frequent use of help had the lowest average score. This finding demonstrates that simple rules such as 'more activity always leads to better learning' or 'more help always leads to lower achievement' are insufficient in online learning.

The pedagogical value of learning analytics becomes apparent precisely at this point. Analytic systems can reveal not only a student's final score but also the behavioural pathway leading to that outcome. As Lockyer and colleagues (2013) emphasised, this visibility is only meaningful when contextualised within the teaching environment. For example, a high demand for answers may be linked to the difficulty of the subject matter in one group of students, to the design of the task in another, and to the ease of use of the support tool in yet another situation. The system merely reveals the pattern. Its pedagogical significance must be assessed by the teacher in conjunction with lesson design and additional evidence.

Previous studies in the field of online and distance learning have also shown that digital behavioural traces can be used to understand the teaching process. Akcapınar and Bayazıt (2018) examined the relationship between video interactions and learning approaches, whilst Koyuncu et al. (2022) investigated the role of system logs in the classification of academic achievement. Gushchina and Anikina (2026) demonstrated that non-linear relationships may exist between digital behaviour, psychological characteristics and learning outcomes. This study extends that line of inquiry in the direction of unsupervised profiling. Without pre-assigning a 'success' or 'risk' label, students' diverse online working styles are made visible.

Using data from the EDM Cup 2023, Pu et al. (2024) demonstrated that click behaviours, such as directly seeking answers, may be associated with student performance. The present study addresses such behaviours not as individual predictor variables, but as patterns co-occurring at the student level. Consequently, its contribution lies more in descriptive student segmentation than in performance prediction. The profiles provide a starting point for teachers to identify which behavioural dimensions to examine more closely.

Implications for Teaching and Student Support

For behavioural profiles to be used in online teaching, analytical outputs must be presented in a way that is action-oriented yet cautious. Automatically labelling a student as 'failing', 'abusive', 'at risk' or 'passive' is problematic from both a scientific and an ethical perspective. These labels do not account for the student's context and carry the risk of stigmatisation. A more appropriate approach is for the system to indicate which behaviours are unusual or conspicuous, and for the educator to verify these against other information.

For students showing high levels of help and answer requests, the first step should not be to restrict the help mechanism. The teacher can examine when help was requested, whether the student made an independent attempt first, and whether the explanatory tools were understandable. Metacognitive feedback on help-seeking skills can improve the quality of help utilisation (Roll et al., 2011). Similarly, for a high-intensity independent problem-solving profile, focusing solely on increasing the number of activities may be unnecessary. The student's pace of work, task difficulty and learning outcomes should be assessed together.

A low-interaction profile can be used as an indicator of the need for early communication in online courses. However, low activity does not always equate to low motivation. Access issues, task distribution, differing study schedules or learning activities outside the platform may not appear in the logs. Therefore, learning analytics dashboards should be designed as a tool for generating questions rather than an automated decision-making system. The question 'Why is this student attending less frequently?' is more pedagogical and safer than the judgement 'This student is at risk'.

For distance and online education institutions, the potential of this approach lies in its ability to prioritise different support needs across large student groups. In large-scale online courses, it is not feasible for teaching staff to manually review each student's behavioural history. Behavioural segmentation can help ensure that the teacher's attention is used more efficiently by highlighting specific patterns. However, automated profiling must be assessed in conjunction with the support available to the student, the pedagogical design of the course and institutional policy. The aim of learning analytics is not to reduce the student to data, but to enable the teacher to ask more meaningful questions using the data.

This perspective is also consistent with the general trend in the field of educational data mining. Romero and Ventura (2020) demonstrate that EDM and learning analytics have evolved not only for prediction but also for purposes such as personalisation, student modelling and decision support. Aydoğdu (2020) has noted that predictive tasks dominate EDM studies in Turkey. Unsupervised behavioural profiling offers an exploratory tool that complements the prediction-focused approach. Particularly in online teaching, being able to see that students achieve the same learning outcome through different pathways of interaction may be important in the design of personalised support.

Table 4. Potential areas for educators to examine regarding behavioural profiles.

Profile	Initial analytical signal	Topic the educator may examine	Interpretation threshold
Balanced interaction	Moderate support and regular attendance	Individual goals and pace of progress	A low need for support should not be automatically assumed.
High demand for help and responses	High demand for help and responses	Timing of assistance, quality of explanation, problem-solving strategy	Intent or 'system abuse' cannot be deduced from logs alone.
High-intensity independent resolution	Very high problem density, low support	Work pace, task difficulty, balance of support utilisation	High volume does not necessarily imply direct risk or burnout.
Low interaction	Low continuity and limited activity	Access, time management, task design, communication needs	Low interaction does not directly imply dropping out of school or a lack of motivation.

Note: The items in the table are not automatic intervention rules, but potential questions that may guide a teacher's assessment.

Limitations

The first limitation of the study is that the data source is derived from a single online maths platform. ASSISTments has specific age groups, content types and task structures. Therefore, it cannot be assumed that the four profiles will emerge in the same way across different learning management systems, in higher education or in programmes delivered entirely remotely. The profiles need to be re-evaluated using different datasets.

The second limitation is the interpretability preference in the choice of the number of clusters. The K=2 solution produced a higher Silhouette value. K=4 was selected because it provided more detailed and educationally interpretable segments. Consequently, this study does not claim that K=4 is the statistically correct or natural number of clusters. The final Silhouette value of 0.2381 also indicates that there is significant overlap between the clusters.

The third limitation is that the profile names are based on the researcher's interpretation. Although the clusters can be defined by observed variables such as support, persistence and intensity, the students' motivation, emotional state, intention or actual learning strategy have not been measured directly. Consequently, it is not appropriate to derive concepts such as 'gaming', 'wheel-spinning', 'burnout' or 'risk of dropping out' directly from the available data.

The fourth limitation is that the achievement score is only available for certain students and is used in a post-hoc manner. Differences in average scores provide a descriptive context regarding the academic significance of the profiles. However, they do not indicate a causal relationship or the effect of an intervention. Similarly, the high accuracy in the auxiliary classification analysis demonstrates that the cluster labels can be reproduced from the same characteristics. This does not constitute independent external validity.

The fifth limitation is the reduction of the temporal dimension to a single summary profile at the student level. A student's behaviour at the start of a term may differ from their behaviour at the end of the term. Static segmentation cannot capture these transitions. Monitoring weekly or task-based profile changes may be more useful for providing early support in online learning.

Future Research

Future studies will assess whether the profile structure can be replicated across different online learning platforms. External validation will be carried out using learning management system records obtained from open and distance learning programmes. This will enable the distinction between platform-specific behaviours and more general online learning patterns.

Temporal profiling will be developed. The transition of students from one behavioural profile to another within weekly or monthly timeframes will be examined. This approach will enable the tracking of changing learning behaviour rather than relying on a single static label. The timing of interventions will also be assessed in conjunction with these transitions.

Profile interpretations will be validated by teachers and subject matter experts. Educators will be asked to evaluate the comprehensibility and usefulness of the clusters, as well as the potential risks of misinterpretation. Rather than assigning permanent labels to students in analytical dashboards, the focus will be on presenting behavioural indicators and trends in change.

The relationship between behavioural profiles and independent learning outcomes will be examined using more robust research designs. Measures such as learning gains, retention, task completion and subsequent assessment performance will be used, rather than just average achievement scores. The impact of interventions will be tested using experimental or quasi-experimental designs.

The explainability layer will be developed. Educators will be clearly shown which behavioural indicators account for a pupil appearing to fit a particular profile. These explanations will be used not to generate automated decisions, but to support teachers in reviewing the pupil's context more quickly.

Conclusion

This study has demonstrated that large-scale interaction logs generated on online learning platforms can be used to profile student behaviour independently of achievement labels. Analysis conducted on a final sample comprising approximately 37.7 million aggregated records and 34,961 students yielded four descriptive behavioural profiles. The profiles differed in terms of help usage, direct requests for answers, incorrect responses, persistence and problem-solving intensity. The Silhouette value of the final K-Means solution was 0.2381. This value indicates that the profiles provide a useful segmentation, but should not be interpreted as representing distinct and immutable student types.

The most significant finding of the study is that online student behaviour cannot be reduced to a single indicator of success or engagement. Students who make intensive use of support, demonstrate very high levels of engagement and exhibit low attendance patterns raise different support requirements. Consequently, the pedagogical contribution of learning analytics lies not so much in automatically labelling students, but in highlighting which behavioural patterns the teacher should examine more closely.

The results indicate that behavioural profiling in online and distance learning holds potential for early support, personalisation and instructional design. However, this potential must be addressed in conjunction with human oversight, contextual validation and ethical usage principles. Behavioural segments should not replace the teacher's professional judgement. The most appropriate use is as a decision-support layer that guides the teacher's attention in data-intensive online environments and generates better questions regarding student support.

Ethics and Data Usage Note

This study is based on the analysis of anonymised secondary learning data made available for research purposes as part of the EDM Cup 2023. No new data was collected from students for this study, and no directly identifiable personal information was processed. The profiles presented represent analytical patterns at group level and are not designed for automated, high-impact decisions targeting individual students.

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Monitoring and Translating RAG-Supported Educational Data Mining Literature into Practice for Educators

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Abstract

The Educational Data Mining (EDM) literature is generating an increasing body of evidence for educators in the areas of student achievement, early warning systems, learning analytics, online engagement and personalised learning. The rapid growth of the literature, the technical nature of the language used, and the time required to monitor research regularly make it difficult to utilise this information in teaching practice. This study develops and evaluates a literature-tracking approach based on Retrieval-Augmented Generation (RAG) to support educators in following the EDM literature in a more systematic and reliable manner. In the study, a corpus of 53 articles was classified into five methodological categories, and automatic summaries were generated. The alignment of the summaries with the source text was examined using multiple metrics. The system achieved an overall classification accuracy of 81.1 per cent. A comparison of RAG summaries with those generated by a general-purpose generative language model within the context of the 53-article evaluation corpus showed that RAG outputs yielded higher results in terms of lexical and semantic proximity to the source. Not all factual consistency metrics yielded consistent results. The findings suggest that the approach should be regarded not as an automation that replaces pedagogical decision-making, but as an information brokerage infrastructure that supports the processes of discovering current research, preliminary evaluation and source verification.

Keywords: Educational Data Mining, Open and Distance Learning, Research-Usage Gap, Teacher Professional Learning, Retrieval-Augmented Generation, Source Fidelity

Introduction

Data production in the field of education has increased significantly over the past twenty years. Learning management systems, online course platforms, digital assessment tools, intelligent teaching systems and student information systems generate detailed learning traces. Educational Data Mining (EDM) and learning analytics are two key research areas that have emerged to make sense of this data landscape. EDM research covers a broad range of problem areas, including academic achievement prediction, early identification of the risk of school dropout, analysis of student behaviour patterns, knowledge tracking, personalised learning, feedback and decision support (Romero & Ventura, 2020). The expansion of the field has led to greater methodological diversity. At the same time, research findings that could be useful for teachers and educators have also multiplied rapidly.

The pedagogical value of the EDM literature does not stem solely from the development of new algorithms. The research generates insights into which indicators may be meaningful within the teaching process. It also provides evidence regarding risk signals in student behaviour, the relationship between online interactions and learning outcomes, and potential interventions. Early warning models demonstrate how indicators such as learning management system activities, attendance records and assessment results can be interpreted. Research into learning monitoring and personalised learning also focuses on students' changing learning situations over time. Consequently, the EDM literature serves as an important source of information not only for data science researchers but also for teachers, instructional designers, academic advisers and distance learning practitioners.

The fact that a field of research is valuable in terms of application does not necessarily mean that the knowledge generated is regularly utilised by practitioners. One of the fundamental problems in educational research is the gap between research and practice. Teachers face barriers to utilising academic research, such as time constraints, access issues, methodological complexity and technical jargon (van Schaik et al., 2018). The lack of clarity regarding how findings can be translated into classroom practice is also a significant challenge. The evidence-informed practice approach does not aim to eliminate the teacher's professional judgement. It advocates for the evaluation of research findings in conjunction with context, experience and student needs (Nelson & Campbell, 2017). Recent studies also demonstrate that the use of research is a systemic process in which trust, relationships, skills and organisational structures all play a role (Hagevold et al., 2026).

It is also insufficient to define the use of research merely as 'the teacher applying research findings'. Mausethagen and colleagues (2025) note that studies on the use of research in education sometimes position the teaching

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profession as a passive recipient of information and that there is a need for more profession-sensitive conceptualisations. Taking this criticism into account, this study regards the educator not as the end-user of the system, but as a professional decision-maker who evaluates research evidence within their own context. Consequently, the tool developed aims to make the evidence more visible, searchable and verifiable, rather than presenting research evidence in the form of a 'prescription to be applied'.

This discussion becomes even more significant when EDM is concerned. The literature in this field is extensive in terms of both volume and methodological language. The same teaching problem can be addressed using different technical frameworks, such as logistic regression, decision trees, support vector machines, artificial neural networks, deep learning, Bayesian models or time series analysis. Educators do not need to know all the mathematical details of these methods. Instead, they require a reliable overview of what the study does, what data it uses, what findings it reaches, and under what conditions these findings can be interpreted. When technical complexity leads to the research being completely sidelined, the potential contribution of EDM to teaching practice remains limited.

Producing more research alone is not sufficient to bridge the gap between research and practice. Knowledge-mediation mechanisms that present research knowledge in a comprehensible, structured and verifiable manner are also required. Studies examining teachers' engagement with research emphasise the importance of accessible communication channels and research-rich professional environments. van Schaik et al. (2018) identify innovative communication networks and school–university partnerships as supportive conditions. Mills et al. (2025) demonstrate that workload and time pressures constitute persistent barriers to engagement with research. Kowalczuk-Walędziak and Ion (2024), meanwhile, highlight the need for collaboration between teachers, school leadership, universities and teacher training providers. These findings suggest that tools supporting educators must reduce the burden of selecting, organising and verifying information.

The context of open and distance education makes this requirement even more apparent. Online and blended learning environments are data-rich settings where learning behaviour can be observed through digital traces. Consequently, EDM, learning analytics and AI-based decision-support approaches form a natural intersection with distance education research. A systematic review of EDM studies in Turkey has shown that student achievement prediction and artificial neural networks feature prominently (Aydoğdu, 2020). More recent studies also address teachers' digital competences in distance education and their ability to relate educational research to technology as key issues (Jaya, 2026). Consequently, transforming the EDM literature into a knowledge resource accessible to educators is also meaningful in terms of professional learning in digital and distance education.

In recent years, large language models and generative artificial intelligence systems have begun to offer powerful tools for summarising and explaining research texts. Whilst these tools can make long and technical texts more readable in a short space of time, one of the fundamental risks in the transmission of academic knowledge is the generation of statements not found in the source. Particularly when teachers are making decisions regarding lesson design, student support or assessment based on a research summary, a fluent yet unsupported explanation can pose a significant problem. Factual inconsistency in abstractive summarisation has long been a recognised issue (Maynez et al., 2020). A recent systematic review examining RAG applications in education also emphasises that generation based on external information sources offers advantages in terms of accuracy and timeliness, but does not entirely eliminate the risk of hallucination (Li et al., 2025).

Retrieval-Augmented Generation (RAG) gains significance at this point as an approach aimed at linking the generation process to external and verifiable sources (Lewis et al., 2020a). The true value of a RAG system for educators lies not merely in its ability to generate better text, but in the fact that the generated information can be grounded in a specific source corpus and that the source text can be referenced when necessary. However, the 'RAG' label alone does not guarantee reliability. The summarisation model used, the retrieval strategy, the scope of the source text and the evaluation approach all determine the quality of the output. Therefore, a literature monitoring system developed for educators must both organise research and clearly evaluate the relationship between summaries and their sources.

This requirement forms the starting point of this study. The developed prototype classifies EDM articles into methodological categories and generates a short automatic summary for each article. The aim is to support educators in scanning the literature more easily. The technical architecture is not the aim of the study, but rather a means of making research information accessible. Consequently, the paper focuses on three functions: the structuring of the literature, the conversion of long academic texts into a concise and traceable format, and the verification of source fidelity.

An important limitation of the study must be stated at the outset. In the current experiment, no usability testing with teachers or in-class implementation was carried out. Changes in teaching outcomes were also not measured. Consequently, the study does not claim that the system enhances teacher performance or ensures that research findings are better applied in the classroom. The focus here is on the reliability of an information organisation

infrastructure that could support the initial stage of research utilisation. The study does not propose a solution that, on its own, bridges the gap between research and classroom practice. Instead, it examines a prototype information intermediary that could reduce the cost for teachers of accessing current research and subjecting it to preliminary evaluation.

Aim of the Study

The primary aim of this study is to develop an information brokerage approach that can support teachers and other education professionals in monitoring the rapidly expanding Educational Data Mining literature in a more organised, rapid and reliable manner. The study also assesses the technical reliability of this approach. The aim is not to automate the teacher's pedagogical decision-making. The objective is to reduce the burden of accessing, pre-screening, summarising and verifying sources of current research.

To this end, the system undertakes two key knowledge brokerage tasks. The first is to facilitate the educator's navigation of the literature by classifying EDM studies according to broad methodological families. Secondly, it converts long and technical academic texts into short summaries whilst making visible the extent to which these summaries align with the source text. Thus, classification and summarisation are treated not as technical success metrics in their own right, but as tools used to convey research information to the educator in an accessible and verifiable manner.

The research questions of the study are set out below.

AS1. To what extent can the developed system correctly classify the 53-article EDM corpus into five broad methodological categories that will facilitate educators' structured review of the literature?

AS2. How do the summaries generated by the system compare with the source text in terms of lexical, semantic and factual alignment?

AS3. When compared with summaries generated by a general-purpose generative language model for the same articles, in what respects does the RAG-supported approach differ in terms of source fidelity?

The answers to these questions are used not so much to demonstrate the system's direct usability within the classroom, but rather to assess whether a research monitoring and professional learning tool for educators possesses a reliable knowledge infrastructure.

Method

Research Design

The study is a design and evaluation study. No data was collected from human participants. An automated classification and summarisation pipeline was developed using a corpus of published academic articles. The system's outputs were subsequently evaluated against predefined labels and source fidelity criteria. Consequently, the study is not an empirical teacher intervention. It constitutes the technical validation of a knowledge-mediation prototype designed to support educators' access to research.

Although different system versions were tested during the development process, the article is based solely on the results of the final five-category version. Thus, the research questions were answered by examining the classification and source fidelity performance of the final workflow selected for educator-focused use.

Study Corpus

The evaluation corpus consists of 53 EDM articles. During the project phase, the articles were divided into five broad categories based on their methodological focus. The categories were defined as Review/Survey, Deep Learning/ANN, Statistical Methods, Classical Machine Learning and Time Series. The distribution is 21, 11, 10, 6 and 5 articles respectively. This structure has been treated as a high-level taxonomy, enabling the educator to see which methodological approach a study employs without needing to know all the technical details.

The categories indicate the research approach used, rather than pedagogical subject headings. This distinction is important. Two studies may address the same student performance prediction problem. One might use a statistical model, whilst the other might use deep learning. Therefore, the classification does not, on its own, convey the pedagogical significance of the study. It provides a filter that makes the methodological structure of the literature more manageable. The contextual content is understood through the abstract provided alongside the classification label.

The set of 53 articles was identified in the IEEE Xplore Digital Library, ScienceDirect (Elsevier), Scopus, Web of Science (WoS), SpringerLink, ACM Digital Library, SAGE Journals, Taylor & Francis Online, ERIC (Educational Resources Information Centre) and the Wiley Online Library, published between 2020 and 2025 and containing the terms "student dropout prediction", "university transition prediction", "graduation time prediction", "Artificial Neural Networks (ANN)", "Long Short- -Term Memory (LSTM)", "Recurrent Neural Networks (RNN)", "Educational Data Mining (EDM)", "Learning Analytics", "Academic Analytics", "Early Warning Systems", "Early Notification Systems", "Student retention", "Higher education data analysis", "Administrative data in education", "Student success modelling", "Machine learning for student outcomes", "Machine learning in higher education", "Deep learning for student outcomes", "Deep learning in higher education", "Institutional data mining", "Identification of at-risk students", "Predictive modelling in higher education" and "Machine learning for student outcomes". This set of 53 articles was not considered a statistically representative sample of the EDM field, but rather as the evaluation corpus for the developed prototype.

Literature Monitoring Workflow

The system combines four core functions to make academic articles easier for educators to search through. Firstly, the text is extracted from the PDF file. Subsequently, relevant text segments are made searchable. The article is assigned to a broad methodological category and a short abstract is generated. On pages where direct text extraction proves insufficient, optical character recognition (OCR) support is utilised.

A Sentence-BERT-based embedding model and the ChromaDB vector database were used to make the texts semantically searchable (Reimers & Gurevych, 2019). The methodological classification of articles was carried out via a hybrid framework that combines DeBERTa-based zero-shot classification with category-specific keyword signals (He et al., 2021). To prevent systematic reviews and survey studies from being forcibly assigned to technical categories, 'Review/Survey' was defined as a separate category.

A BART-based model was used in the summarisation stage (Lewis et al., 2020b). Long texts were processed in sections, and section summaries were combined. The aim of this stage was to enable the teacher or educator to gain a quick overview of the research problem, methodology and key findings before reading the entire article. As the generated summaries can reformulate the source text, source fidelity was also assessed.

Data Analysis and Validity

Classification performance was evaluated by comparing the system's predictions with the ground truth labels defined within the scope of the project. In addition to overall accuracy, precision, recall and F1 scores, as well as macro-F1, were reported to account for class imbalance.

The alignment of the summaries with the source was not based on a single metric. Lexical overlap was examined using ROUGE and trigram overlap. Semantic similarity was assessed using BERTScore. For signals related to factual consistency, natural language inference and question-answering-based faithfulness metrics were utilised (Lin, 2004; Zhang et al., 2020; Laban et al., 2022; Fabbri et al., 2022). This multi-faceted approach enables a distinction to be made between proximity to the source text and factual support.

The outputs of RAG and Gemini (3.1 Pro Model) were compared within the context of a 53-article evaluation corpus. For each metric, a paired Wilcoxon signed-rank test was applied. Multiple comparisons were corrected using the Holm method. The comparison was used to examine how the two summarisation approaches differed in terms of source fidelity.

A significant limitation in terms of validity is that the creation of the actual method labels was carried out by the researchers. Therefore, the classification results were treated as system performance relative to the provided labels . The results have not been generalised to the wider EDM population.

Findings

Methodological Classification of the EDM Literature

The final system correctly classified 43 out of 53 articles, achieving an overall accuracy of 81.1 per cent. The Macro-F1 score was 0.81 and the weighted-F1 score was 0.80. The highest recall was observed in the Time Series and Review/Survey categories. All studies in both classes were correctly identified. Recall stood at 50 per cent in the Classical Machine Learning class, 60 per cent in the Statistical Methods class and 72.7 per cent in the Deep Learning/ANN class.

These results indicate that the system provides a usable initial filter for distinguishing between the broad families of methods in the literature; however, the labels should not be regarded as the final expert decision. In particular,

whilst recall is 1.00 in the 'Review/Survey' class, precision is 0.70. In other words, the system identified all review articles but also incorrectly labelled some empirical studies as reviews. From an educator's perspective, this implies that the 'Review/Survey' filter may be useful for a quick scan of the literature, but this category should not be automatically accepted as definitive.

Table 1. Class-based classification performance of the final system.

Category	Articles (n)	Precision	Recall	F1
Time Series	5	1.00	1.00	1.00
Statistical Methods	10	0.86	0.60	0.71
Deep Learning / ANN	11	1.00	0.73	0.84
Classical Machine Learning	6	1.00	0.50	0.67
Review / Survey	21	0.70	1.00	0.82

Note: Overall accuracy = 81.1 per cent (43/53), macro-F1 = 0.81 and weighted-F1 = 0.80.

Alignment of Summaries with the Source

The average trigram overlap for the 53 RAG-based summaries is approximately 0.89. This value indicates that the summaries are highly traceable to the local word sequences in the source text. The absolute level of the ROUGE scores, however, is low. The main reason for this is that the short summaries are compared against the full source text. Consequently, the ROUGE scores should not be interpreted in the same way as in a classical 'gold reference summary' evaluation. The average BERTScore values indicated a higher level of semantic proximity between the source and the summaries.

A more critical finding is that different faithfulness metrics do not yield results in the same direction. The overall average of the original NLI scores remained low, and even in some summaries that clearly corresponded to the source, the NLI produced low scores. QA-faithfulness, on the other hand, exhibited greater variability depending on the category. This demonstrates that the reliability of academic summaries cannot be reduced to a single automated metric. In a system designed specifically for educators, enabling the user to navigate back from the summary sentence to the source passage—rather than merely displaying a 'confidence score'—would constitute a more robust design principle.

Table 2. Source alignment and source fidelity metrics for RAG-based summaries.

Metric	Mean	Standard Deviation	Minimum	Median	Maximum
ROUGE-1 F1	0.0425	0.0105	0.0219	0.0407	0.0728
ROUGE-2 F1	0.0398	0.0100	0.0209	0.0382	0.0699
ROUGE-L F1	0.0402	0.0099	0.0186	0.0390	0.0649
BERTScore F1	0.7414	0.0659	0.6358	0.7341	0.8874
NLI Score (Original)	0.1105	0.1317	0.0056	0.0523	0.7525
Trigram Overlap	0.8852	0.0467	0.7742	0.8966	0.9661
QA Faithfulness	0.3749	0.3820	0.0000	0.2262	1.0000

Note: Values are calculated based on 53 RAG-based summaries. ROUGE indicates the lexical overlap between the summaries and the full source text; BERTScore indicates semantic similarity; NLI and QA-faithfulness indicate factual support signals; whilst trigram overlap indicates overlap with local phrase sequences in the source text.

Comparison of RAG and Gemini Summaries

In the comparison within the context of a 53-article evaluation corpus, the RAG approach demonstrated higher averages than Gemini outputs in terms of ROUGE-1, ROUGE-2, ROUGE-L, BERTScore and trigram overlap. The most pronounced difference was observed in the trigram overlap metric. The RAG average was 0.8842, whilst the Gemini average was 0.1414. Following Holm correction, the difference is statistically significant at the $p <$ .001 level ( ). The average BERTScore was 0.7396 for RAG and 0.7153 for Gemini. This difference is also statistically significant (Holm-corrected $p < .001$).

In contrast, the original NLI score is 0.0982 for RAG and 0.1001 for Gemini, and there is no significant difference between the two systems ($p = .845$). Although the average QA-faithfulness score is 0.3629 for RAG and 0.2476 for Gemini, the difference did not reach statistical significance following Holm correction ($p = .139$). These results should not be generalised to suggest that 'RAG outperforms Gemini across all metrics'. A more accurate interpretation is that the RAG model preserves the lexical and semantic traces of the source text more strongly, whilst automatic factual consistency metrics reveal a more complex picture between the systems.

This distinction is important from the perspective of educator-focused use. In a literature-tracking tool, proximity to the source facilitates the user's ability to quickly verify a claim in the original text. However, high source overlap does not imply that the summary is pedagogically adequate or correctly interpreted. Therefore, the system should not be viewed as a tool that provides ready-made answers to teachers. A more appropriate role is that of a research navigation layer that highlights relevant articles, provides a brief preview and facilitates verification.

Table 3. Comparison of RAG and Gemini summaries within the context of a 53-article evaluation corpus.

Metric	RAG Mean	Gemini Mean	Average Difference	Holm p
ROUGE-1 F1	0.0426	0.0209	+0.0217	< 0.001
ROUGE-2 F1	0.0399	0.0089	+0.0310	< 0.001
ROUGE-L F1	0.0402	0.0165	+0.0237	< 0.001
BERTScore F1	0.7396	0.7153	+0.0243	< 0.001
Original NLI	0.0982	0.1001	-0.0019	,845
Trigram overlap	0.8842	0.1414	+0.7428	< 0.001
QA-faithfulness	0.3629	0.2476	+0.1153	,139

Note: p-values are those following Holm's multiple comparison correction for the seven primary measures.

Discussion and Conclusion

Making the EDM Literature Accessible to Educators

The most significant finding of this study is that the automated workflow developed for the EDM literature should be re-conceived not merely as a technical classification tool, but as a knowledge-mediation mechanism that brings research knowledge closer to educators. The problem educators face in accessing research is not merely a matter of being unable to find articles. The real difficulty lies in determining which studies are relevant within a limited timeframe, deciphering technical language, understanding findings without detaching them from their context, and assessing how meaningful they are for one's own classroom. From this perspective, automated classification and summarisation gain value not as a substitute for research, but as a layer that reduces the entry costs of engaging with research.

The literature on the use of research is consistent with this interpretation. van Schaik et al. (2018) demonstrated that the use of academic knowledge by teachers is shaped at multiple levels, such as the quality of research evidence, individual competencies, school organisation and communication channels. Nelson and Campbell (2017) also emphasise that evidence-informed practice is not merely a 'transfer of evidence', but that evidence must be considered in conjunction with professional context and judgement. A more recent systematic review by Hagevold and colleagues (2026) shows that trust, relationships, skills and sustainable structures all play a role in the use of research. Consequently, the contribution of an AI tool may lie not so much in automating the teacher's decision-making, but rather in enhancing the accessibility and traceability of research information.

This framework explains why the study focuses on information access and source fidelity rather than technical details. An educator may wish to follow current EDM research to increase student engagement. In this case, the first question will not typically concern the embedded model used. The educator will be more interested in knowing which student problem the study addresses, what type of data it uses, and what findings it reaches. The relevance of the findings to their own online course is also important. Furthermore, they will wish to see whether the summary is supported by the source. The prototype developed does not yet directly meet all these requirements. However, it organises the literature and provides a brief, traceable pre-reading guide.

The system's five-category taxonomy should be interpreted with care from a pedagogical perspective. The categories 'Time Series', 'Statistical Methods', 'Deep Learning/ANN', 'Classical Machine Learning' and 'Review/Survey' do not directly determine classroom strategy. However, they provide a quick contextual overview of the type of research. Review/Survey articles may be useful for identifying general trends. Time Series studies can provide a starting point for examining student behaviour that changes over time. Classical Machine Learning and Deep Learning studies, on the other hand, can help in understanding prediction and early warning applications. Thus, the method label acts as a filter that facilitates navigation within the literature.

Transition from Research to Practice: Discovery, Validation and Local Adaptation

A broader contribution of this study to teachers' professional learning is that it highlights the 'staying up to date' problem. Studies examining teachers' participation in research indicate that engagement with research is valuable for professional development, but that issues of time, workload and institutional support limit this engagement

(Mills et al., 2025). Kowalczuk-Walędziak and Ion (2024) demonstrate that different stakeholders play a collaborative role in examples of successful research engagement. These findings suggest that an AI-based literature monitoring tool cannot, on its own, create a 'research culture', but can be integrated into the infrastructure of well-designed professional learning processes.

A school, faculty or distance learning centre could add new EDM studies to the system at regular intervals. The system can categorise articles by methodology, generate short summaries and display source links. A teacher or academic team could select a few studies from this pool that are relevant to their own problem. The selected studies can be discussed during a professional learning session. In such a use case, artificial intelligence does not determine which application is correct. It enables team members to find relevant research more quickly and to discuss it on the basis of a shared starting point. This approach is consistent with the idea of integrating research knowledge with professional judgement.

This usage model is particularly meaningful in open, online and distance education. In distance learning environments, a wide range of digital traces can be generated, such as login frequency, content access, assessment history, forum participation, video viewing behaviour and progress over time. Consequently, the potential value of EDM findings is high for distance education practitioners. A systematic review within the Turkish context demonstrates that EDM studies have become a significant area of research (Aydoğdu, 2020). More recent studies, meanwhile, emphasise the importance of teachers' digital skills in distance education and the use of technology in educational research (Jaya, 2026). Access to current EDM research can also be regarded as a professional requirement for practitioners who manage digital learning environments and make teaching decisions.

There is a clear distinction between access to research knowledge and the application of that research in the classroom. A brief summary of an academic study does not provide a teacher with a direct teaching prescription. An EDM model may have demonstrated high predictive success using LMS data from a specific university and a specific course. The same indicator may not have the same meaning in another school. Similarly, a behavioural indicator found to be effective for early warning in one study may yield different results across different student groups. The fundamental principle of evidence-informed practice comes to the fore here. Research evidence must be evaluated in conjunction with the local context and professional judgement (Nelson & Campbell, 2017).

A three-stage approach is appropriate for the pedagogical use of the proposed information brokerage framework. The first stage is exploration. The educator reviews current research in terms of subject matter and methodology. The second stage is validation. Claims deemed significant in the automated summary are checked against the source text. The third stage is local adaptation. Findings are evaluated in terms of the student group, lesson structure, ethical considerations and the institution's data capacity. In its current form, the system is designed to support the exploration and validation stages. Local adaptation, however, requires the joint professional judgement of the teacher, the institution and, where necessary, researchers.

Table 4. Example information flow for the transformation of EDM research knowledge into educational practice.

Research area	Initial information the system can provide	The educator's possible next step	Points to note
Early warning / success prediction	Quickly identifying relevant studies and brief findings	Reviewing the current indicators in their own class. Discussing which pupils require additional support	Predictive indicators developed by other organisations should not be applied without being validated locally.
Data monitoring / personalised learning	Summarising current approaches to modelling student knowledge over time	Assessing what types of evidence can be used in feedback and learning pathway design	The model output is not the pedagogical decision itself. It must be interpreted in conjunction with teaching objectives.
Learning analytics / online engagement	Highlighting research on the relationship between digital interaction and learning outcomes	Reviewing participation patterns in class activities	The context, privacy and ethical implications of digital traces must be taken into account.
Review / Survey	Quick access to trends on a specific EDM topic	Selecting which applications to examine in more detail at a professional learning session	The scope of the compilation and the inclusion criteria must be checked.

Note: The table is a conceptual usage example based on research-use literature and system functions, rather than direct teacher user data from the current experiment.

Source Fidelity and the Reliable Use of Artificial Intelligence in Education

Findings on source fidelity are central to this usage logic. Within the context of a 53-article evaluation corpus, the RAG model demonstrated significantly higher trigram overlap compared to Gemini. This result indicates that the summaries remain closer to the phrasing patterns in the source text. From an educator's perspective, this may facilitate tracing the connection between the summary and the source. However, the result does not imply that RAG produces more accurate information in every instance. NLI scores did not distinguish between the two systems. The difference in QA-faithfulness was also not found to be statistically significant. Lexical proximity to the source text is a significant advantage. However, it does not, on its own, represent all dimensions of factual reliability.

This finding is consistent with the broader debate regarding the use of generative artificial intelligence in educational technologies. Recent educational research on RAG indicates that external information sources can offer advantages in terms of accuracy, recency and explainability. However, retrieval errors and hallucinations during the generation phase may persist (Li et al., 2025). Therefore, source attribution must be visible in a system provided to educators. Users should not be encouraged to rely solely on a single automated score. In the next version, each summary sentence from will be displayed alongside the source passage on which it is based. This will enable the educator to access the relevant section directly.

This approach is also important from the perspective of AI literacy. Educators must be able to critically evaluate the output of generative AI. Understanding the circumstances under which the system may not be reliable and referring back to the source are part of this process. Recent studies in the literature examine the effects of artificial intelligence on online learning, teachers' digital skills and the management of distance education from various perspectives (Jaya, 2026; Kesim, 2026; Nhan, 2025). The contribution of this study lies in its approach to artificial intelligence not as a teaching tool that interacts directly with the student, but as a professional knowledge tool that facilitates the educator's ability to keep abreast of current research.

Limitations

The findings of this study should be interpreted within the context of certain limitations. Firstly, the systematic search and sampling protocol used to construct the corpus of 53 articles is not fully documented in the project artefacts. Consequently, the corpus cannot be regarded as a sample representative of the entire EDM literature. In future work, the databases, date range, search strings, and inclusion and exclusion criteria will be clearly reported. The screening process will also be documented in detail.

Secondly, as the ground-truth labels were created by the researchers themselves, the performance is calculated relative to these labels, which achieved an 81.1 per cent classification accuracy. In future work, labelling will be carried out independently by at least two subject matter experts. Inter-rater agreement will be reported using a measure such as Cohen's kappa.

Thirdly, the BART model used was developed on general-purpose news summarisation data. The model has not been specifically adapted for scientific EDM texts. This may affect the format of the summaries and the selection of content.

Fourthly, this study did not measure usability, comprehensibility, trust, decision support or the impact on classroom practice with teacher or educator participants. Consequently, the proposed contribution for educators is based not on direct user impact but on the potential of the research monitoring infrastructure. In future work, this contribution will be evaluated with real users.

Future Research

In the next phase of the research, studies focusing on the educator's actual usage process will be conducted. Task-based usability studies will be carried out with teachers, teaching staff and distance learning specialists. Participants will be asked to identify the relevant EDM study for a specific teaching problem. They will also be asked to evaluate the system summary and verify the source. They will be expected to explain how the research finding could be used in their own contexts. Time savings, accuracy of understanding, perceived usefulness, trust and intention to use the research will be measured.

Secondly, a study will be carried out to develop an educator-focused interface. The interface will display the research problem, the data used, the key findings, the potential implications for teaching, the limitations and the source excerpt in separate sections. The section on potential implications for teaching will not be presented as a definitive recommendation. This section will be labelled as an interpretation or a possible application and will be supported by a link to the source.

Thirdly, a system for periodic literature monitoring will be developed. New EDM articles will be automatically indexed. Weekly or monthly summaries will be generated based on the educator's areas of interest. New findings will be linked to previous studies. This will create a more sustainable usage structure for educators keeping up with current research whilst under a heavy teaching workload .

Fourthly, a comparative study examining the transfer from research to practice will be carried out. Educators who use only traditional article access will be compared with those who use a system-supported literature monitoring environment. Their ability to interpret research findings correctly, identify contextual limitations and design feasible changes to their teaching will be assessed. In this way, the contribution of the knowledge brokering approach to the process of translating research into practice will be directly tested.

Conclusion

This study has evaluated a RAG-supported literature monitoring prototype through the problem of transforming the Educational Data Mining literature into a more accessible information source that can be monitored not only by researchers but also by teachers and education professionals. The final system classified 53 articles into five broad methodological categories with 81.1 per cent accuracy and a macro-F1 score of 0.81. This result demonstrates that automatic tagging can be used for initial screening and navigation within the literature; however, human review remains necessary, particularly due to false positives in the 'Review/Survey' class.

On the summarisation side, a comparison of RAG and Gemini within the context of the 53-article evaluation corpus showed that the RAG approach offered stronger traceability in terms of both lexical and semantic proximity to the source text. In contrast, NLI did not distinguish between the two systems. The difference in QA-faithfulness also did not reach statistical significance. Therefore, the study's conclusion is not that RAG has completely resolved the issue of hallucination. A more significant finding is that a source-constrained summarisation approach offers a structure capable of redirecting the user back to the source text.

Further evaluation is required for teachers to apply the findings from the EDM literature in the classroom. The context of the research, the student group, the type of data, ethical considerations and local teaching objectives must be addressed with professional judgement. The proposed system should not be positioned as an artificial intelligence that makes decisions in the teacher's place. The system should be regarded as a professional learning tool that facilitates finding research, pre-reading and verification. In the next phase, the infrastructure will be tested with actual educators. Its contribution to the processes of understanding, selecting and adapting research knowledge to local practice will be directly examined.

Ethics and Data Usage Note

This study is based on text processing and methodological classification of published academic articles. No personal data was collected from teachers, pupils or any other human participants. The numerical findings reported in the study were derived from outputs in project notebooks and assessment workbooks.

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Between Adoption and Resistance: Teachers' Experiences with Artificial Intelligence in the Classroom

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Abstract

Teachers react to artificial intelligence in schools by quickly adopting it, trying it briefly, or not using it at all. However, the factors underlying this variation remain insufficiently understood, as existing evidence is dominated by large-scale survey research that tends to treat adoption and resistance as discrete outcomes. This study addresses this gap by examining how teachers' perceptions of and engagement with AI are represented in the empirical literature. A Scopus search yielded 97 peer-reviewed articles, of which 56 open-access full texts were retained for analysis. Lexicon-based sentiment analysis was applied to the findings and discussion sections, complemented by word-frequency analysis and a qualitative close reading of a purposive subsample of 23 articles. The automated analysis classified the literature as predominantly positive (53 positive, 3 negative). In contrast, close reading revealed a considerably more balanced distribution (10 positive, 7 neutral-cautious, 6 negative-skeptical). Lexicon-based tools often miss the cautious and critical tone in academic writing. Thematic analysis found three positions: adoption, experimentation followed by withdrawal, and non-engagement. These are influenced by practical constraints, professional routines, and teachers' views on effective teaching. Concerns about AI anxiety, trust, professional autonomy, and academic integrity are important but not often measured frequently. The study suggests that adopting and resisting AI should be seen as part of the same process, not as opposite choices. It discusses the impact on teacher training and methods for analyzing literature with AI.

Keywords: Artificial intelligence, teacher perceptions, technology adoption, resistance, sentiment analysis, thematic analysis

Introduction

The rapid change of generative artificial intelligence tools into classrooms since late 2022 has produced responses among teachers. While some educators have integrated AI tools directly and immediately into lesson planning and feedback, others have experimented cautiously before withdrawing, and still others have avoided engagement altogether. Research has shown different teaching patterns, but it's not clear why teachers choose one over another, especially in studies beyond surveys.

The literature often views adoption and resistance as separate categories instead of related points on a continuum. Additionally, most studies use self-reported surveys or small interviews from one setting, raising questions about their generalizability to broader research.

This study addresses both limitations by treating adoption and resistance as parts of the same underlying process shaped by practical considerations, professional routines, and teachers' own conceptions of effective teaching and by applying computational sentiment and thematic analysis to a systematically retrieved corpus of published literature, rather than collecting new primary data. The remainder of this paper proceeds as follows: Section 2 reviews the existing literature on teacher AI adoption and resistance; Section 3 describes the search, retrieval, and analytical procedure; Section 4 presents the findings; and Section 5 discusses their theoretical and practical implications.

Artificial Intelligence and Generative AI are quickly being used in schools, changing how teaching is done, how students are assessed, and what teachers do. Studies look at how teachers use these technologies by using models like the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Technological Pedagogical Content Knowledge.

In TAM, Perceived Usefulness and Perceived Ease of Use are key factors in teachers' decisions to use AI tools. UTAUT2 adds factors like performance expectancy, effort expectancy, social influence, facilitating conditions, and technology anxiety. The AI-TPACK framework goes further, focusing on pedagogical, content, and ethical competence, highlighting the need for specialized knowledge in teaching, subject matter, and ethics for effective AI integration (Celik, 2023b; Mishra & Koehler, 2006). While large-scale quantitative surveys generally report positive overall attitudes and high perceived usefulness of AI among educators (Al Darayseh, 2025), qualitative close readings and sensemaking analyses reveal a far more complex reality. Large-scale metrics often mask

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underlying anxieties, institutional ambiguities, and professional tensions, treating adoption as a binary outcome rather than an ongoing, non-linear process of professional sensemaking (Nie et al., 2025) Research on how teachers use AI tools shows three different ways they interact with these tools, ranging from fully adopting them to resisting them.

1. Active and Collaborative Adoption: Teachers see AI as a helpful tool for creating lesson plans, customizing learning materials, giving feedback, and handling administrative work (Hamamra et al., 2025). Skilled teachers adjust AI suggestions to fit their unique classrooms and learning goals instead of accepting them without question (Choi et al., 2026).
2. Experimentation Followed by Withdrawal: Many teachers start trying new teaching methods because they are curious or because their school expects them to, but then they stop or don't continue using these methods in their classes (Choi et al., 2026). This withdrawal often happens because of the "productivity paradox." During this phase, checking and fixing AI outputs that are wrong, biased, or culturally inappropriate takes more effort and time than using old methods. As a result, teachers often skip AI outputs or go back to using traditional methods.
3. Non-Engagement, Active Resistance, and Bypassing: Some teachers decide not to use AI because they worry it might make students less skilled at thinking, reduce human interaction, lack proper rules, or go against true intellectual growth (Choi et al., 2026).

Analyzing these interaction dynamics using CORDTRA mapping, Choi et al. (2026) identified seven ways teachers interact when creating lessons: direct adoption, elaborated adoption, initial rejection, revised adoption, follow-up guided use, complex interaction, *and* bypassing AI. Similarly, Ellis et al. (2025) found five types of teacher involvement with GenAI: avoiding, being aware, creating, teaching, and fully integrating it. There is a clear positive link between having hands-on experience, understanding AI, and having a good view of technology (Prilop et al., 2025). Teachers who feel more confident using AI are less worried about technology, while those with little experience often feel more anxious or doubtful (Parviz & Arthur, 2025). The main obstacles to successfully integrating sustainable practices are unclear rules, poor digital systems, limited time, and not enough specialized training (Hamamra et al., 2025; Kalim et al., 2026). The empirical literature highlights several critical psychological and ethical dimensions that moderate teacher engagement:

AI Anxiety and Identity Tensions: AI anxiety is the worry about fast technological changes, fear of mistakes in AI teaching, concerns about losing jobs, and feeling that professional status is at risk (Parviz & Arthur, 2025).

System Opacity and Trust Deficits: AI models are often seen as "black boxes," which means their inner workings are not clear. This, along with the potential for bias, incorrect information, and unexpected results, makes people less trusting of them (Nie et al., 2025).

Loss of Human Agency and Depersonalization: Teachers are worried that using too much AI in education might make learning less personal, weaken the important bond between teachers and students, and reduce empathy and human interaction in the classroom (Hamamra et al., 2025).

Academic Integrity and Assessment Redesign: Main worries in all fields include students relying too much on AI, using AI to create text without permission, and automated plagiarism checkers not being reliable (Kalim et al., 2026). In response, teachers are increasingly redesigning assessments by shifting away from traditional take-home essays toward process-based, reflective, staged, or monitored in-class evaluations (Kalim et al., 2026). Automated sentiment analysis in academic literature often wrongly labels careful or critical discussions as positive, missing the detailed risks and systemic issues noted in qualitative research. To connect initial acceptance with successful teaching, schools need to go beyond basic technical training. Lasting integration involves setting clear ethical guidelines, supporting teacher independence, and developing strong AI-TPACK skills through practical, subject-specific professional development. (Prilop et al., 2025)

Methodology

A systematic search was conducted in Scopus, refined to articles addressing teacher experience with AI adoption and resistance (n = 97), of which 65 were open access. After retrieval, de-duplication, and filtering of non-article files, 56 full-text articles were included in the sentiment and lexical analysis (Figure 1).

Table 1. Search Strategy

Component	Terms / Value
Database	Scopus
Population terms	teacher*, educator*, instructor*

Technology terms	"artificial intelligence", "generative AI", "ChatGPT"
Attitude/behavior terms	adoption, resistance, acceptance, perception*, attitude*
Context terms	"teacher experience*", "teaching experience*"
Publication period	PUBYEAR > 2019
Language	English
Document type	Article, Conference paper
Subject area	Social Sciences (SOCI)

TITLE-ABS-KEY (("teacher" OR "educator*" OR "instructor*") AND ("artificial intelligence" OR "generative AI" OR "ChatGPT") AND ("adoption" OR "resistance" OR "acceptance" OR "perception*" OR "attitude*") AND ("teacher experience*" OR "teaching experience*")) AND PUBYEAR > 2019 AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (SUBJAREA , "SOCI"))*

Table 2. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Empirical studies (K-12 or higher education) • Published 2020-present • English language • Reports teacher-level data on AI adoption/resistance	Purely theoretical/conceptual papers without empirical data • Studies focused solely on student populations • Non-English full text • Duplicate or preprint versions of included studies

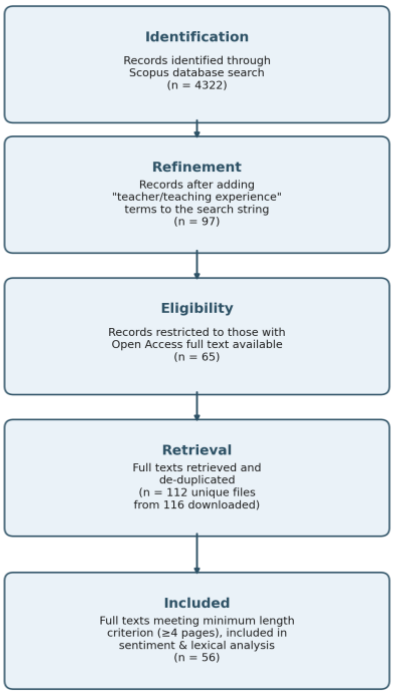


Figure 1. PRISMA-style flow diagram of article identification and inclusion.

Results

Sentiment analysis was conducted at three levels of analytical depth. At the abstract level (n = 97), automated lexicon-based analysis (VADER) classified 96.9% of articles as positive and 3.1% as negative, with no neutral classifications. At the full-text findings/discussion level (n = 56), the same tool yielded a nearly identical distribution (94.6% positive, 5.4% negative). However, when a subsample of 23 articles with substantial excerptable content was examined through close reading, the distribution shifted markedly: 43.5% positive, 30.4% neutral/cautious, and 26.1% negative.

The study found that using word-based sentiment analysis often misses important, careful, or opposing ideas in academic writing. This happens because these ideas are usually hidden in words that seem positive, even when the overall argument shows worry or doubt. The sentiment classification table has shown above as Figure 2.

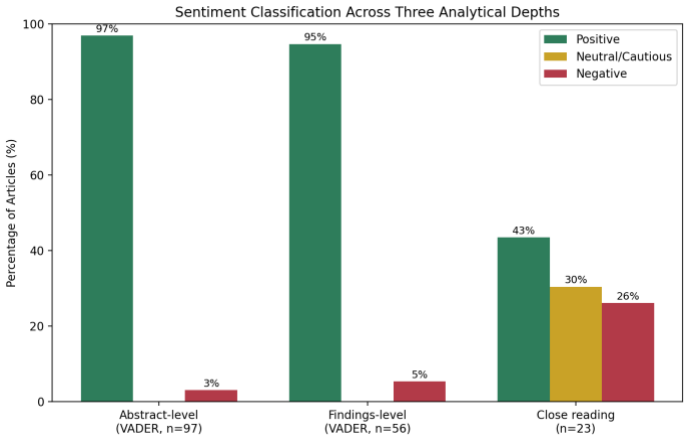


Figure 2. Sentiment classification across three analytical depths.

The study found that articles could be categorized into three behavioral patterns instead of just adoption or resistance:

- *Immediate/full adoption:* Faculty directly and fully integrate AI outputs into lesson planning and show strong intention to continue using them.

- *Experimentation followed by withdrawal:* Teachers try AI tools but decide not to use the outputs, or they remove AI-enabled tasks from assignments to avoid cheating.

- *Non-engagement/avoidance:* A group called “GenAI Observers” who use AI very little or not at all.

This shows that adoption and resistance can happen at the same time and depend on the context, supporting the study’s main theory. Example teacher voices are shown below.

Table 3. Representative Teacher Voices

Category	Representative Quote	Source
Adoption (Positive)	"AI, because it helps me create materials in minutes instead of hours."	Mendekenova et al., 2025
Adoption (Positive)	"ChatGPT is my best colleague in teaching."	Mendekenova et al., 2025
Adoption (Positive)	"AI enables me to tailor instruction to each student’s unique needs."	Hamamra et al., 2025
Resistance (Negative)	"They use ChatGPT not as an assistant but as the brain, which is wrong."	EFL Teachers’ Experiences, 2026
Resistance (Negative)	AI risks becoming a "sausage factory," churning out generic texts and lesson plans.	Prilop et al., 2025
Resistance (Negative)	"No one’s learning anything — it’s just a totally useless, futile exercise."	Ellis et al., 2025
Withdrawal / Hesitancy (Mixed)	"AI sometimes reduces the direct communication between me and my students."	Hamamra et al., 2025
Withdrawal / Hesitancy (Mixed)	"I don’t know if I’m assessing the student or the AI."	EFL Teachers’ Experiences, 2026
Withdrawal / Hesitancy (Mixed)	"I’ve been hesitant to use it … I don’t want it to learn from me."	Ellis et al., 2025

The analysis of word frequency across the corpus mainly focused on common educational words and technology terms. However, a detailed reading showed that some important themes were not well-represented in the vocabulary, such as anxiety related to AI, trust in institutions, and academic honesty, even though these were key issues in several studies included. Across the full text corpus, dominant terms are shown in Figure 3.

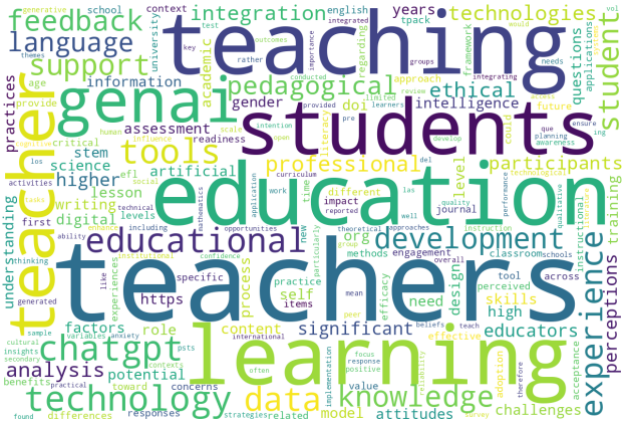


Figure 3. Word cloud of dominant terms across the full-text corpus.

Methodological Discrepancy Between Automated Sentiment Analysis and Qualitative Close Reading

A key finding of this study is the big difference between results from automated sentiment analysis and those from detailed reading. Automated analysis said 96.9% of abstracts and 94.6% of full-text sections were positive, suggesting widespread excitement and easy acceptance of AI in education. However, detailed reading of a specific sample showed a different view (n = 23) revealed a significantly more balanced and nuanced landscape: 43.5% positive (n = 10), 30.4% neutral-cautious (n = 7), and 26.1% negative-skeptical (n = 6). This methodological discrepancy highlights the inherent limitations of lexicon-based computational tools (e.g., VADER, Asent) in parsing academic prose. Lexicon tools frequently misinterpret scholarly hedging, conditional statements, and critical framing (Prilop et al., 2025). When an author mentions that GenAI has potential benefits but also needs a lot of thinking to check its results and can affect students' independence, automated tools pick up words like "promising" or "benefits" as positive. This hides the important warnings that come after. So, using only automated text analysis can lead to an overly positive view in educational technology writing, making teachers' real worries and challenges hard to see (Nie et al., 2025; Zawacki-Richter et al., 2019).

Beyond Binary Acceptance: Different Levels of Teacher Involvement

The study's qualitative findings show that teachers' interactions with AI are not simple, clear-cut decisions, but rather flexible positions in an ongoing process of understanding (Nie et al., 2025). The empirical literature reveals three primary engagement positions:

Active and Collaborative Adoption: Teachers in this group use GenAI as a teaching assistant to simplify lesson planning, create various teaching materials, write feedback, and reduce paperwork (Hamamra et al., 2025). Good teachers don't just take AI suggestions without considering them. They keep making these suggestions better to fit their own subjects (Choi et al., 2026).

Experimentation Followed by Withdrawal: This group includes teachers who start trying something new out of curiosity or because they are required to, but then stop or take a break from using it actively. This is often missed in surveys that focus on numbers (Choi et al., 2026). These educators experience a "productivity paradox," where guiding, reviewing, and fixing incorrect or made-up AI results takes more time and mental effort than old-fashioned preparation methods (Kalim et al., 2026). They often avoid using AI tools and stick to traditional, non-digital methods.

Non-Engagement and Principled Avoidance: This choice is a thoughtful decision not to use AI in teaching. It's not about being afraid of technology but about valuing students' critical thinking, maintaining human relationships, and keeping control over teaching methods (Ellis et al., 2025).

Factors Influencing the Acceptance and Rejection of Ideas

The way teachers are assigned to different engagement roles is influenced by long-standing psychological, teaching, and ethical considerations. AI Anxiety and Lack of Trust: The unclear workings of algorithms, along with worries about technical problems, losing jobs, and losing professional standing, cause significant AI anxiety among teachers (Parviz & Arthur, 2025).

Pedagogical Beliefs and Professional Identity: Teachers who believe in the traditional way of teaching see AI as something that disrupts their lesson plans and reduces their control in the classroom (Choi et al., 2023).

Academic Integrity and Assessment Issues: There are worries about students relying too much on unauthorized help, plagiarism, and the unreliability of AI tools used to detect cheating, leading to serious problems in evaluating students (Derakhshan et al., 2026; Kalim et al., 2026).

This study shows that adopting and resisting AI in education are not completely opposite but are connected parts of how professionals understand and adapt to new technology. The findings suggest that traditional adoption models, like TAM or UTAUT, don't fully work for complex technologies like GenAI. To really understand how to integrate GenAI, we need to look at more than just how useful or easy it is to use. We should also consider ethical responsibility, trust in the system, professional independence, and AI-TPACK (AI-supported Technological Pedagogical Content Knowledge) as key ideas (Celik, 2023; Derakhshan et al., 2026). The research provides clear advice for school leaders, curriculum creators, and policy makers:

Creating Effective AI-TPACK and Ethical Skills: Professional development should move from basic tool shows to practical, subject-specific workshops. Training needs to emphasize creating effective prompts, carefully checking AI results, aligning with teaching methods, and making ethical choices (Prilop et al., 2025).

Creating Clear Rules for AI Use: Institutions need to make clear, adaptable, and ethical guidelines for teachers and students to remove the confusion about AI use (AlZubaid, 2026; Hamamra et al., 2025).

Respecting Teachers' Choices: Schools should not force teachers to use AI. Teachers should have the freedom to decide when to use, change, or avoid AI tools if they don't help with learning goals (Choi et al., 2026).

Implications and Future Research Directions

This study warns against using only automated sentiment analysis or text-mining tools in literature reviews and meta-analyses. Future reviews using AI should use a mix of methods, combining computer text analysis with detailed qualitative readings to accurately capture academic details. Future research should focus on:

- Conducting longitudinal qualitative and mixed-methods studies to track how teachers' interaction positions evolve over time as AI tools mature.
- Empirically measuring the cognitive load and verification effort associated with checking AI outputs and its impact on teacher burnout.
- Investigating cross-disciplinary differences (e.g., STEM vs. Humanities) in how educators construct trust in AI applications.

Conclusions

This study shows that adopting and resisting AI in education are not completely opposite but are connected parts of how professionals understand and adapt to new technology. The findings suggest that traditional adoption models, like TAM or UTAUT, don't fully work for complex technologies like GenAI. To really understand how to integrate GenAI, we need to look at more than just how useful or easy it is to use. We should also consider ethical responsibility, trust in the system, professional independence, and AI-TPACK (AI-supported Technological Pedagogical Content Knowledge) as key ideas (Celik, 2023; Derakhshan et al., 2026). The research provides clear advice for school leaders, curriculum creators, and policy makers:

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The Effect of Content-Grounded SpeakToPDF Educational Chatbot on Pre-Service Teachers' Generative Artificial Intelligence Attitudes and Online Self-Regulation Skills

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Abstract

This study examined changes in pre-service teachers' generative artificial intelligence (GenAI) attitudes and online self-regulation following use of SpeakToPDF, a course-grounded chatbot based on Retrieval-Augmented Generation (RAG). A single-group pre-test/post-test design involved 84 matched participants in an undergraduate course at a Turkish state university. The 12-week measurement window included 11 weeks of chatbot availability. Data from the Generative Artificial Intelligence Attitude Scale and Online Self-Regulation Questionnaire were analysed using paired-samples t-tests and correlations. Neither total score changed significantly, and all reported change-effect confidence intervals included zero. GenAI attitudes were positively associated with self-regulation at both measurements; the difference between these correlations was not significant. These findings do not establish either a beneficial effect or an absence of effect. They suggest that access to course-grounded AI alone may be insufficient to produce measurable change and support further investigation of explicit metacognitive scaffolding within chatbot-supported learning.

Keywords: Educational chatbot, retrieval-augmented generation, pre-service teachers, GenAI attitudes, online self-regulation.

Introduction

Generative artificial intelligence has expanded opportunities for personalised support and immediate feedback in higher education (Crompton & Burke, 2023). In teacher education, its value depends on how future teachers engage with AI and incorporate it into their learning. Attitudes towards GenAI and the ability to regulate online learning are therefore relevant outcomes when evaluating educational chatbot use.

Self-regulation involves goal setting, strategy use, and reflection (Zimmerman, 2002). Educational chatbots may support these processes, but their contribution depends on instructional design (Guan et al., 2025). Xu et al. (2025) emphasise the importance of metacognitive support and identify risks when learners delegate monitoring and reflection to AI. Attitudes and self-regulation should consequently be examined together rather than assuming that access to AI improves both.

RAG systems retrieve relevant material before generating responses, allowing a chatbot to connect its answers to course resources. SpeakToPDF combines this approach with Google's Gemini model and is accessed through the institutional learning management system (LMS). This study investigates its use in an authentic teacher-education course, asking whether GenAI attitudes and online self-regulation change over the implementation period and whether the relationship between the two constructs changes. The focus is on measured learning-related dispositions rather than on testing the factual accuracy of chatbot responses.

Methodology

Design and participants

A single-group pre-test/post-test design was used (Shadish et al., 2002). Participants attended the Open and Distance Learning course at Atatürk University Kazım Karabekir Faculty of Education in spring 2024–2025. Of 93 pre-test and 98 post-test respondents, 84 could be matched using student IDs and names; nine pre-test-only and 14 post-test-only respondents were excluded. The matched sample included 65 women (77.4%) and 19 men (22.6%); 52 studied primary school teaching and 32 social studies teaching. Mean age was 20.35 years (SD = 2.45), and 64 participants (76.2%) reported prior AI experience. Participation was voluntary, with written informed consent obtained before data collection.

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Chatbot and implementation

SpeakToPDF segments and vectorises instructor-uploaded PDF materials and retrieves relevant passages as context for Gemini. Students access weekly materials and the chatbot through the LMS. They can request explanations, summaries, answers, and topic reviews, and continue with follow-up questions. Responses display the source PDF and page number; the interface also provides a warning for questions outside the available course material. These features are intended to focus interaction on course content and support source verification.

The measurement window extended from the pre-test in Week 1 to the post-test in Week 12. Chatbot availability covered 11 weeks, excluding the Week 7 midterm examination. Students received initial training on access, use, limitations, and verification of responses. Course materials were added weekly, and students could use the chatbot during and outside class. Use was optional; individual interaction frequency was not systematically logged.

Measures and analysis

GenAI attitudes were measured with the 13-item, five-point Generative Artificial Intelligence Attitude Scale (GAIAS; Marengo et al., 2025), comprising eight positive- and five negative-attitude items. Negative items were reversed for the total score. Pre-test/post-test Cronbach's alpha values were .80/.80 for the total, .90/.94 for positive attitudes, and .55/.78 for negative attitudes. Given the low pre-test reliability of the negative subscale, its change analysis was treated as supplementary.

Online self-regulation was measured with the full 24-item, five-point Online Self-Regulation Questionnaire (OSLQ; Barnard et al., 2009), using the Turkish adaptation by Kilis and Yıldırım (2018). Its six dimensions cover goal setting, environment structuring, task strategies, time management, help seeking, and self-evaluation. Total-scale alpha was .90/.92; subscale coefficients ranged from .63 to .83 at pre-test and .65 to .84 at post-test.

Analyses used paired-samples t-tests, Cohen's d with 95% confidence intervals, and Pearson correlations in IBM SPSS 27. The change in the attitude–self-regulation correlation was assessed using Steiger's (1980) test for non-overlapping dependent correlations. A sensitivity analysis indicated a minimum detectable effect of approximately d = 0.31 at N = 84 and power .80; non-significant tests were therefore not treated as proof of no effect.

Results

Neither GAIAS nor OSLQ total scores changed significantly (Table 1). Mean differences were small, and all effect-size confidence intervals included zero. The largest positive subscale change was in help seeking (d = 0.18, p = .098), while self-evaluation showed a small non-significant decrease (d = −0.09). The negative-attitude result should be interpreted cautiously because of its low pre-test reliability.

Table 1. Pre-test and post-test comparisons (N = 84)

Measure	Pre-test M (SD)	Post-test M (SD)	t	p	d [95% CI]
Positive Attitudes	3.83 (0.70)	3.92 (0.79)	1.15	.252	0.13 [−0.09, 0.34]
Negative Attitudes	3.35 (0.60)	3.29 (0.74)	−0.77	.442	−0.08 [−0.30, 0.13]
GAIAS total	3.38 (0.46)	3.46 (0.61)	1.40	.164	0.15 [−0.07, 0.37]
Goal Setting	3.26 (0.72)	3.35 (0.76)	0.99	.327	0.11 [−0.11, 0.33]
Environment Structuring	3.95 (0.84)	3.99 (0.77)	0.49	.628	0.05 [−0.16, 0.27]
Task Strategies	3.40 (0.74)	3.50 (0.73)	0.92	.360	0.10 [−0.12, 0.32]
Time Management	2.96 (0.76)	3.11 (0.93)	1.41	.161	0.15 [−0.06, 0.37]
Help Seeking	3.10 (0.72)	3.24 (0.74)	1.67	.098	0.18 [−0.04, 0.40]
Self-Evaluation	3.30 (0.86)	3.21 (0.83)	−0.81	.423	−0.09 [−0.31, 0.13]
OSLQ total	3.34 (0.57)	3.41 (0.61)	1.00	.320	0.11 [−0.11, 0.33]

Note. All tests have 83 degrees of freedom. Negative-attitude means are raw scores; items were reversed when calculating the GAIAS total. CI = confidence interval. Negative-attitude analyses are supplementary.

GenAI attitudes were positively correlated with OSLQ total scores at both measurements (Table 2). The difference between correlations was not significant, $Z_2^* = 0.49$, p = .623. Environment structuring showed the strongest post-test association with attitudes (r = .382), whereas time management was not significantly associated at either measurement.

Table 2. Correlations between GAIAS total and OSLQ scores

OSLQ measure	Pre-test r	p	Post-test r	p
OSLQ Total	.405	.001	.345	.001
Goal Setting	.374	.001	.244	.025
Environment Structuring	.370	.001	.382	.001
Task Strategies	.321	.003	.303	.005
Time Management	.194	.076	.106	.336
Help Seeking	.238	.029	.277	.011
Self-Evaluation	.250	.022	.300	.006

Note. N = 84. Pearson correlations. The comparison of total-score correlations uses Steiger's test for dependent correlations.

Discussion

The study found no statistically significant change in GenAI attitudes or online self-regulation after course-integrated SpeakToPDF use. Positive associations between the constructs were observed at both measurements, and the difference between correlations was not significant. The results therefore describe limited measured change within this cohort; they do not establish that the chatbot had no effect, nor that it caused the observed stability.

Several explanations merit further investigation. Relatively favourable initial attitudes may have reduced room for improvement, and course-grounded assistance may influence specific study activities more directly than broad attitudes or self-regulation. Because participation in chatbot use was optional and interaction logs were unavailable, differences in exposure could also have obscured changes among more active users. These explanations remain tentative under the present design.

The small upward tendency in help seeking is compatible with the chatbot's role as an accessible consultation channel. Conversely, the slight decline in self-evaluation raises a question about whether learners continue to monitor their own understanding when assistance is readily available. Neither pattern was statistically significant, so neither should be interpreted as a demonstrated benefit or harm. Both suggest useful targets for subsequent studies of metacognitive support (Xu et al., 2025).

For practice, instructors can accompany chatbot access with tasks that require students to explain concepts in their own words, compare answers with the original PDF, and reflect on what remains unclear. Designers can make source verification and self-reflection part of the interaction process. Such recommendations extend the study's pedagogical interpretation; their effectiveness was not directly tested here.

Limitations and future research

The absence of a comparison group leaves maturation, history, testing, and novelty effects uncontrolled. A single-institution sample limits generalisability, while the sample size provides limited sensitivity to small effects. Low reliability of the negative-attitude pre-test and some OSLQ subscales further warrants caution. Self-report measures and missing interaction logs constrain interpretation of actual learning behaviour and dose–response relationships. Future studies should combine controlled designs, usage logs, and behavioural outcomes, and compare versions with and without explicit metacognitive scaffolding across institutions.

Conclusions

Among 84 pre-service teachers, 11 weeks of access to an LMS-integrated RAG chatbot did not yield statistically significant changes in GenAI attitudes or online self-regulation. Their positive association remained detectable at both measurements. The findings support cautious evaluation of course-grounded AI and further testing of pedagogical designs that combine assistance with deliberate learner reflection, rather than assuming that tool access alone produces measurable development.

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Micro-Credential as an Architect of the Educator's Professional Brand: From a «Diffuse Brand» to Resilient Identity in the Age of Uncertainty

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Abstract

This paper theorises and empirically validates the micro-credential «Image Communications and Brand Management» as an instrument for forming the professional brand of future educators under conditions of digital transformation and societal uncertainty. Building on the concept of the «diffuse brand» of the educator - an integrated professional image combining habitual identity, digital presence and institutional ambassadorship - the paper shows how a purpose-designed micro-credential architecture operationalises lifelong learning competencies. A baseline survey of bachelor's-level students at Kryvyi Rih State Pedagogical University revealed significant gaps in digital identity formation: only 26.7% of respondents reported confident self-assessment of their professional competencies, while digital identity emerged as the least formed component. A seven-module micro-credential structure, an interactive modelling methodology (role-play, AI-assisted brand-book creation) and portfolio-based assessment are presented. Findings are situated within the ICETOL 2026 theme of building resilience through micro-credentials and lifelong learning, arguing that the educator's professional brand is a core resilience competency rather than a cosmetic add-on.

Keywords: micro-credentials, professional brand of the educator, diffuse brand, digital identity, lifelong learning, professional resilience, artificial intelligence in education

Introduction

The accelerating digitalisation of contemporary society is reshaping the professional role of the educator at its foundations. The teacher is no longer only a transmitter of disciplinary knowledge but a public intellectual, facilitator and institutional ambassador whose professional reputation is formed across a multi-platform digital ecosystem: social networks, educational platforms, online courses and professional communities. Personal branding - the strategic self-presentation of the professional self, long analysed in organisational communication (Lair et al., 2005) - has entered higher education research: personal branding proves to be a critical factor in academic career advancement, particularly for women (Heriberta et al., 2024), and the way teaching staff are represented on institutional web resources significantly predicts overall university brand equity and prospective students' behavioural intentions (Irshad, 2026).

Yet teacher education programmes remain oriented primarily towards subject and methodological competencies, leaving self-presentation, strategic communication and professional reputation management conspicuously underdeveloped (Orfali et al., 2024). In Ukraine this gap is intensified by wartime conditions: teachers have become prominent carriers of societal resilience, civic values and information integrity in the face of active disinformation campaigns, and digital identity has turned from a desirable asset into a professional necessity.

This paper addresses the research question: how can a micro-credential - a short-cycle, modular, certified learning unit aligned with the European Council Recommendation on micro-credentials (Council of the European Union, 2022) - systematically introduce professional branding competencies into teacher education? We present the design and pilot evaluation of the micro-credential "Image Communications and Brand Management", developed at Kryvyi Rih State Pedagogical University (KSPU), as an evidence-based response to the gap between the importance of professional brand formation and its neglect in current curricula.

Theoretical Framework

The educator's «diffuse brand». Contemporary scholarship treats teacher professional identity as dynamic, relational and digitally mediated rather than static (Yaremchuk et al., 2024; Orfali et al., 2024). Systematic review evidence further shows that AI-driven personalised learning environments raise the demands placed on educators' professional roles and visibility (Hardaker & Glenn, 2025). In Ukrainian scholarship this discussion is only beginning, and systematic methodologies for integrating personal branding tools into teacher preparation remain scarce (Savchenko & Safian, 2026). The present study addresses this lacuna.

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We propose the concept of the "diffuse brand" of the educator: a dynamic, integrated professional representation in which the boundaries between professional competence and personal authenticity become maximally transparent. The diffuse brand comprises three interdependent components: (a) a habitual component - the educator's visual culture, professional style and physical presence as elements of professional communication; (b) digital identity - mastery of digital communication instruments, educational content creation and online reputation management; and (c) an institutional component - conscious identification with the brand of the educational institution, the educator acting as its ambassador. The defining property is not the excellence of any single component but the coherence and authenticity of their integration, which produces "pedagogical trust capital": a reputation that accumulates gradually, requires systematic maintenance and constitutes the educator's most durable professional asset.

Micro-credentials as lifelong learning architecture.

The Council of the European Union (2022) defines a micro-credential as the record of learning outcomes acquired in a short learning experience, assessed and certified in ECTS-linked, portable and stackable digital form. International experience shows micro-credentials to be an effective vehicle for the continuing professional development of teachers precisely because their short-cycle format allows new competency domains to be integrated without displacing core disciplinary content (Myroshnichenko, 2024). Article 34 of the Law of Ukraine «On Education» (2017) similarly treats micro-credentials as components of educational programmes aimed at the acquisition of applied competencies. The micro-credential is therefore the optimal architectural form for introducing professional branding competencies into teacher education.

Methodology

The study, conducted at KSPU, combined a needs-assessment survey and the design and pilot of the micro-credential. Survey. A structured questionnaire was administered to bachelor's-level pre-service teachers within the framework of the micro-credential pilot. It measured the baseline formation of four diffuse-brand components: emotional self-regulation and psychological resilience; readiness for communicative interaction and self-presentation; confidence in professional competencies; and awareness of the habitual component. Attention to digital identity was additionally assessed qualitatively, as it proved the least quantifiable component in the survey format.

Micro-credential design

The micro-credential «Image Communications and Brand Management» is organised as a seven-module sequence aligned with the progressive formation of the diffuse-brand components (Table 1). The pedagogical methodology rests on interactive modelling - the systematic immersion of students in realistic professional scenarios. Two role-play formats anchor this approach: the "Job Interview" role-play, alternating the roles of candidate and school principal, and the "Teachers' Council" business simulation, in which students present educational projects and navigate complex communicative situations. Both formats are followed by mandatory debriefing with peer and faculty feedback; without this reflective dimension, role-play risks becoming a performance exercise rather than a formative professional identity experience.

Alongside interactive modelling, the micro-credential integrates AI tools as technological scaffolding: ChatGPT and Gemini for personal mission and values articulation, Canva AI for visual brand-book development, Leonardo AI and Adobe Firefly for portfolio imagery, and platform-native analytics for monitoring digital presence. A principled commitment underlies this integration: AI tools are used as instruments of reflection rather than automation. Students critically evaluate generated outputs and adapt them to their authentic professional context, in explicit alignment with the ethics module.

Table 1. Structure of the micro-credential «Image Communications and Brand Management»

No.	Module title and content focus	Expected outcomes
1	Foundations of teacher professional branding: brand concept, professional identity, values, positioning; SWOT of professional profile	Articulated professional identity; individual learning trajectory
2	Habitual image of the educator: visual culture, professional style, pedagogical etiquette	Visual-communicative culture aligned with the professional environment
3	Digital identity and SMM: digital presence, educational content, online reputation	Digital communication skills; online reputation management

4	Communication and public speaking: rhetoric, storytelling, audience interaction	Communicative competency and confident public performance
5	Educator brand in the institutional environment: corporate culture, educator as ambassador	Corporate identity awareness and social responsibility
6	Ethics and academic integrity: professional and digital ethics, academic responsibility	Ethical consciousness and responsible digital behaviour
7	Capstone project: personal brand integration - Personal Brand Portfolio (brand-book, strategy, digital profile)	Formed holistic "diffuse brand" of the educator

Results

Table 2 summarises the baseline survey findings.

Table 2. Survey results: baseline formation of diffuse-brand components

Brand component / indicator	High level of formation	Implication for micro-credential design
Emotional self-regulation and psychological resilience	28%	Core priority; addressed by Module 4 and the capstone role-play
Readiness for effective interaction with students and faculty	30%	Developed across Modules 4-5; interactive modelling is the primary vehicle
Confidence in own knowledge and professional competencies	26.7%	Critically low; addressed by SWOT analysis (Module 1) and portfolio building (Modules 2-3)
Awareness of the habitual component and compliance with professional requirements	36.7%	Relatively higher baseline; deepened and extended in Module 2
Attention to digital identity and online reputation management	Insufficient	Most significant gap; addressed by Modules 3 and 7 (AI tools and digital portfolio)

The data reveal a structural imbalance: relatively stronger formation of traditional brand components (habitual image, basic communication) coexists with critically underdeveloped modern digital and reputational competencies. The confidence deficit - only 26.7% of respondents report high competency self-assessment - suggests that current teacher education programmes are failing to produce the professional self-efficacy that effective public-facing practice requires. These findings directly validate the micro-credential's design logic: Module 1 (SWOT self-analysis and personal mission) addresses the confidence deficit; Modules 3 and 7 with the AI tool integration respond to the digital identity gap; and the role-play methodology of Modules 4-5 builds the communicative resilience registered as low in the baseline survey. The capstone brand-book project integrates all dimensions into a tangible, portfolio-format demonstration of the formed diffuse brand.

Discussion: Teacher Branding as a Resilience Competency

Within the ICETOL 2026 theme of building resilience through micro-credentials and lifelong learning, a well-established diffuse brand enhances the educator's resilience in four key respects. First, technological advancement: the rapid development of digital technologies and artificial intelligence is transforming the traditional role of the teacher; with a well-established digital identity these tools cease to be a threat and become a resource for professional growth, audience expansion and stronger pedagogical influence (Hardaker & Glenn, 2025). Second, information security: in conditions of information warfare and disinformation, an educator whose professional brand is grounded in clear values and proven competence serves as a beacon of trust and critical thinking, shaping students' information literacy rather than merely countering manipulation. Third, institutional stability: educators who consciously identify with their institution's brand strengthen its reputation, attractiveness and competitiveness (Irshad, 2026), buffering the effects of reorganisations and funding turbulence. Fourth, personal resilience: the confidence and self-regulation deficits documented above are addressed directly by interactive modelling, which allows self-presentation strategies to be tested without risk to real reputations.

The stackable, portable nature of micro-credentials (Council of the European Union, 2022) makes these competencies continuously updatable across the career span - a decisive property in the age of uncertainty. The study's limitation is its single-institution, baseline design; longitudinal measurement of the micro-credential's effects on graduates' digital identity and employability is planned as the next stage of research.

Conclusions

1. The «diffuse brand» concept integrates the habitual, digital and institutional components of the educator's professional image and provides a coherent theoretical ground for a purpose-designed micro-credential architecture.

2. Baseline evidence from KSPU confirms a critical gap in professional self-efficacy and digital identity among pre-service teachers, validating the need for targeted intervention.

3. The seven-module micro-credential «Image Communications and Brand Management», built on interactive modelling and reflective use of AI tools, operationalises lifelong learning competencies for the teaching workforce.

4. The educator's professional brand should be treated not as a cosmetic add-on but as a core resilience competency in an uncertain information landscape, and professional branding competencies deserve an explicit place in teacher education curricula.

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Technological Innovations and Personalization in Distance Education: Adaptive Environments as a Response to the Limitations of the Self-Instructional Model

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Abstract

Distance Education (DE) has established itself as an indispensable strategic tool for corporate education, being extensively adopted by the Brazilian Army through the Army Institute of Economics and Finance (IEFEx) to train thousands of administrative agents via fully self-instructional courses. Although this format ensures training continuity by valuing autonomy and reducing institutional costs, the model is significantly hindered by the limitations of instructionism. In the absence of continuous human mediation, teaching frequently reverts to the passive and standardized transmission of information, anchored in extensive PDF readings and static video lectures that fail to bridge the gap between theory and daily practice. This approach restricts critical thinking capacity, ignores the diversity of student profiles, and generates cognitive overload, thereby compromising engagement and deep learning. In light of this scenario, this study aimed to investigate how teaching personalization and the use of emerging technologies can promote more dynamic, contextualized, and student-centered learning experiences. The research adopted a qualitative, exploratory, and applied approach, using the courses offered by the IEFEx, responsible for the training of Brazilian Army administrative agents, as the empirical field. Empirical data collection occurred in 2025 through questionnaires distributed to a significant sample, resulting in 4,307 student responses and 28 participating teaching agents. The questionnaires combined Likert-scale statements and open-ended questions, were processed using Bardin's Content Analysis technique, supported by Artificial Intelligence for the initial categorization of the vast volume of textual data. The results demonstrated that while the self-instructional model favors autonomy and expanded access to training, persistent issues remain regarding low engagement, excessive dependence on textual materials, a lack of personalization, and limited practical and interactive activities. Both students and teaching agents expressed a significant demand for active methodologies, adaptive pathways, simulators, AI-based virtual tutors, and greater multimedia diversification. The findings further indicate that the mere digitization of content is insufficient to guarantee meaningful learning in complex corporate contexts. It is concluded that the evolution of corporate DE in the Brazilian Army requires transcending the instructionist paradigm toward more flexible, personalized, and connectivist educational models. Therefore, it is recommended to incorporate adaptive environments, AI tools, operational simulators, and multimedia strategies aligned with contemporary learning theories to strengthen student protagonism, reduce transactional distance, and promote more effective and contextualized formative experiences in the digital age.

Keywords: Distance Education; Technological Innovation; Artificial Intelligence; Adaptive Environments; Self-Instructional Model.

Introduction

Contemporary society is undergoing a radical transformation driven by Information and Communication Technologies (ICT), which profoundly affect modes of communication, work, and especially learning, as noted by Gómez (2015) and Bates (2016). In this rapidly evolving context, Distance Education (DE) has moved beyond being a mere emergency alternative to establish itself as a strategic tool for democratizing access to knowledge. Within the realm of public management and organizational operations, corporate education, grounded in the concepts of Meister (1999) as a strategic training ecosystem, has turned to DE to ensure the continuous learning of its workforce, aiming for efficiency, effectiveness, and institutional transparency.

The Brazilian Army (EB), with its extensive reach comprising over 1,086 military organizations and an active-duty force exceeding 212,000 personnel, reflects the colossal challenges inherent in corporate training on a national scale. Faced with logistical and budgetary constraints, the Secretariat of Economy and Finance (SEF) tasked the Army Institute of Economics and Finance (IEFEx) with the mission of qualifying its administrative staff through DE. Starting in 2021, this initiative led to the widespread adoption of fully self-paced courses, achieving significant certification figures: 26,114 in 2021, rising to an impressive 53,800 in 2023. More recently, in 2024 and 2025, over 30,000 annual certifications were recorded.

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Although the self-paced course model has ensured the continuity of corporate training, it faces substantial challenges. This modality is characterized by autonomous access to instructional materials, without the direct mediation of instructors or tutors, prioritizing student independence, a concept widely championed by Charles Wedemeyer (Costa, 2019). While this feature values learner autonomy and reduces institutional costs, it also renders the model highly susceptible to instructionist practices, often limiting it to the linear transmission of information through extensive readings and standardized video lectures.

This scenario raises fundamental questions regarding the model's pedagogical quality: how can engagement, critical reflection, and deep learning be ensured in environments lacking real-time human interaction? How can we overcome the instructionist paradigm that treats students as a homogeneous mass, ignoring the diverse profiles, learning paces, and practical needs of each individual?

Recent educational literature, supported by authors such as Holmes *et al*. (2019) and Lamattina and Peralta (2024), suggests that the answer to these limitations lies in the adoption of advanced technological innovations. The integration of Artificial Intelligence (AI), the creation of adaptive learning paths and environments, and the use of simulators and virtual reality are emerging as trends capable of personalizing the educational process and breaking away from the passivity inherent in traditional systems.

Therefore, this article aims to investigate how technological innovations and personalized instruction can address the limitations of the self-instructional model in corporate distance education. Through qualitative, exploratory, and applied research, this study analyzes the perceptions of thousands of students and dozens of teaching agents regarding the educational practices implemented at IEFEx. It seeks to understand these users' contemporary demands for emerging technologies, such as AI and adaptive environments, and to propose pedagogical alternatives that empower students and foster active, contextualized learning in the digital age.

Theoretical development

The Limits of the Instructionist Model in Self-Instructional Courses

Historically, distance education established itself based on pedagogical models rooted in behaviorism (with foundations tracing back to B. F. Skinner) and cognitivism (rooted in the work of Jean Piaget and Robert Gagné's Theory of Instruction). The first generation of distance education was strongly marked by an instructionist perspective, in which learning is understood as an individual process of receiving and repeating information, and teaching often reflects the logic of the Theory of the Industrialization of Education proposed by Otto Peters (2012). In this scenario, the student is treated as a passive recipient who follows linear paths, completes standardized reinforcement exercises, and undergoes predominantly objective, summative assessments.

This tendency toward instructionism is exacerbated in the context of self-instructional courses, which lack the continuous dialogue facilitated by a tutor or instructor. As Demo (2003) warns, instructionism restricts the student's autonomy and critical thinking skills, limiting learning to the superficiality of rote memorization and fostering a reliance on pre-formatted answers. Ribeiro and Cunha (2020) caution that the instructionist model overlooks the potential of technology to bridge cognitive gaps; instead, it reproduces "banking education", a concept widely criticized by Paulo Freire, and disregards the diversity of students' sociocultural and professional contexts.

Given the near-universal access to information on the internet, offering students courses limited to PDFs or slide presentations has become obsolete. Authors such as Anderson and Dron (2012) emphasize the need to move beyond the first generation of distance education, evolving instead toward socio-constructivist and connectivist approaches. However, applying these principles within closed, non-tutored systems requires a technological and pedagogical reinvention of instructional design (Filatro, 2008).

Multimedia Learning Theory and Cognitive Load Reduction

Before moving on to Artificial Intelligence, the first step in enhancing self-instructional environments is the proper design of media. Educational planning for these courses must mitigate "transactional distance"—a concept defined by Michael Moore (2008) as the space for potential misunderstandings created by the physical and communicative gap between the student and the institution. In this regard, Cognitive Load Theory, developed by John Sweller, highlights the importance of organizing content into precise modules to avoid overloading the student's working memory (Santos & Tarouco, 2007). Complementarily, Multimedia Learning Theory, formulated by Richard Mayer, advocates for the effective and strategic integration of text, audio, and images (Araújo *et al*., 2019). In courses lacking direct tutoring, the use of infographics, mind maps, interactive simulators, and explanatory videos is not merely decorative; rather, it is an essential pedagogical tool that facilitates meaning-making, fosters knowledge retention, and reduces the cognitive load inherent in dense text. Furthermore, simulating a "guided didactic

conversation", as advocated in Börje Holmberg's Theory of Dialogic Communication, proves fundamental when creating these materials, as it fosters communicative empathy (Toda & Rodrigues, 2018).

AI-Driven Innovations and Adaptive Environments

The paradigm shift required to move beyond instructionism calls for tools that offer dynamism and ongoing monitoring. Advances in digital technologies have introduced new pedagogical possibilities, with AI emerging as the most transformative factor in contemporary education. Holmes *et al*. (2019) attest that AI-based systems possess the unique ability to personalize the learning process, adapting content and activities based on student performance and generating individualized learning paths.

According to Lamattina and Peralta (2024), the adoption of Virtual Learning Environments (VLEs) with adaptive features represents the primary innovative response to the limitations of instructionist models. Such systems go beyond merely making files available; they employ algorithms to analyze learner data and interactions, adjusting content difficulty, recommending supplementary materials, and providing immediate feedback, thereby creating a flexible learning experience.

In addition to adaptive environments, the use of AI-powered intelligent virtual tutors can provide continuous support, simulating a teacher's presence to address questions and facilitate formative interventions. Fadel *et al*. (2024) also highlight the potential of immersive technologies, such as Virtual Reality (VR) and Augmented Reality (AR), to bridge the gap between abstract knowledge and the real world. The use of simulators allows students to practice operational skills and solve problems without the risks associated with real-world environments, making them valuable tools for active learning methodologies, a concept strongly supported by Moran's (2018) analysis of student agency.

Methodology

To achieve the proposed objectives, this research adopted a qualitative approach of an exploratory and applied nature, following the methodological premises of Severino (2007) and Gil (2008). The qualitative method enabled the revelation of meanings and the exploration of behavioral patterns and the subjects' perceptions regarding the educational model experienced.

The research scope focused on the training courses offered by the SEF and coordinated by the IEFEx. Empirical data were collected in 2025 via structured digital questionnaires on the Google Forms platform, administered to two distinct groups: teaching agents (content creators and coordinators) and students, both those who completed the courses and those who dropped out.

The final sample included the voluntary participation of 28 teaching agents (50% of the total team invited) and 4,307 students. The data collection instruments combined Likert-scale statements (to assess levels of agreement regarding quality, infrastructure, autonomy, and teaching methods) with open-ended questions, allowing participants to freely record the challenges they faced and offer suggestions for educational and technological improvements.

Textual responses from the open-ended questions were subjected to the Content Analysis technique systematized by Bardin (2016), structured into the stages of pre-analysis, material exploration, and results processing. To organize the vast volume of qualitative student data (thousands of responses), the Gemini Pro Artificial Intelligence tool was used to assist in the initial categorization of thematic axes, supporting the organization and preliminary identification of emerging patterns in the textual data.

Data analysis and discussion

Evaluating virtual courses from the users' perspective makes it possible to determine the extent to which technological innovations are required to enhance the educational experience. Analysis of the empirical data revealed convergences between recent literature and the practical reality experienced by Brazilian Army personnel and students.

The Limits of the Current Model and Instructionist Stagnation

Initial quantitative findings indicated a high level of approval regarding the model's organizational effectiveness. For 88.9% of the students, the managerial conduct of the IEFEx was satisfactory. However, when intellectual engagement and teaching methods were specifically analyzed, the first signs of shortcomings emerged.

A critical indicator revealed that approximately 78% of students felt encouraged to seek additional information from external sources, suggesting that the courses provide some stimulus for autonomous knowledge acquisition.

Nevertheless, the remaining responses indicate opportunities to strengthen this dimension, particularly by incorporating more engaging and diversified learning resources (Figure 1). In practical terms, this reflects the limitations of the instructionist model: learning is confined to the strict boundaries of closed content, prioritizing memorization over critical reflection, a point previously highlighted by Demo (2003).

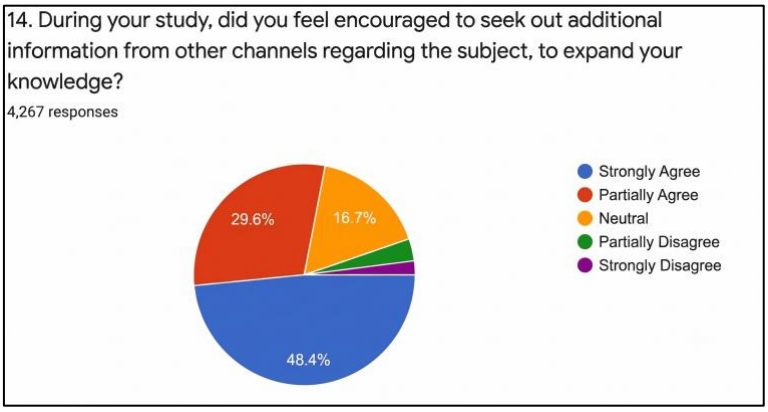


Figure 1

The content analysis of the open-ended questions confirmed this instructionist stagnation. One of the most recurring themes in student feedback centered on an over-reliance on text-based formats. Students voiced strong complaints regarding the excessive use of PDF handouts and video lectures that amounted to little more than reading slides containing legal statutes. In the students' view, simply transposing dry regulations does not constitute genuine instruction, reinforcing the perception that the material lacks a connection to real-world, everyday challenges.

Although all participating teaching agents acknowledged the contribution of technological resources and media to the learning process, 32.1% only partially agreed with this assessment, suggesting opportunities for improvement and further diversification of instructional materials (Figure 2).

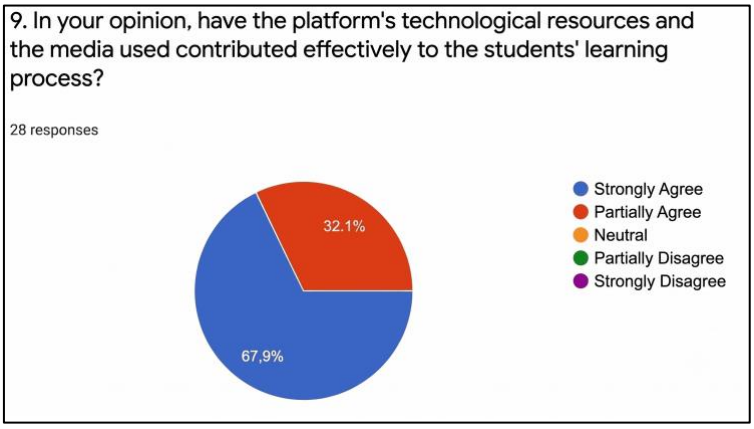


Figure 2

These data corroborate the theoretical assertions of Tony Bates (2016) and Araújo *et al*. (2019) that Richard Mayer's Multimedia Learning Theory is not being fully applied, resulting in cognitive overload and disengagement.

The Demand for Personalization and Adaptive Learning Paths

One technological response to the limitations of standardized instruction is personalization. Responses to the questionnaires revealed a clear demand, from both educators and students, for a flexible, adaptive, and modular organizational structure.

For those responsible for developing course content, the primary suggestion regarding course design was the ability to create more detailed learning paths and schedules that accommodate individual routines (Figure 3). One instructor highlighted the value of adaptive learning paths for organizing related courses that can be completed progressively.

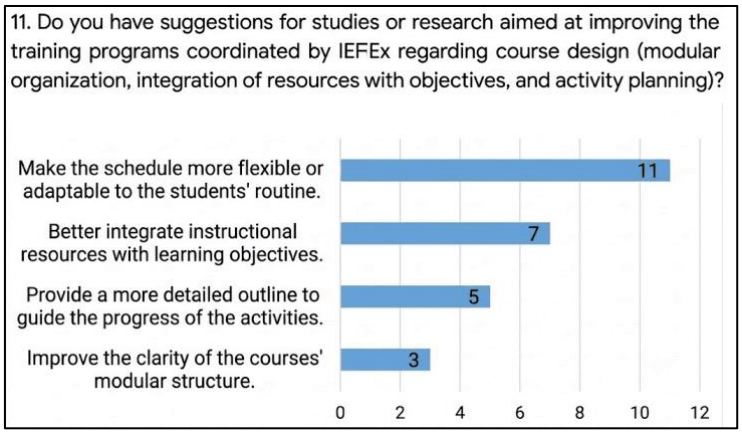


Figure 3

Among students, this demand emerged regarding suitability for the target audience and modular structuring. Participants requested that courses be divided into levels (basic, intermediate, and advanced), criticizing the fact that the "one-size-fits-all" course model has become obsolete. As Lamattina and Peralta (2024) point out, adaptive learning management systems resolve this impasse by adjusting content and learning paths in real time based on the user's analytical response.

Artificial Intelligence and Practical Simulations as Opportunities

Contemporary educational trends based on AI, simulations, and the metaverse did not go unnoticed by the survey respondents, emerging spontaneously in their answers as the most viable alternatives to address low interactivity.

Regarding technology and innovation, students demonstrated a high level of digital maturity by directly calling for the integration of algorithms to personalize instruction. Some proposed using AI as an organic support tool to clarify questions, suggesting the system act as a "virtual tutor" or chatbot. Similarly, educational stakeholders view AI as a catalyst for productivity in content creation and assessment, suggesting training programs that utilize AI tools for content generation.

Alongside the use of algorithms, there was also a widespread desire for technology-anchored active learning methodologies. The primary criticism of summative assessment translated into an explicit preference for practical assessments. Students strongly advocated for the inclusion of administrative system simulators that replicate government and military management software (such as SISCOFIS, SIAPPE, and Compras.gov.br). These demands reinforce Malcolm Knowles's andragogy, which emphasizes practical problem-solving as a central motivator for adult learning (Ferreira *et al*., 2022). The use of Augmented Reality (AR), the metaverse, and simulations, advocated by Fadel *et al*. (2024) is not science fiction, but rather a pragmatic demand from today's corporate education learners seeking to reduce cognitive load, a concept proposed by Sweller.

Conclusions

This study highlights that overcoming the rigidity of instructionism in the design of self-paced corporate distance learning courses is a complex yet urgent challenge. The experience observed within the Brazilian Army's training network attests to the institution's capacity for logistical adaptation. However, it is evident that merely transposing PDF manuals and relying on assessments based on rote memorization limits learner engagement and underutilizes the intellectual potential of this modality.

The research identified a significant gap between current technology and user demands. A collective need for personalization emerged: the requirement to tailor courses to the student's prior expertise and, through case studies and operational simulators, connect them directly to the daily routines and challenges encountered within military units.

A key pathway for advancing this landscape for evolving this landscape lies in the decisive adoption of emerging technological innovations, notably Artificial Intelligence and Adaptive Learning Environments (Lamattina & Peralta, 2024). These mechanisms enable the design of individualized educational pathways, adjusting complexity levels and media resources to each student's specific progress. Furthermore, virtual tutoring tools based on generative algorithms and automated forums provide real-time feedback and reduce the "transactional distance" identified by Moore, bridging the interaction gap left by the absence of continuous face-to-face instruction.

In summary, shifting from the instructionist standardization analyzed by Peters (2012) toward the constructivist and connectivist educational perspective proposed by Anderson and Dron (2012) will require managers to have the courage to incorporate artificial intelligence, promote practical simulation, and redesign materials with high-quality multimedia grounded in the concepts of Mayer and Sweller. The development of educational ecosystems centered on the student rather than the content will serve as the ultimate guarantee for strengthening the learners' autonomy, critical thinking, and efficiency in an era of constant and imminent technological evolution.

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Designing Interactive Simulation-Based Laboratories for Teaching Prepress Colour Management in Technical and First-Year Higher Education

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Abstract

Teaching prepress colour management is challenging in technical/vocational and first-year higher education because professional colour-management systems operate as computational "black boxes": learners receive RGB-to-CMYK conversions, gamut warnings, or proofing results without being able to inspect the colourimetric logic that produces them. This design-and-development study presents an openly accessible, browser-based learning environment that makes these hidden processes visible through nine interactive simulation-based laboratories covering additive and subtractive colour synthesis, CMYK separation with screen angles, Total Area Coverage, colour spaces and gamut boundaries, Grey Component Replacement and Under Colour Removal, Tone Value Increase, ICC rendering intents with Black Point Compensation, and ISO-oriented soft-proofing logic. The instructional design draws on the Cognitive Theory of Multimedia Learning and simulation-based science education, with emphasis on spatial contiguity, signalling, segmenting, guided inquiry, and immediate visual feedback. Instead of production-grade ICC look-up tables, the platform applies lightweight heuristic transformations in CIELAB space so that learners can manipulate variables and observe the consequences of modelling decisions in real time. An internal reference-guided technical audit against Adobe Photoshop's Colour Engine under an ISO Coated v2 (FOGRA39) comparison context indicated that the heuristic model preserves in-gamut colours and applies hue-preserving chroma compression to out-of-gamut colours; these results are interpreted as evidence of educational plausibility rather than metrological equivalence. The study contributes a transparent, cost-free educational architecture supporting classroom demonstration, guided laboratory work, and self-paced exploration. A classroom-based evaluation of learner outcomes is outlined as the next research phase.

Keywords: prepress colour management; simulation-based learning; technical education; first-year higher education; graphic arts education; interactive visualisation

Introduction

Colour management — the process of achieving predictable colour reproduction across heterogeneous imaging devices — is a foundational competency in graphic arts, printing, and visual communication education (Kipphan, 2001). In professional prepress workflows, transformations between RGB displays and CMYK print conditions are handled by colour management modules that rely on three-dimensional look-up tables (LUTs) embedded in ICC profiles (International Color Consortium, 2010). Although operationally effective, these systems hide their internal logic from learners: a student receives a CMYK output for a given RGB input but cannot observe the conversion to CIELAB, the gamut-boundary detection, the chroma compression, or the black-generation strategy that produced the result (Green, 2010).

Green (2010) characterises commercial colour management software as an epistemological "black box" whose internal algorithmic compromises remain obscured from the user. In educational settings, this opacity fosters procedural software dependency — knowing how to operate the software — without the conceptual understanding of why specific transformations occur that would enable graduates to diagnose problems and adapt to new technologies. From the perspective of cognitive load theory and multimedia learning research, opacity also generates avoidable extraneous processing: when constructs such as CIELAB coordinates, colour-difference tolerances, and gamut boundaries are separated from their visible consequences, learners must split attention between abstract representations and software outputs, which hinders the construction of coherent mental models (Mayer, 2009; Sweller et al., 2019).

A substantial body of evidence supports interactive simulation as a response to this problem. Computer simulations enhance science instruction when learners can actively manipulate variables and observe the consequences (Rutten et al., 2012), and virtual laboratories make invisible processes visible while offering flexible, low-cost access to experimentation (de Jong et al., 2013; Potkonjak et al., 2016). Brinson (2015) found that in 89% of recent

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comparison studies, learning outcome achievement in virtual or remote laboratories was equal to or higher than in traditional hands-on laboratories, while a meta-analysis of 145 studies reported a large overall effect of simulation-based learning on complex skill development in higher education (g = 0.85; Chernikova et al., 2020). Such environments are most effective when inquiry is adequately guided (Lazonder & Harmsen, 2016). In colour science specifically, Zhu (2023) showed that interactive, browser-based tutorials improved student comprehension relative to lecture-based instruction, although that work addresses display colourimetry rather than prepress production.

These considerations are particularly pertinent to technical/vocational programmes and first-year university cohorts, where prior knowledge is heterogeneous and licences for professional software, calibrated monitors, and measurement instruments are frequently unavailable. Yet the prepress domain remains underserved by educational technology. Professional tools such as Adobe Photoshop are quantitatively accurate but instructionally opaque (Green, 2010); the X-Rite Fundamentals of Color and Appearance course presents colour theory through passive video lectures (X-Rite, 2024); PhET's Color Vision simulation covers only introductory additive mixing (PhET Interactive Simulations, n.d.); and Zhu's (2023) open tutorials do not address CMYK separation, ink limits, dot gain, rendering intents, or proofing tolerances.

This paper therefore reports a design-and-development study (Richey & Klein, 2014) of an openly accessible, browser-based learning environment that translates prepress colour management into nine interactive simulation-based laboratories. Three research questions guide the work: (RQ1) How can complex prepress colourimetric processes be represented through transparent, interactive simulations suitable for technical and first-year higher education? (RQ2) To what extent can heuristic modelling approximate the behaviour of standard ICC-based colour transformations for educational purposes? (RQ3) How does simulation design that prioritises algorithmic transparency align with established principles for reducing extraneous cognitive load? The study contributes (1) a transparent, client-side simulation architecture for prepress colour education, (2) a reference-guided internal audit of heuristic colourimetric models that approximate ICC-based workflows without requiring profile data, and (3) a pedagogical framework linking simulation transparency to cognitive load reduction. The platform is openly archived (Korakakis, 2026); its source code and a browser demonstration are available at https://github.com/gk1966/prepress-color-labs and https://prepress-colour-labs.netlify.app/.

Methodology

Research design

The study follows the design-and-development research tradition (Richey & Klein, 2014) as a Type 1 product study: it documents the rationale, architecture, and internal validation of a specific educational artefact rather than measuring learner outcomes. Technical evidence for this phase is provided by a reference-guided internal audit against a professional colour engine, while a quasi-experimental learner study is outlined as future research.

Platform architecture and accessibility

The platform was developed as a strictly client-side web application (HTML5, CSS3, JavaScript) that runs in any modern browser without installation, registration, or server-side processing. Unlike conventional colour management modules that interpolate empirically measured 3D LUTs, it performs all conversions through lightweight heuristic models in CIELAB space, keeping the underlying logic inspectable and modifiable. This architectural choice serves two goals simultaneously: it removes the cost and infrastructure barriers that constrain technical/vocational institutions, and it turns the transformation logic itself into learning content. The application, its integrated manual, and citation metadata are released under an MIT licence and permanently archived on Zenodo (Korakakis, 2026).

The nine interactive laboratories

The environment comprises nine self-contained laboratories that isolate specific colourimetric concepts and progress from foundational to complex phenomena, implementing the segmenting principle (Mayer, 2009). Laboratories 01–02 externalise the physical distinction between additive and subtractive reproduction: sRGB values are converted to linear light before channel addition, while inks are modelled as broadband filters whose spectral absorption graph demonstrates additivity failure. Laboratory 03 visualises CMYK separation with amplitude-modulated screening at standard angles (C 15°, M 75°, Y 0°, K 45°), showing how the four halftone plates combine and how angle conventions prevent moiré interference. Laboratory 04 computes Total Area Coverage in real time and generates visual smearing artefacts when substrate-specific ink limits (e.g., 330% for ISO Coated v2) are exceeded. Laboratory 05 plots gamut polygons for sRGB, Adobe RGB, and the FOGRA39 CMYK condition on the CIE 1931 chromaticity diagram. Laboratory 06 demonstrates Grey Component Replacement and Under Colour Removal across five levels, transferring the achromatic component of the CMY

mixture to the K channel. Laboratory 07 generates Tone Value Increase curves using a Murray–Davies/Yule–Nielsen-inspired teaching model (Murray, 1936; Yule & Nielsen, 1951), with ISO 12647-2 reference values as didactic anchors for coated, uncoated, and newsprint-like conditions (International Organization for Standardization [ISO], 2013). Laboratory 08 simulates the four ICC rendering intents with Black Point Compensation, displaying all four mappings of the same input colour side by side (Figure 1). Laboratory 09 implements soft-proofing tolerance logic by computing CIEDE2000 colour differences (Sharma et al., 2005) against a single-patch teaching threshold of 3.0, aligned pedagogically with ISO 12647-7 (ISO, 2016) without claiming certified proofing status (Figure 2).

Instructional design, guided inquiry, and transparency

The instructional design operationalises three principles of the Cognitive Theory of Multimedia Learning (Mayer, 2009). Spatial contiguity is implemented by placing numerical parameters — CIELAB coordinates, ΔE_{2000} values, ink percentages — directly beside their visual consequences; signalling is supported through gamut-status indicators, live readouts, and tolerance badges; and segmenting is realised through the nine-laboratory sequence. Because guided inquiry outperforms unguided discovery (Lazonder & Harmsen, 2016), each laboratory includes an integrated scientific companion with learning objectives, theoretical background, inquiry prompts, self-check activities, and local observation notes. A dedicated Technical Notes section explicitly documents every modelling simplification, converting approximation boundaries from hidden assumptions into visible learning content.

Heuristic colourimetric modelling

Replacing empirical 3D LUTs with continuous heuristic functions is a deliberate pedagogical trade-off: LUTs are precise but opaque, whereas heuristics can be written as equations, discussed, modified, and linked directly to visual output (Green, 2010; Morovic, 2008). For rapid gamut-boundary detection, the engine approximates the FOGRA39 envelope with a continuous sinusoidal function:

$$C^*_{max} \approx 40 \cdot \sin((L^* / 100) \cdot \pi) \qquad [1]$$

in which maximum printable chroma peaks in the mid-tone region ($L^* \approx 50$) and collapses at both tonal extremes. If the chroma of an input colour exceeds the boundary value for its lightness, the coordinate is classified as out-of-gamut and compressed towards the boundary while hue angle and lightness are retained, approximating a hue-preserving perceptual rendering strategy consistent with the perceptual salience of unintended hue shifts (Fairchild, 2013). The engine also models Black Point Compensation following Adobe Systems Incorporated (2006), rescaling source lightness to the minimum printable lightness of the destination condition:

$$L^*_{new} = L^* \cdot ((100 - L_{Kmin}) / 100) + L_{Kmin} \qquad [2]$$

so that learners can observe why shadow detail would otherwise be clipped in a relative colorimetric conversion.

Internal reference-guided audit

To assess whether the heuristic engine behaves plausibly under a familiar prepress reference condition, ten sRGB samples — neutral greys, skin tones, and saturated out-of-gamut colours — were converted in Adobe Photoshop using the Adobe Color Engine (sRGB IEC61966-2.1 to ISO Coated v2/FOGRA39, perceptual intent, Black Point Compensation enabled) and compared with the platform's teaching-mode output. FOGRA39 was selected as a widely available legacy teaching condition that remains accessible in common software defaults, not as a claim of current production certification. The comparison is a consistency check of the educational model, not a claim of metrological equivalence to a professional colour engine.

Results

Table 1 summarises the audit. The heuristic engine reproduced the categorical behaviour expected of a colour management system: all in-gamut samples passed through unchanged ($\Delta E_{2000} = 0.0$), slightly out-of-gamut samples received moderate chroma compression ($\Delta E_{2000} = 3.7–6.2$), and extreme out-of-gamut samples underwent strong compression ($\Delta E_{2000} = 14.7–26.4$).

Table 1. Reference-guided internal audit of the heuristic gamut-mapping algorithm using ten sRGB samples.

Sample	Colour description	RGB input	Gamut status	ΔE_{2000}
1	Neutral Grey	128, 128, 128	In-gamut	0.0
2	Light Skin Tone	240, 200, 180	In-gamut	0.0
3	Dark Green	0, 100, 0	In-gamut	0.0

4	Sky Blue	70, 130, 210	Out-of-gamut	3.7
5	Bright Magenta	255, 0, 255	Extreme out-of-gamut	26.4
6	Pure Red	255, 0, 0	Extreme out-of-gamut	16.3
7	Cyan	0, 255, 255	Extreme out-of-gamut	14.7
8	Pastel Pink	255, 182, 193	Slightly out-of-gamut	4.1
9	Deep Purple	75, 0, 130	Slightly out-of-gamut	6.2
10	Paper White	255, 255, 255	In-gamut	0.0

Two cases illustrate the behaviour. For the in-gamut light skin tone (RGB 240, 200, 180), Photoshop returned C:7 M:27 Y:30 K:1, while the platform kept the colour unchanged, consistent with its direct pass-through rule. For the out-of-gamut sky blue (RGB 70, 130, 210), Photoshop signalled a gamut warning and the platform reported ΔE_{2000} = 3.7 under the perceptual intent, indicating active hue-preserving compression. The engine thus distinguishes printable from unprintable regions and intervenes only when required — the central conceptual behaviour the laboratories are designed to teach.

Figures 1 and 2 show the two laboratories in which this logic is most visible to learners. In Laboratory 08, the same out-of-gamut input is mapped side by side under all four ICC rendering intents with live ΔE_{2000} readouts, making the algorithmic differences between intents directly comparable. In Laboratory 09, the computed colour difference between screen and simulated print is evaluated against a single-patch teaching threshold ($\Delta E_{2000} \leq 3.0$), introducing learners to ISO-oriented proof-evaluation logic (ISO, 2016).

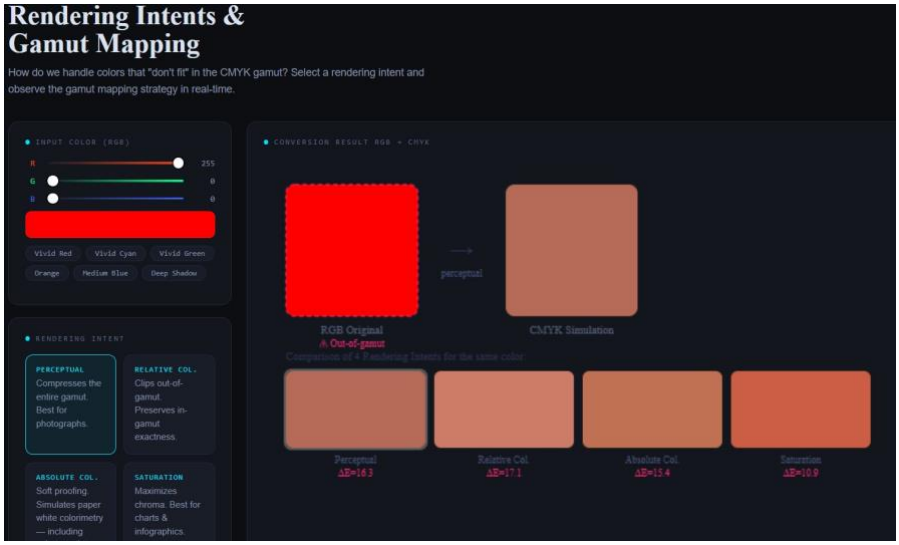


Figure 1. Laboratory 08 — Rendering Intents and Gamut Mapping: an out-of-gamut red (RGB 255, 0, 0) mapped under all four ICC rendering intents with real-time ΔE_{2000} values.

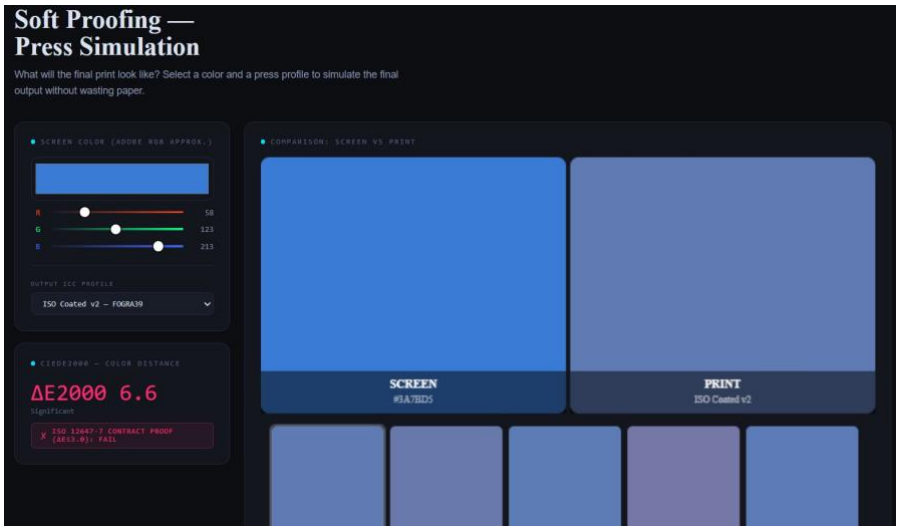


Figure 2. Laboratory 09 — Soft Proofing and Press Simulation: a computed ΔE_{2000} = 6.6 exceeds the single-patch teaching threshold ($\Delta E_{2000} \leq 3.0$) for ISO Coated v2.

The learning design was additionally reviewed against Nielsen's (1994) usability heuristics and Mayer's (2009) multimedia principles: the laboratories were mapped to visibility of system status, match with real-world terminology, user control, error prevention, spatial contiguity, signalling, segmenting, and coherence, and this mapping is documented in the integrated manual.

Discussion

The audit results highlight the educational value of the heuristic approach in answer to RQ2: the platform behaves plausibly where plausibility matters pedagogically — preserving printable colours and visibly compressing unprintable ones — while remaining fully inspectable. Where conventional prepress software returns CMYK values without revealing the trade-offs behind them, the visualisation of chroma compression helps explain why saturated screen colours must be moderated for reflective print media, directly addressing the theory–practice gap created by black-box tools (Green, 2010).

With respect to RQ3, transparency operates as a cognitive-load intervention. Aligning numerical parameters with their visual consequences in space and time reduces the split attention that opaque tools impose (Mayer, 2009; Sweller et al., 2019), while continuous manipulation of input variables with immediate feedback scaffolds the cause-and-effect mapping required for robust, transferable mental models. The guided-inquiry companion channels this interactivity: learners formulate a prediction, manipulate variables, record observations, and interpret the outcome against the stated approximation limits — the pattern of supported inquiry that meta-analytic evidence identifies as most effective (Chernikova et al., 2020; Lazonder & Harmsen, 2016).

As a free, client-side application, the platform also addresses equity of access (UNESCO, 2019). Commercial prepress packages require licences, institution-specific laboratories, and continuous maintenance that many technical/vocational schools cannot sustain, whereas a browser-based deployment supports immediate entry in classrooms, homes, and blended or distance settings — an affordance repeatedly emphasised in the virtual-laboratory literature (de Jong et al., 2013; Potkonjak et al., 2016). For first-year cohorts, the laboratories support classroom demonstration and guided laboratory work; for self-paced learners, the integrated manual provides the structure that unguided exploration lacks.

Limitations and future research

The core design principle is an explicit trade-off between numerical precision and instructional transparency, and its boundaries must be acknowledged. The sinusoidal gamut boundary of Equation [1] varies with lightness but not with hue angle, whereas real ICC LUTs encode hue-specific asymmetries of the FOGRA39 volume. Laboratory 05 projects gamuts onto a two-dimensional chromaticity diagram without a lightness axis; the Tone Value Increase curves are heuristic teaching models anchored to ISO 12647-2 reference values rather than measured press data; the engine operates entirely in CIELAB without spectral rendering; and Laboratory 09 cannot establish the absolute colour state of a learner's display, so it teaches ISO-style tolerance logic rather than certified contract proofing. All simplifications are documented in the platform's Technical Notes. The main limitation, however, is the absence of learner-outcome data: the present study validates the design and its technical plausibility, not its instructional effectiveness. The next research phase will combine Technology Acceptance Model measures (Davis, 1989) with a pre-test/post-test comparison of conceptual understanding between students using the platform and students using conventional software.

Conclusions

This study presented the design, development, and internal technical validation of an open, browser-based environment of nine simulation laboratories for teaching prepress colour management in technical/vocational and first-year higher education. By replacing opaque ICC/LUT workflows with inspectable heuristic transformations in CIELAB space, the platform makes normally hidden processes — gamut mapping, Black Point Compensation, Tone Value Increase, ink limiting, and proof-evaluation logic — visible, manipulable, and discussable. A reference-guided audit indicated categorical consistency with a professional colour engine while making no claim of metrological equivalence. Grounded in multimedia learning theory and the simulation-based learning evidence base, the platform offers a transparent, cost-free educational architecture that lowers access barriers without sacrificing conceptual rigour. Classroom-based evaluation of conceptual understanding, usability, and transfer of colour-management knowledge is the immediate next step.

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An Analysis of Graduate Theses on Digital Literacy in Higher Education

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Abstract

This study aims to reveal the general trends in graduate theses and dissertations on digital literacy in higher education in Türkiye. The study was carried out using document analysis, a qualitative research method. A total of 116 theses and dissertations (81.9% master's theses, 18.1% doctoral dissertations) retrieved from the Council of Higher Education (CoHE) National Thesis Center database were included in the analysis based on predetermined criteria. The findings indicate that thesis production in the field of digital literacy has increased markedly since 2019, with 68.1% of all studies completed between 2022 and 2025. While these studies were conducted across 60 different universities, output was notably concentrated at Atatürk, Bahçeşehir, Anadolu, and Çanakkale Onsekiz Mart Universities. In terms of research methodologies, the quantitative approach predominated (77.59%), with survey and correlational survey designs being the most prevalent within this approach (70.69%). Regarding data sources, undergraduate students (53.45%) and preservice teachers (36.21%) collectively constituted 89.66% of the data source pool. In the thematic distribution, preservice teacher education and pedagogical practices (32.76%) and technology- and digital tool-focused studies (21.55%) were prominent. Although interdisciplinary studies constituted the second largest group overall (30.17%), domains other than language education (14.66%)—which accounted for nearly half of this group—such as health sciences, sports sciences, and other social sciences (communication, business administration, tourism, etc.) remained notably limited individually.

Keywords: Digital literacy, higher education, university, document analysis, graduate theses

Introduction

In today's era of rapid technological advancement, the ways individuals access, process, and communicate information are undergoing a profound transformation (Uslu et al., 2025). This transformation has expanded the traditional boundaries of literacy, moving beyond merely reading printed texts on paper into a new dimension in which texts are generated and critically discussed across digital platforms (Sang, 2017). This competency area, emerging as an imperative of the digital world, is termed "digital literacy" (Gilster, 1997). First conceptualized in the literature in 1997, digital literacy is defined as the ability to understand, evaluate, and effectively use information from a variety of sources via computers and the internet (Martin, 2008). Extending far beyond the mere operation of a technological tool, this skill entails a synergy of technical, cognitive, social, and emotional capabilities (Gökoğlu et al., 2025).

The implications of digital literacy in education have become increasingly prominent as teaching and learning processes have transformed. While information access in traditional instructional environments was largely restricted to printed materials and face-to-face classroom interactions, it has now expanded into a much broader ecosystem comprising online learning platforms, digital libraries, open educational resources, video content, and interactive applications (Wang & He, 2022). Consequently, this necessitates that students possess the competencies to select, evaluate, and utilize digital resources for academic pursuits (Gilster, 1997). In higher education, digital literacy requires students to conduct research, access scholarly sources, uphold academic integrity, and actively engage in technology-enhanced learning (Uzun & Çelik, 2020). Concurrently, digital literacy has become indispensable for faculty members, as the pedagogically effective integration of digital tools is now essential in instructional design, assessment and evaluation, distance education practices, and student engagement (Nawaz & Kundi, 2010).

According to Sönmez and Gül (2014), solving problems effectively in the digital age requires individuals to possess the cognitive skills subsumed under digital literacy. Similarly, international organizations such as the Organization for Economic Co-operation and Development (OECD) regard digital literacy—within the framework of 21st-century skills—as a fundamental prerequisite for survival and active citizenship in modern society, recommending that member states update their educational policies to foster environments conducive to digital literacy (Göktaş, 2025). According to the Partnership for 21st Century Skills (P21, 2019), the 21st century is recognized as an era in which technology- and digitalization-based literacies come to the forefront in the educational landscape (Duran & Özen, 2018; Prensky, 2001). Looking at the European context, the "Digital

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Competence Framework for Citizens" (DigComp), developed and continuously updated by the European Commission, serves as a benchmark standard to facilitate the adaptation of all segments of society to technological transformation and to ensure informed, safe, and critical usage (Ng, 2012; Vuorikari et al., 2016). Common geographic and interdisciplinary trends in US- and European-centered academic research indicate that digital literacy is a multidimensional construct integrated with media, information, and technology literacies (Covello, 2010). In Asian countries, digital literacy research and applications are shaped by rapidly growing youth populations and substantial investments in educational technologies. For instance, recent studies conducted in Asian nations such as China and Indonesia highlight the critical need for digital literacy during crises such as pandemics. These studies have demonstrated that students with advanced digital skills deploy metacognitive learning strategies and information verification skills substantially more effectively (Türesin, 2025).

The global acceleration of digitalization holds paramount significance for universities (Gömükpınar, 2022). Across the higher education ecosystem, the capacity of students (associate, undergraduate, and graduate) to succeed in their academic careers, navigate and filter complex databases, and prepare for the future workforce is inextricably linked to their digital literacy. The digitalization process in Turkish higher education attained an institutional footing with the "Digital CoHE" (Dijitalleşen YÖK) initiative launched by the CoHE in 2019. Within this framework, initiatives were instituted both to upgrade universities' technical infrastructure and to enhance faculty members' digital competencies (CoHE, 2019). Consequently, investigating the current state and research trends in digital literacy within higher education institutions has become imperative for formulating forward-looking strategies (Richter et al., 2019; Santos et al., 2019).

Research questions

This study aims to systematically examine master's theses and doctoral dissertations on "digital literacy" in higher education in Türkiye. By delineating academic progress and orientations in digital literacy, this study aims to portray the current state in higher education and provide a foundation for future scholarly research in this domain. In line with the research aim, the study sought answers to the following research questions:

1. What is the distribution of graduate theses and dissertations on digital literacy by publication year?
2. What is the distribution of graduate theses and dissertations on digital literacy by degree type?
3. What is the distribution of graduate theses and dissertations on digital literacy by university?
4. What is the distribution of graduate theses and dissertations on digital literacy by research methodology?
5. What is the distribution of graduate theses and dissertations on digital literacy by data sources?
6. What is the distribution of graduate theses and dissertations on digital literacy by topic?

Methodology

The study's methodological framework was grounded in a qualitative research approach. Within this framework, document analysis—a qualitative research method that enables the in-depth, unmanipulated examination of written and electronic materials pertinent to a specific phenomenon, time period, or concept—was employed (Creswell, 2014). This approach involves the objective and systematic examination, classification, and interpretation of written materials (specifically, graduate theses and dissertations in this study) that contain empirical data on the targeted topics and conditions (Yıldırım & Şimşek, 2013).

Data sources and research scope

The data source for this study comprises graduate theses and dissertations on digital literacy from higher education institutions in Türkiye. To access the relevant studies, a systematic search was conducted in May 2026 on the CoHE National Thesis Center database. As part of the search strategy, the keywords ("dijital okuryazarlık" OR "dijital okuryazar" OR "dijital okur yazarlık" OR "dijital okur-yazarlık") were searched across thesis titles, yielding an initial identification of 644 thesis records.

In accordance with the exclusion criteria delineating the study's scope, the contents, academic disciplines, and target populations of the identified theses were examined in detail. Accordingly, a total of 238 theses identified as falling outside the scope of teaching and learning processes—the contextual focus of this research—were excluded (60 in Economics and Administrative Sciences, 31 in Health Sciences, 30 in Communication and Media, 11 in Technology/Informatics, 8 in Sports Sciences, and 98 in other Social Sciences and Humanities). Although these studies fell within the field of educational sciences, an additional 215 studies were excluded because their target populations did not include higher education but instead focused on K–12 (elementary, middle, and high school) populations. Furthermore, upon full-text screening, 73 theses in which digital literacy was not the primary research

focus and was addressed merely as a superficial subdimension, along with 2 theses subject to access restrictions, were removed from the review pool. As a result of this multi-stage filtering process, 528 theses were excluded, and a total of 116 graduate theses and dissertations (95 master's theses and 21 doctoral dissertations) were determined as the final data source of the study.

Data analysis

The theses and dissertations included in the study were categorized according to the research questions. In line with this purpose, the researchers developed a data extraction form in Microsoft Excel. The form comprised eight categories: "Thesis ID, Thesis Title, Publication Year, Degree Type, University Name, Research Methodology, Data Sources, and Thesis Topic." The studies included in the review were initially read by the first author, and the corresponding data were entered into the relevant categories on the form. Subsequently, the second author cross-checked the completed codings. Both authors mutually evaluated any discrepancies, and the coding process was finalized by reaching a consensus on divergent points. The findings obtained from the analyses were presented using calculated frequencies and percentages.

Results

Distribution of theses on digital literacy by publication year

When examining the distribution of graduate theses and dissertations on digital literacy by publication year in the higher education context, it is evident that research output has gained momentum over time. The seminal thesis in this field was completed in 2008, and research output remained remarkably limited over the eleven years between 2008 and 2018 (n = 4, 3.45%). Beginning in 2019, production accelerated as scholarly interest in the topic expanded markedly, demonstrating a steady increase between 2019 and 2021 (n = 30, 25.86%). The most pronounced surge and concentration in the literature occurred between 2022 and 2025, with the vast majority of reviewed studies (n = 79, 68.10%) being produced during these four years. Annual output followed an upward trajectory throughout this interval: 20 studies in 2022 (17.24%), 14 in 2023 (12.07%), 21 in 2024 (18.10%), and 24 in 2025 (20.69%), peaking in 2025. The relatively low number of studies recorded for 2026 (n = 3, 2.59%) is attributable to the database search being conducted in May 2026, with the calendar year still underway; therefore, this figure should be interpreted as a provisional value that is expected to rise by year-end.

Distribution of theses on digital literacy by degree type

The majority of graduate theses and dissertations on digital literacy are master's theses (n = 95, 81.9%), whereas doctoral dissertations remain comparatively limited (n = 21, 18.1%). When evaluated alongside the temporal trends delineated in Section 3.1, this distribution reveals a noteworthy pattern: during the 2008–2018 period—when very few studies represented the field—doctoral dissertations predominated (n = 3/4, 75.0%). However, this trend reversed during the 2019–2021 period (n = 6/30, 20.0%), and between 2022 and 2025, the share of master's theses expanded further, reducing the proportion of doctoral dissertations to 13.9% (n = 11/79). This finding suggests that while the domain was initially shaped by a limited number of theoretical and in-depth investigations, its rapid post-2019 expansion was predominantly driven by applied master's-level studies; conversely, doctoral-level output did not keep pace with this expansion.

Distribution of theses on digital literacy by the university

It was determined that the 116 analyzed theses and dissertations were produced across 60 different universities, with research output notably concentrated around specific institutions. The top four producing institutions—Atatürk University (n = 8, 6.9%), Bahçeşehir University (n = 6, 5.2%), Anadolu University (n = 5, 4.3%), and Çanakkale Onsekiz Mart University (n = 5, 4.3%)—collectively accounted for 20.7% (n = 24) of the total output. When evaluated by graduate level, master's theses were predominantly clustered at Atatürk University (n = 6, 6.3%), Bahçeşehir University (n = 5, 5.3%), and Çanakkale Onsekiz Mart University (n = 5, 5.3%). Among doctoral dissertations, Anadolu University produced the highest number (n = 3, 14.3%), followed by Atatürk University and Gazi University (n = 2, 9.5% each). Conversely, 33 out of the 60 universities (55.0%) were represented by only a single study; 26 of these 33 institutions (43.3%) produced their sole study at the master's level, while the remaining 7 (Ankara, Biruni, Harran, Maltepe, Mersin, Selçuk, and Zonguldak Bülent Ecevit Universities) produced theirs at the doctoral level. This distribution indicates that while graduate output in the field of digital literacy is concentrated within a small number of well-established institutions, it is simultaneously dispersed across a broad spectrum of universities (55% with a single study). This wide dispersion is evident at both the master's and doctoral levels.

Distribution of theses on digital literacy by data sources

When the data sources of digital literacy theses and dissertations were examined, it was determined that undergraduate students (n = 62, 53.45%) and preservice teachers in faculties of education (n = 42, 36.21%) collectively accounted for 89.66% (n = 104) of the data source pool, representing the most frequently consulted sources in the literature. This distribution aligns with the thematic focus on teacher education and pedagogical practices outlined in Section 3.6, as a substantial proportion of these studies capitalize on the accessibility advantage afforded by student and preservice teacher populations within faculties of education. In contrast, studies involving other higher education stakeholders—such as faculty members (n = 7, 6.03%) and administrative staff (n = 2, 1.72%)—as well as those relying directly on document and curriculum analyses (n = 3, 2.59%), remained remarkably limited. When analyzed at the graduate level, student-derived data (undergraduate students + preservice teachers) was found to be markedly more dominant in doctoral dissertations (76.19%, 16/21) compared to master's theses (48.42%, 46/95); this suggests that master's theses tended toward relatively more diverse data sources (faculty members, administrative staff, documents). In a small number of these (n = 7), multiple data sources (e.g., students and faculty members or preservice teachers) were used concurrently; these studies were categorized by their predominant data source. This heavily student- and preservice teacher-weighted pattern indicates that the convenience of accessibility plays a decisive role across the field. In contrast, faculty members, administrative staff, and document-based data sources remain underrepresented in the literature.

Distribution of theses on digital literacy by topic

As a result of the thematic content analysis, the theses and dissertations were grouped into four main categories: (1) Pedagogical and Professional Practices, (2) Technology- and Digital Tool-Focused Studies, (3) Measurement- and Variable Relationship-Based Studies, and (4) Interdisciplinary Applications. The largest group comprised pedagogical and professional practices (n = 38, 32.76%); these studies predominantly addressed preservice teachers' digital literacy levels and their relationships with various variables. Technology- and digital tool-focused studies, which ranked second (n = 25, 21.55%), encompassed contemporary phenomena such as distance education, artificial intelligence literacy, cybersecurity, and social media, yet were largely concentrated on distance education applications. Measurement- and variable relationship-based studies ranked third (n = 18, 15.52%), linking digital literacy to variables such as academic achievement, self-efficacy, and critical thinking. Although interdisciplinary applications constituted the second-largest group overall (n = 35, 30.17%), no single discipline within this category carried substantial standalone weight; rather, this group represented a fragmented aggregate consisting of language education (n = 17, 14.66%), health sciences (n = 7, 6.03%), sports sciences (n = 5, 4.31%), and social sciences such as communication, finance, and tourism (n = 6, 5.17%). This distribution indicates that digital literacy research remains heavily centered on educational sciences and has not yet adequately expanded into disciplines such as natural sciences, engineering, law, and social work.

Discussion and Conclusions

In this study, graduate theses and dissertations on digital literacy in Türkiye were examined with respect to publication years, degree types, universities, research methodologies, data sources, and thematic distributions. The findings reveal critical conclusions about the field's developmental trajectory and research orientations.

The findings indicate that the volume of theses and dissertations, which remained limited between 2008 and 2018, increased markedly after 2019. Notably, the production of 68.1% of all studies between 2022 and 2025 demonstrates that scholarly interest in digital literacy has intensified substantially in recent years. This surge can be linked to the heightened importance of digital competencies following COVID-19. It has been documented that the pandemic transformed educational research (Bakker & Wagner, 2020) and prompted a bibliometric spike in digital literacy literature (Türesin, 2025). Moreover, the "Digital CoHE" (Dijitalleşen YÖK) initiative launched by the CoHE (CoHE, 2019; Gömükpınar, 2022) may have contributed to this expanding interest.

The finding that 81.9% of the studies were conducted at the master's level suggests that doctoral-level research output remains nascent. Given that digital literacy is a relatively emerging domain of inquiry (Gilster, 1997; Martin, 2008), this may account for the scarcity of theoretical and foundational investigations at the doctoral level. From an institutional perspective, production was concentrated in long-standing institutions such as Atatürk, Anadolu, and Gazi Universities, whereas a single thesis or dissertation accounted for 55% of the universities. This disparity indicates that research capacity remains centralized within specific academic hubs, corroborating the findings of Çilingir (2017).

Regarding research methodologies, the quantitative approach (77.59%) and survey designs (70.69%) were predominant. Conversely, the remarkably low prevalence of qualitative studies (6.03%) suggests that the individual experiences and contextual nuances of digital literacy have not been sufficiently explored. In this regard, Ng (2012) underscores that the technical, cognitive, and socio-emotional dimensions of digital literacy warrant more in-depth

methodological approaches. Although the proportion of mixed-methods research (16.38%) is encouraging, the lack of explicit specification regarding sub-designs in several studies represents a methodological limitation (Creswell, 2014).

In the distribution of data sources, undergraduate students (53.45%) and preservice teachers (36.21%) accounted for the vast majority of the sample. This pattern confirms that research has maintained a focus on higher education. However, the limited representation of faculty members and administrative personnel indicates that the professional and organizational dimensions of digital literacy remain under-investigated (Uslu et al., 2025).

Regarding thematic distribution, pedagogical and professional practices constituted the largest category (32.76%), followed by technology- and digital tool-focused studies (21.55%). This aligns with trends observed in the international literature (Wang & He, 2022). Furthermore, although interdisciplinary studies formed the second largest aggregate group, domains beyond language education (14.66%)—such as health sciences, sports sciences, and other social sciences (communication, business administration, tourism, etc.)—remained individually limited. This points to a pressing need for in-depth inquiries into digital literacy across diverse disciplines (Nawaz & Kundi, 2010). Finally, the markedly higher adoption of mixed methods in doctoral dissertations than in master's theses (33.33% vs. 12.63%) suggests that advanced-level investigations gravitate toward more multidimensional and rigorous research designs.

In conclusion, although graduate theses and dissertations on digital literacy in Türkiye have increased substantially in recent years, doctoral-level research output remains limited. Studies predominantly rely on quantitative and descriptive methods, focus on higher-education samples, and lean toward technology-oriented topics. In contrast, greater encouragement of qualitative and mixed methods, diverse age and occupational cohorts, and interdisciplinary investigations will advance the scholarly knowledge base in this domain. For future research, the following recommendations are offered:

- The number of doctoral dissertations should be increased to deepen the theoretical foundations of digital literacy and foster the field's scientific maturity. Specifically, supporting conceptual frameworks and theory-building endeavors would be advantageous.
- The more frequent adoption of qualitative research methodologies (case study, ethnography, document analysis) and mixed-methods designs (exploratory sequential, convergent parallel) could yield a richer understanding of the contextual and process-oriented dimensions of digital literacy.
- Investigating the digital literacy levels and distinct requirements of varied demographic groups—such as faculty members, administrative staff, older adults, and individuals with special needs—could strengthen the practical and applied outcomes of the domain.
- Beyond the limited body of literature in fields such as health sciences, sports, and language education, digital literacy investigations should be expanded into disciplines including engineering, law, the arts, and social work.

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From the Industrial Laboratory to the Browser: An Open-Access Halftone Simulator for Vocational and Distance Graphic Arts Education

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Abstract

Technical and vocational graphic arts education requires learners to understand how digital imaging algorithms shape printed and screen-based visual communication. Concepts such as halftoning, colour separation, rosette formation, tone value increase (TVI), screen ruling, resolution and viewing-distance effects are central to prepress competence, yet they are difficult to teach through static textbook images, and access to a shared print laboratory cannot be assumed in distance and hybrid learning. This design-and-development case study presents Raster Halftone Lab, an open-access, browser-based simulation environment for upper-secondary technical and vocational education and training (TVET) and introductory tertiary programmes in graphic arts, graphic design and visual communication. The development method combined instructional design analysis, modelling of core prepress phenomena and iterative implementation as a zero-installation, client-side web application using HTML5, CSS and the Canvas API. The current version provides eight interactive panels covering amplitude- and frequency-modulated screening, Floyd–Steinberg serpentine error diffusion, Bayer ordered dithering, CMYK separation, rosette generation with automatic rosette-type detection, halftone-cell quantisation, substrate-specific tone value increase and contrast-sensitivity-based viewing-distance effects. The paper reports the design findings, frames parametric literacy as an instructional goal and discusses use scenarios for classroom, blended and distance delivery. The application is publicly available as open-access software.

Keywords: Open and distance learning, technical and vocational education and training (TVET), web-based simulation laboratory, parametric literacy, halftone prepress, graphic arts education

Introduction

In print production, the transformation of continuous-tone images into printable dot structures is governed by well-defined algorithms. Halftone screening determines how tone, detail and colour are reproduced on paper, and its parameters — screen ruling (LPI), addressable resolution (DPI), screen angles, dot shape and substrate behaviour — interact in ways that directly shape visual quality (Kipphan, 2001; Lau & Arce, 2008). Professional competence in prepress therefore requires more than recognising final results: practitioners must be able to anticipate how numerical and algorithmic decisions propagate into visible phenomena such as rosettes, moiré, tonal jumps and dot gain.

These relationships are difficult to teach with static media. A textbook can show a rosette or a moiré pattern, but it cannot let the learner vary a screen angle by two degrees and watch the pattern collapse. Research on interactive simulations in science education documents consistent learning benefits when learners manipulate models and observe immediate feedback (Rutten et al., 2012), and virtual laboratories have been shown to complement or, under conditions, substitute physical laboratories (Brinson, 2015; de Jong et al., 2013; Heradio et al., 2016; Potkonjak et al., 2016). The PhET project demonstrated that freely available browser simulations can achieve wide adoption across educational levels (Perkins et al., 2006; Wieman et al., 2008). No comparable open simulation environment, however, has addressed the halftone prepress domain that is central to graphic arts curricula.

The need is sharpened by distance and hybrid delivery. The interruption of education during the COVID-19 pandemic exposed how vulnerable technical education becomes when learning depends on physical infrastructure (Bozkurt et al., 2020). In graphic arts, the shared print laboratory — with its presses, proofing devices and loupe inspection routines — is precisely the resource that distance learners cannot access. In Greece, where graphic arts education spans vocational upper-secondary schools and university departments, research also indicates limited availability of discipline-specific open educational resources (Christoforidou & Georgiadou, 2022).

This paper frames the instructional goal of the project as parametric literacy: the learner's ability to translate visual intentions into explicit numerical and algorithmic choices, and to reason about the perceptual and production-related consequences of those choices. The construct is related to computational thinking (Wing, 2006) but is

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anchored in a specific professional practice, where the operator negotiates between what a client sees and what a raster image processor computes.

The purpose of this design-and-development case study is therefore twofold: (a) to describe how industrial halftone processes were transformed into an open, browser-based, parameter-driven learning environment — Raster Halftone Lab — and (b) to identify design features that allow the same environment to support exploratory use in upper-secondary TVET, more quantitative analysis in introductory tertiary programmes, and flexible deployment in distance and blended learning. The following sections present the development methodology, the resulting environment and its design findings, and conclusions with directions for classroom evaluation.

Methodology

The project followed a design-and-development research approach, corresponding to product design and development research in which the development of a specific instructional product is documented and analysed to extract context-specific design knowledge (Richey & Klein, 2005). The process was organised in three iterative phases.

Phase 1: Instructional design analysis. The target audiences were defined as upper-secondary TVET learners in graphic arts specialisations and first-year students of graphic design and visual communication, together with the distance and blended settings in which both groups increasingly study. Core curriculum concepts were mapped (screening, separation, rosette geometry, tone value increase, resolution and perception), along with typical misconceptions, such as confusing display artefacts with genuine print moiré.

Phase 2: Modelling of prepress phenomena. Each phenomenon was expressed as an explicit, inspectable model rather than a black box: clustered-dot amplitude-modulated (AM) screening through parametric spot functions for round, elliptical, square, diamond, line and inverted dots; frequency-modulated (FM) screening through Floyd–Steinberg error diffusion with serpentine scanning (Floyd & Steinberg, 1976) and Bayer ordered dithering (Bayer, 1973), whose spectral characteristics differ from blue-noise approaches (Ulichney, 1988); CMYK separation and rosette formation through overprinted screens at conventional angle offsets; tone value increase through a substrate-dependent quadratic model peaking in the midtones; reproducible grey levels through halftone-cell quantisation, where the number of levels approximates $(\mathrm{DPI}/\mathrm{LPI})^2$; and perceptibility through the Mannos–Sakrison contrast sensitivity function combined with viewing distance expressed in cycles per degree (Mannos & Sakrison, 1974).

Phase 3: Iterative implementation. The models were implemented as a zero-installation, client-side web application using HTML5, CSS and the JavaScript Canvas API, with no backend and no dependencies, so that the environment runs from a single folder or a static URL on school and home hardware alike. Design constraints adopted at this stage included immediate recomputation on every parameter change, numerical readouts next to every visual result, and explicit display-sampling guidance that warns users when the dot pitch approaches the display's own pixel grid and on-screen moiré may be an artefact of the monitor rather than a property of the raster. The application is released as open-access software under an MIT licence and archived with a DOI (Korakakis, 2026); it is publicly available at https://raster-halftone-lab.netlify.app/ and https://gk1966.github.io/raster-halftone-lab/, with source code at https://github.com/gk1966/raster-halftone-lab.

Results

Architecture and interface

Raster Halftone Lab consists of four static files (application, logic, styling and a scientific manual) and organises the domain into eight interactive panels (Table 1). A shared control vocabulary — tone, LPI, DPI, angle, dot shape, substrate, ink and viewing distance — recurs across panels, so that learners meet the same parameters in progressively richer contexts. Four substrate profiles (coated gloss, coated matt, uncoated, newsprint) affect paper white and tone value increase consistently everywhere. Each panel combines a large canvas with sliders and numerical feedback, including the effective tone after TVI, the number of reproducible grey levels and the spatial frequency of the raster at the chosen viewing distance.

Table 1. The eight interactive panels of Raster Halftone Lab v1.0.

Panel	Simulated phenomenon	Main adjustable parameters
01 AM dot	Clustered-dot amplitude-modulated (AM) screening; dot growth, shape behaviour and kissing points	Tone, preview zoom, LPI, DPI, dot shape, screen angle, substrate, ink

02 AM / FM	Side-by-side comparison of an ordered AM grid and density-modulated FM micro-dots	Tone, macro zoom, low-pass blur, substrate
03 CMYK image	Real-time separation of a source image into C, M, Y and K halftone channels	Per-channel tone values, overall scale, LPI, substrate
04 Rosette	CMYK overprint geometry, clear- and dot-centred rosettes, automatic rosette-type detection, moiré	Per-channel screen angles and tones, LPI
05 CSF	Mannos–Sakrison contrast sensitivity function; perceptibility of the halftone structure	LPI, viewing distance, spatial frequency readout (c/deg)
06 Cell	Halftone-cell quantisation; reproducible grey levels as $(DPI/LPI)^2 + 1$	DPI, LPI, tone
07 Compare	The same nominal tone rendered by AM and FM strategies simultaneously	Tone, shared screening parameters
08 Illusion	Viewing-distance effect: fusion of visible dots into continuous tone	LPI, dot colour, viewing distance

Figure 1 shows the overall interface: the panel tabs across the top, the active control groups on the left and the simulation canvas with its numerical readouts on the right. A permanent display indicator reports the device pixel ratio and current dot pitch, and a three-level sampling-risk message tells the learner whether on-screen moiré can be trusted as a property of the simulated raster.

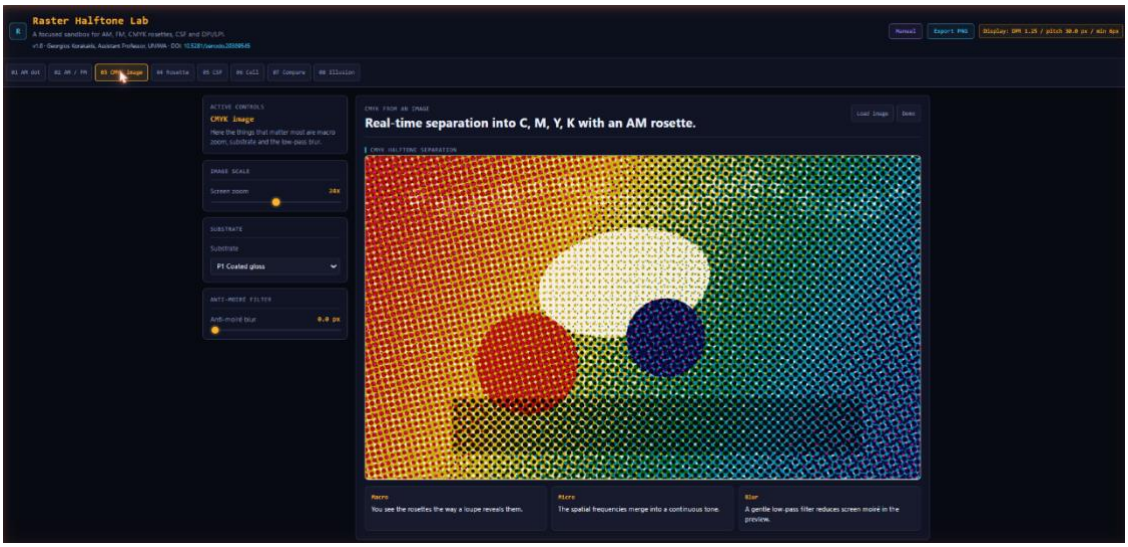


Figure 1. The Raster Halftone Lab interface (panel 03, CMYK image separation): panel tabs, active control groups, simulation canvas, explanatory cards and the display-sampling indicator (top right).

Making screening strategies visible and comparable

The first design finding is that placing screening strategies side by side, under identical tonal input, makes their different logics immediately discussable. Figure 2 shows 0–100% tone ramps rendered by the application's three strategies: the AM clustered dot grows dot area on a fixed grid; Bayer ordered dithering switches fixed micro-dot patterns according to a threshold matrix, producing visible periodic texture; and Floyd–Steinberg serpentine error diffusion distributes quantisation error to neighbouring pixels, producing an aperiodic structure. In classroom use the ramps anchor questions that connect algorithm to appearance: why AM midtones risk a visible jump when dots touch (the kissing point differs per dot shape), why ordered dithering shows patterning that error diffusion avoids, and why FM structures tolerate no fixed screen angle at all.

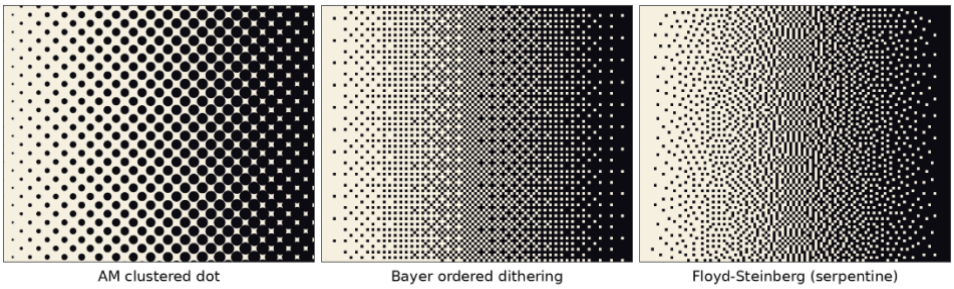


Figure 2. Tone ramps (0–100%) rendered with the screening algorithms implemented in the application: AM clustered dot (left), Bayer 8×8 ordered dithering (centre) and Floyd–Steinberg serpentine error diffusion (right).

The cell panel adds the quantitative counterpart: at a given addressability, the halftone cell contains $(\mathrm{DPI}/\mathrm{LPI})^2$ addressable micro-dots, so raising the screen ruling at fixed DPI reduces the number of reproducible grey levels.

Colour separation, rosettes and moiré

The separation and rosette panels connect single-channel screening to four-colour reproduction. The image panel separates a source image into C, M, Y and K channels, each screened at its own angle (Figure 3), while the rosette panel isolates the overprint geometry. With the conventional angle offsets the overprint forms a stable rosette (Figure 4); the panel classifies the result automatically as clear-centred or dot-centred, and deliberately mis-set angles produce low-frequency moiré. Because every angle is a slider, the fragility of the 30-degree separation between the chromatic channels — and the special position of yellow — becomes an experiment rather than a rule to memorise (Kipphan, 2001).

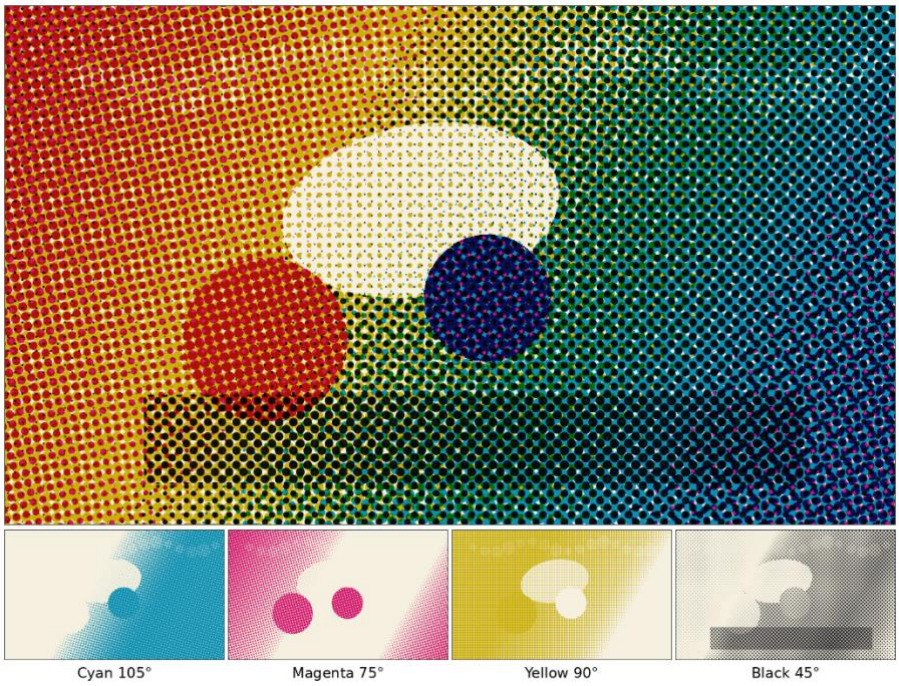


Figure 3. The application's real-time CMYK separation of its built-in demo image (top) and the four single-channel halftone plates at their screen angles (bottom).

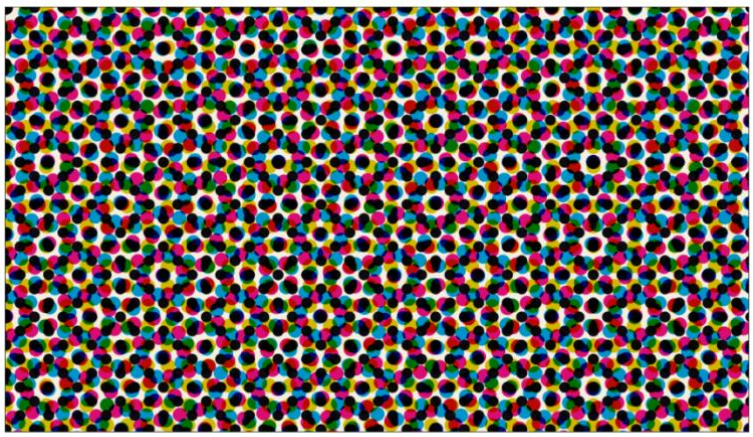


Figure 4. CMYK overprint rendered with the application's rosette model at its default channel angles (C 105°, M 75°, Y 90°, K 45°), producing a clear-centred rosette.

Substrate behaviour and tone value increase

Tone value increase is modelled as a substrate-dependent midtone gain added to the nominal tone, with peaks of approximately 14%, 16%, 22% and 28% for coated gloss, coated matt, uncoated and newsprint profiles respectively (Figure 5). The same model feeds every panel, so switching the substrate visibly thickens midtone dots, warms the paper white and reduces usable tonal range. This turns dot gain from an abstract press-room complaint into a parametric behaviour that learners can anticipate and compensate for, in line with standard production practice (Kipphan, 2001).

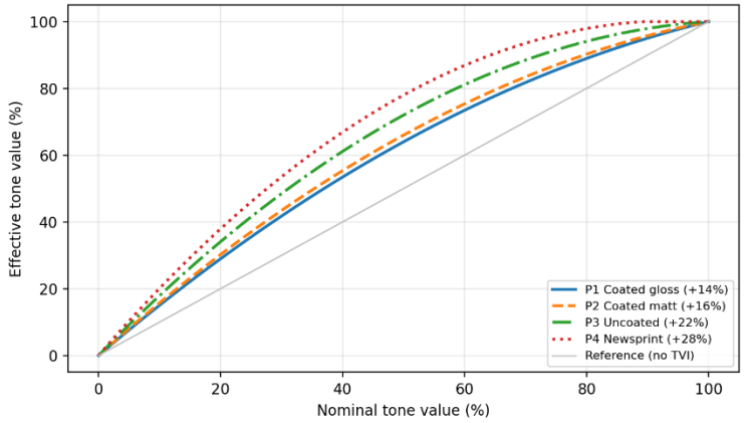


Figure 5. The substrate-specific tone value increase model implemented in the application: effective versus nominal tone for the four substrate profiles.

Perception and viewing distance

Two panels address the perceptual side of halftoning. The CSF panel implements the Mannos–Sakrison contrast sensitivity function and converts screen ruling and viewing distance into spatial frequency in cycles per degree, showing when the halftone structure crosses the limit of perception (Mannos & Sakrison, 1974). The illusion panel makes the same point experientially: the identical raster is viewed at increasing simulated distances until dots fuse into continuous tone. Together they explain why newsprint survives at 85 LPI while fine art printing demands far higher rulings.

Use scenarios across educational levels

The design findings indicate that a single parameter-driven environment can serve different cognitive levels through the depth of the questions asked of it, rather than through separate versions. In upper-secondary TVET, panels support teacher-guided demonstration and exploratory visual inquiry: learners predict, manipulate and describe. In first-year applied programmes, the same modules support quantitative tasks — verifying the $(DPI/LPI)^2$ relationship, reading TVI compensation from the curves, or computing the viewing distance at which

a given ruling becomes invisible. In distance and blended delivery, the zero-installation format lets a teacher demonstrate over video, share a parameter recipe in a learning management system, and assign asynchronous exploration with the same visual feedback and explanatory language for every participant; the display-sampling guidance is critical here, because remote learners view the simulation on uncontrolled screens.

Conclusions

This case study described the transformation of industrial halftone processes into an open-access, browser-based simulation laboratory for graphic arts education. The design findings suggest that lightweight client-side simulation can make complex prepress relationships visible, adjustable and discussable; that a shared parameter vocabulary across panels supports the development of parametric literacy — the ability to translate visual intentions into explicit numerical choices; and that the zero-installation web format allows the same environment to serve classroom demonstration, individual practice and asynchronous distance learning without adaptation.

The study has clear limitations. It reports design and development findings, not measured learning outcomes: no controlled classroom evaluation has yet been conducted. The simulations are transparent teaching models, not certified production tools, and are explicitly framed as complements to — not substitutes for — calibrated proofing, densitometric measurement and press-room experience. Screen-based viewing also differs physically from printed output.

Future work will therefore focus on classroom evaluations across TVET and tertiary settings, examining learning outcomes, usability and the transfer of parametric reasoning to authentic production tasks, and on extending the environment with additional modules. The application is freely available at https://raster-halftone-lab.netlify.app/ and as archived open-access software (Korakakis, 2026), and is recommended for use as a guided inquiry resource within learning management systems in graphic arts, graphic design and visual communication programmes.

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Fabry-Perot interferometry interactive simulator: A web-based tool for experimental learning of optical communication dispersion compensation

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Abstract

There is a lack of web-based education tools that allow lecturers to teach chromatic dispersion compensation techniques to optical communications students. This work presents an online simulator that lets students simulate and visualize chromatic dispersion compensation with the Fabry-Perot interferometer (FPI) in long-distance optical fiber. The simulation tool has as input parameters the mirror reflectivity and the round-trip time delay, that directly modifies the cavity length, that the student can update in real time allowing them to explore and learn on the fly. The cavity length, initial pulse width, laser chirp, link length, fiber dispersion and pulse shape can also be modified. The tool also comes with six graphical plots that display the signal time and frequency domain alongside its evolution through the fiber. Results can be measured with the bandwidth-distance product, the pulse widening rate and the pulse width reduction obtained by the interferometer effect on the pulse. The numerical Python class can reproduce the analytical Gaussian broadening law to within 0.1% for pulses that fit the simulator constraints. The default scenario shows that the FPI can re-compress a 317 ps dispersed pulse to 101 ps, at the cost of transmitting only 15% of the pulse energy. The work also addresses how complex optical concepts can be taught through virtual laboratories that narrow the gap between optical communications theory and hands-on implementation in real communication systems.

Keywords: Online education, remote learning, fiber optics, channel equalization, interferometer design, student simulation.

Introduction

Chromatic dispersion imposes a hard physical limit on long-distance optical fiber links. Signal pulses are broadened due to the group velocity (GV) of light in silica. Because GV depends on the wavelength used, the spectra components of a short pulse arrive at divergent times. The components then overlap its neighbours and produce inter-symbol interference (ISI), which results in a reduction of bit rate and communication distance (Agrawal, 2002; Keiser, 2011). The dispersion parameter in standard single-mode at 1550 nm is $D \approx 17$ ps/(nm·km), so dispersion management is taught at every introductory optical communications subject (International Telecommunication Union [ITU], 2016).

Optical equalization using interferometers was proposed as a compact method to reduce dispersion and laser chirp effects (Cimini et al., 1990; Gnauck et al., 1991). Fabry-perot devices were later implemented alongside planar lightwave circuits too (Stone & Stulz, 1987), (Takiguchi et al., 1994; Sharma et al., 1994). To display dispersion compensation using this technique, the hardware needed to observe it is expensive and rarely available to undergraduate students as it requires a few kilometres of optical fiber, picosecond sources, and fast detectors with tunable interferometers. However, the underlying physics can be accurately simulated by computing the underlying model which is a partial differential equation (PDE) whose solution can be presented as a closed-form broadening factor. This solution allows lecturers to teach interferometer links wave optics, filter theory and system-level performance without optical hardware (Hariharan, 2007).

Virtual workshop environments are a proposed solution to these constraints for science and engineering education (Ma & Nickerson, 2006; Potkonjak et al., 2016; Heradio et al., 2016). Virtual lessons can achieve comparable learning results to the physical ones, and more so when they make otherwise invisible results visible just like the phase and group delay of optical pulses in this case (de Jong et al., 2013; Wieman et al., 2008). Following the reality-virtuality continuum terminology, the presented tool sits at the complete virtual end of it (Milgram & Kishino, 1994). The provided virtual workshop complements the physical bench with an interactive, physically faithful model and supports the hands-on experience, reflection, conceptualisation and experimentation of optical equalization with interferometer structures (Kolb, 1984; Feisel & Rosa, 2005).

This work contribution is a web-based FPI dispersion compensation simulator designed for experiential learning. It also provides a validation tool for numeric analysis and physics theory and a set of guided scenarios that teach the trade-offs of interferometric equalization in long-distance fiber communication links.

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Methodology

Physical model

The simulator uses the linear pulse-propagation model of Agrawal (2002). The input field is a chirped (super-)Gaussian pulse

$$A(0,t) = exp\left[-\frac{1+jC}{2}\left(\frac{t}{T_0}\right)^{2m}\right], \quad (1)$$

where T_0 is the pulse initial width, C the laser chirp and m the pulse order, being $m = 1$ for a Gaussian pulse. Propagation over a length z of fiber with group-velocity dispersion β_2 is applied in the frequency domain through the fiber transfer function

$$H_{fib}(\omega, z) = exp\left(j\frac{\beta_2}{2}\omega^2 z\right), \quad (2)$$

and the dispersed pulse is recovered by an inverse Fourier transform. For a Gaussian input, the broadening predicted by this model has the closed form $T_1/T_0 = \sqrt{[(1 + C\beta_2 z/T_0^2)^2 + (\beta_2 z/T_0^2)^2]}$ (Agrawal, 2002), which is used below to validate the numerical core.

The equalizer is a FPI placed at the end of the link. Its transfer function is

$$H_{FPI}(f) = \frac{1-R}{1-Re^{j2\pi f\tau}}, \quad (3)$$

where R is the mirror (intensity) reflectivity and τ is the cavity round-trip delay, proportional to the cavity length. The response is periodic, with a free spectral range FSR = $1/\tau$ and a resonance width FWHM = FSR/$\mathcal{F}$, where $\mathcal{F} = \pi\sqrt{R}/(1 - R)$ is the finesse (Hariharan, 2007). The two controls map directly onto these quantities. The delay τ sets the spacing of the resonances, and the reflectivity R sets how sharp they are and how strongly they shape the pulse phase and amplitude.

Performance metrics

For every simulation the tool computes the pulse width Δt as the full width of the envelope at $1/e$ of its peak amplitude. It then accounts for three indicators for the unfiltered and filtered outputs: (i) the widening rate, i.e. the ratio between the final and initial widths of each signal; (ii) the pulse width reduction $\Delta t_{unf} - \Delta t_{FPI}$ obtained with the interferometer; and (iii) an estimate of the bandwidth-distance product, $B{\times}L = 187\ L/\sigma$ (Gb/s·km, with σ in ps and L in km), where σ is the rms width of the output power pulse. The constant comes from the 3 dB optical bandwidth of a Gaussian pulse, $f_{3\ dB} = 0.440/t_{FWHM} = 0.187/\sigma$ (Keiser, 2011, Eq. 14.11). Δt and σ are measured in the same way for all outputs, so that the three indicators are directly comparable across configurations.

Implementation

NumPy and SciPy are used as the numerical core for the tool. The time window spans ±500 ps with 10 000 samples or 0.1 ps resolution, and propagation is evaluated at intermediate distances with 10 km steps by default to build the evolution plots. Flask is used for the web server which exposes the model, and the browser front end, written in JavaScript with Plotly, renders the results. No setup is needed on the student side, and the application is also distributed as a Docker container for local or institutional deployment.

The interface (Figure 1) is divided into a parameter input panel and a graph area. The panel contains input fields paired with sliders for T_0, C, L, β_2, m, the display carrier frequency, τ and R. It also includes a short theory card with the FPI transfer function and three presets: optimal compensation, low reflectivity and over-compensation. These presets act as starting points for guided activities and can be further modified by teachers according to their subject guide. The plotting area shows six synchronised figures: input and output pulses in time, their frequency-domain representation, the three-dimensional evolution of the pulse along the fiber in time and frequency, and zoomed views of the input and output fields including the oscillating carrier. A results panel lists the indicators described above, and a user guide documents every parameter.

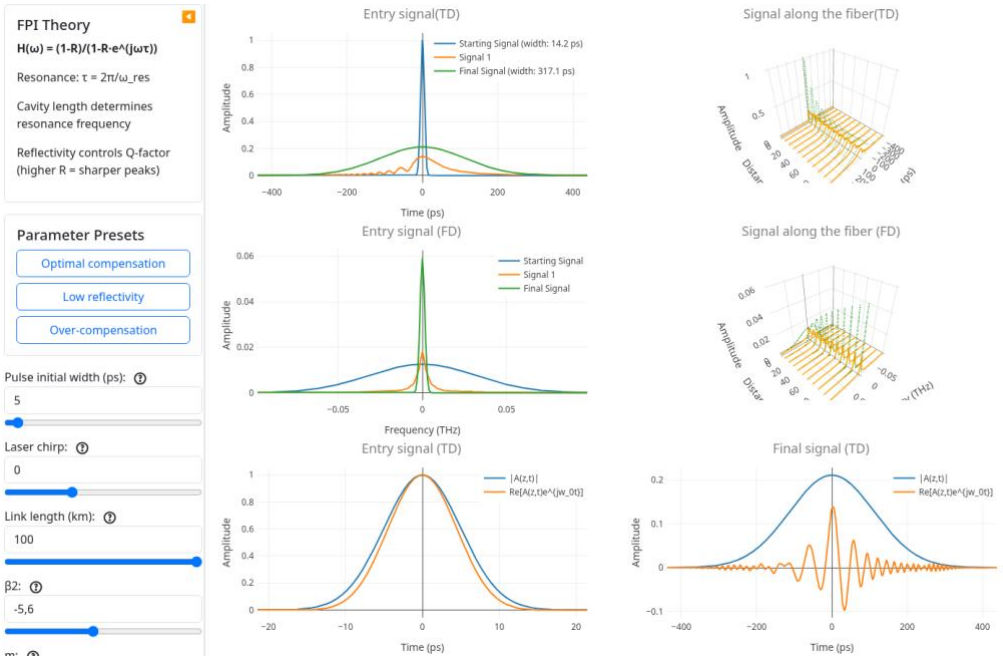


Figure 1. Interface of the FPI simulator: theory card, presets and parameter controls (left) and the six interactive plots (right).

Learning design

The tool is intended to support one laboratory session organised around Kolb's (1984) experiential cycle. Students first run the optimal compensation preset and observe the broadening and re-compression of the pulse (concrete experience). They then relate the plotted spectra to the FPI resonances (reflective observation) and connect the measured widths to the broadening formula and to the FSR and finesse of the cavity (abstract conceptualisation). Finally, they vary τ, R, L and C to reach target indicators and explain the observed trade-offs (active experimentation). Because the whole cycle runs in the browser, the same activity can be carried out in class, as homework assignments or in online courses.

Results

Validation of the numerical core

The default scenario uses a 5 ps Gaussian pulse without chirp, a 100 km fiber link with $\beta_2 = -5.6$ ps^2/km which corresponds to anomalous dispersion, $D \approx 4.4$ ps/(nm·km) at 1550 nm, typical of reduced-dispersion fibers, and an FPI with $\tau = 12.5$ ps and $R = 0.8$. The measured input width is 14.3 ps and the unfiltered output width is 317.1 ps, a 22.2 times broadening. This matches the analytical prediction of 317.1 ps to within 0.1%. The same agreement holds for the 50 km preset obtaining 159.1 ps measured versus 159.0 ps predicted. For a chirped source $C = 2$, the pulse broadens to about 696 ps, wider than the ±500 ps window. The envelope then wraps around the window edges and the measured width of 671.8 ps falls 3.4% short of the analytical value. This limit is itself instructive: students can see that numerical tools have a domain of validity, and the window is being made adjustable in the next update.

Guided scenarios

Table 1 summarises the configurations that students can simulate with the current presets and sliders. Figure 2(a) shows the pulse envelopes for the default scenario, and Figure 2(b) shows the power response of the interferometer overlapped on top of the input pulse spectrum.

Table 1. Simulated performance for representative scenarios ($T_0 = 5$ ps, $\beta_2 = -5.6$ ps^2/km). Widths at 1/e amplitude; $B{\times}L$ in Gb/s·km, computed from the rms width σ; E_{FPI} is the fraction of the pulse energy transmitted by the FPI.

Scenario	L (km)	C	τ (ps)	R	Δt_{unf} (ps)	Δt_{FPI} (ps)	$B{\times}L_{unf}$	$B{\times}L_{FPI}$	E_{FPI}
Optimal compensation (preset)	100	0	12.5	0.8	317.1	100.7	235.9	417.6	14.9%
Low reflectivity (preset)	100	0	12.5	0.3	317.1	212.4	235.9	292.3	60.6%

Scenario	L (km)	C	τ (ps)	R	Δt_{unf} (ps)	Δt_{FPI} (ps)	$B{\times}L_{unf}$	$B{\times}L_{FPI}$	E_{FPI}
Over-compensation (preset)	50	0	5.0	0.8	159.1	75.8	235.2	417.7	31.6%
Short delay	100	0	5.0	0.8	317.1	123.8	235.9	469.9	31.6%
Long delay	100	0	25.0	0.8	317.1	91.6	235.9	196.1	11.1%
Chirped source	100	2	12.5	0.8	671.8	99.0	108.3	108.5	11.1%

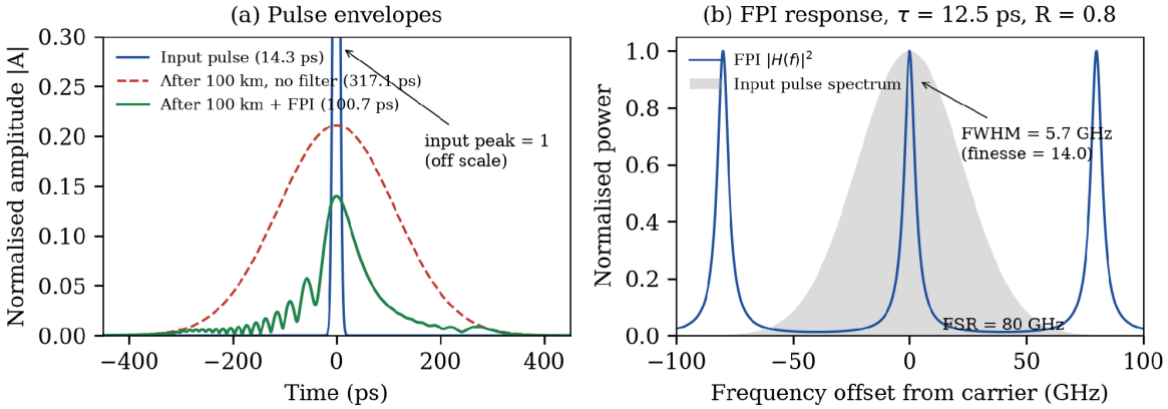


Figure 2. Default scenario. (a) Envelope of the input pulse, the pulse after 100 km without equalization and the pulse after the FPI. (b) Power transmission of the FPI (τ = 12.5 ps, R = 0.8) and normalised spectrum of the input pulse.

In the default scenario the FPI reduces the output width from 317.1 ps to 100.7 ps. Relative to the 14.3 ps input pulse, the width ratio falls from 22.2 to 7.0, and the estimated $B{\times}L$ rises from 235.9 to 417.6 Gb/s·km, a factor of 1.77. This gain is smaller than the 3.15-fold reduction of the 1/e width because σ also counts the low-level tails that the filter leaves around the main pulse. With a chirped source the same interferometer narrows the 1/e width from 671.8 to 99.0 ps, but $B{\times}L$ hardly changes (108.3 to 108.5 Gb/s·km): about 40% of the filtered energy lies outside the main pulse, partly in tails that wrap around the window, and σ counts it.

What students can learn

To lead students to reason on what setting compresses the pulse the most, scenarios have been designed to help students answer this question. Increasing R or τ narrows the resonances and shortens the output pulse (100.7 ps at τ = 12.5 ps, 91.6 ps at 25 ps). However, it also reduces the transmitted energy from 60.6% at R = 0.3 to 14.9% and then 11.1%. Nor does a shorter pulse always mean a higher $B{\times}L$. At τ = 25 ps the FSR of 40 GHz falls inside the pulse spectrum, the neighbouring resonances add side lobes of up to 57% of the peak, and $B{\times}L$ drops to 196.1 Gb/s·km, below the 235.9 of the unfiltered link. In Figure 2(b), the resonance is only 5.7 GHz wide with R = 0.8 (FSR = 80 GHz, finesse 14), far narrower than the pulse spectrum which is about 53 GHz FWHM. Applying only the magnitude of H_{FPI} yields a 109.5 ps pulse, while applying only its phase yields 268.2 ps. In this regime the transmissive FPI hence reshapes the pulse primarily by spectral filtering, and a smaller contribution from its dispersive phase. This insight links directly to the literature on optical equalizers, which uses reflective and all-pass structures such as the Gires-Tournois interferometer, or cascaded Mach-Zehnder stages, to correct phase without discarding remaining energy (Cimini et al., 1990; Gnauck et al., 1991; Takiguchi et al., 1994).

The same observation lets lecturers discuss the importance of the $B{\times}L$ term. A narrower filter reduces pulse width, but it also limits the bandwidth available to the signal pulse, so the $B{\times}L$ term should be read together with the transmitted energy, the filter bandwidth and the shape of the output, since σ penalises the energy spread into tails and side lobes. Balancing these settings is the kind of engineering common sense the tool aims to train.

Next steps

The implemented model is linear, deterministic and has no simulated noise. It does not yet include fiber attenuation, receiver noise or bit-error-rate estimation. The time window is also fixed but can be changed by the lecturer. A classroom study with pre- and post-tests on the dispersion compensation topic and an outcome quiz is also planned for the next course of Optical Communications at the University of Jaén.

Conclusions

A web-based virtual laboratory is presented for chromatic dispersion compensation with the Fabry-Perot interferometer. The simulation tool turns the complex optical communication theory of pulse broadening and interferometric filtering into an easily explainable topic thanks to its graphical plots and its set of analytical result metrics. It runs in the browser, requires no optical hardware and no setup from students. The tool reflects the broadening law to within 0.1% for pulses that fit the simulation scope. The default configuration shows that the interferometer can re-compress a 100 km dispersed pulse from 317 ps to 101 ps. The addition of guided scenarios makes visible the price of that compression, such as the energy discarded by a high-finesse transmissive filter. Students can leverage this tool to move from observing an effect to analyzing the engineering trade-offs, which is the main goal of experiential learning in this domain. Future work will cover the previous limitations and also include reflective settings such as the Gires-Tournois interferometer configuration.

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Mach-Zehnder optical equalizer implementation on virtual learning environment: Fostering optical fiber communication optimization learning

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Abstract

Lessons in optical communications equalization techniques can be hard going for students new to the subject. This work goal is to present lecturers and students a complement for the optical communications subject which offers an interactive, gamified simulator of Mach-Zehnder interferometer (MZI) equalization for chromatic dispersion compensation in long-distance optical fiber. The simulator has been designed as a browser-based tool for hybrid education that requires no installation. The tool lets users configure the delay and number of cascaded MZI stages and has real-time visual feedback through six data plots and resulting metrics such as the bandwidth-distance product B×L, the pulse widening rate and the transmitted energy. The addition of challenges with scores and B×L targets has the goal of gamifying the experience and turning the tool into an optimization game for newcomers. With the recalibrated challenges, the simulated MZI raises the $B{\times}L$ of the link from about 236 to between 350 and 693 Gb/s·km, and an analytical far-field model predicts the output pulse width to within 2% when the delayed replicas are well separated. Because $B{\times}L$ is computed from the rms width of the output, all 24 of the 140 configurations explored that exceed 300 Gb/s·km have side lobes below 30% of the main peak, whereas a score based on the $1/e$ width of the central lobe alone would reward trains of near-equal pulses that do not equalize the signal. The discussion addresses how this finding can itself be used to teach metric literacy, and how the tool supports STEM laboratory work in remote learning environments.

Keywords: Online education, educational assessment, simulation, dispersion correction, distance learning, interferometer design, fiber optics.

Introduction

Engineering education without physical laboratories has always impeded lecturers to properly transfer the hands-on experience. Emergency remote teaching showed how quickly physical courses can be disrupted, and how different well-planned online learning is from a rushed transfer of face-to-face content (Hodges et al., 2020). Optical filters are designed by reasoning about complex transfer functions that come from textbook derivations which give little feel for what changing a parameter does to a pulse. And in this case, hands-on photonics is particularly at risk due to requirements for testing the optical filters on the bench (fiber spools, picosecond sources, tunable interferometers) being expensive enough to thwart distance learning.

Chromatic dispersion is a good concept to help close this gap. It limits the bit rate and distance of a fiber link (Agrawal, 2002), and it can be canceled out with optical equalizers built from interferometric structures (Cimini et al., 1990). Mach-Zehnder interferometers are reasonable building blocks for these equalizers. They are simple to describe, can be cascaded into lattice filters, and they were implemented as planar lightwave circuits for dispersion equalization (Madsen & Zhao, 1999; Okamoto, 2006), (Takiguchi et al., 1994; Sharma et al., 1994). Digital laboratories are a well-established answer to the access problem and can match physical experiments in learning outcomes when they make imperceptible quantities visible (de Jong et al., 2013; Potkonjak et al., 2016). The cascaded MZI raises a pedagogical question to make students reason on how to optimize a design with several coupled parameters when they cannot iterate on hardware.

Gamification can be the answer to that question where the use of game design elements outside games (Deterding et al., 2011), has been reported to improve cognitive, motivational and behavioural outcomes in a meta-analysis of experimental studies (Sailer & Homner, 2020), although effects depend on context and design (Hamari et al., 2014). Individual elements such as points and progression levels can raise performance without changing a student's motivation (Mekler et al., 2017). The value of these levels depends on how well they are aligned with the learning goal as rewarding the wrong goal would lead the teaching session in an unintended direction for the lecturer (Landers, 2014). This paper presents a browser-based MZI equalizer simulator with a light gamification layer, evaluates its numerical behaviour, and examines whether its scoring rule rewards the physics it is meant to teach.

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Methodology

Model implementation

The tool implements a linear pulse-propagation model of Agrawal (2002). The input is a chirped (super-)Gaussian pulse of initial width T_0, chirp C and order m. It goes through a fiber of length L and group-velocity dispersion β_2 via the transfer function $H_{\text{fib}}(\omega,L) = \exp(j\beta_2\omega^2 L/2)$, evaluated with FFTs over a ±500 ps window with 10 000 samples or 0.1 ps resolution. The equalizer simulates a cascade of N MZI stages where each stage has two 3 dB couplers and an arm imbalance that introduces a delay τ, so that

$$H_{MZI}(f) = \left[\frac{1}{2}(1 + e^{-j2\pi f\tau})\right]^N = e^{-j\pi N f\tau}\cos^N(\pi f\tau). \quad (1)$$

The power response $\cos^{2N}(\pi f\tau)$ is periodic with free spectral range FSR = $1/\tau$. Increasing N narrows each passband and given that the phase is linear, the MZI only delays the pulse by $N\tau/2$ and operates on the spectrum through its magnitude. The output waveform is the sum of $N + 1$ delayed replicas of the dispersed pulse with binomial weights. It is assumed that the phase offset places a passband at the central frequency for the incoming optical pulse.

For L much larger than the dispersion length $L_D = T_0^2/|\beta_2|$, the dispersed envelope maps the input spectrum onto the time domain through $f = t/(2\pi|\beta_2|L)$. The output amplitude can be approximated as

$$|y(t)| \approx exp\left(-\frac{t^2}{2T_z^2}\right)\left|cos\frac{\tau t}{2|\beta_2|L}\right|^N, T_z = \frac{|\beta_2|L}{T_0}, \quad (2)$$

with a first null at $t_0 = \pi|\beta_2|L/\tau$ and side lobes centred at $\pm 2t_0$. Setting $|y| = e^{-1}$ gives a prediction of the output width that the tool's measured value can be compared with.

Performance metrics

The pulse width Δt is the full width at $1/e$ of the peak amplitude, measured outwards from the peak. The tool then outputs for each result (i) the widening rate, (ii) the width reduction compared to the unfiltered output, and (iii) $B{\times}L = 187\, L/\sigma$ Gb/s·km, where σ (ps) is the rms width of the output power pulse and L is in km. The constant comes from the 3 dB optical bandwidth of a Gaussian pulse, $f_{3\text{ dB}} = 0.440/t_{\text{FWHM}} = 0.187/\sigma$ (Keiser, 2011, Eq. 14.11), and the rms width, unlike the $1/e$ width, includes any side lobes of the output. For this work we add two diagnostics that are not directly displayed in the interface, the fraction of pulse energy transmitted by the filter E and the side-lobe level, defined as the largest output amplitude beyond the first null t_0 relative to the main peak.

Implementation and interface

The backend is implemented with Flask for the web application which calls the numerical Python class that contains all equations and performs the simulator computations. The frontend uses JavaScript and Plotly for the interactive plots. It is intended to run in any browser without student setup requirements or in a Docker container for teachers to deploy. The interface from Figure 1 has a parameter input panel that can modify the pulse width, chirp, link length, β_2, pulse order, carrier frequency, MZI delay and number of stages from 1 to 50. A gamification challenge panel and six data plots of the pulse are also included. The waveform and the spectrum at the input and output are visually represented in the plots alongside their evolution through the fiber link.

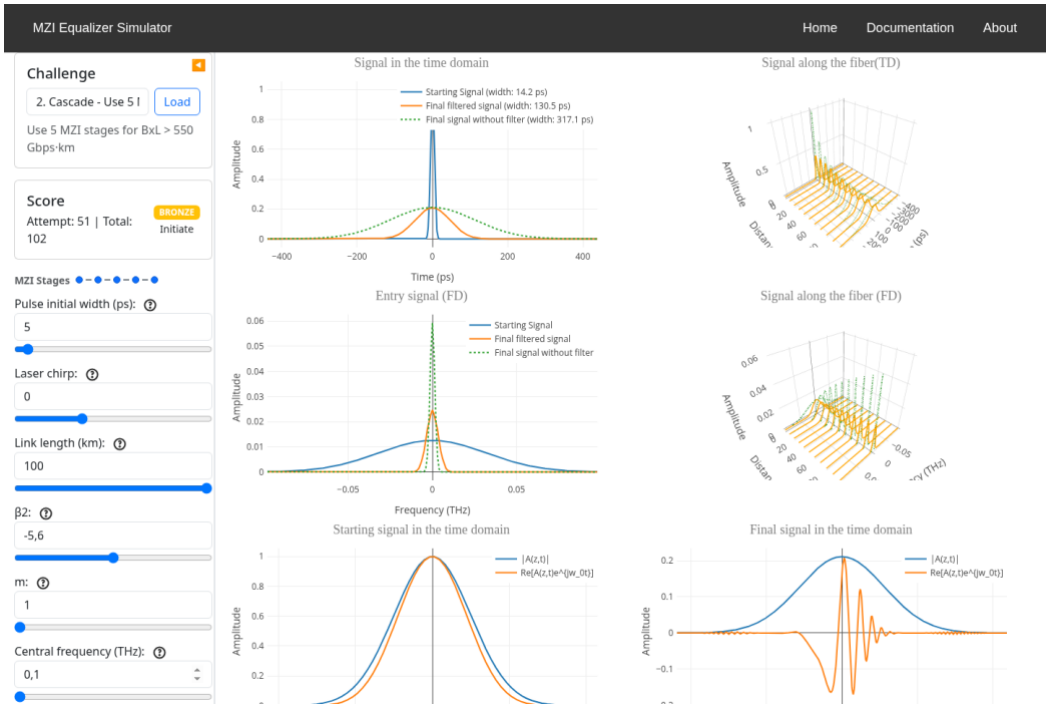


Figure 1. Interface of the MZI simulator during a challenge: challenge selector, score and badge panel, cascade control and pulse input parameters (left) and interactive plots (right).

Game design

Four challenges, detailed in Table 1, give students a target $B{\times}L$ and a starting configuration. Pressing Simulate evaluates the attempt with a score from 0 to 100. If the target is achieved the attempt earns 50 points plus a bonus of up to 50 proportional to the relative excess, and otherwise it earns a partial credit 50 $B{\times}L$/target. Attempts accumulate in a total, and four badges (Bronze, Silver, Gold, Platinum) are unlocked at 100, 250, 500 and 1000 points. The design is meant to support three mechanisms known to help learning. Explicit goals direct effort (Locke & Latham, 2002), immediate and specific feedback closes the gap between attempt and target (Hattie & Timperley, 2007), and visible progress supports the feeling of competence (Ryan & Deci, 2000). Because the cycle of proposing a configuration, observing the result, interpreting it and trying again runs entirely in the browser, it follows Kolb's (1984) experiential cycle and can be used in class, as homework assignments or in online courses.

Results

Behaviour of the four challenges

Table 1 lists the four challenge presets simulated with the tool where each link is a chirp-free 5 ps pulse in a fiber with $\beta_2 = -5.6$ ps^2/km. Without a filter the 100 km link has a width of 317.1 ps ($B{\times}L = 235.9$) and the 200 km link 626.4 ps ($B{\times}L = 236.7$). All four presets reach their targets. Playing them once in order accumulates 202 points, which unlocks the Bronze badge, and higher badges require repeated and improved attempts with at most 100 points per attempt.

Table 1. Challenge presets. Δt_{MZI}: measured output width; Δt_{th}: far-field prediction; E: transmitted energy; Side: side-lobe level (fraction of the main peak). Widths in ps, $B{\times}L$ in Gb/s·km.

Challenge	L (km)	τ (ps)	N	Δt_{MZI}	Δt_{th}	$B{\times}L$	Target	Score	E	Side
1. First Steps	100	12	1	190.5	189.7	350.1	340	51	61.9%	0.11
2. Cascade	100	10	5	130.5	126.3	564.8	550	51	40.1%	0.02
3. Precision	100	12	12	94.9	73.2	660.8	650	50	23.2%	0.04
4. Pulse Master	200	8	12	216.6	212.7	693.3	680	50	33.7%	0.00

The far-field model replicates the measured width to within 0.5% for a single stage, for example, 103.0 versus 103.5 ps at $\tau = 25$ ps, and 480.5 versus 479.1 ps for $L = 200$ km and $\tau = 8$ ps. For challenge 4, the achieved width is within 2%, where the delayed replicas are widely separated: 212.7 versus 216.6 ps. It underestimates the width by 10–40% when several comparable replicas overlap: $N\tau$ approaching the dispersed pulse width $T_z = 112$ ps. The

simple factorisation of Eq. (2) ignores the shift between their envelopes and it leads to more dispersion. Students can therefore use the formula as a first design estimate and learn where it stops working.

What students discover

Exploring the controls, the simulator allows students to catch onto the following three trade-offs. First, increasing τ narrows the main lobe, but $B{\times}L$ for a single stage does not grow with it: it rises from 267 at $\tau = 5$ ps to a maximum of 350 at 12 ps and falls back to 236 at 25 ps and 221 at 60 ps (Figure 3a). Second, this comes at the price of energy. A single stage transmits 89% of the pulse energy at $\tau = 5$ ps but only 50% at 25 ps, and cascading further reduces it to 25% for five stages. Third, more stages help only when the delay is short. At $\tau = 10$ ps $B{\times}L$ rises from 346 for $N = 1$ to 565 for $N = 5$, whereas at $\tau = 25$ ps it stays at 236, 236, 235 and 233 for $N = 1$, 2, 3 and 5.

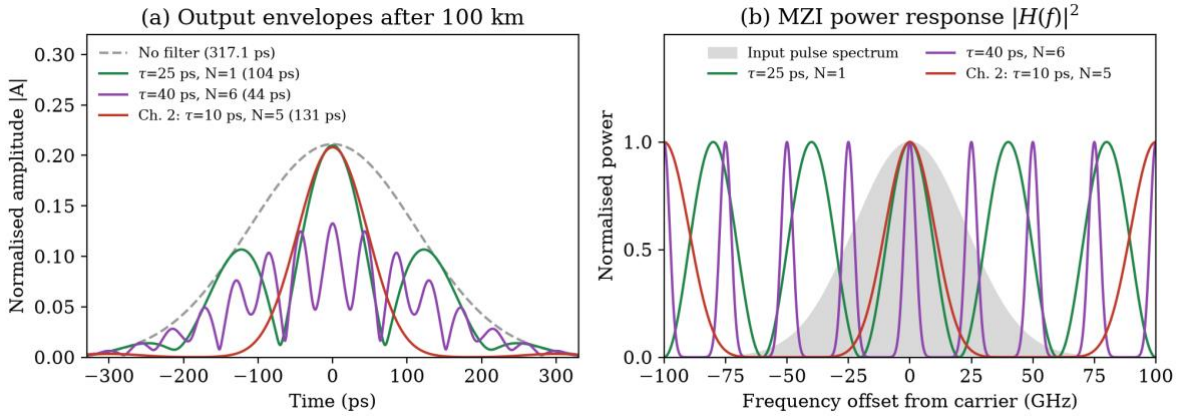


Figure 2. Large delays ($\tau = 25$ ps, $N = 1$ and $\tau = 40$ ps, $N = 6$) compared with challenge 2 ($\tau = 10$ ps, $N = 5$). (a) Output envelopes after 100 km. (b) MZI power responses superimposed on the input pulse spectrum.

Figure 2 explains the third observation and shows what the $B{\times}L$ indicator measures. For $\tau = 25$ and 40 ps, FSR = $1/\tau$ equals 40 and 25 GHz, so neighbouring passbands of the MZI fall inside the 53 GHz-wide pulse spectrum. Each passband is transmitted, and the dispersion converts it into a separate lobe of the output. The output is therefore not one compressed pulse but a central pulse with side lobes at $\pm 2t_0 = \pm 141$ and ± 88 ps whose amplitudes reach 51% and 94% of the main peak. The $1/e$ width measures only the central lobe and falls to 103.5 and 43.7 ps, but the rms width σ includes the side lobes, so $B{\times}L$ stays at 235.8 and 214.6 Gb/s·km, no better than the unfiltered link. With $\tau = 10$ ps (challenge 2) the neighbouring passbands sit at ±100 GHz, where the pulse has almost no spectral content, and five stages raise $B{\times}L$ to 564.8 Gb/s·km with side lobes of only 2%.

To see how general this is, we scanned 140 configurations ($\tau = 4$–80 ps in steps of 4 ps and $N \in \{1,2,3,5,8,12,20\}$) on the 100 km link. Figure 3(b) plots $B{\times}L$ against the side-lobe level. The highest $B{\times}L$ in the scan, 750 Gb/s·km, is reached at $\tau = 8$ ps and $N = 20$, with side lobes below 0.1% and 27% of the energy transmitted. All 24 configurations that exceed 300 Gb/s·km have side lobes below 30% of the main peak (at most 20%), whereas the best output with larger side lobes reaches only 281 Gb/s·km ($\tau = 52$ ps, $N = 20$, side lobes 90%, 6% of the energy), barely above the 236 of the unfiltered link.

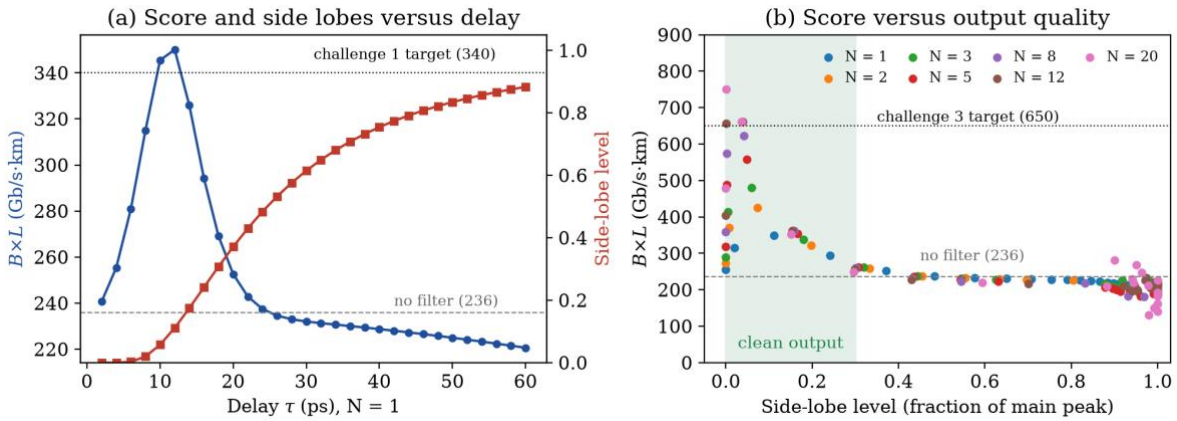


Figure 3. (a) $B{\times}L$ and side-lobe level of a single MZI stage versus delay. (b) $B{\times}L$ versus side-lobe level for the 140 scanned configurations. The shaded band marks side lobes below 30%.

Discussion and limitations

This finding is as useful for a course as it is for the game. A score that rewards a single measurable indicator invites students to optimize the indicator, so the indicator has to be chosen with care. Had the score been based on the $1/e$ width of the central lobe, large delays that create a train of near-equal pulses would have been rewarded: $\tau = 40$ ps and $N = 6$ give the narrowest central lobe of all the configurations discussed here (43.7 ps) but a $B{\times}L$ below that of the unfiltered link. Computing $B{\times}L$ from the rms width σ, as in the bandwidth relation of Keiser (2011), closes this loophole, and instructors can use the contrast between the two widths as an activity in which students reason about where the "extra" bandwidth would have come from. The score still ignores energy, and the five best configurations of the scan transmit only 18–34% of it, so a penalty on the transmitted energy is a natural next correction. Since Mekler et al. (2017) found that points and progression levels alone need not change intrinsic motivation, tying the score more closely to output quality is also the more defensible design.

The MZI simulated in this work is a cascade of identical stages with fixed 3 dB couplers and a single common delay τ. Its phase is therefore linear, so it can only reshape the pulse through its amplitude response. Lattice equalizers with different coupling ratios and phase shifts between stages can also produce the group-delay dispersion needed to correct phase (Takiguchi et al., 1994). Adding these controls is left for future work. The model is linear, deterministic and noise-free. The running total is currently stored in the server process and is not separated per student, and repeated attempts add points without diminishing returns, so a deployment for a class needs per-user storage and a cap. The claims made above about retention and motivation are design intentions, and a pre-/post-test and usability study is planned for the next course of Optical Communications at the University of Jaén.

Conclusions

This work presents a web-based gamified simulator for chromatic dispersion compensation through cascaded Mach-Zehnder equalizers in remote and hybrid teaching settings. The simulation tool offers results displayed with six interactive plots, four scored challenges and four progression levels portrayed by badges, and needs no optical hardware. In the four challenge presets, the MZI raises the $B{\times}L$ of the link from about 236 to between 350 and 693 Gb/s·km, and the closed-form far-field model achieves an output width to within 2% when the delayed models are separated. The analysis also shows that a score based on the $1/e$ width of the central lobe could be gamed by large delays that create a train of near-equal pulses, while the rms-based $B{\times}L$ ranks those outputs no better than the unfiltered link. We regard this contrast as a case study in metric literacy that the tool makes easily understandable. Future work on the simulator tool will add an energy penalty to the score, store progress per student, add adjustable couplers and phase shifters, and evaluate learning outcomes.

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Dispersion Compensation With Learning Analytics on a Web Platform That Enables Comparison Between Lineal and Non-Lineal Techniques

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Abstract

Learning to choose between engineering solutions requires comparing them on evidence, but introductory optical communication courses lack interactive tools for comparing dispersion compensation techniques. This paper presents a web platform that places three families of compensation techniques in the same simulator: etalon interferometers (Fabry-Perot, FPI, and Gires-Tournois, GTI), the Mach-Zehnder interferometer (MZI) and the nonlinear self-phase modulation (SPM) effect. Every simulation reports the bandwidth-distance product ($B{\times}L$) and the pulse widening rate, and a learning-analytics module logs each attempt and builds a comparison table across methods. The default 100 km scenario shows that the analytics rank the techniques differently depending on what metric is used. The GTI gives the shortest output and keeps all the energy, but the lowest $B{\times}L$ with 228 Gb/s·km, against 446 for the FPI and 267 for the MZI. This is given due to the $B{\times}L$ being computed from the root mean square width and counts the GTI's ripples. The FPI leads in the $B{\times}L$ product and is also selected by the platform's rule of minimum widening. The discussion highlights that the latter choice is driven by the way widening is normalised, which turns the platform into a case study on metric choice. The linear filters give identical results for normal and anomalous dispersion for a chirp-free pulse, whereas SPM narrows the pulse only in the anomalous regime from 317 ps to 20 ps at $\gamma = 0.2\ \mathrm{km}^{-1}$ and broadens it in the normal regime. A step-size study is also presented which shows that the SPM results computed with the default 10 km step are not converged. The present tool supports decisions with simulated evidence for hybrid learning environments where lecturers can teach the trade-offs of using the three families of dispersion compensation techniques.

Keywords: Distance learning, phase modulation, interferometer design, fiber optics, simulation tool.

Introduction

The shift towards digital learning ecosystems increases the need to base teaching decisions on evidence. Learning analytics, the measurement, collection, analysis and reporting of data about learners and their contexts in order to understand and optimize learning (Long & Siemens, 2011; Ferguson, 2012), has grown from that need. Its promise depends on closing the loop from data to action (Clow, 2012), and student-facing dashboards are one way of doing it (Verbert et al., 2013; Bodily & Verbert, 2017; Schwendimann et al., 2017). Gašević et al. (2015) warn that analytics must be grounded in learning design rather than in whatever is easy to measure. That warning is relevant to this paper.

Optical fiber communications offers a well-defined domain for this idea. Chromatic dispersion broadens pulses and limits the bit rate and distance of a link (Agrawal, 2002), and it can be counteracted in several ways. Interferometric equalizers filter the pulse spectrum with Fabry-Perot cavities, Gires-Tournois etalons or Mach-Zehnder lattices (Gires & Tournois, 1964; Cimini et al., 1990; Takiguchi et al., 1994; Madsen & Zhao, 1999). A different mechanism is nonlinear. Self-phase modulation (SPM) imposes on the pulse a chirp that, in the anomalous-dispersion regime, balances the dispersive chirp and can even produce solitons (Hasegawa & Tappert, 1973; Mollenauer et al., 1980; Agrawal, 2013). Textbooks introduce these techniques separately. A student rarely gets the chance to put them side by side, change one parameter and see which is best for which conditions, still less to notice that "best" depends on the criterion.

Here we present a platform that puts FPI, GTI, MZI and SPM in one simulation engine and adds a learning-analytics layer. The contributions are (i) a comparison platform with configurable scenarios for four techniques, (ii) a session log that supports evidence-based comparison and (iii) a quantitative study of what the platform shows to students, including two effects that matter for teaching: the dependence of the ranking on the metric definition and the numerical validity of the SPM model.

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Methodology

Propagation and compensation models

All techniques share one simulation engine. A chirped (super-)Gaussian pulse of initial width T_0 and chirp C propagates through L km of fiber with group-velocity dispersion β_2. In the linear case the pulse is dispersed in the frequency domain with $H_{\text{fib}}(\omega,L) = \exp(j\beta_2\omega^2 L/2)$ and the equalizer is applied to the dispersed pulse (Agrawal, 2002). The three linear equalizers are

$$H_{FPI}(f) = \frac{1-R}{1-Re^{j2\pi f\tau}}, \tag{1}$$

$$H_{GTI}(f) = -\frac{r-e^{-j2\pi f\tau}}{1-re^{-j2\pi f\tau}}, r=\sqrt{R}, \tag{2}$$

$$H_{MZI}(f) = \left[\frac{1}{2}(1+e^{-j2\pi f\tau})\right]^N, \tag{3}$$

where τ is the delay, R the intensity reflectivity and N the number of MZI stages. The FPI and the MZI filter the pulse through their amplitude response (the FPI also adds phase), while the GTI has $|H_{\text{GTI}}| = 1$ and acts only on the phase, so it can rearrange the pulse without discarding energy. SPM is simulated by solving the nonlinear Schrödinger equation, $\partial A/\partial z = -(j\beta_2/2)\partial^2 A/\partial t^2 + j\gamma|A|^2 A$, with the symmetric split-step Fourier method (Agrawal, 2013). The nonlinear parameter γ is expressed in km^{-1} for a unit peak power (scaled by the peak amplitude control), and the step h is a user parameter. The soliton number $N_{\text{sol}}^2 = \gamma P_0 T_0^2/|\beta_2|$ tells students when nonlinearity balances dispersion. The default scenario is a chirp-free 5 ps pulse ($L_D = T_0^2/|\beta_2| = 4.5$ km) in a 100 km link with $\beta_2 = -5.6$ ps^2/km. Fiber loss is neglected.

Indicators and learning analytics

The pulse width Δt is the full width at $1/e$ of the peak amplitude, and the platform reports the widening rate and the bandwidth-distance product $B{\times}L = 187\ L/\sigma$ (Gb/s·km, σ in ps, L in km), where σ is the rms width of the output power pulse. The constant comes from the 3 dB optical bandwidth of a Gaussian pulse, $f_{3\text{ dB}} = 0.440/t_{\text{FWHM}} = 0.187/\sigma$ (Keiser, 2011, Eq. 14.11). The tool defines the widening rate of a filter as the output width divided by the width of the *input pulse passed through the same filter*. In this study we also compute the ratio to the original input pulse, the transmitted energy E and the output side structure (largest amplitude beyond one output width from the peak, relative to the peak).

The analytics module records, for each simulation with a filter, the timestamp, the method, the parameters, the $B{\times}L$ and the widening. It aggregates them per method (number of attempts, mean $B{\times}L$, mean widening), counts the sessions, and marks as *Best Method* the technique with the lowest mean widening. A reset button clears the log. No personal data are stored.

Implementation and interface

The engine is a Python package (NumPy, SciPy). The comparative application is a Flask server with a Plotly front end, distributed as a Docker container, with English, Spanish and German interfaces. The interface (Figure 1) has an analytics sidebar (session count, comparison table, best method, bar chart of $B{\times}L$ and widening per method), a parameter panel with a filter selector (FPI, GTI, MZI or none) plus the SPM parameter, and six synchronised plots of the pulse and its spectrum.

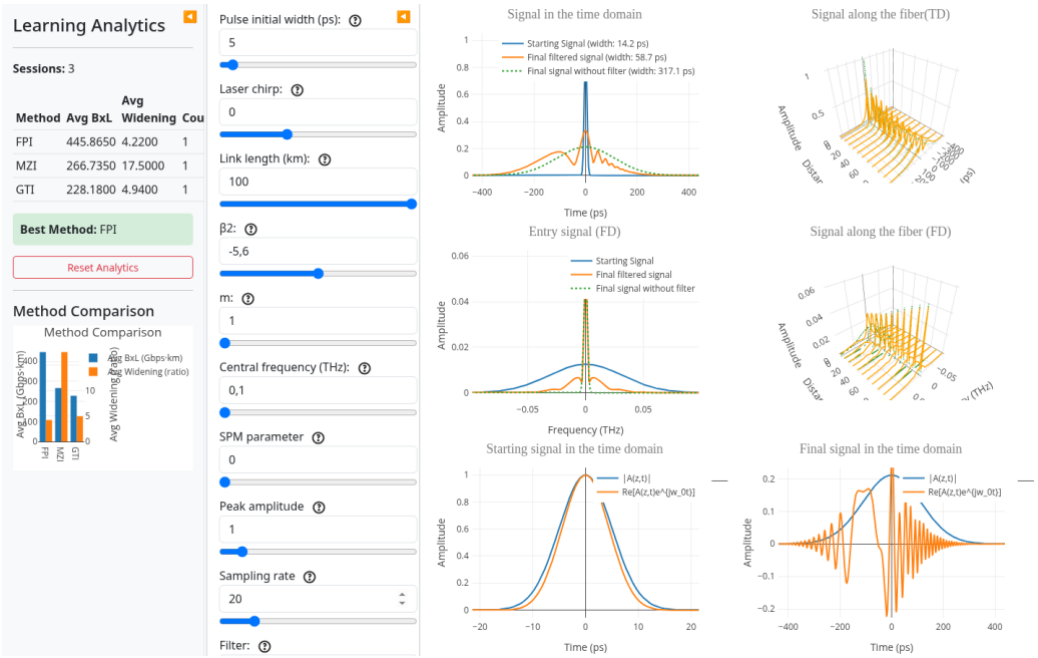


Figure 1. Interface of the comparative platform after three simulations at the default settings: analytics sidebar with the comparison table, the best method and the summary chart (left), parameters (centre) and plots (right).

Learning design

The intended activity is a predict–compare–explain cycle in three tasks. In task 1 students predict which technique will give the best link, simulate the three filters at the default settings and compare their prediction with the analytics table. In task 2 they change the sign of β_2 and repeat. In task 3 they switch off the filters and sweep γ to find the regime in which SPM helps. Each task ends with a written justification, so students have to explain the evidence. Failed predictions are a deliberate part of the design, since attempting a problem before receiving the explanation has been shown to help later learning (Kapur, 2008).

Results

Comparing the linear techniques

Table 1 shows the three filters at the platform defaults (τ = 5 ps, R = 0.77, N = 1; the session of Figure 1) and at settings tuned to each filter. Without a filter the output is 317.1 ps wide ($B{\times}L$ = 235.9, a 22.2-fold broadening of the 14.3 ps input). Running the analytics module on the three default attempts reproduces the table of Figure 1: mean $B{\times}L$ of 445.9 (FPI), 266.7 (MZI) and 228.2 (GTI), mean widening of 4.22, 17.50 and 4.94, and Best Method: FPI.

Table 1. Linear techniques for a 5 ps pulse over 100 km ($\beta_2 = -5.6$ ps^2/km). Δt: output width; $B{\times}L$: from the rms output width σ, in Gb/s·km; $\mathrm{Wid_{tool}}$: widening rate as reported by the platform; $\mathrm{Wid_{in}}$: output width over the original 14.3 ps input; E: transmitted energy; Tail: largest output amplitude beyond one width from the peak (fraction of the peak).

Settings	Filter	Δt (ps)	$B{\times}L$	$\mathrm{Wid_{tool}}$	$\mathrm{Wid_{in}}$	E	Tail
Default	FPI (τ = 5, R = 0.77)	132.4	**445.9**	**4.22**	9.26	35.7%	0.18
	MZI (τ = 5, N = 1)	281.7	266.7	17.50	19.70	88.9%	0.01
	GTI (τ = 5, R = 0.77)	58.8	228.2	4.94	**4.11**	**100%**	0.53
Tuned	FPI (τ = 12.5, R = 0.8)	100.7	**417.6**	**1.66**	7.04	14.9%	—
	MZI (τ = 25, N = 1)	103.5	235.8	7.24	7.24	50.1%	—
	GTI (τ = 12.5, R = 0.8)	48.3	209.4	3.60	**3.38**	**100%**	0.63

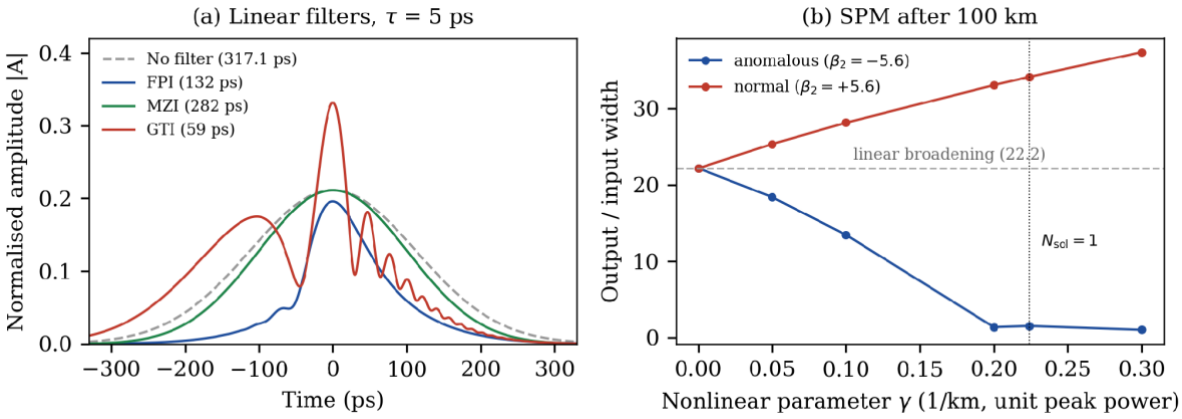


Figure 2. (a) Output envelopes of the three linear filters at the default settings. (b) Width of the output pulse after 100 km with SPM, relative to the input, for both dispersion regimes (h = 0.25 km).

The ranking depends on the indicator. The GTI is first in output width, in the widening relative to the input and in transmitted energy, but last in $B{\times}L$ (Table 1), below even the unfiltered link (228.2 against 235.9 Gb/s·km), because the rms width σ counts its leading shoulder and trailing ripples. The FPI is first in $B{\times}L$ and in the platform's widening, and the reason for the latter is visible in the last two columns. A narrow filter also stretches the launched pulse (the FPI increases the input width from 14.3 to 31.4 ps at the default settings and to 60.7 ps at the tuned ones), so dividing by the filtered input rewards the filter that distorts the input most. The Best Method flag therefore reflects the definition of the indicator and not only the quality of the link. The GTI is not free of drawbacks either. Its ripples reach 53% of the peak (Figure 2a), and its all-pass response assumes that the carrier sits at a resonance. The MZI transmits most of the energy but compensates least at short delays. For long delays it produces side lobes, because neighbouring passbands of its periodic response fall inside the pulse spectrum.

This is the kind of evidence-informed decision the platform is meant to train. Students who only read the Best Method label would select the FPI, but students who read the table would see that the answer depends on what is valued (link speed, output pulse shape, energy) and that the indicator itself needs scrutiny. We regard this as a strength of the design, provided the interface is explicit about the definition, and the widening should be redefined relative to the original input (see Conclusions).

Effect of the dispersion regime

For a chirp-free input the three linear filters give exactly the same widths and $B{\times}L$ for $\beta_2 = -5.6$ and +5.6 ps^2/km. The reason is that the two dispersed fields are complex conjugates of each other. For a filter with a real impulse response, $H(-f) = H^*(f)$, so the filtered fields are also conjugates and their envelopes coincide. The equalizers therefore compensate for dispersion of either sign in the platform, and only a chirped launch or a detuned carrier would break the symmetry. SPM behaves differently (Table 2 and Figure 2b). In the normal regime the nonlinear chirp adds to the dispersive one and the output broadens monotonically, from 317 ps to 535 ps at $\gamma = 0.3$ km^{-1}. In the anomalous regime the two chirps have opposite signs and the pulse is compressed, down to 19.7 ps for γ = 0.2 km^{-1} ($N_{sol}^2 = 0.89$), close to the fundamental soliton condition $N_{sol} = 1$ ($\gamma = 0.224$ km^{-1}), where the output is 21.9 ps wide. This is the observation the platform is designed to make possible for students: interferometers act in both regimes, but SPM helps only in the anomalous one and only within a range of power. For $N_{sol} > 1$ the pulse evolves periodically with distance (at $\gamma = 0.5$ km^{-1} the output is 8.7 ps wide), so the result at a given length is no longer monotonic and we restrict the discussion to $\gamma \leq 0.3$ km^{-1}. The $B{\times}L$ values for solitonic outputs are indicative only, because the relation $f_{3\,dB} = 0.187/\sigma$ assumes a Gaussian pulse.

Table 2. SPM after 100 km for a 5 ps chirp-free pulse (h = 0.25 km). Widths in ps, $B{\times}L$ in Gb/s·km.

		Anomalous ($\beta_2 = -5.6$)		Normal ($\beta_2 = +5.6$)	
γ (km^{-1})	N_{sol}^2	Δt	$B{\times}L$	Δt	$B{\times}L$
0	0	317.1	235.9	317.1	235.9
0.05	0.22	263.1	276.3	362.5	208.7
0.10	0.45	192.3	344.8	402.5	188.9
0.20	0.89	19.7	893.4	472.7	161.5
0.224	1.00	21.9	1091.3	488.3	156.5

		Anomalous ($\beta_2 = -5.6$)		Normal ($\beta_2 = +5.6$)	
γ (km^{-1})	N_{sol}^2	Δt	$B{\times}L$	Δt	$B{\times}L$
0.30	1.34	14.5	1371.7	534.6	143.2

Numerical validity of the SPM model

The nonlinear simulations are only as good as their step size, and the platform exposes the step h as a parameter with a default of 10 km. In the anomalous case with $\gamma = 0.2$ km^{-1} the output width is 94.5 ps for $h = 10$ km, and then 23.7, 20.1, 19.9, 19.7 and 19.7 ps for $h = 5$, 2, 1, 0.5 and 0.25 km. The default step exceeds both the dispersion length (4.5 km) and the nonlinear length ($1/\gamma P_0 = 5$ km), so it is not in the converged regime and would suggest a $B{\times}L$ of 226 instead of 893. The error is smaller in the normal regime (442 versus 473 ps, 7%). We therefore recommend $h \leq 1$ km for SPM and use it in this study, and we plan to warn students in the interface when h exceeds the characteristic lengths. A convergence test can itself be set as a short student task.

Limitations

The analytics are deliberately light. They log only the filter attempts (SPM appears in the plots and in a third $B{\times}L$ indicator but is not yet added to the comparison table), they are stored in server memory for the whole application, and they are not separated per student or saved between server restarts, so "learning analytics" here means session-level comparison and not longitudinal tracking. The model is noise-free and lossless, and it has no bit-error estimation. The educational impact has not been measured. The claims about critical thinking are design intentions and will be tested with a pre-/post-test and questionnaire in the next course of Optical Communications at the University of Jaén.

Conclusions

We presented a web platform that compares dispersion compensation by Fabry-Perot, Gires-Tournois and Mach-Zehnder filters and by self-phase modulation, with a session-level analytics module that supports evidence-based comparison. In the default 100 km scenario the GTI gives the shortest output (58.8 ps, with all the energy) but the lowest $B{\times}L$ (228 Gb/s·km), because its ripples widen the rms width, whereas the FPI leads in $B{\times}L$ (446 Gb/s·km) and is also selected by the platform's minimum-widening rule, the latter because the widening is normalised to a filtered input that the FPI itself stretches. The three linear filters compensate either sign of dispersion, while SPM compresses the pulse only in the anomalous regime (317 ps to about 20 ps at $\gamma = 0.2$ km^{-1}), and its results need a step of 1 km or less to be reliable. The lesson for teaching is that students should be trained to read what an indicator measures before acting on it. This is what learning analytics is meant to support and where it can mislead. Future work will define widening relative to the original input, add a multi-criteria view and the SPM to the comparison table, store analytics per student, warn about unconverged SPM steps, and evaluate the learning outcomes with students.

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Students' Experiences and Needs Regarding Online and Alternative Assessment in Distance Higher Education: Emerging Digital Challenges

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Abstract

Purpose: Technology-mediated assessment plays an increasingly important role in online and distance higher education, particularly within digitally mediated learning environments. Despite the growing use of online examinations and alternative assessment formats, students' perspectives on these approaches remain underexplored, especially in humanities-oriented postgraduate programs. This study examines postgraduate students' experiences and perceived needs regarding online written examinations and project-based assessment in distance higher education. It also explores how issues related to fairness, emotional experience, digital conditions, and the growing use of artificial intelligence shape students' perceptions of assessment in online learning environments. Methodology: A qualitative research design was adopted. Data were collected through three online focus groups with postgraduate students enrolled in humanities-oriented distance education programs at the Hellenic Open University. Purposive sampling ensured that all participants had experience with both online written examinations and project-based assessment formats. The discussions were conducted via videoconferencing using a semi-structured format focused on students' emotional experiences, perceptions of learning value and fairness, support needs, and views regarding the role of digital technologies and AI in assessment practices. The data were analyzed using inductive thematic analysis. Findings: The findings revealed clear differences between assessment approaches. Online written examinations were mainly associated with anxiety, time pressure, and technical uncertainty, with students expressing concerns about fairness and unequal digital conditions. Participants also described online examinations as limiting opportunities for deeper reflection and meaningful demonstration of understanding. In contrast, project-based assessment was perceived as more supportive of meaningful learning, autonomy, reflection, and sustained engagement with course content. Students emphasized that project-based tasks allowed them to work at their own pace and develop analytical and critical thinking skills more effectively. Participants also highlighted the importance of clear assessment guidelines, communication with instructors, and timely feedback in online learning environments. Students additionally referred to the growing influence of digital tools and artificial intelligence in shaping assessment practices, raising questions related to authenticity, transparency, and equitable evaluation. Implications: The study highlights the need for more pedagogically grounded and digitally responsive assessment practices in online higher education. The findings contribute to current discussions on educational technology, online learning design, authentic assessment, and assessment practices in the age of AI. The study suggests that assessment in digitally mediated learning environments should prioritize meaningful learning, student agency, fairness, and inclusive digital pedagogy.

Keywords: distance higher education, online assessment, project-based assessment, educational technology, student experience, digital learning

1. Introduction and Research Aim

Assessment is a central component of distance higher education, influencing students' learning experiences, engagement, and academic development. In humanities-oriented programmes, assessment is expected to support critical thinking, interpretation, and reflection rather than the reproduction of knowledge. The increasing use of online examinations has raised concerns regarding anxiety, time pressure, technical uncertainty, and fairness. At the same time, alternative assessment approaches, particularly project-based assignments, are increasingly viewed as supporting deeper learning, autonomy, and meaningful engagement with course content.

These issues have become more prominent in the context of rapid digital transformation and the growing use of artificial intelligence (AI) in higher education, which introduces new challenges related to authenticity, transparency, and assessment design. Despite growing interest in online and alternative assessment, limited research has explored how students who have experienced both formats compare them in terms of learning value, fairness, emotional impact, and support needs.

The aim of this study is to explore postgraduate students' experiences and perceived needs regarding online written examinations and project-based assessment in distance higher education. More specifically, the study examines

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how students experience these assessment formats, the challenges and support needs they identify, and how they perceive their learning value and fairness. By focusing on students who have experienced both approaches, the study seeks to provide a comparative understanding of assessment practices in contemporary distance learning environments.

2. Literature review

Assessment in distance higher education has evolved alongside the expansion of online learning and digital technologies. In humanities-oriented programmes, assessment is expected to support critical thinking, interpretation, and reflection while also responding to the demands of increasingly digital learning environments (Heil & Ifenthaler, 2023). Recent discussions emphasize the need to move beyond the assessment of content knowledge towards evaluating higher-order competencies, such as critical thinking, creativity, and ethical judgement (Desai, 2025; Vlachopoulos & Makri, 2024).

Online written examinations are often associated with anxiety, time pressure, and concerns regarding technical reliability, which may affect students' performance and perceptions of fairness (Henderson et al., 2024; Maphosa et al., 2024). In contrast, alternative assessment approaches, particularly project-based assignments, are considered more conducive to meaningful learning, allowing students to engage with content over time and demonstrate understanding through analysis, reflection, and application (Danielson & Björkman, 2025; Dawson et al., 2021). However, the effectiveness of such approaches depends on clear expectations, transparent criteria, and constructive feedback.

Current research also highlights the importance of fairness, student agency, and equitable access to learning resources in online assessment environments (Fialho et al., 2023; Levy-Feldman, 2025). At the same time, the increasing use of digital tools and artificial intelligence raises new questions regarding authenticity, transparency, and assessment design (Desai, 2025). Although both online examinations and alternative assessment approaches have been widely studied, limited research has explored how students who have experienced both formats compare them in terms of learning value, fairness, emotional impact, and support needs, particularly within humanities-oriented distance education.

3. Methodology

This study adopted a qualitative research design to explore postgraduate students' experiences of online written examinations and project-based assessment in distance higher education. Data were collected through three online focus groups with 18 postgraduate students enrolled in humanities-oriented distance education programmes. Purposive sampling was employed to ensure that all participants had direct experience with both assessment formats, enabling meaningful comparison between online examinations and project-based assignments.

The focus groups were conducted via videoconferencing and followed a semi-structured discussion guide aligned with the study's aims. Discussions explored students' experiences of assessment, perceived challenges and support needs, as well as their views on learning value, fairness, and emerging digital issues related to assessment practices. Each session lasted approximately 60–75 minutes and was audio-recorded with participants' informed consent before being transcribed verbatim.

The data were analysed using inductive thematic analysis. Through an iterative coding process, themes were identified across the focus group discussions, focusing on students' emotional experiences, perceptions of learning and fairness, support needs, and views regarding digital technologies and artificial intelligence in assessment. Participation was voluntary, and anonymity and confidentiality were maintained throughout the study.

4. Findings

4.1 Students' Experiences of Online and Project-Based Assessment

Students' accounts revealed clear differences between online written examinations and project-based assessment. Online examinations were predominantly described as stressful and emotionally demanding, with participants highlighting time pressure, difficulties in managing complex questions, and concerns about the rigidity of assessment conditions. The inability to seek clarification during examinations further contributed to feelings of anxiety and insecurity.

In contrast, project-based assessment was generally perceived as more supportive of learning and personal engagement. Participants emphasized that projects allowed them to work at their own pace, engage more deeply with course content, and demonstrate understanding through analysis, synthesis, and reflection. Many students

reported a stronger sense of ownership over their work and associated project-based assessment with meaningful learning and greater confidence.

4.2 Fairness, Support Needs, and Emerging Digital Challenges

Students identified several challenges related to online assessment, particularly technical uncertainty, including concerns about internet connectivity, platform stability, and file submission processes. These issues were perceived as increasing stress and potentially affecting performance. Participants also emphasized the importance of clear assessment guidelines, communication with instructors, preparation opportunities, and timely feedback.

Perceptions of fairness differed considerably between assessment formats. Project-based assessment was viewed as providing greater opportunities for meaningful learning and authentic demonstration of knowledge, whereas online examinations were often associated with performance under pressure and unequal assessment conditions. Concerns about fairness were linked not only to assessment design but also to differences in technological access and home learning environments.

Participants additionally referred to the growing use of digital tools and artificial intelligence in higher education. While some viewed these technologies as valuable learning supports, others raised concerns regarding transparency, academic integrity, and equitable evaluation. Overall, students emphasized that fair assessment should consider both academic standards and the broader digital conditions within which learning takes place.

5. Discussion

The findings highlight important differences in how students experience assessment in distance higher education. Online written examinations were largely associated with stress, time pressure, and concerns regarding fairness, particularly when technical conditions and assessment constraints affected students' ability to demonstrate their knowledge. These findings support previous research linking online assessment to increased anxiety and perceived uncertainty (Henderson et al., 2024; Maphosa et al., 2024).

In contrast, project-based assessment was perceived as more supportive of meaningful learning, allowing students to engage more deeply with course content, develop ideas over time, and demonstrate understanding through analysis and reflection. The findings reinforce previous research emphasizing the educational value of alternative assessment approaches and the importance of student autonomy and engagement (Dawson et al., 2021; Tuzgen et al., 2025).

Fairness emerged as a central dimension of assessment quality. Participants associated fair assessment not only with transparency and clear expectations but also with equitable digital conditions and access to resources. In addition, students' reflections on digital tools and artificial intelligence suggest that assessment practices must increasingly address issues of authenticity, transparency, and responsible technology use. Overall, the findings support the need for assessment approaches that prioritize meaningful learning, student agency, and inclusive digital pedagogy in distance higher education.

6. Implications and Future Directions

The findings of this study have important implications for assessment design in distance higher education. Participants' experiences suggest that assessment formats are not simply mechanisms for measuring learning outcomes but also shape students' emotional experiences, engagement, and perceptions of fairness. The concerns expressed regarding online written examinations indicate that high-stakes assessment formats may place considerable emphasis on performance under pressure while simultaneously exposing students to technical and contextual factors beyond their control.

In contrast, project-based assessment was perceived as offering greater opportunities for meaningful learning, reflection, and the application of knowledge. These findings support ongoing calls for assessment approaches that promote critical thinking, student agency, and authentic engagement with learning tasks. At the same time, students emphasized the importance of clear assessment criteria, transparent expectations, timely feedback, and effective communication with instructors, highlighting the role of supportive assessment practices in distance learning environments.

The study also points to emerging challenges associated with the growing use of digital technologies and artificial intelligence in higher education. Students acknowledged the potential value of such tools for learning support, while also raising concerns regarding transparency, authenticity, academic integrity, and equitable evaluation. These issues suggest the need for assessment policies and practices that provide clear guidance on the responsible use of AI while maintaining fairness and educational quality.

Future research could extend these findings by exploring assessment experiences across different academic disciplines and institutional contexts. Comparative and mixed-methods studies may provide further insight into how students experience online and alternative assessment approaches. In addition, further investigation of students' perspectives on AI-informed assessment practices could contribute to the development of more inclusive and pedagogically meaningful assessment frameworks for digitally mediated higher education.

7. Conclusion

This study contributes to current discussions on assessment in distance higher education by foregrounding students' perspectives on online written examinations and project-based assessment. Rather than viewing assessment solely as a mechanism for measuring learning outcomes, the findings highlight its broader role in shaping students' engagement, confidence, and sense of fairness within digitally mediated learning environments.

The study suggests that students value assessment approaches that allow for reflection, meaningful engagement with course content, and opportunities to demonstrate understanding beyond performance under time-constrained conditions. At the same time, the findings underline the importance of considering the wider digital context in which assessment takes place, including access to resources, technological conditions, and the increasing presence of artificial intelligence in academic work.

As higher education continues to adapt to digital transformation, assessment practices may need to move beyond traditional distinctions between examinations and assignments towards approaches that better support meaningful learning, transparency, and equitable participation. Understanding students' experiences can contribute to the development of assessment frameworks that are both pedagogically sound and responsive to emerging digital challenges.

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Examining Changes in Pre-Service Elementary Mathematics Teachers' Perceptions of Gifted Learners and Mathematics Instruction for Gifted Learners through Metaphor Analysis

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Abstract

This study examines how pre-service elementary mathematics teachers' perceptions of gifted learners, mathematics instruction for gifted learners, activity design for these learners, and teacher roles changed following direct interaction with gifted middle school students at Science and Art Centers (BİLSEM). A qualitative research approach and phenomenological design were employed. The study group consisted of 22 fourth-year pre-service elementary mathematics teachers enrolled in the Mathematics Instruction for Gifted Students course at a state university in the Western Black Sea Region of Türkiye. Following the theoretical component of the course, participants developed and implemented mathematics activities for gifted middle school students at BİLSEM in four groups. Data were collected twice through a metaphor-based open-ended questionnaire administered via Google Forms, before and after the implementation. The qualitative data were analyzed using MAXQDA 2022 through coding and thematic analysis. Before the implementation, gifted learners were predominantly conceptualized as a "valuable object waiting to be discovered" and a "fast-operating entity," whereas after the implementation, the "questioning and deepening subject" theme emerged prominently. Teacher-role metaphors also shifted from "authoritative/information transmitter" toward "guide/direction-giver." The findings indicate that direct, structured practice experiences may contribute to changes in pre-service teachers' conceptualizations of gifted learners and their teaching roles.

Keywords: gifted learners, pre-service elementary mathematics teachers, metaphor analysis, teacher education, mathematics instruction

Introduction

Gifted students are defined as identified individuals who differ from their peers in cognitive, creative, or social-emotional domains. In Türkiye, Science and Art Centers (BİLSEM) stand out as an important institutional structure in the education of gifted students (Akarsu, 2000). Nevertheless, recognizing the characteristics of gifted students in mathematics by teachers is important for conducting instructional processes that are responsive to these students' needs. Indeed, in a study conducted with pre-service mathematics teachers, mathematical giftedness was associated with characteristics such as problem posing and developing original solutions to problems (Yazgan-Sağ, 2022). A study examining teacher education policies for the education of gifted students in Türkiye found that teachers did not receive sufficient pre-service education in this field, that teachers had educational needs in this area, and that existing policies had not yet achieved a stable structure (Özdemir & Kır, 2022). A recent systematic review in the international literature also indicates that preparation for educating gifted students in pre-service teacher education remains a limited area of research (Lutz et al., 2025).

The literature indicates that pre-service teachers' perceptions of gifted individuals have been examined through metaphors. Özbey Gökçe and Çakmakçı (2021) examined the metaphorical perceptions of 137 pre-service teachers enrolled in special education, preschool education, and psychological counseling and guidance programs regarding gifted children and classified the metaphors under themes such as productivity, power, value, sensitivity, uniqueness, instructiveness, and brilliance. Similarly, Bulut (2018) examined metaphors produced by 102 pre-service elementary teachers regarding gifted individuals and found that the participants perceived these individuals as potentially beneficial with appropriate education; as different and requiring special attention; as valuable individuals who need to be discovered; and as valuable, intelligent individuals with a high knowledge capacity who perform at a higher level than their peers and require guidance. Erdoğan and Güçyeter (2019), on the other hand, examined metaphors produced by 279 pre-service teachers regarding the concepts of gifted intelligence and giftedness and determined that the categories of an appropriate environment, high performance, and being different from peers were particularly prominent in the metaphors associated with both concepts. The researchers also stated that pre-service teachers attributed largely similar meanings to the concepts of gifted intelligence and giftedness and used these concepts interchangeably.

In this study, following an instructional experience in which pre-service elementary mathematics teachers enrolled in the "Mathematics Instruction for Gifted Students" course went beyond purely theoretical content and directly

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interacted with gifted middle school students at BİLSEM, changes in their perceptions of the concept of gifted students, the mathematics instruction process for these students, activity design, and teacher roles were examined. The main research question was formulated as follows: "Is there a thematic change in pre-service teachers' metaphor-based perceptions before and after the implementation, and if so, around which themes does this change occur?"

Methodology

Research Model

A qualitative research approach was adopted and a phenomenological design was used in the study. Phenomenology is a qualitative research approach that aims to reveal the common meaning of individuals' experiences regarding a particular phenomenon and to explain the essence underlying these experiences (Creswell & Poth, 2018, p. 75). The phenomenon examined here is pre-service teachers' perceptions of gifted students and mathematics instruction for these students.

Study Group

The study group consisted of 22 fourth-year pre-service elementary mathematics teachers enrolled in the Elementary Mathematics Teaching program at the Faculty of Education of a state university in the Western Black Sea Region of Türkiye and taking the "Mathematics Instruction for Gifted Students" course taught by the researcher. All participants were fourth-year students and proceeded to the implementation stage after completing the theoretical component of the course.

Implementation Process

The theoretical component of the course focused on the cognitive developmental characteristics, learning rates, problem-solving tendencies, affective needs, and identification processes of gifted individuals. In addition, various pedagogical discussions were conducted within the framework of differentiated instruction practices, enrichment approaches, multilayered curriculum arrangements, and creativity-based learning perspectives. During the implementation stage, the pre-service teachers were divided into four working groups and developed and implemented mathematics activities for gifted middle school students studying at a Science and Art Center (BİLSEM). The activities incorporated mathematical modeling problems, STEM, gamification-based activities, and dynamic geometry software. Each group's implementation lasted approximately two class hours; throughout the process, the pre-service teachers' experiences in developing activities, observing student responses, and reevaluating the instructional process came to the fore.

Data Collection Instrument

A form consisting of metaphor-based open-ended questions was used as the data collection instrument. The form was administered twice via Google Forms; the first section was structured to collect responses before the implementation, and the second section was structured to collect responses after the implementation. Before the implementation, the participants were asked to explain each of the following with a metaphor: (a) the concept of "gifted student," (b) the process of mathematics instruction for gifted students, (c) the process of preparing mathematics activities for these students, (d) the mathematics learning process of gifted students, and (e) the teacher role. After the implementation, the same questions were repeated with the addition of the expression "now." Each item was presented using the sentence pattern "_____ is like _____; because _____."

Data Analysis

The qualitative data obtained were analyzed using the MAXQDA 2022 qualitative data analysis program. The qualitative data obtained were analyzed using the MAXQDA 2022 program. During the analysis process, the data were first coded, and then thematic structures were created according to similar patterns of meaning. Relationships among the codes were examined using various visualization tools, and trends in changes in metaphorical perceptions were evaluated from a holistic perspective.

Results

The findings of the study are presented in four sections. The first section addresses the metaphor themes related to the concept of "gifted student" before the implementation, and the second section addresses the themes related to the same concept after the implementation. The third section compares the themes presented in the first two

sections. The fourth section presents and compares the themes related to the instructional process and teacher role before and after the implementation collectively.

Metaphor Themes Related to the Concept of Gifted Student Before the Implementation

As shown in Table 1, before the implementation, the metaphors produced by the pre-service teachers regarding the concept of gifted student clustered around five themes.

Table 1. Metaphor themes and frequencies related to the concept of "gifted student" before the implementation

Theme	f	Example Metaphors
Valuable object waiting to be discovered	7	Pearl, diamond, gold mine, brilliant, jewelry box
Fast-operating entity	6	Running horse, sports car, rabbit, fast-charging adapter, machine
Containing inherent hidden potential	4	Fish, sapling, spark, seed
Difficult/special individual	3	Mountain peak, obstacle for a camel, labyrinth
Versatility/adaptability	2	Chameleon, compass
Total	22	

The metaphors containing the statement "It is a spark because it can turn into a great light when the right environment is provided" represented the theme of inherent hidden potential, whereas the statement "It is a fast-charging adapter because all chargers charge, but fast-charging adapters charge in a shorter time" represented the theme of a fast-operating entity. These initial themes show that the pre-service teachers positioned the gifted student primarily around two basic characteristics: being "valuable" and "fast."

Metaphor Themes Related to the Concept of Gifted Student After the Implementation

After the implementation, it was observed that the metaphor themes diversified markedly and that the frequency of the "questioning and deepening subject" theme increased.

Table 2. Metaphor themes and frequencies related to the concept of "gifted student" after the implementation

Theme	f	Example Metaphors
Questioning and deepening subject	7	Diver, compass inside a labyrinth, sapling, explorer, archaeologist, universe under a magnifying glass
Childlike/individual waiting to be discovered	5	Child waiting to be discovered, toy, child asking questions, fast-charging adapter
Valuable object	3	Pearl, diamond, gold
Fast-operating entity	4	Machine, high-performance sports car
Hidden potential by nature	2	Sapling, fish
Adaptability/ability	1	Compass
Total	22	

In particular, the statement "It is like a compass inside a labyrinth because, although I think they will struggle even though they are gifted, they always have the ability and potential to find the right path within themselves" indicates that the gifted student has shifted from being a passive object waiting to be discovered to becoming a subject who constructs their own learning path.

Change in Metaphors Related to the Concept of Gifted Student Before and After the Implementation

The change in the metaphors presented above before and after the implementation is summarized in Table 3.

Table 3. Transition matrix of metaphor changes

Theme Before the Implementation		Theme After the Implementation	Number of Transitions
Valuable object (7)		Valuable object (3)	4
Fast-operating entity (6)		Fast-operating entity (4)	2
Hidden potential by nature (4)		Hidden potential by nature (2)	2
Versatility/adaptability (2)		Versatility/adaptability (1)	1
Difficult/special individual (3)		-	3
		Questioning and deepening subject (7)	7
		Childlike/individual waiting to be discovered (5)	5
Total	22	22	24

Change in Themes Related to the Instructional Process and Teacher Role Before and After the Implementation

The themes related to the instructional process and teacher roles showed a marked shift before and after the implementation.

Table 4. Distribution of teacher-role metaphors before and after the implementation

Theme	Before the Implementation	After the Implementation	Example Metaphors
Authoritative/information transmitter	7	4	Master, makeup (permanent), gardener
Guide/direction-giver	10	12	Guide, guiding star, steering a ship, sailor
Facilitator/supporter	5	6	Carpenter, support, bicycle with training wheels, chef
Total	22	22	

Before the implementation, statements such as "I am a master because I know how the machine will respond to its development and maintenance and can therefore repair and guide it accordingly" were dominant, whereas after the implementation, statements such as "I am like a guide because, rather than directly directing them, I try to shed light on their finding their own paths" became more frequent.

Conclusions

In this study, the metaphors produced by 22 pre-service elementary mathematics teachers before and after an implementation experience in which they directly interacted with gifted students at BİLSEM were examined thematically. The findings revealed that before the implementation, gifted students were predominantly described through the images of a "valuable object waiting to be discovered" and a "fast-operating entity," whereas after the implementation, these images were largely replaced by the theme of the "questioning and deepening subject." This finding is consistent with the results of Türksoy and Karabulut (2022), who reported that pre-service elementary teachers positioned gifted students particularly as valuable individuals requiring sensitivity; however, the present study provides a new dimension concerning how such conceptualizations may differ following direct practical experience.

A similar shift was observed in teacher-role metaphors; expressions of "information transmitter/master" were replaced by expressions of "guide/guiding star." This change is consistent with the teacher education literature suggesting that pre-service teachers' knowledge and understanding of instructional processes may develop through practical experience. Indeed, Njiku (2025) demonstrated that the teaching practicum reinforces the development of pre-service teachers' mathematical pedagogical content knowledge. Pre-service teachers' face-to-face encounters with BİLSEM students may have contributed to the development of an understanding of the teaching role that is not limited to knowledge transmission and that supports students' learning processes. Student responses such as "I was honestly happy that they liked the activity" and "What will you use us for again?" were considered concrete experiential elements that played a role in the formation of this awareness.

On the other hand, it is noteworthy that the technical-mechanical framework evident in the statement "I am a master because I know how the machine will respond to its development and maintenance and can therefore repair and guide it accordingly" persisted partially after the implementation among some participants. This result indicates that some pre-existing conceptualizations held by pre-service teachers may be more resistant to change despite the practical experience. Indeed, Tanase and Wang (2010) found that some beliefs of pre-service teachers may be more resistant to change than others. Accordingly, thematic drama, video analyses, and micro-teaching practices may be incorporated into the program to address such resistance during the course process conducted with the participants.

Among the limitations of the study, its implementation with 22 participants from a single state university restricts generalizability. In addition, the fact that the implementations were limited to only two class hours may not be sufficient for a more in-depth understanding; one participant explicitly expressed this limitation by stating, "If I were to conduct the implementation again, I would definitely allow more time." Future studies are recommended to incorporate longer-term implementations, samples from different universities, and mixed-methods designs (e.g., metaphor + interview).

In conclusion, relying solely on theoretical knowledge left pre-service teachers' perceptions of gifted students superficial, whereas structured and supported practical experiences can be said to transform these perceptions into a "teacher who becomes a guide" and a "questioning subject."

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Natural or Artificial Intelligence? How Generative AI Transforms the Role of Higher Education Faculty

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Abstract

Generative artificial intelligence (AI) is increasingly transforming teaching and learning processes in higher education, raising fundamental questions about the future role of faculty. While prior research has predominantly focused on student outcomes and assessment-related challenges, relatively little attention has been paid to how educators themselves interpret and experience these changes. This study explores how faculty members at a German distance learning university of applied sciences perceive the impact of generative AI on their professional roles. Empirical data were collected through a structured expert workshop involving 17 faculty members and analysed using the Gioia methodology. The analysis resulted in four aggregate dimensions: the emergence of new AI-related meta-competencies, the relational teaching practice, the epistemic transformation of teaching and the institutional reorganization of authority and assessment. The findings suggest that educators largely perceive generative AI not as a threat but as a catalyst for redefining their professional identity. Traditional knowledge transmission becomes less central, while learning facilitation, guidance, reflection, and the promotion of critical thinking gain importance. The study contributes an empirically grounded framework for understanding faculty role transformation in AI-mediated higher education and provides implications for institutional development and faculty support.

Keywords: faculty role transformation, generative AI, higher education, Gioia methodology, AI literacy, distance learning, qualitative research

Introduction

The rapid proliferation of generative artificial intelligence (AI) systems is challenging established conceptions of teaching and learning in higher education (Miao & Holmes, 2023; Urmeneta & Romero, 2024). Existing research has primarily focused on student learning outcomes, academic integrity, and assessment-related challenges associated with AI adoption (Kasneci et al., 2023). Comparatively little attention has been paid to how educators themselves perceive and interpret these developments and how generative AI influences their professional identity and role perceptions (Mah & Groß, 2024). This gap is particularly relevant in distance learning contexts, where digitally mediated interaction, spatial separation, and highly heterogeneous learner groups have long shaped pedagogical practice. These characteristics may influence both the opportunities and challenges associated with AI adoption and therefore affect how faculty experience AI-induced role transformation (Sanders & Mukhari, 2024; Mah & Groß, 2024).

Previous studies have examined professional role identity in the context of digitally mediated higher education (Blumentritt et al., 2019, 2020; Markgraf et al., 2024; Schwinger et al., 2022). Their findings suggest that, despite rapid changes in teaching formats, faculty members continue to see themselves primarily as knowledge transmitters, explainers, and subject-matter experts, while also taking on roles as motivators and facilitators of learning (Markgraf et al., 2024; Schwinger et al., 2022). Building on this research, the present study examines how faculty members at a German distance-learning university of applied sciences understand the growing influence of generative AI on their professional roles. It aims to identify emerging role dimensions and explore perceived changes in academic work.

Methodology

Data were collected during a structured, virtual expert workshop in Microsoft Teams, referred to as a “Think Tank”, involving 17 faculty members from diverse disciplinary backgrounds at a German distance-learning university of applied sciences. The two-hour session was audio-recorded and automatically transcribed using Microsoft Teams. The transcript was subsequently reviewed and corrected manually. The resulting dataset was supplemented by collaborative digital whiteboards documenting the participants’ reflections.

The collected material was analysed using the Gioia methodology, a qualitative inductive approach aimed at developing theoretically meaningful concepts and gaining deeper insights while maintaining proximity to participants' own interpretations and experiences. The Gioia methodology is based on the assumption that

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individuals can serve as "knowledgeable agents" in the investigation of a particular topic when a systematic research procedure is followed (Gioia et al., 2013). Consistent with the Gioia methodology, the first-order analysis adhered closely to informant-centric terms, thereby foregrounding participants' interpretations and maintaining the connection between the empirical data and the emerging theoretical concepts. Although Gioia et al. suggest that a large number of first-order concepts typically emerge rapidly during the initial stages of analysis, the present analysis yielded only 26 first-order concepts. These concepts were subsequently compared, refined, and grouped by the authors into second-order themes that captured emerging patterns and more abstract researcher-driven interpretations.

In a final analytical step, second-order themes were synthesized into aggregate dimensions representing the central aspects of faculty role transformation associated with generative AI. The resulting data structure, developed through several collaborative sessions involving all authors, provided a transparent link between empirical observations and theoretical abstraction, thereby enhancing analytical rigor and interpretive credibility. ChatGPT was also used during the analytical process, primarily as a critical tool to challenge the authors' interpretations and emerging analytical ideas.

The Gioia methodology was particularly appropriate for this study because it facilitates the systematic investigation of organizational sensemaking processes. By preserving participants' voices while progressively abstracting higher-order concepts, the approach enables the development of theoretically grounded insights into how faculty members interpret and respond to the transformative implications of generative AI in higher education (Langley & Abdallah, 2011; Gioia et al., 2013).

Results

The analysis yielded 26 first-order concepts, eight second-order themes, and the following four aggregate dimensions: (1) the emergence of new meta-competencies in dealing with AI (2) relational teaching practice, (3) the epistemic transformation of teaching, and (4) the institutional reordering of authority and assessment. The overall data structure is presented in Table 1.

Table 1: Gioia Data Structure: First-Order Concepts, Second-Order Themes, and Aggregate Dimensions

Aggregate Dimensions	Second-Order Themes	First-Order Concepts
Emergence of New Meta-Competencies in Dealing with AI	Teaching the (critical) use of AI as a core competence of academic teaching	Trainer for the critical use of AI
		Healthy skepticism toward AI
		Integrating AI meaningfully rather than banning it
		Changing competencies through digitalization and AI
Relational Teaching Practice	Situational and adaptive understanding of the teaching role	Role depends on context and students
		Supervision conversations are becoming more important
	Social-normative and developmental role	Role model for attitudes and communication
		Human resonance is important
		Creating genuine encounters
		Fostering self-efficacy and self-confidence
	Curating and structuring study content	Teaching essential disciplinary knowledge and methodological competence
		Providing orientation in an abundance of information
		Bridge-builder between theory and practice
Epistemic Transformation of Teaching	Thinking as an epistemic value	Understanding thinking as a step in the process of generating knowledge
		Guiding and encouraging students to think for themselves
		Fostering enjoyment of thinking
	Didactic shift toward designing the learning process	Guide
		Impulse giver
		Learning companion
Institutional Reorganization of		Tension between learning support and authority
		Loss of authority due to AI

Authority and Assessment	Erosion of traditional teaching authority and emergence of new foundations of legitimacy	AI takes over our tasks
		Safeguarding academic standards
	Assessment architect for ensuring assessment validity	Critical assessment architect
		Grading is becoming more time-consuming
		Identifying students' own work

Across all dimensions, participants of the expert workshop described generative AI less as a threat to their professional relevance and more as a catalyst accelerating ongoing changes in higher education. Importantly, this does not imply that disciplinary knowledge and methodological expertise become irrelevant. Rather, participants emphasized a changing epistemic function of faculty: from primarily providing knowledge toward selecting, structuring, contextualizing, and critically engaging with increasingly abundant information. Faculty members reported that traditional knowledge transmission is becoming less central as students increasingly gain direct access to sophisticated AI-generated information and explanations. As a result, the role of educators is shifting toward facilitating learning processes, curating information, supporting reflection, and fostering independent judgment.

A further key finding concerns the relational dimension of teaching. Participants emphasized that the increasing availability of AI does not diminish the importance of human interaction; rather, it reinforces the value of context-sensitive and individualized forms of support. Faculty described their role as adapting to students' individual needs, providing opportunities for genuine human interaction, and supporting students' self-efficacy and personal development. In this sense, the perceived transformation extends beyond changes in knowledge-related tasks and highlights the social and developmental functions of faculty that are not readily substituted by AI.

At the same time, participants highlighted tensions regarding authority, academic integrity, and assessment validity. The increasing availability of AI-generated outputs challenges established examination formats and requires institutions to reconsider how learning achievements can be assessed meaningfully. This creates a dual role for faculty: they are expected to act as supportive learning facilitators while simultaneously retaining responsibility for assessment, academic standards, and the verification of students' independent achievement. Furthermore, participants consistently emphasized the growing importance of AI literacy, not only as a technical capability but also as a critical reflective competence enabling responsible and effective engagement with AI systems. Faculty thus increasingly assume responsibility not only for using AI themselves, but also for enabling students to engage with AI critically, responsibly, and purposefully.

Taken together, the four dimensions suggest that AI-induced faculty role transformation is not characterized by the replacement of one role with another. Rather, it involves a rebalancing and expansion of existing responsibilities: faculty remain disciplinary experts while increasingly acting as facilitators of learning, curators and contextualizers of knowledge, facilitators of critical thinking, relational and developmental supporters, educators for critical AI use, and guardians of academic standards and assessment validity.

Conclusions

In summary, the findings suggest that generative AI is reshaping rather than replacing the role of higher education faculty. Rather than viewing this development as a threat, the educators surveyed largely perceive it as an opportunity to redefine and strengthen their professional identity. As the emphasis on traditional knowledge transmission decreases, greater importance is attached to learning facilitation, reflective practice, guidance, and the promotion of critical thinking. These findings imply that the integration of generative AI does not reduce the significance of educators; instead, it highlights the enduring value of distinctly human pedagogical competencies in higher education. In particular, supporting self-directed learning, fostering critical reflection, and helping students navigate increasingly complex information environments emerge as central responsibilities of academic staff in an AI-enhanced educational landscape.

While the findings are limited to a single institutional context, they provide initial empirical insights into how faculty members make sense of AI-related transformation. Future research should examine whether similar role perceptions emerge across different higher education settings and national contexts.

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Sociological Metacognition, Artificial Intelligence and Learning in an African Context: Theoretical framework, empirical study and proposals for experimentation

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Abstract

The rapid adoption of generative Artificial Intelligence (AI) in education raises critical questions regarding learning effectiveness, equity, and learner autonomy, particularly in Sub-Saharan African contexts characterized by multilingualism, unequal access to educational resources, and strong sociocultural diversity. This paper proposes an integrative framework combining metacognition, social constructivism, critical sociology, and African epistemologies to analyze the role of AI as a mediator of learning. The framework is grounded in an empirical study conducted at the École Supérieure Polytechnique of Cheikh Anta Diop University (ESP/UCAD, Senegal) involving 22 student groups (~110 learners) engaged in the development of an AI-assisted Text-to-SQL system. A Metacognitive Composite Index (MCI), combining AI interaction monitoring and reflective reporting activities, was developed to evaluate learners' metacognitive regulation. Results reveal a very strong correlation between MCI and academic performance ($r = 0.973$, $p < 0.001$), indicating that explicit metacognitive regulation is the strongest predictor of success in an AI-integrated learning environment. Building on these findings, the paper proposes three experimental directions focusing on AI tutoring in African languages, AI-supported collective metacognition, and equitable adaptive AI systems. The study contributes empirical evidence from a Francophone African context and highlights the importance of designing AI-enhanced learning environments that foster reflective and autonomous use of AI rather than dependency.

Keywords: metacognition; sociological constructivism; artificial intelligence; learning; sub-Saharan Africa; national languages; digital sovereignty; Text-to-SQL; educational inequalities.

Introduction

The rapid adoption of generative AI tools in education raises fundamental questions about learning equity, particularly in Sub-Saharan Africa. Structural tensions — colonial educational heritage, unrecognized multilingualism, overcrowded classrooms, and digital divides — create a highly heterogeneous learning environment into which large language models (LLMs) are being deployed without adequate pedagogical design (African Union, 2024).

These tensions converge around a concept long confined to individual cognitive psychology: metacognition. Defined by Flavell (1976) as "knowledge and control of one's own cognitive processes," metacognition has been progressively enriched by sociological and constructivist perspectives. While Piaget laid its developmental foundations, it is Vygotsky (1986) who reveals its fundamentally social nature: all cognitive regulation is first intersubjective before being internalized. Bourdieu (1980) further reminds us that this internalization does not occur in a neutral space — it is structured by the social, cultural, and linguistic capital of learners.

The emergence of LLMs in education opens a new configuration: can AI play the role of Vygotsky's "more capable peer," supporting metacognitive development where teachers are overloaded? Or does it reproduce, through training biases and interaction patterns, the linguistic and social hierarchies inherited by African education from colonialism? (Nekoto et al., 2020)

This paper addresses these questions in four stages: (1) a theoretical framework crossing metacognition, sociological constructivism, and African context; (2) an original empirical study conducted at ESP/UCAD on the TranspoBot project (Text-to-SQL with LLM, L3 GLSi, N=22 groups); (3) analysis of the potentials and sociological tensions of AI as a metacognitive mediator; (4) three rigorously operationalized experimental proposals (EP1–EP3)..

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Methodology

II. THEORETICAL FRAMEWORK

A. Metacognition: From Psychology to Sociology

Metacognition encompasses two complementary dimensions (Brown, 1987; Flavell, 1976): metacognitive knowledge (what the learner knows about their own cognitive functioning) and metacognitive regulation (planning, monitoring, and evaluation strategies). These dimensions are not strictly individual properties — they are socially transmitted, institutionally valued or ignored, and linguistically structured.

Nelson and Narens (1990) formalized the architecture of metacognition around two levels — the object level (task processing) and the meta level (monitoring and control) — connected by ascending (monitoring) and descending (control) information flows. It is precisely this dual flow that generative AI can potentially support, by externalizing certain monitoring functions.

B. Social Constructivism

Vygotsky (1986) posits that higher psychological functions — including metacognition — emerge first in social interaction before being internalized. The Zone of Proximal Development (ZPD) designates the gap between what a learner can accomplish alone and what they can achieve with peer or expert support. Wood, Bruner and Ross's scaffolding (Wood et al., 1976) is the mechanism by which this support is progressively withdrawn as the learner gains autonomy.

In this framework, AI can be conceived as dynamic, adaptive scaffolding — provided its pedagogical design targets progressive autonomy rather than dependence. This distinction is fundamental: an LLM that provides answers without soliciting the learner's reflection is not a Vygotskian tutor — it is an oracle. Our empirical data (Section III) operationalizes this distinction.

C. Bourdieusian Sociology of Inequalities

Bourdieu (1980) conceptualizes habitus as a set of durable dispositions incorporated through socialization, orienting practices without mechanically determining them. In the school domain, certain habitus — notably those of socially advantaged classes with high cultural capital — are aligned with institutional requirements, particularly with legitimate forms of epistemic reflexivity.

Bernstein (1975) refines this analysis with the theory of linguistic codes: the "elaborated code" (complex syntax, decontextualization, explicit reasoning) is valued by school and formal assessment systems, while the "restricted code" is systematically penalized. Current LLMs are massively trained on elaborated code in English and Western academic French — thus reproducing a linguistic hierarchy that critical sociology identified decades ago.

D. African Epistemologies and Ubuntu Philosophy

African epistemologies, notably Ubuntu philosophy ("I am because we are"), propose a radically communal conception of cognition (Mbiti, 1969; Wiredu, 1980). Knowledge is not an individual property stored in an isolated brain; it is a relational practice, distributed in the community, actualized in interaction. This ontology is coherent with Vygotsky's historical-cultural psychology, while radicalizing it.

It invites us to think of a collective metacognition — where the group regulates its own cognitive processes in a distributed manner — and to design AI systems that support this collective regulation rather than imposing an individualizing Western model. This is particularly relevant for the socio-cognitive conflict model of Doise and Mugny (1981).

E. Synthesis

TABLE I — THEORETICAL FRAMEWORK SYNTHESIS

Tradition	Key Author(s)	Core Contribution	AI Implication
Cognitive Psych.	Flavell, Brown, Nelson	Monitoring / Control	AI as external cognitive mirror
Social Constructivism	Vygotsky, Wood	ZPD, scaffolding	AI as adaptive tutor (ZPD)
Critical Sociology	Bourdieu, Bernstein	Habitus, linguistic codes	Risk of inequality reproduction

Interactionism	Doise & Mugny	Socio-cognitive conflict	AI as debate facilitator
African Epistemologies	Mbiti, Wiredu	Communal cognition	AI in local languages

III. EMPIRICAL STUDY: THE TRANSPOBOT PROJECT

A. Pedagogical Device

The TranspoBot project is a semester-long integrative project consisting of building a Text-to-SQL system exploiting an LLM for urban transport management. The device is based on the principle of "critical AI assumption": rather than prohibiting generative AI tools — a prohibition we consider illusory and pedagogically counterproductive — the device explicitly integrates them into the learning task, making reflexivity on the LLM a standalone evaluation criterion.

This approach directly operationalizes the theoretical framework: the LLM is designed as a Vygotskian "more capable peer" whose ZPD the student must learn to exploit. Criterion C3 (LLM/Text-to-SQL, 25 points) captures this metacognitive dimension: it evaluates not whether the system works, but whether the student understands why and how it works or fails, how they manage hallucinations, and how they design prompts.

TABLE II — EVALUATION GRID (TranspoBot)

Criterion	Description	Max.	Metacognitive Dim.
C1 – Modeling	Conceptual & relational schema	20	Abstract thinking
C2 – Backend	Server, API, database arch.	20	Technical skill
C3 – LLM/SQL	Prompt design, hallucination management	25	AI Monitoring (core)
C4 – Interface	UX/UI quality	15	Cognitive design
C5 – Deployment	Production (Railway/Vercel/Render)	10	DevOps
C6 – Report	Documentation, reasoning justification	20	Retrospective control
C7 – Presentation	Argumentation, Q&A	15	Communication
Bonus	Innovation	+10	Advanced autonomy

B. Descriptive Statistics

The study covers the entire cohort: N = 22 groups (~110 students) across two parallel classes (Class A: 9 groups, Class B: 13 groups). Group size ranges from 3 to 5 members. Table III presents the descriptive statistics.

TABLE III — DESCRIPTIVE STATISTICS

Indicator	Class A (n=9)	Class B (n=13)	Global (N=22)
Mean /20	13.96	12.94	13.35
Median /20	14.08	13.60	13.60
Std. Dev.	1.19	1.23	1.29
Min /20	12.32	9.76	9.76
Max /20	16.32	14.72	16.32
Mean IMC (%)	67.4%	62.4%	64.5%
Bonus awarded	2 groups	1 group	3 groups (13.6%)

The global mean of 13.35/20 (66.8% of the maximum) indicates a satisfactory level of mastery, consistent with the project's complexity. The relatively low standard deviation (1.29) signals a homogeneous distribution, without floor or ceiling effects — indicative of a well-calibrated rubric. The difference between classes (+1.02 pts for A vs. B) is not statistically significant ($t = 1.93$, $p = 0.067 > 0.05$), confirming population homogeneity.

C. The Metacognitive Composite Index (MCI)

We propose a synthetic indicator — the Metacognitive Composite Index (MCI) — combining the two criteria most directly related to cognitive regulation:

MCI = (C3_LLM + C6_Report) / 45 × 100

C3 captures real-time cognitive regulation during LLM interaction (monitoring: error identification, prompt correction). C6 captures retrospective regulation (control: choice documentation, reasoning explicitness, post-hoc evaluation). Together, they correspond to Nelson & Narens's (1990) metacognitive model: ascending flux (monitoring) and descending flux (control). The global MCI mean is 64.5% (Class A: 67.4%, Class B: 62.4%).

D. Correlational Analysis

Table IV presents Pearson correlation coefficients between each criterion (as % of maximum) and the final grade /20.

TABLE IV — CORRELATIONS WITH FINAL GRADE

Criterion	r	p-value
MCI composite (C3+C6)	0.973	< 0.001
C6 – Report (retrospective control)	0.963	< 0.001
C3 – LLM/SQL (AI monitoring)	0.942	< 0.001
C4 – Interface	0.950	< 0.001
C2 – Backend	0.942	< 0.001
C7 – Presentation	0.942	< 0.001
C1 – Modeling	0.874	< 0.001
C5 – Deployment	0.721	< 0.001

The MCI presents the highest correlation with the final grade ($r = 0.973$, $p < 0.001$). This result directly supports the paper's central thesis: in an AI-integrated learning context, explicit metacognitive regulation — the ability to document, justify, and identify LLM errors — is the strongest predictor of academic performance, surpassing purely technical competencies.

Stated differently: students who "think about" their LLM usage systematically outperform those who submit to it passively — empirically validating the Vygotskian distinction between active use (scaffolding, ZPD) and passive use (crutch, dependence) of generative AI.

E. Visualizations



Classe	N groupes	Moy. /20	Méd. /20	Écart-type	Min /20	Max /20	Moy. LLM%	Déploi. absent	Bonus accordés
A	9	13.96	13.92	1.19	12.32	16.32	68.4%	0	3
B	13	12.94	12.96	1.23	9.76	14.72	62.5%	1	2
Global	22	13.35	13.60	1.29	9.76	16.32	64.9%	1	5

Fig. 1. Analytical dashboard — TranspoBot project (N=22 groups, L3 GLSi ESP/UCAD). (a) Grade distribution; (b) Group-level grades; (c) Criterion mastery radar; (d) Boxplots by criterion and class; (e) Criterion-grade correlations; (f) Scatter C3_LLM × final grade (r^2=0.887); (g) Mention distribution; (h) Summary statistics table.

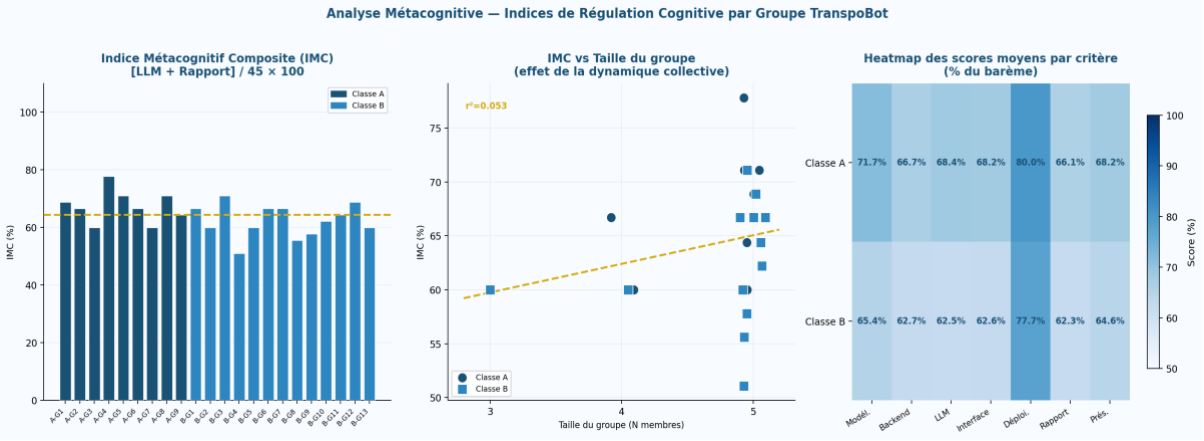


Fig. 2. Metacognitive analysis. (a) MCI per group (global mean: 64.5%); (b) MCI vs. group size; (c) Criterion score heatmap by class. Note: Group B-G4 (MCI=51.1%, grade=9.76/20, no deployment) constitutes the prototype high-risk profile.

F. Discussion of Empirical Results

The central result (MCI r=0.973) constitutes an empirical validation of the theoretical framework in a Francophone African university context. It confirms that the Nelson & Narens monitoring+control model, transposed into an AI learning device, robustly predicts academic performance.

The group B-G4 profile — sole failing group (9.76/20), lowest MCI (51.1%), absent deployment — illustrates the risk identified in the theoretical framework: without pedagogical design requiring reflexivity, AI may inhibit rather than support the metacognitive development it claims to foster. This case operationalizes the oracle/tutor distinction for experimental proposal EP3.

Three limits must be acknowledged: (i) single-institution study (N=22 groups), requiring external replication; (ii) MCI is a proxy, not a validated metacognition instrument (MAI not administered); (iii) students' sociolinguistic background was not systematically collected, limiting the Bourdieusian interpretation.

IV. AI AND METACOGNITION IN AFRICAN CONTEXTS

A. Potentials

1) Externalized metacognitive prosthesis: In classes of 60–100 students, teachers lack the attentional bandwidth to individually monitor each learner. Intelligent Tutoring Systems (ITS) model learner cognitive states in real time. Our data confirms the effectiveness of this externalization: criterion C3, which measures monitoring quality, is the third strongest predictor of final grade (r=0.942).

2) Automated Socratic questioning: LLMs can be prompted to adopt a Socratic posture — asking questions rather than providing answers — forcing learners to verbalize and explicate their thinking. This is directly homologous to Vygotskian scaffolding, provided questions are calibrated to the learner's ZPD and formulated in their language of thought (often a national language).

3) Reflexive learning journals: Session summary generation systems allow learners to visualize error patterns, progress, and strategies. Criterion C6 (report) is a manual version of this principle: its high correlation (r=0.963) suggests that retrospective verbalization of reasoning is a central competency to develop.

B. Sociological Risks

The enthusiasm for AI in African education must be tempered by rigorous analysis of five key risks:

- Linguistic bias: LLMs favor elaborated-code Western expression, penalizing learners whose mother tongue is not academic French or English (Nekoto et al., 2020).
- Cognitive dependence risk: if AI performs metacognitive regulation instead of the learner, it inhibits the competencies it claims to support (cf. Group B-G4).
- Digital divide: unequal access to electricity, internet, and devices creates new forms of academic exclusion.

- Teacher disintermediation: in African contexts where teachers hold strong moral-communal roles, AI substitution risks destructuring high-value socializing pedagogical relationships.
- Data extractivism: learning data collected by foreign platforms constitutes epistemic dispossession, undermining African digital sovereignty (Mbacké, 2025).

V. EXPERIMENTAL PROPOSALS

A. EP1 — AI Tutoring in Wolof and Metacognitive Development

Research question: Does interaction with an AI tutor in Wolof significantly improve metacognitive regulation in Senegalese terminal students, compared to a French-language AI tutor?

Empirical anchor: The TranspoBot study shows that criterion C3 (LLM monitoring quality, r=0.942) is the third strongest predictor of global grade. EP1 tests the hypothesis that linguistic alignment between the interaction language (Wolof) and the learner's language of thought amplifies this effect, via Vygotsky's inner speech mechanism.

TABLE V — EP1 DESIGN (RCT, 3 arms)

Group	Condition	N	Duration
G1 (Exp. A)	AI tutor in Wolof (LLM + Masakhane corpus)	80	16 weeks
G2 (Exp. B)	AI tutor in French	80	16 weeks
G3 (Control)	Traditional instruction (no AI)	80	16 weeks

Primary instrument: MAI (52-item Metacognitive Awareness Inventory), translated and validated in Wolof. Secondary: standardized mathematics test, think-aloud protocols coded on Schraw's grid, MCI adapted for secondary level. Main hypotheses: (H1.1) G1 > G2 > G3 on MAI at T16; (H1.2) linguistic condition effect is moderated by family cultural capital; (H1.3) adapted MCI ≥ 65% (TranspoBot mean threshold) predicts T16 performance.

B. EP2 — AI-Augmented Collective Metacognition

Research question: Does an AI-facilitated structured debate device foster collective metacognition in Francophone African university student groups?

The AI plays the role of digital Socratic seminar facilitator: it identifies divergent positions, reformulates disagreements without resolving them, asks each member to explicate their reasoning, and generates an end-of-session argument map. Sites: ESP/UCAD (Dakar) and Université de Bouaké (Côte d'Ivoire). Design: quasi-experimental, one semester, 16 experimental groups vs. 16 control groups (5 students each, ~160 students total). Hypotheses: (H2.1) Experimental groups show significantly higher Group Metacognition Scale (Goos et al., 2002) scores at T14; (H2.2) Individual metacognitive transfer (delta MAI) is higher in experimental condition; (H2.3) Intra-group MCI variance mediates the collective metacognition effect.

C. EP3 — Algorithmic Detection of Metacognitive Inequalities

Research question: Can LLM interaction patterns detect and predict metacognitive inequalities linked to sociolinguistic origin, and can equitable algorithmic adjustment reduce them?

Phase 1 (6 months): 500 learners interact freely with a standardized AI tutor. Interaction logs (prompt quality, request frequency, meta-query capacity) are analyzed by supervised ML (Random Forest, Gradient Boosting, LSTM) to predict MAI score, dominant Bernstein code, and socioeconomic background. Phase 2 (10 weeks): A/B test of an equitable adaptive mechanism — the tutor detects metacognitive profile in real time and adjusts its linguistic register, question complexity, and scaffolding density.

TABLE VI — EP3 EQUITY INDICATORS

Equity Indicator	Operationalization	Target (TranspoBot-calibrated)
Risk detection	Predicted MCI < critical threshold → alert + adjustment	MCI < 55% (B-G4 profile)
Equal treatment	Reduction of MCI gap between sociolinguistic groups	≥ 30% reduction

Equal opportunity	Comparable MCI progression rates across groups	Gap < 5 points
Prediction accuracy	ML model on MAI score	RMSE < 8/250

Main hypotheses: (H3.1) LLM interaction patterns predict MAI score with RMSE < 8/250; (H3.2) Dominant Bernstein code is the strongest predictor of metacognitive interaction quality; (H3.3) Equitable algorithmic adjustment reduces the metacognitive gain gap between sociolinguistic groups by ≥ 30%.

VI. DISCUSSION

A. Theory–Empirics–Experimentation Articulation

The paper's three-stage structure reflects a deliberately iterative scientific approach. The TranspoBot results do not merely illustrate the theoretical framework: they modify it. In particular, the exceptionally high MCI correlation (r=0.973) invites a revision of the classical hierarchy between technical and metacognitive competencies in AI learning devices. Contrary to a technocentric view, it is cognitive regulation competencies — documenting, justifying, correcting — that best predict performance, not programming or software architecture skills.

This result has a direct implication for experimental proposal design: the MCI, initially conceived as a research indicator, becomes an operational pedagogical diagnostic tool. The MCI < 55% threshold identified in TranspoBot data as an alert signal constitutes an empirically grounded parameter for EP3's detection mechanism.

B. Implications for African Educational Policy

Converging results from this study argue for: (1) explicit integration of metacognition as an evaluated competency in African ICT and STEM curricula; (2) teacher training in designing pedagogical devices that require AI reflexivity rather than mere instrumental use; (3) development of multilingual AI tools in national languages; (4) establishment of African digital sovereignty infrastructure ensuring learning data remains a continental common good, consistent with the African Union's 2024 Continental AI Strategy (African Union, 2024).

VII. CONCLUSION

This paper has presented an integrative theoretical framework articulating sociological metacognition, social constructivism, African epistemologies and artificial intelligence, grounded in an original empirical study at ESP/UCAD. The central result — r = 0.973 between the Metacognitive Composite Index and academic performance in an LLM learning device — constitutes, to our knowledge, the first quantitative empirical demonstration of the preponderant role of metacognitive regulation in an AI learning context in Francophone Africa.

This result legitimizes a paradigm shift in the design of AI-integrated pedagogical devices in Africa. The question is no longer "how to use AI to improve scores?" but "how to design devices that develop learners' capacity to regulate their AI usage?" The three experimental proposals formulated in this paper render this question empirically testable — and ensure that the answers will be grounded in African realities, conducted by African researchers, for African learners.

ACKNOWLEDGMENT

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Preparing Future Cybersecurity Professionals Through Human-AI Collaboration: Design of an AI-Augmented SOC Learning Environment

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Abstract

The growing integration of Artificial Intelligence (AI) into cybersecurity operations is transforming the competencies required of future cybersecurity professionals. While AI-powered tools increasingly support threat detection, incident investigation, and security monitoring, educational approaches that prepare learners to collaborate effectively with AI in realistic operational environments remain limited. This paper presents SOC Lite, an AI-augmented educational platform designed to simulate the workflows of a modern Security Operations Center (SOC). The platform enables students to engage in authentic cybersecurity tasks, including threat analysis, incident investigation, and decision-making activities supported by Generative AI technologies. Rather than positioning AI as a replacement for human expertise, SOC Lite emphasizes human-AI collaboration by encouraging learners to critically evaluate, validate, and refine AI-generated insights. The paper describes the pedagogical rationale, instructional design principles, and architecture of the platform. Drawing on authentic learning and experiential learning approaches, SOC Lite seeks to bridge the gap between classroom instruction and professional cybersecurity practice while fostering cybersecurity competencies, AI literacy, critical thinking, and responsible decision-making. The paper concludes by outlining an evaluation framework for investigating learning outcomes and student experiences in AI-supported cybersecurity education.

Keywords: Cybersecurity Education, Human-AI Collaboration, Generative AI, AI Literacy, Authentic Learning, Security Operations Center, Educational Technology.

Introduction

Artificial Intelligence (AI) is rapidly transforming cybersecurity operations (Miller, 2019; NIST, 2024). Security Operations Centers (SOCs) increasingly employ AI-powered tools to support threat detection, alert prioritization, incident investigation, evidence analysis, and decision-making. Rather than functioning solely as automation tools, contemporary AI systems actively participate in cybersecurity workflows by generating recommendations, summarizing evidence, identifying potential threats, and supporting analysts during investigations. As a result, cybersecurity professionals are increasingly required to work collaboratively with AI systems in complex and dynamic operational environments (Miller, 2019).

This transformation creates new challenges for cybersecurity education. Traditional cybersecurity curricula primarily focus on technical competencies such as network security, digital forensics, incident response, and vulnerability assessment (ACM et al., 2017). While these skills remain essential, future cybersecurity professionals must also learn how to interact effectively with AI-generated recommendations, critically evaluate AI outputs, validate evidence, and maintain responsibility for final decisions. Recent research suggests that the growing integration of Generative AI creates new metacognitive challenges that extend beyond traditional digital literacy and AI tool usage (Levin et al., 2025). The ability to collaborate with AI while preserving independent judgment is becoming a critical workforce competency.

At the same time, higher education institutions are actively exploring the integration of AI into teaching and learning (Zawacki-Richter et al., 2019). However, many existing educational implementations rely on general-purpose AI tools (Luckin et al., 2016) that are detached from authentic professional contexts and domain-specific decision-making environments. Students may learn how to use AI systems, but they often lack opportunities to experience how AI is integrated into real-world cybersecurity workflows. Consequently, there is a growing need for educational environments that allow learners to engage in realistic cybersecurity investigations while interacting with AI systems in meaningful and professionally relevant ways.

To address these challenges, we developed SOC Lite, an AI-augmented Security Operations Center learning environment designed to support cybersecurity education through authentic, scenario-based learning activities. SOC Lite combines multiple specialized AI agents with human-centered decision-making processes, enabling students to investigate cybersecurity incidents, analyze evidence, evaluate AI-generated recommendations, and

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reflect on their decisions. Rather than positioning AI as a replacement for human expertise, the platform encourages students to critically engage with AI-generated information and actively participate in the investigative process.

The purpose of this paper is to present the design of SOC Lite as an educational environment for preparing future cybersecurity professionals. Specifically, we describe the pedagogical foundations of the platform, its AI-augmented architecture, and the learning activities it supports. We also outline how SOC Lite can be used to foster cybersecurity competencies, AI literacy, critical thinking, evidence-based reasoning, and Human–AI collaboration skills. By integrating authentic cybersecurity scenarios with AI-supported decision-making, SOC Lite aims to provide a learning environment that reflects the realities of contemporary cybersecurity practice while preparing students for an increasingly AI-enabled workforce.

Methodology

This paper follows a design-oriented methodology. Rather than reporting the results of a completed empirical intervention, it presents the pedagogical rationale, design principles, and implementation structure of SOC Lite as an AI-augmented cybersecurity learning environment. The design process was guided by three complementary perspectives: authentic learning, experiential learning, and Human–AI collaboration (Herrington et al., 2014; Kolb, 2015). Together, these perspectives informed the development of scenario-based learning activities, AI-supported investigation workflows, and reflective decision-making tasks.

Theoretical Foundations

The design of SOC Lite is grounded in authentic learning (Herrington et al., 2014; Reeves et al., 2002). Authentic learning emphasizes realistic tasks, meaningful contexts, and engagement with problems that resemble professional practice (Herrington et al., 2014). This approach is particularly relevant to cybersecurity education because security professionals routinely operate under conditions of uncertainty, incomplete evidence, and time-sensitive decision-making. By simulating Security Operations Center workflows, SOC Lite enables students to engage with cybersecurity incidents in ways that approximate professional investigative practice.

Experiential learning also informed the platform design (Kolb, 2015). In SOC Lite, students do not only read about cybersecurity incidents or observe demonstrations; they actively investigate scenarios, interact with AI agents, evaluate evidence, make decisions, and reflect on their reasoning (Kolb, 2015). This learning cycle supports the development of practical cybersecurity competencies together with reflective awareness of the decision-making process.

The third design foundation is Human–AI collaboration. As AI becomes increasingly embedded in cybersecurity workflows, students must learn not only how to use AI tools but also how to collaborate with AI-generated recommendations responsibly. This requires learners to question AI outputs, validate evidence, recognize uncertainty, and maintain responsibility for final decisions. An important aspect of effective Human–AI collaboration is contestability—the learner's ability to challenge, question, and critically evaluate AI-generated recommendations rather than accepting them uncritically. Within cybersecurity investigations, contestability supports critical thinking, evidence-based reasoning, and responsible decision-making. These capabilities align with emerging discussions concerning advanced Human–AI collaboration competencies, including planning, monitoring, evaluation, and reflection (Kojukhov et al., 2025; Levin et al., 2025; Luckin et al., 2016).

SOC Lite Learning Environment

SOC Lite was designed as an AI-augmented Security Operations Center learning environment. The platform presents students with realistic cybersecurity scenarios and supports their investigations through a set of specialized AI agents. These agents provide analytical assistance while preserving the student's role as the final decision-maker (NIST, 2024). The platform includes four main AI-supported components. The Threat Analysis Agent assists students in identifying potential threats, assessing severity, and formulating initial hypotheses. The Evidence Investigation Agent supports the examination of logs, alerts, indicators, and supporting evidence. The Governance and Compliance Agent highlights relevant policy, ethical, and procedural considerations. The Reflection Agent encourages learners to justify their decisions, consider alternative explanations, and evaluate the quality of their reasoning.

Unlike general-purpose AI tools, SOC Lite embeds AI support within a structured cybersecurity workflow. This allows learners to experience AI as part of a professional decision-making environment rather than as a detached chatbot or productivity assistant. The platform is designed to support inquiry, evidence validation, and reflective decision-making rather than automated answer generation. The SOC Lite architecture combines a human-centered investigation workspace with a collection of specialized AI agents that support different stages of cybersecurity analysis. The architecture was designed to mirror the division of responsibilities commonly found in operational

Security Operations Centers while preserving the student's role as the primary decision-maker. Through this architecture, learners experience how AI technologies can augment cybersecurity investigations without replacing human judgment.

Figure 1 illustrates the overall architecture of SOC Lite and the interaction between learners and specialized AI agents.

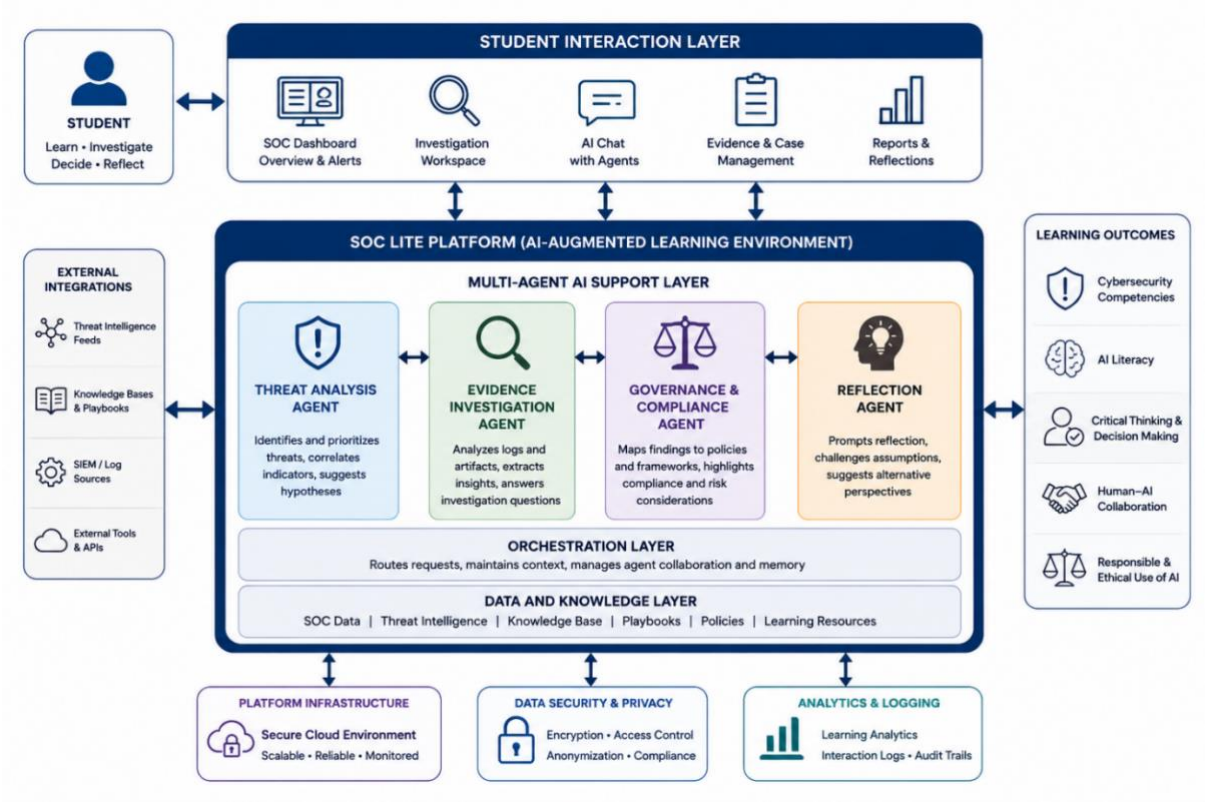


Figure 1. SOC Lite Architecture and Human–AI Collaboration Components

Learning Design

Learning activities in SOC Lite are organized around scenario-based investigations (Herrington et al., 2014). Each activity begins with the presentation of a cybersecurity incident, such as a suspicious login, compromised account, phishing attempt, or ransomware-related alert. Students are asked to investigate the case, collect and evaluate evidence, interact with AI agents, and formulate a justified decision.

Students investigate incidents, analyze logs, identify indicators of compromise, formulate incident response recommendations, and justify remediation actions before reflecting on the investigation process.

The learning process follows six stages. First, students receive the scenario and initial context. Second, they plan an investigation by identifying what information is needed and which questions should be explored. Third, they collaborate with AI agents to obtain analysis, explanations, and alternative interpretations. Fourth, they validate evidence by checking logs, comparing recommendations, and assessing the reliability of AI-generated outputs. Fifth, they make and justify a final decision. Finally, they reflect on the investigation process, the role of AI support, and lessons learned (Kolb, 2015).

This structure encourages students to treat AI recommendations as resources for inquiry rather than final answers. It also enables instructors to observe how students engage with AI during authentic cybersecurity decision-making tasks.

Figure 2 presents the AI-augmented learning cycle that guides student investigations within the platform.

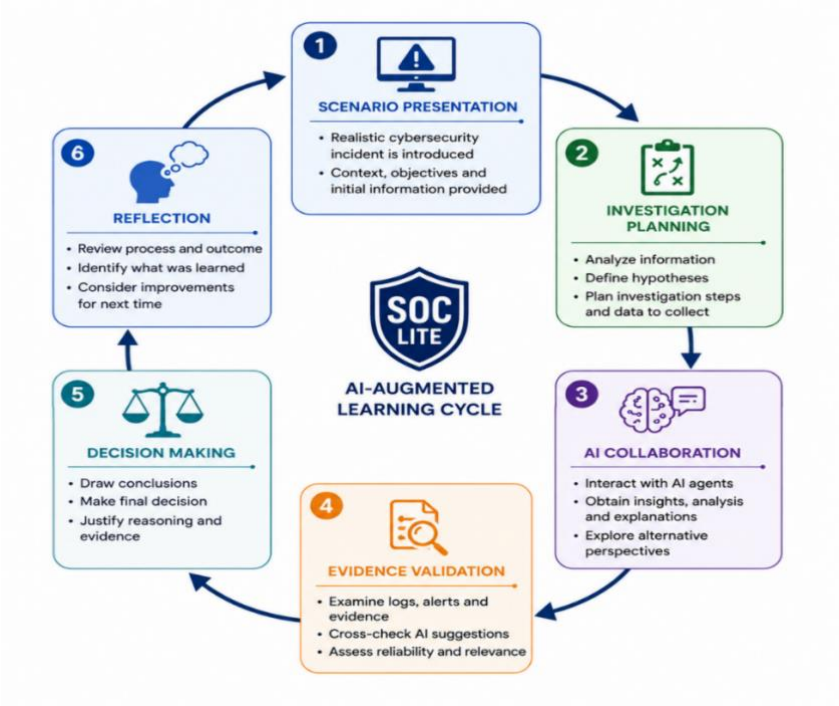


Figure 2. SOC Lite AI-Augmented Learning Cycle

Data Sources and Evaluation Design

Although the present paper focuses on the design of the learning environment, SOC Lite was built to support future empirical evaluation. The platform records interaction data that can be used to examine how students collaborate with AI during cybersecurity investigations (Miller, 2019). Relevant data sources include student decisions, evidence requests, AI-agent interactions, explanation consultations, challenge actions, reflection reports, and final justifications.

The evaluation design focuses on three guiding research questions:

RQ1. How do students collaborate with AI agents during cybersecurity investigations?

RQ2. How does SOC Lite support the development of cybersecurity competencies and AI literacy?

RQ3. Which Human–AI collaboration competencies (e.g., planning, monitoring, evaluation, and reflection) emerge during AI-assisted cybersecurity learning activities?

These questions will guide future classroom-based evaluation of SOC Lite. Planned analyses will examine both technical learning outcomes and Human–AI collaboration behaviors (Luckin et al., 2016), including evidence-based reasoning, critical evaluation of AI recommendations, reflective practice, and responsible decision-making.

Results

Educational Outcomes

The present study focuses on the design of the SOC Lite learning environment and its pedagogical foundations. As classroom implementation and empirical evaluation are planned for a forthcoming pilot deployment, the following section presents the expected educational outcomes and evaluation directions associated with the platform.

As the current paper presents the design of the SOC Lite learning environment rather than the results of a completed intervention, this section outlines the expected educational outcomes that the platform is designed to support in AI-augmented cybersecurity learning contexts. The platform integrates authentic cybersecurity investigations with AI-supported analysis, enabling students to develop both technical cybersecurity expertise and Human–AI collaboration skills (Luckin et al., 2016).

First, SOC Lite supports the acquisition of cybersecurity competencies through realistic incident investigation activities (ACM et al., 2017). Students analyze alerts, examine evidence, evaluate threats, and formulate responses

in a manner similar to professional Security Operations Center workflows. These activities promote practical understanding of cybersecurity concepts while providing opportunities for applying theoretical knowledge in authentic contexts.

Second, the platform promotes AI literacy (Zawacki-Richter et al., 2019) by exposing learners to AI-supported investigative processes. Students interact with specialized AI agents that provide recommendations, explanations, and alternative interpretations. Through these interactions, learners gain experience understanding both the capabilities and limitations of AI technologies within professional environments.

Third, SOC Lite encourages critical thinking and evidence-based reasoning (Brown et al., 1989). Students are expected to evaluate AI-generated recommendations, validate supporting evidence, compare alternative explanations, and justify their conclusions. Rather than treating AI outputs as authoritative answers, learners are encouraged to engage in active inquiry and independent reasoning.

Finally, the platform supports Human–AI collaboration skills that are becoming increasingly important in cybersecurity practice. Learners must balance AI recommendations with professional judgment, evaluate uncertainty, and maintain responsibility for final decisions.

Table 1. Educational Outcomes and Example Evaluation Indicators

Educational Outcome	Example Evaluation Indicator
Cybersecurity Competence	Threat detection accuracy
AI Literacy	Explanation consultation frequency
Critical Thinking	Contestability rate
Evidence-Based Reasoning	Evidence verification rate
Human-AI Collaboration	AI-agent utilization diversity
Reflective Practice	Reflection quality score

The precise operational definitions and measurement procedures associated with these indicators are currently under development and will be refined through the ongoing pilot deployment and subsequent empirical evaluation studies.

Pilot Deployment and Evaluation Framework

Preliminary pilot deployment activities are currently underway within a cybersecurity laboratory course involving an initial cohort of approximately seven undergraduate students. The pilot will examine how learners interact with AI agents during scenario-based investigations and how AI-supported activities contribute to cybersecurity competencies, AI literacy, and Human–AI collaboration skills. Data sources will include interaction logs, evidence requests, AI consultations, reflective reports, and final decision justifications. The pilot will provide initial insights into the educational value of the platform and inform future larger-scale studies.

Conclusions

The increasing integration of Artificial Intelligence into cybersecurity operations requires educational approaches that prepare students not only to understand cybersecurity concepts, but also to collaborate effectively with AI-supported systems. Future cybersecurity professionals will need to evaluate AI-generated recommendations, validate evidence, interpret explanations, and maintain responsibility for final decisions in complex operational contexts.

This paper presented SOC Lite as an AI-augmented Security Operations Center learning environment designed to address this educational challenge. Grounded in authentic learning and experiential learning principles, SOC Lite enables students to engage in realistic cybersecurity investigations while interacting with specialized AI agents that support threat analysis, evidence investigation, governance awareness, and reflection.

The main contribution of SOC Lite is its integration of cybersecurity learning with Human–AI collaboration. Rather than positioning AI as an automated problem solver, the platform encourages learners to treat AI-generated outputs as inputs for inquiry, verification, and reflection. In this way, SOC Lite supports the development of cybersecurity competencies, AI literacy, critical thinking, evidence-based reasoning, and responsible decision-making.

The planned pilot deployment in a cybersecurity laboratory course will provide an initial opportunity to evaluate how students interact with AI agents during authentic investigation tasks. Data collected through interaction logs, student decisions, evidence requests, and reflective reports will inform future improvements to the platform and support larger-scale empirical studies.

Future work will focus on classroom implementation, analysis of student interaction patterns, and evaluation of learning outcomes. These studies will help clarify how AI-augmented learning environments can support the preparation of cybersecurity professionals capable of working effectively, critically, and responsibly with intelligent systems.

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A Systematic Review of Inclusive Education Strategies for Identified Needs in Higher Education Institutions: Current Challenges and Future Directions

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Abstract

Through this systematic review we critically examine inclusive education practices being used for students with diagnosed needs within Higher Education Institutions (HEIs) with a focus on Azerbaijan's educational environment. Using the PRISMA framework and a thematic analysis, this research compiled data from forty-one (41) peer-reviewed articles to identify current best practices, continuing challenges and significant gaps in the existing literature (e.g., curriculum, technology integration, faculty development, institutional support).

While there is an increasing commitment worldwide to develop inclusive policies for higher education, the findings show that HEIs still have a lot of challenges in implementing these strategies effectively, and these challenges are especially severe in the Azerbaijani context. instructors do not get specialized training; there are inconsistent institutional procedures; and the barriers to digital and physical accessibility still exist. Assistive technology provides excellent results in terms of student success, but these technologies continue to be underused because there is very little technological infrastructure to support using this equipment and providing enough training for faculty and students to use it. To correct the shortcomings, the paper provides colleges & universities evidence based recommendations to create inclusive environments by developing faculty professional development, improving institutional policies & implementing assistive technology on a comprehensive level.

Keywords: inclusive education; student identification; higher education in Azerbaijan; assessment tools; systems review

Introduction

The development of inclusive education policies has been a major focus area globally. The main objective of this guideline is to ensure equal access to education for all learners, including persons with disabilities. The United Nations Sustainable Development Goals (SDGs) aim to create more inclusive and equitable societies for persons with disabilities, but only 30% of the SDG targets for persons with disabilities have been achieved. UN DESA 2024. In addition to demonstrating that policies are not keeping pace with reality, the low completion rate of SDG goals makes it difficult for SODs to transition to TIEs.

Faculties in college or university are not adequately trained in inclusive education practices. In pre-kindergarten through high school, teachers have (IEPs) individualized Education Plans as a guide for the kind of support needed for Students of Determination (SoDs), but no equivalent standard exists at HEIs and that puts such students at a disadvantage (Guliyeva, N. 2025). The transition from high school to HEIs is also created by the existing lack of effective and systematic coordination between the two types of educational institutions. As a result, many of these students are not fully prepared both academically and socially at their time of entry into an HEI. The Ministry of Education is dedicated to making education available for everyone and meeting the Sustainable Development Goals by 2030. They are committed to making education available for everyone, but there are still issues that need to be addressed (Mammadova, L. & Valiyev, A. 2020). Educators in Higher Education Institutions have shared their concerns about the lack of interventions designed specifically for Students with Disabilities and the fact that educators are not provided with adequate training to properly support students with disabilities. Assistive technology and the support systems designed to assist with inclusive practices are affected by cultural beliefs, the preparedness of faculty members, and institutional policies. There is a stigma associated with disability that creates barriers for students' ability to participate academically and socially in fully inclusive campus environments (Aliyeva, T., & Çakır, H. 2025). There is an urgent need for HEIs to assess their Instructional Methods and Assessment Procedures in a systematic manner to confirm that they are implementing inclusivity guidelines in a manner that is consistent with the intended purpose of the Inclusivity Guidelines and supports the needs of all learners. There is a large gap between what the institutional policy frameworks say and their actual implementation. This gap exists in the form of inconsistencies in providing accessibility, inconsistencies in the preparedness of faculty and staff and inconsistencies in providing institutional resources to support inclusive practices (Mammadova, R., Gahramanova, K., & Mammadova, K. 2025). While there is a significant body of research on

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both Primary and Secondary Education related to Inclusion in India, there is a tremendous absence of comprehensive, systematic Reviews of the effective Strategies for Inclusion at the University Level (Mikayilova, Ulviyya & Orujova, Lalakhanim & Babayeva, Ulkar. 2023).

Even though the world continues to develop its consciousness of the Inclusive Education Programme as a Recognized fundamental Human Rights, still the levels of application of the same in the Higher Education Institutions have been inconsistent with students with disabilities and other identified students as well. Most countries have implemented inclusive education policies and practices. Still, limited evidence supports successful implementation of these practices and policies within higher education in the Republic of Azerbaijan (Adnan, A. H., & Hafiz, I. A. 2001). Current research has primarily concentrated on inclusive education in primary and secondary levels of education, and therefore there is little knowledge of inclusive education within the Higher Education Institutions in Azerbaijan regarding the developing strategies, challenges, and organizational influences. In turn, decision-makers and higher learning leaders and staff members have very little evidence-based information to help them develop and implement successful inclusive education practices within higher education institutions (Almoghyrah, H. 2023).

This research study uses an international and Azerbaijani perspective on inclusive education in higher education and addresses the barriers that higher education institutions (HEIs) and their faculty must overcome when trying to create an inclusive learning environment (Al-Obaidi, A., & Budosan, B. 2011). The article identifies research gaps and provides future recommendations for developing a more inclusive higher education system in Azerbaijan.

Main questions

What are the best ways that Higher Education Institutions (HEIs) in Azerbaijan can successfully use Inclusive Education (IE) Practices to create equal learning opportunities for the identified students (IS)?

Sub questions

What are some examples of ways to implement Inclusive Education (IE) Strategies for IS in Higher Education Institutions (HEI) across the world and in Azerbaijan?

What challenges do HEIs and their faculty face when they deliver Inclusive Education (IE) Practices?

What types of research gaps exist regarding IE in HE, and what future directions would be beneficial for the continued evolution of IE in Azerbaijan?

This research will examine the strategies for inclusive education, the operational barriers of these strategies, and the future directions for research in higher education institutions. The study will construct a systematic review of peer-reviewed literature to identify evidence-based strategies and recommendations for higher education institutions (HEIs), teachers and policymakers in HEIs. The results will support to determine the current lacks and give recommendations to upgrade the inclusive policy and practice of the higher education institutions of Azerbaijan (Buetow, S., & Zawaly, K. 2022).

As inclusive education is described in this research, it includes a variety of instructional strategies which allow all students to have an equal opportunity to learn, regardless of their ability level or whether they have disabilities. Students who require any specific assistance or accommodation in their education are referred to as "Identified Students" (IDS) in Azerbaijan. Inclusive educational practices improve the learning environment for all students, because they are responsive to a wide array of individual student needs (Denhart, H. 2008). Individualized Education Plans (IEPs) are a strategy used to support the educational needs of students by providing individualized instruction designed to meet their specific needs.

Problem Statement

Global awareness of inclusive education has increased, but many students with disabilities studying in higher education institutions in Azerbaijan continue to face numerous barriers. Teachers are often not adequately prepared and trained to support ISS (identified) students, resulting in institutions making inconsistent and ineffective adjustments. Inclusive education policies have been endorsed in a number of higher education institutions in Azerbaijan, but the nature of the implementation of these policies is largely tied to inconsistent and ineffective support systems provided for the diverse requirements of the ISS (Dey, R., Kassim, S., Maurya, S., Mahajan, R. A., Kadia, A., & Singh, M. 2024). The inclusive education policy, which has yielded positive results in schools, is being gradually implemented in higher education institutions across Azerbaijan (Getzel, E. E. 2008).Preparing a program does not equal proper implementation. Higher education institutions do not implement IEPs at the higher education levels, while special measures are used in elementary and secondary schools (Goodley, D., Lawthom, R., Liddiard, K., & Runswick-Cole, K. 2019). Teachers lack intervention standards to teach students with

disabilities to participate, learn, and socialize in a college/university classroom. This hinders teachers from understanding the learning needs of (METs) as most of them do not fully understand the learning needs of METs, leading to haphazard approaches to teaching and learning. Although policies have been created and adopted by higher education institutions, many have failed to implement inclusive education into their programs. This is in direct conflict with international best practices such as (UDL) and Individualized Learning Plans, and therefore ekpyrotic education in higher education has quite significant gaps compared to international best practices. Everyone can benefit from UDL, Teachers must design classroom environments that are adaptable to support all types of students (Goodwin, K., Farquharson, K., Yeager Pelatti, C., Schneider-Cline, W., Harvey, J., & Bush, E. 2022). However, IEPs require the provision of academic support (Gravel, B., & Wilkerson, T. 2017). In contrast, Azerbaijan lacks the infrastructure to meet the educational needs of METs, which creates significant barriers to serving the needs of METs (Hackman, H. W., & Rauscher, L. 2004).

Methodology

This systematic review of literature (SLR) follows the PRISMA process, which is becoming the standard way of doing research in social science because it's a method of conducting research that provides a very structured way of conducting research, and can be very transparent and reliable (Heiman, T., & Precel, K. 2003). In the case of this research we focus on students with special needs in Higher Education Institutions (HEIs) in Azerbaijan. The specific aims of this study are to: (1) determine the current inclusive education strategy used at HEIs internationally and in Azerbaijan; (2) identify the challenges associated with implementing inclusive education at HEIs from both the faculty member's perspective and the student's perspective; and (3) highlight research gaps and opportunities for future research to improve inclusive education at HEIs (Heiman, T., & Precel, K. 2003). The database we searched were; Scopus, Web of Science and Google Scholar. The search was targeted to peer reviewed articles published between 2015 and 2024 related to the inclusive strategies and challenges in HEIs. The study selection was focused on studies with clear goals, sound methods, and credible results (Heiman, T., & Precel, K 2017). Studies relating to either primary or secondary education were excluded along with opinion pieces and non-peer reviewed material. In the study selected 41 studies from 1,500 records screened (which excluded duplicated records) for final qualitative analysis (Hott, B. L., Jones, B. A., Randolph, K. M., Kuntz, E., McKenna, J. W., & Brigham, F. J. 2021). The researcher used the mixed thematic coding and developed coding scheme methodology to analyze instructional strategies, technological interventions, faculty development, and institutional policies (Kidd, M. P., Sloane, P. J., & Ferko, I. 2000). The study used a standardized process and developed an agreement between coders by using two independent coders who systematically selected and categorized the attributes (i.e. study focus, methodology and findings). A summary/comparative table was used to combine all the results to both identify current strategies to educate special needs individuals, identify all of the barriers that exist, determine future research needed to overcome those barriers.

Results

Apart from the teaching framework, IEPs provide an individualized educational plan for the SODs to receive personalized learning support. Individualized Education Programs (IEP) assist SODs to increase their engagement and achievement level, as demonstrated by studies in Malaysia and Saudi Arabia (Kidd, M. P., Sloane, P. J., & Ferko, I. 2000). The effectiveness of these efforts is frequently hindered by the lack of understanding among staff of disability concerns. Many teachers are not trained to prepare and implement IEPs. Other forms of support that are available to teachers are technology-based interventions. There exists many effective types of assistive technologies (AT) that may be used by SODs. There is evidence to support the use of technologies such as screen readers and voice to text, as well as adaptive software, as effective technology-based interventions, to improve the access of individuals with disabilities to educational resources (Lee, L. W., & Low, H. M. 2014). The ability of SODs to access and utilize AT effectively in their education will be based on the availability and effectiveness of the AT available to them (McLaughlin, M. J., & Thurlow, M. 2003). According to Pacheco et al., (2018) an organisation has to be carrying out its daily activities to ensure an effective system of accessing computer technology through the establishment of a complete technical guidance and support infrastructure within the institution, and the training must be accessible to all members of the campus community, as this is essential for making this process efficient. Further, peer mentoring and straightforward guidance systems are useful for learners who want to be included in the process of learning. Peer mentoring creates a sense of belonging (Pacheco, E., Lips, M., & Yoong, P. 2018). As a result, students will be able to tackle both academic and social issues. Even if we try, many institutional, attitudinal, and structural barriers remain. The gap between what is promised and what happens is an important problem that needs to be addressed. Beauchamp-Pryor (2007) shows that although most universities claim to have policies that favor inclusion, these policies are often inconsistent. Some universities are good at including students with disabilities, while others struggle to provide even basic accommodations. Matshedisho (2007) notes that these differences lead to sharp differences in practices. There should be a single national policy

framework that regulates how inclusion is achieved, so that all higher education institutions comply with it (Matshedisho, K. R. 2007). Teaching staff who are less prepared to make lessons inclusive create obstacles. According to Moriña (2017), many teaching staff have not received sufficient training in inclusive teaching strategies, which involuntarily leads to the exclusion of secondary vocational education institutions (Moriña Díez, A., López, R. G., & Molina, V. M. 2014). Sharma et al. (2008) suggest that teaching staff have negative attitudes towards inclusion due to cultural perceptions and lack of disability education. Montgomery and Marks (2006) state that engagement with inclusion can significantly improve faculty attitudes toward the inclusion of students with disabilities. Physical and logistical barriers make access difficult. Inaccessibility of campus infrastructure, inadequate transportation services, and lack of resources limit students' full participation in academic activities (Sharma, U., Forlin, C., & Loreman, T. 2008)

Table 1. Summary of Reviewed Articles

Author(s) and Year	Research Focus	Methodology / Study Type	Relevance to Inclusive Education
Guliyeva (2025)	Historical development and contemporary trends in Azerbaijan's education system	Historical and educational analysis; verification required	Provides national educational context rather than direct evidence of higher education inclusion
Mammadova & Valiyev (2020)	Student participation in Bologna Process reforms in Azerbaijani and European higher education	Surveys and interviews	Examines student participation and institutional reform, rather than IEP implementation
Aliyeva & Çakır (2025)	Digital accessibility in education	Bibliometric analysis	Identifies research trends concerning digital accessibility
Mammadova et al. (2025)	Effects of COVID-19 on children with disabilities and their families in Azerbaijan	Methodology requires verification	Provides disability-related educational context outside the specific higher education population
Mikayilova et al. (2023)	Status of inclusive education in Azerbaijan	Book chapter; research methods require verification	Discusses the national context of inclusive education
Adnan & Hafiz (2001)	Educational experiences of disabled learners in Malaysia	Study design requires verification	Provides historical international context for inclusive education
Almoghyrah (2023)	Challenges in implementing individualized education plans for children with Down syndrome in Saudi Arabia	Teachers' perspectives; data collection method requires verification	Identifies potential implementation barriers in school-level IEP provision
Al-Obaidi & Budosan (2011)	Mainstream educational opportunities for children and adolescents with physical and mental disabilities in Iraq	Study design requires verification	Provides contextual evidence concerning educational access
Buetow & Zawaly (2022)	Researcher bias in health research	Methodological discussion	Supports reflection on researcher bias, rather than providing direct evidence of inclusive education
Denhart (2008)	Perceptions of students with learning disabilities in higher education	Methodology requires verification	Addresses students' experiences of disability and academic inclusion
Dey et al. (2024)	Systematic literature review of Islamic capital markets	Systematic literature review	Not directly relevant to inclusive education; removal should be considered
Getzel (2008)	Persistence and retention of students with disabilities in higher education	Methodology requires verification	Examines strategies and support systems related to student retention
Goodley et al. (2019)	Critical disability studies	Theoretical discussion	Provides a critical conceptual perspective on disability and inclusion
Goodwin et al. (2022)	Quality of IEP goals for children with traumatic brain injury	Evaluation of IEP goals	Provides evidence about IEP quality, but concerns children rather than university students
Gravel & Wilkerson (2017)	Computational representations in physics education	Book chapter	Relevant to educational representations, but not direct evidence of IEP support
Hackman & Rauscher (2004)	Universal instructional design and social justice education	Methodology requires verification	Provides a conceptual foundation for accessible instructional practices
Heiman & Precel (2003)	Academic strategies of university students with learning disabilities	Study of academic strategies	Examines learning-related experiences of students with disabilities

Heiman et al. (2017)	Accessibility and perceived usability of ICT among university students with disabilities	Empirical study; precise methods require verification	Addresses accessibility barriers associated with educational technology
Hott et al. (2021)	Quality and implementation issues in rural individualized education programs	Descriptive review of 133 rural IEP documents	Provides school-level evidence concerning IEP documentation
Kidd et al. (2000)	Disability and labour-market outcomes among British males	Labour-market analysis	Provides socioeconomic background, not evidence of thematic coding or higher education strategies
Lee & Low (2014)	Evolution of special education in Malaysia	Historical or policy-oriented analysis; verification required	Provides background on the development of special education
Matshedisho (2007)	Access to higher education for disabled students in South Africa	Study design requires verification	Addresses disability rights, institutional access, and inclusion
McLaughlin & Thurlow (2003)	Educational accountability for students with disabilities	Policy-oriented discussion; verification required	Provides a framework for understanding accountability and disability-related educational policy
Mendoza & Heymann (2024)	Implementation of inclusive education interventions in low- and lower-middle-income countries	Systematic review	Offers comparative evidence on inclusive education interventions
Milić Babić & Dowling (2015)	Social support, barriers, and future perspectives of students with disabilities in Croatian higher education	Methodology requires verification	Examines barriers and social support in university settings

Table 1 Con…

Ministry of Education (MOE, 2024)	**Inclusion of students with disabilities in the United Arab Emirates education system**	**Government policy and informational webpage**	**Provides national policy context concerning educational inclusion and accessibility in the UAE**
Montgomery & Marks (2006)	Use of technology to develop writing independence among students with disabilities	Educational technology study; specific design requires verification	Highlights the potential contribution of assistive technology to independent writing
Moriña Díez et al. (2015)	Experiences of university students with disabilities and the role of lecturers	Biographical-narrative approach	Examines the role of university lecturers in facilitating or limiting inclusion
Nadeem (2020)	Provision of services to students with disabilities in federal higher education institutions in the UAE	Doctoral dissertation; specific methods require verification	Provides institutional context concerning disability support services in UAE universities
Naeem et al. (2023)	Development of conceptual models through thematic analysis	Qualitative methodological article	Provides methodological guidance for thematic analysis rather than direct evidence on inclusive education
O'Shea et al. (2016)	Social inclusion and deficit discourses in higher education	Study of inclusion and deficit discourses; specific design requires verification	Examines how institutional and social narratives influence the inclusion of students
Pacheco et al. (2018)	Digital technologies, higher education, and vision impairment	Study of digital accessibility; specific design requires verification	Addresses accessibility challenges associated with digital learning technologies
Plotner & Marshall (2015)	Postsecondary education programs for students with intellectual disabilities	Study of implementation facilitators and barriers; methods require verification	Identifies institutional issues affecting inclusive postsecondary programs
Rante et al. (2020)	Inclusive education practices and research in Indonesia	Systematic literature review	Provides comparative evidence on inclusive education in Indonesia; higher education relevance must be checked
Sharma et al. (2008)	Effects of training on pre-service teachers' attitudes, concerns, and sentiments concerning inclusive education	Teacher education study; specific methods require verification	Provides background evidence concerning educator preparation and attitudes
Singal et al. (2015)	Educational experiences and life outcomes of young people with disabilities in Ghana	Study of young people's experiences; specific methods require verification	Provides contextual evidence concerning education and disability in Ghana
Singh et al. (2013)	Mindfulness-based treatment of aggression amo	Waiting-list control study	Concerns behavioral intervention rather than inclusive higher education strategies

	ng individuals with mild intellectua l disabilities

Source: Compiled from the reference entries in the supplied image. Bibliographic corrections to Moriña Díez et a l. (2015) and O'Shea et al. (2016) follow the editorial feedback. The original articles have not been independentl y verified.

According to the results of a systematic review, implementing inclusive education for Identified Students (ISS) in comprehensive education institutions (CEIs) is not easy. While people are beginning to understand the importance of inclusive practices, there are large gaps between policies and their implementation. This section focuses on studies that analyze the findings. One of the main themes found in the literature is the gap between inclusive education policies and practices (Mendoza, M., & Heymann, J. 2022). Higher education institutions (DavamYTM) demonstrate their alignment with international systems such as the UN Development Goals (SDGs), and actual developments and changes are observed in the implementation of inclusive education policies. In Azerbaijan, comprehensive educational institutions are notable for implementing inclusive education policies for METs. Research shows how many academics fail to support METs, which limits their school achievement and educational participation (Milic Babic, M., & Dowling, M. 2015). This gap is further exacerbated by the fact that there are not many widely used training programs available for teachers. Very few institutions offer opportunities and development opportunities for inclusive practices among teachers. But the nature of these programs is somewhat of a landscape among YTMs. Various studies show that teachers' perspectives, and therefore their academic experiences, influence how resources are received, thus leading to unequal training programs across institutions with varying levels of inclusion (Ministry of Education (MOE). 2024). Monitoring the implementation of education policies highlights the importance of developing a standard framework for better adoption and effective implementation of inclusive education policies in classrooms. Teacher development demonstrates the effectiveness of inclusive teaching. Albert Band's cognitive theory establishes the relationship between behavioral, cognitive, and personal social characteristics that influence an individual's behavior and the environment (Montgomery, D. J., & Marks, L. J. 2006). Teachers' beliefs and practices influence their ability to implement inclusive practices. Educational reformers should have structured training programs for teachers, which should be based on adult learning principles and provide for continuous improvement. Continuous and appropriate development increases teachers' skills, knowledge and confidence, improving accessibility and inclusion in higher education. A study was conducted on the existence of public higher education institutions in Baku and Ganja, as well as good and bad practices (Nadeem, F. 2020). In addition to teaching assistive technology to the accessibility sections of this facility, he has been active in administering exams to them and formally creating Student Support Plans. On the other hand, it indicated that some teachers were aware of what the METs required, that the physical resources of the building were capable of meeting these needs, and that the required Support Units provided a high level of support (Naeem, M., Ozuem, W., Howell, K., & Ranfagni, S. 2023). In some situations, there were uneven approaches to identifying and recording METs, indicating an urgent need for better data collection and input, including system reforms.

Conclusion

This systematic literature review examined inclusive education strategies, institutional challenges, accessibility measures, and support mechanisms in higher education institutions, with particular emphasis on their implications for Azerbaijan. The review synthesized findings from 41 studies to identify effective approaches to inclusive higher education and highlight the institutional, pedagogical, and policy-related factors influencing their implementation. The findings indicate that successful inclusive higher education requires a comprehensive and coordinated approach involving Universal Design for Learning (UDL), accessible educational infrastructure, individualized student support services, faculty professional development, and inclusive institutional policies (O'Shea, S., Lysaght, P., Roberts, J., & Harwood, V. 2015). These strategies contribute to improving educational accessibility, strengthening student participation, and creating more equitable learning environments for students with disabilities and diverse educational needs. Nevertheless, the reviewed literature identifies persistent barriers, including inadequate institutional resources, insufficient faculty preparation, limited accessibility infrastructure, inconsistent policy implementation, and negative attitudes toward disability and inclusion. An important finding of the review concerns the geographical imbalance in existing research. Much of the available literature focuses on higher education institutions in Western countries, whereas empirical investigations addressing inclusive education in developing countries and post-Soviet contexts, particularly Azerbaijan, remain comparatively limited (Plotner, A. J., & Marshall, K. J. 2015). This research gap highlights the importance of developing context-sensitive inclusive education strategies that reflect Azerbaijan's institutional structures, educational policies, socioeconomic conditions, and cultural characteristics. From a methodological perspective, the review followed a structured identification, screening, eligibility assessment, and inclusion process informed by PRISMA 2020 reporting principles (Rante, S. V. N., Helaluddin, Wijaya, H., Tulak, H., & Umrati. 2020). A total of 1,500 records were

reported as screened, and 41 studies were retained for the final thematic synthesis. However, the initial identification count, duplicate removals, title-and-abstract exclusions, full-text assessments, and specific reasons for full-text exclusion require verification against the original search and screening records before the PRISMA flow can be considered complete. The primary publication window of 2015–2024 should also be applied consistently to the included studies (Singal, N., Mahama Salifu, E., Iddrisu, K., Casely-Hayford, L., & Lundebye, H. 2015). Earlier foundational publications and research published in 2025 may be cited as supplementary contextual evidence, but they should be distinguished from the studies included in the systematic synthesis unless explicitly justified by the eligibility protocol. The findings have several implications for educational policy and institutional management in Azerbaijan. Higher education institutions should prioritize the development of comprehensive accessibility frameworks, strengthen disability support services, provide continuous professional training for academic staff, and establish systematic mechanisms for evaluating inclusive educational practices (Singh, N. N., Lancioni, G. E., Karazsia, B. T., Winton, A. S. W., Myers, R. E., Singh, A. N. A., Singh, A. D. A., & Singh, J. 2013). Furthermore, cooperation among government authorities, university administrators, educators, students, and disability advocacy organizations is essential for translating inclusive education policies into sustainable institutional practices.

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Exploring the Deployment of AI/Ml Architecture for Granular Computation of Learning Outcomes in a Foundational Online MBA Course

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Abstract

Higher education institutions worldwide face increasing pressure from societal stakeholders to demonstrate meaningful and measurable graduate outcomes. Outcome-Based Education (OBE) is a pedagogical framework promoted to address these expectations. However, computing course outcome (CO) attainment, with granularity for large cohorts, is manual and taxing.

This paper explores the measurement of outcomes with Bloom's taxonomy levels for 927 questions used in formative and summative evaluation of seventy students in a foundational online MBA course. The evaluation used multiple question types: case based MCQs, concept based MCQs, case based short descriptive questions, case based long descriptive questions and a project. The faculty spelt out course outcomes.

A tiered AI/ML architecture was deployed — from GPT-5.0/5.4 for multiple-choice questions to a course-configured Custom GPT for long-form descriptive questions to a 22-call agentic pipeline for the project. The automation outputs were iterated with the faculty.

The six Bloom's taxonomy levels and COs were mapped for each question into a matrix. The Faculty validated the CO × Bloom matrix. Each rubric element, for each question, was evaluated for the matrix using the architecture. Outcomes were computed for every student, question, question type, evaluation type and for the overall course.

Attainment of the five course outcomes for overall performance, ranged between 56% and 63% for the batch; and between 43% and 62% for the six Bloom's taxonomy verb levels. AI based outcome computation for the project was 32% lower than faculty based scores, reflecting greater realism exhibited by AI evaluation in open-ended project-based learning. Bloom's taxonomy analysis indicated lower attainment for 'evaluating' and 'creating' levels.

This architecture enables visibility into individual student and question performance, feedback on pedagogy and evaluation effectiveness for students and faculty. It can inform personalized learning and enables automation for all courses. It has potential to save significant faculty and support services staff time. It can serve OBE reporting for accreditation with granular transparency and process authenticity. It provides feedback to the institution on the redesign of curricular aspects by surfacing gaps between intended and achieved outcomes.

The authors recommend the adoption of this architecture as a replicable institutional standard for AI-assisted OBE reporting across courses and programmes.

Keywords: Outcome-Based Education; Course Outcome Attainment; Bloom's Taxonomy; Large Language Models; Agentic AI; Multi-Agent Systems; Automated Assessment; Assurance of Learning; Higher Education; NBA/NAAC Accreditation

Introduction

Many countries have raised questions on how relevant their higher education (HE) system is for their economy and society. The trust of Americans in the US higher education has eroded (Clark et al., 2026). Those who see HE as very important has fallen by more than half in the period 2010-25. Those who see education as not so important in the same period has moved up from near zero to above 20% (Saad, 2025, as cited in Clark et al., 2026). Financial pressures on HE institutions has increased. Students increasingly look for meaningful employment. Companies are hiring employees with skills and ability to adapt.

Europe seeks to increase its competitiveness through its Union of Skills strategy. The issues it seeks to tackle include scarcity of skilled graduates, slow adaptation of education and training systems to technology and green transition, declining basic and digital skills amongst youth and an unprepared workforce for decarbonisation. The Union of Skills advocates for a comprehensive strategy that integrates education, training, and employment policies to drive innovation, decarbonisation, resilience, democracy, and social equity. The European Union

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encourages network alliances of universities for cross-border mobility and scale as well as micro-credentials which are skill focussed (European Commission, 2026).

Institutions are eliminating programs, cutting majors and working on better efficiency without impacting students and programs. The focus is on return in return on investment on a program. Degrees of value have become important. Students cite job and career outcomes as the number 1 reason for postsecondary study. Employers in the US have started hiring based on non-degree credentials focussed on skills (Clark et al., 2026). The UK has created a market driven regulator, "Office for Students" to focus on degree quality, outcome transparency and value for money. It is emphasizing on degree apprenticeships and vocational programs to tackle the skills gap. HEIs which consistently yield lower than required outcomes are penalized through financial means, reduced admission intakes and loss of accreditation. In 2024, Texas focused its state funding for community colleges on student outcomes and not student time spent in the class (Office for Students, 2019).

India which has huge demographic dividend aims to deploy this dividend for economic productivity. This needs to largely be contributed by its higher education system which graduates close to 10 million graduates every year. Outcome orientation is now a part of accreditation of its technical programs by the National Board of Accreditation (National Board of Accreditation, n.d.). It is also part of the standards specified by the University Grants Commission (University Grants Commission, n.d.). In similar ways, the HEIs of other countries face the pressure of outcomes and returns from higher education.

Meanwhile, Artificial Intelligence is impacting all stakeholders and their needs in ways which are unfolding based on the development of the AI landscape. Across countries, the state and the education system like their economic organization counterparts trying to appreciate, utilize and govern the utilization of AI.

All of this has placed a lot of expectation on HEIs to demonstrate meaningful and measurable graduate outcomes. The expectations of various stakeholders and returns on education from their HEIs is translated to outcomes from education in any form, whether university based, distance, online, micro credentials, continuing education.

The key challenge and gap currently in this is accurately measuring economic returns on degrees and credentials (Clark et al., 2026). "The challenges of measuring it [ROI] well are immense because the data systems literally are not there." –A participant at the 2025 Forum on the New Era of Higher Education, Deloitte University (Clark et al., 2026).

Existing automation for course outcome computation has largely relied on rule-based frameworks that pre-link each question to a course outcome and compute attainment as an aggregate percentage against a fixed threshold (Bhuvaneshwari et al., 2025), with no granularity below the aggregate mark.

The first question in this is - what is to be measured. This paper presents a model which measures course outcomes with explainability and transparency, starting at the most granular level and ground up. It uses AI/ML architecture to automate the process near the learning space and stakeholders involved, thereby providing feedback and explainability to stakeholders to re-design the curriculum, pedagogy and assessment and its execution towards the outcomes needed. In the bargain it frees up faculty and institutional time to focus on outcomes with micro and macro levels together.

Methodology

End-to-end integration model

This paper adopts an end-to-end integration model that covers both Formative Evaluation (FE) and Summative Evaluation (SE), comprising a five-step pipeline architecture (Figure 1), with each step implemented through its own AI-agentic pipeline or Python subfunctions. The five steps work together to process evaluation data; from question classification and answer-script extraction through AI-based grading and CO × Bloom attainment computation, producing the final course-level attainment matrix. Faculty were part of the process from the outset: they defined the course outcomes initially, and validated the architecture's output at the required steps.

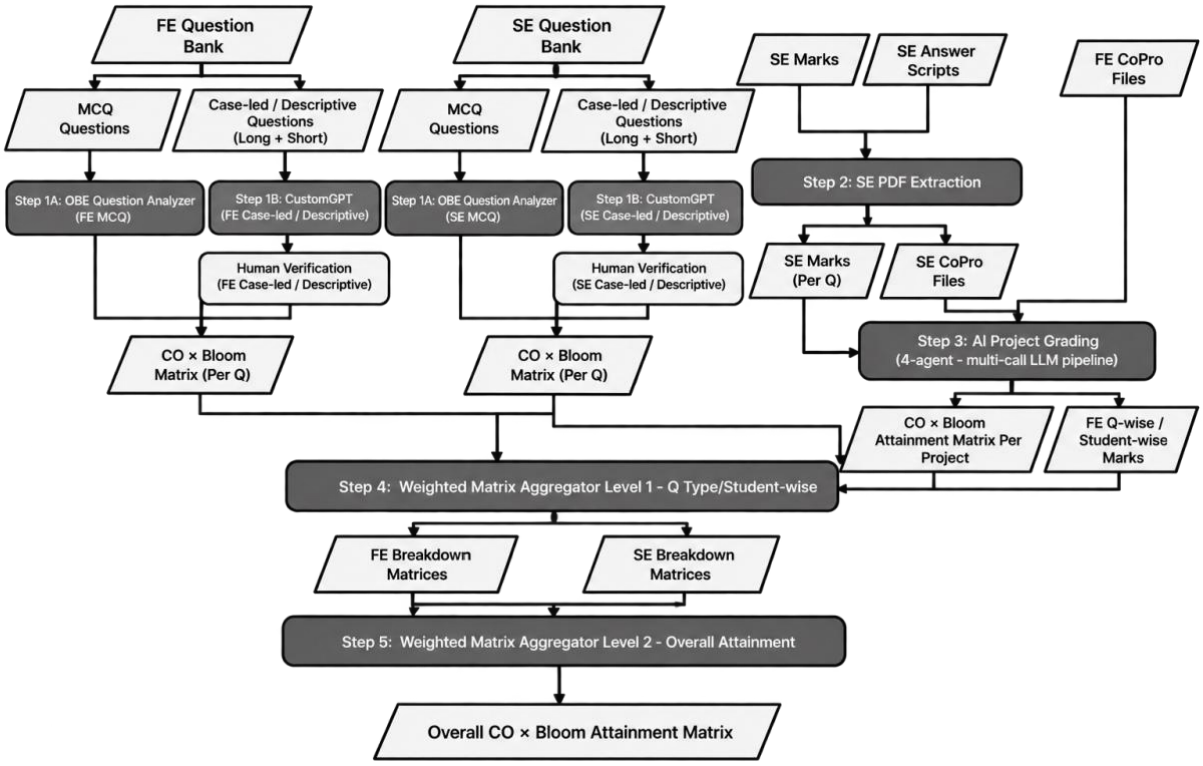


Figure 1: Five step AI Architecture Design for Computation of Course Attainment

Evaluation structure

The formative and summative evaluation together contained 927 questions spread over four question types that include case based Multiple Choice Questions (MCQs), concept based Multiple Choice Questions (MCQs), case based short/long descriptive questions and course project (CoPro) questions , administered in both formative and summative evaluation. Formative and summative evaluation are weighted 30% and 70% respectively in the final attainment.

Tiered model architecture

The model architecture (Figure 1) uses a tiered approach, with AI/ML applied where interpretation or grading is required and Python subfunctions used for extraction, rule-checking, aggregation, and other deterministic operations. Step 1 realizes this tiering for question classification: Multiple Choice Question (MCQ) classification (Step 1A) uses a two-agent GPT-5.4-mini/GPT-5.4 pipeline, with the primary model classifying each question against the CO × Bloom matrix and the adjudicator handling flagged cases. Case based descriptive questions (Step 1B) are processed through a course-configured Custom GPT for similarly styled classification. Faculty validate each descriptive question's CO × Bloom matrix arrived at by the Custom GPT, as well as the aggregate CO × Bloom matrix produced from the MCQ pipeline. The course project (Step 3) uses a four-agent pipeline, making 22 AI calls per project across its four agents, that extracts the problem addressed, generates a benchmark, derives the CO × Bloom scoring target, and grades the submission using evidence from the student's response. Python subfunctions (Steps 2, 4, and 5) support the summative answer-script extraction, validation rules, marks processing, and the aggregation of individual student results into the final CO × Bloom attainment matrix.

CO × Bloom's Attainment Computation

The course project allows students to identify a work place problem and develop their own solution or response to the articulated project problem. Consequently, the evidence demonstrating particular COs and Bloom's levels is unique for each student for course projects, in contrast to the other assessment types where there is an expected solution or response desired. Therefore, the CO × Bloom attainment for the course project is derived from the evidence demonstrated in each student's submission**,** rather than by simply applying the student's obtained marks to a pre-defined CO × Bloom mapping. Accordingly, for course projects, the CO × Bloom attainment is computed in this architecture based on the student's actual submission at Step 3 of the architecture (Figure 1). Wilcoxon test is used for explaining the direction and significance of difference in attainment by AI vs faculty in Course Projects.

For other question types, the CO × Bloom attainment is computed using the pre-defined CO × Bloom mapping from Step 1 of the architecture (Figure 1) of each question and the marks obtained by the student for specific question attempted form the question bank.

Results

Adopting this tiered end-to-end integrated architecture, overall attainment of the five course outcomes for a foundation online MBA course, ranged between 56% and 63% for the batch. Attainment by Bloom's taxonomy level ranged more widely, between 43% and 62%, and was lowest at the two highest-order levels, Evaluate and Create. For certain course outcomes, higher-order Bloom's levels may not be applicable (indicated by -NA- in Table 1). This reflects the nature of the respective course outcomes and their associated question classification.

It is observed in applicable higher order levels students didn't score as well as in lower order Bloom's indicating gap in teaching-learning support that would have provided students with higher order thinking in that respective course.

Table 1. Overall Course Attainment of CO x Bloom Distribution

Bloom Level / CO#	L1	L2	L3	L4	L5	L6	Total CO Attainment
CO1	65%	56%	56%	50%	-NA-	-NA-	56%
CO2	100%	50%	57%	50%	-NA-	-NA-	58%
CO3	0%	67%	57%	67%	50%	-NA-	61%
CO4	-NA-	100%	67%	33%	-NA-	-NA-	63%
CO5	50%	57%	60%	50%	50%	43%	56%
Total Bloom Attainment	62%	60%	59%	56%	50%	43%	58%

Table 2 presents the CO × Bloom's attainment obtained using the proposed architecture in comparison with the attainment based on actual scores. For the course project, the attainment was 32% lower than the corresponding faculty score for the Formative component and 29% lower for the Summative component. This variation is attributed to the fact that Course Project attainment is computed from the evidence demonstrated in each student's actual submission, based on a project situated in a workplace context. For other question types, attainment is computed directly from the student marks using the predefined CO × Bloom mapping of each question. Consequently, the resulting attainment remains identical to the score-wise attainment.

Table 2. Course Actual Attainment Vs Model Attainment

Evaluation	Q - Type	Actual Attainment %	Model Attainment %
Formative	Case based MCQ	70%	70%
Formative	Case based Long Descriptive	47%	47%
Formative	Concept based MCQ	70%	70%
Formative	Course Project	77%	45%
Summative	Case based MCQ	60%	60%
Summative	Case based Short Descriptive	68%	68%
Summative	Case based Long Descriptive	51%	51%
Summative	Course Project	70%	41%
Summative	Concept based MCQ	62%	62%
	Total	65%	58%

The Wilcoxon signed-rank test (Table 3) identified Faculty–AI grading differences of significance in six of nine assessment dimensions. Faculty assigned significantly higher grades for Stage 1–Title ($p < .001$), Stage 1–Problem Statement ($p = .025$), Stage 2–Concept ($p < .001$), Stage 3–Concept ($p = .009$), and Stage 3–Context ($p < .001$), whereas AI assigned significantly higher grades for Stage 2–Analysis ($p < .001$). No significant differences were found for Stage 1–Objectives ($p = .306$), Stage 2–Context ($p = .294$), or Stage 3–Analysis ($p = .346$).

This finding provides a contrasting perspective to previous studies on AI-based grading of open-ended responses, where large language models have generally been reported to assign more lenient scores than human raters (Yavuz et al., 2025; Gaggioli et al., 2025). AI grading that uses large language models (LLM) for evaluation, can draw upon a broader body of knowledge and publicly available information related to industry practices, problem contexts, and possible solution approaches. This provides a broader contextual basis for interpreting the evidence demonstrated in the student's submission than that of an individual faculty's experience and domain exposure. This could have led to the AI-based evaluation resulting in lesser attainment than the corresponding faculty scores

Table 3. Wilcoxon Signed-Rank Test on Course Project Elements

Course Project Elements	W	W+	W-	p
Stage 1 - Title	0	190	0	0
Stage 1 - Problem Statement	64.5	211.5	64.5	0.02538
Stage 1 - Objectives	95	95	158	0.30646
Stage 2 - Concept	0	276	0	0.00003
Stage 2 - Context	67.5	122.5	67.5	0.2935
Stage 2 - Analysis	8	8	202	0.00029
Stage 3 - Concept	35.5	174.5	35.5	0.00947
Stage 3 - Context	19.5	256.5	19.5	0.00031
Stage 3 - Analysis	107	107	169	0.34575

This architecture reduced the total effort required to compute the CO × Bloom's Taxonomy attainment matrix, for a single course offering from a conservative estimate of 152 person-hours to approximately 4 hours 10 minutes, a reduction of 147.8 hours (97.3%) as shown in Table 4. The gains were not distributed evenly across the underlying workflow with the largest reductions occurring in the most labour-intensive stages. This indicates that the architecture delivers its greatest efficiency where manual effort was previously most concentrated, with direct implications for the scalability of AI-assisted OBE reporting across courses and programmes.

Table 4. Comparison of Manual and AI-Assisted Effort for CO × Bloom's Taxonomy Attainment Computation

Task Category	Manual (Hrs)	AI Assisted (Hrs)	Hours saved	% Reduction
Question classification (927 Qs → CO × Bloom)	47	2	45	95.7%
Dataset preparation / cleaning	6	0.58	5.42	90.3%
Student-wise mapping & individual computation	87	1.33	85.67	98.5%
Consolidation / validation / overall attainment	12	0.24	11.75	97.9%
TOTAL	152	4.17	147.83	97.3%

Conclusions

The research on computation of attainment of learning outcomes has largely studied the problem in parts. It either presented new methods and tools for computation, explored models for computing parts of this problem, application of Bloom's taxonomy at different levels of the course/ program or from the usage of various types of technology or empirical studies using software packages available in the market.

Software solutions for learning outcome computation are generic. Vendors claim some customization at additional cost. The objective is to ensure the institution meets the needs on outcome measurement to the satisfaction of the accrediting agency concerned. Do these solutions help design new quality improvement initiatives and monitor their efficacy for individual stakeholders- student progression, faculty reflection and design of curriculum, pedagogy and assessment in a dynamic fashion?

Software solutions in the market are not designed based on student/ faculty/institution profile where teaching and learning practices and needs are highly contextualized and dynamic. This computation architecture demonstrated granularity to individual, student, faculty and question level. It therefore promises a different level of explainability, contextualization in design and accuracy of measurement for dynamic control and agility in real time academics. This goes much beyond computations meant for accreditation agencies- a pathway to much higher levels of quality assurance. The AI/ML architecture saves precious faculty time and conserves it for human control

and redesign for better learning. This empowerment of faculty enables them to be much more productive for themselves and the institution. Faculty are able to identify gaps in course outcome articulation w.r.t. to the reality of the course delivery- pedagogy, assessment methods, results and student personas. They can plan better for the next batch. The student is able to see their learning outcomes at micro levels and not just meso (course) or macro (program) level. There is potential to include co and extracurricular activities as well in such computations to design and paint an institutional landscape of outcome contributions. This empowers students better for self-directed learning much beyond the pedagogical contours followed by institutions. Data of students, their performances, question banks are scaffolded from vendor codes and environments. This is a big plus for privacy and governance. The institution saves recurring software costs. It also saves staff time involved in data migration and alignment of vendor solution with institutional needs amongst others. Most importantly the institutional quality assurance cell has reason to feel far more empowered much beyond the contributions they make today.

Back of the envelope calculations in this case showed a 147.8 hours saving for one course with 90% faculty time and 10% staff time. The present study also examined whether Faculty- and AI-generated grade points differed significantly across assessment dimensions using the Wilcoxon signed-rank test. The analysis was limited to identifying statistically significant paired differences and their direction rather than establishing interchangeability or comprehensive agreement between Faculty and AI assessment. Future research could extend this validation using Cohen's Kappa, ICC, correlation, Bland–Altman analysis, and effect-size measures to examine inter-rater agreement, consistency, association, systematic bias, and the practical magnitude of observed differences.

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An Intent-Aware Hybrid RAG Architecture for Academic Advising Systems

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Abstract

A combination of institution policies and structured student data is required to develop academic advising systems. Conventional document-based RAG systems can retrieve academic policies but cannot directly access structured student records without additional tools. In this paper, we describe an intent-aware hybrid architecture that incorporates policy and student data access routes requests using an LLM and performs model-based reasoning. We evaluate the proposed architecture using synthetic student records and a knowledge base built from publicly available university policies. Classifying intent in 100 examples from 4 classes resulted in a routing accuracy of 94%. A qualitative analysis demonstrated that the proposed hybrid architecture provided data and evidence at the record level, and was therefore able to address student record-level and multi-system advising questions. In contrast, the RAG-only baseline was generally policy-level and/or vague. Qualitative observations suggest potential benefits for factual grounding and personalization, although these improvements require further quantitative evaluation. Due to the synthetic nature of the data and the qualitative comparison, broader experimentation is required to substantiate these findings.

Keywords: retrieval-augmented generation; academic advising; intent classification; structured student data; hybrid reasoning.

1. Introduction

Academic advising depends on an understanding of both institutional and individual academic factors. A student wanting to know if they can graduate next semester requires information on program requirements and on the student's earned credits, completed courses, and GPA. Many university policies are contained in documents, but information on students' academic progress is typically contained in information systems. A document assistant is not sufficiently equipped to respond to many personalized questions.

Answering systems use retrieval-augmented generation (RAG) to base answers on texts (Lewis et al., 2020). It is possible to improve the system's usefulness in academic advising by incorporating an intent-aware orchestration layer that selects between policy retrieval, SQL data access, and advisory reasoning. To discourage authoritative (i.e. unsupported) answers, we perform a retrieval sufficiency check (Asai et al., 2024).

The study aims to address three research questions: (RQ1) how does intent-aware routing modify the outputs of RAG-only advising? (RQ2) What role does a retrieval sufficiency check play in avoiding unsupported policy answers? (RQ3) What influence does access to structured student information have on the types of suggestions given by the system? The study offers an integrated system, a privacy-preserving synthetic academic test environment, and quantitative and qualitative results. The study also offers an augmented language model that leverages tools to reason about student academic information. These ideas motivate selecting SQL access when the answer depends on a database. In this paper, tool selection is made through semantic intent classification rather than a fixed list of keywords. The design remains deliberately narrower than a general autonomous agent: its tools and data sources are constrained to the advising scenario.

2. Related Work

RAG integrates retrieval and conditional generation in a single framework. This helps to reduce reliance on model parameters (Lewis et al., 2020). Other dense semantic representations like Sentence-BERT and dense passage retrieval improve passage matching (Reimers & Gurevych, 2019; Karpukhin et al., 2020). RAG focuses on retrieval and generation in modular fashion (Gao et al., 2024). Hallucination occurs when the evidence is unavailable or used incorrectly (Ji et al., 2023).

Toolformer and ReAct enabled language models to interact with tools or alternate between reasoning and physical actions (Schick et al., 2023; Yao et al., 2023). Self-RAG and Adaptive-RAG promoted reflective and conditional retrieval (Asai et al., 2024; Jeong et al., 2024). For academic advising, these innovations allow us to make an important distinction. Document grounding is required for policy questions, while authorized access to structured

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records is required for student-specific questions. Unlike most existing proposals, the present architecture integrates these sources in advising requests, and does not rely on document retrieval for all cases.

Other papers also support the notion that selecting a tool and evaluating the support provided by the tool's output for the final answer are two distinct tasks. Adaptive-RAG adjusts the retrieval complexity to the question, and Self-RAG reviews evidence during retrieval and generation (Jeong et al., 2024; Asai et al., 2024). The focus of this work is to develop a similar integrative system for academic advising, using a combination of document retrieval, structured queries and incorporating advisory reasoning. This work is not the first to develop an embedding model and SQL engine. It aims to integrate various sources in a novel way for a specific domain.

Gevher et al. (2025) investigated the use of generative AI chatbots for administrative learner support in higher education, comparing their responses with those of a rule-based chatbot. This study demonstrates the relevance of generative AI to student support services. However, our work extends this direction by integrating policy retrieval, structured student data access, and intent-aware routing for personalized academic advising.

3. System Architecture

3.1 Intent routing and knowledge sources

An LLM-based classifier routes questions to four intents: student_data (student records), policy_lookup (institutional rules), advice (suggestions), and general (other conversation). The orchestration layer selects the pathway based on the intent. Possible pathways are the policy RAG, SQL-based record lookup, and model reasoning. Questions requiring both student records and a policy are addressed through the integration and coordination of the sources after routing. Unlike a fixed keyword dispatcher, the classifier interpret the meaning of the question.

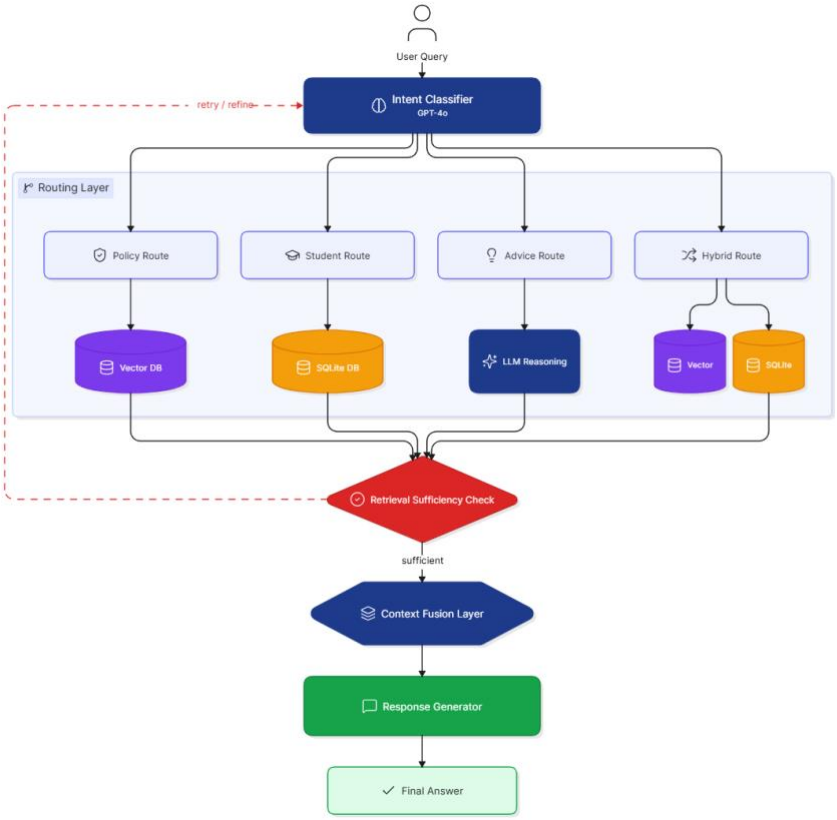


Figure 1. Intent-aware routing, evidence sufficiency, and multi-source response generation.

Intent labels describe the main purpose of a question. Example: Asking for current GPA is record-dependent, while asking for academic probation rule is policy-dependent. A question like, “Can I graduate next semester if I pass CSE420 and maintain my GPA?”, may require both record- and policy- dependent evidence. Multi-source paths can be initiated from the routing layer after question classification. The response generator is expected to differentiate the two types of evidence and not treat them equally.

The structured branch uses a relational SQLite database to model student records, courses, enrollments, degrees, grade-point equivalences, and semester GPAs. Database calls are constrained to SELECT statements and scoped to the student context. This design prevents language model from modifying student records. This is a simple protection mechanism; it does not by itself implement production-level access control and management.

3.2 Retrieval sufficiency and response generation

The policy subsystem retrieves passages using dense embeddings and cosine similarity, and returns the most relevant top-k. Prior to policy-based response generation, an LLM determines if the retrieved information is sufficient to answer the user's question. Not sufficient evidence prompts the LLM to produce a qualified response instead of making a policy assertion. The SQL subsystem employs a relational SQLite database and permits only SELECT queries. The results of these queries are fused with policy passages and provided as context for the hybrid questions. This is considered a prototype-level control, and does not constitute a complete production authorization or other comparable control for privacy.

The retrieved evidence is passed to a shared response generator. If document evidence is used, sufficiency is checked to determine if the retrieved policy passages answer the user's question. A policy answer is given for a sufficiency result; otherwise, a qualified response or non-authoritative general advice is provided. For a combined policy and record question, the results from the database and policy passages are fused prior to response generation. A highly similar policy passage may still omit critical personal details to make a case decision.

4. Dataset and Implementation

To process samples of student records, the authors created a synthetic university dataset comprised of 6 academic programs at the undergraduate, graduate, and doctoral levels. The dataset contains information related to students, enrollment, courses, credits, grades, and GPA and degree requirements for each semester. With this information, students can answer questions related to their GPA and academic standing, including which courses they still need to take in order to graduate and their progress toward graduation. Information about academic policies was created from publicly available academic and policy web pages at Arizona State University. The information was organized according to its content, and possible redundant information was removed.

The implementation uses GPT-4o for intent classification and response generation, with SQL-based access to structured student records. A passage of policy is embedded using a sentence transformation method. The policy passages are ranked using cosine similarity and the evidence is integrated into the response or policy information is integrated where necessary. In the experiments, consistent retrieval and prompting configurations were used across compared query types.

5. Evaluation Methodology

Policy documents and student records provide complementary evidence. Policies describe institutional conditions such as probation, academic standing, and graduation requirements; the relational tables contain facts that vary by student and semester. For example, identifying the number of credits required by a program is a document or degree-rule task, whereas calculating how many credits a particular student has completed requires enrollment data. A defensible graduation assessment needs both the governing requirement and the individual's progress toward it.

In the structured path, tool invocation translates a natural-language information need into a read-only query over the synthetic records. The resulting rows are treated as evidence for answer generation. This is related to text-to-SQL research (Yu et al., 2018), but the submitted study does not provide a separate benchmark of SQL execution accuracy. The implementation description therefore establishes the access mechanism and its constraint, while the reported numerical evaluation remains focused on intent routing.

5.1 Intent routing evaluation

A benchmark of 100 manually labeled advising questions was balanced across student_data, policy_lookup, advice, and general intents (25 questions per category). The predicted class for each question was compared with its manual label, and accuracy was calculated as the fraction routed correctly. This study reports aggregate accuracy but does not provide per-class precision, recall, or a confusion matrix; these are therefore not inferred here.

The qualitative comparison included policy definitions, requests for individual GPA and remaining courses, graduation-readiness questions, and requests for advice on improving academic standing. These examples probe distinct information needs: some require a policy passage, others require a student-record lookup, and still others

require both. The two configurations were compared on the information available to their answer-generation process, not on a new numerical scoring instrument.

Qualitative criteria were interpreted for each question. Accuracy concerns whether a response is consistent with the available institutional rule or student record. Personalization concerns whether it addresses the particular student rather than offering only generic information. Hallucination resistance concerns unsupported claims, especially invented GPA or progress details. Completeness concerns whether the response covers the necessary parts of the request. Tool selection appropriateness concerns whether the system used the information source needed for the question. These criteria describe the review framework; the submitted study does not report independent numerical ratings for them.

5.2 End-to-end comparison and ablations

Two configurations received representative advising questions: (i) a RAG-only baseline that retrieves policy passages but cannot query student records and (ii) the proposed intent-aware hybrid with policy retrieval, SQL lookup, and model reasoning. The authors examined outputs for accuracy, personalization, hallucination resistance, completeness, and appropriate tool selection. The comparison is observational and qualitative, without independent raters, inter-rater agreement, or numerical scores for these dimensions. Hybrid questions that combine policies and records were considered in this qualitative analysis; they were not presented as a fifth class in the 100-query routing benchmark.

The study also considered removing SQL access, intent classification, or the sufficiency check. These ablations describe directional behavior rather than controlled estimates of effect size. Consequently, only routing accuracy is reported as a quantitative outcome.

The sufficiency component was examined through observed answer behavior rather than a separate quantified accuracy or hallucination-reduction score. Its purpose is to prevent the system from treating superficially relevant text as complete evidence. Similarly, the ablations reported in the submitted study are directional observations about removing components, not controlled numerical estimates of each component's causal contribution. These boundaries are important when interpreting the findings.

6. Results and Discussion

6.1 Intent routing performance

The classifier correctly assigned 94 of 100 questions, yielding 94% routing accuracy. Six misclassifications were reported, primarily in questions where student-specific data and policy requirements overlapped, including graduation and academic probation scenarios. The aggregate result indicates promising intent recognition on this constructed test set but does not establish performance across institutions or unseen real-world student requests.

Table 1. Intent routing benchmark and aggregate result.

Intent / metric	Reported value
student_data	25 queries
policy_lookup	25 queries
advice	25 queries
general	25 queries
Total / correctly classified	100 / 94
Misclassified / accuracy	6 / 94%

6.2 RAG-only versus hybrid responses

For policy-only questions, the RAG-only system could retrieve relevant institutional regulations. The hybrid initially produced an insufficiently grounded policy answer when routing bypassed retrieval; after routing adjustments and sufficiency verification, its policy answers were reported to align with the baseline. This observation demonstrates that intent routing alone does not guarantee grounding. For record-dependent questions, the baseline lacked access to individual GPA and enrollment data, whereas the hybrid could retrieve the necessary structured evidence. The improvement in personalized responses is partly expected from the difference in available information sources, not solely from the routing algorithm.

Table 2. Representative qualitative differences between baseline and hybrid responses.

Advising question	RAG-only baseline	Intent-aware hybrid

What is my GPA?	Cannot access student record	Retrieves GPA from record
Which courses remain?	States general requirements	Identifies outstanding courses
Can I graduate next term?	Summarizes policy	Combines policy, credits, GPA
How can I improve standing?	Provides generic guidance	Uses academic history for advice

The hybrid also appeared less likely to invent student-specific facts when a valid SQL result was available. However, the study did not measure hallucination rates numerically; statements about lower risk are qualitative observations. For open-ended advice, both configurations produced coherent recommendations, and differences were more subjective.

6.3 Ablation observations

Removing SQL access eliminated the record-level basis for GPA, remaining-credit, and eligibility answers. Without intent classification, inappropriate pathway selection was observed more frequently in questions combining policy and personal data. Without the sufficiency check, policy answers could be generated from retrieved context that did not adequately support the claim. The complete architecture appeared more stable across the illustrated categories, but the ablation observations are not quantified and should not be interpreted as causal effect-size estimates.

A graduation question illustrates the distinction: Can I graduate next semester if I pass CSE420 and keep my current GPA? Answering requires the applicable degree requirements and the student's own credits, completed courses, and GPA. A policy-only response can describe graduation rules but cannot establish whether the student meets them. A record-only response may calculate progress but omit institutional conditions. The hybrid route is intended to retrieve both forms of evidence, assess their sufficiency, and present the conclusion with appropriate qualifications. This example describes the proposed behavior rather than a separately scored test case.

The same principle applies to academic probation and improvement advice. A question asking for the definition of probation primarily calls for a policy source; a question asking whether the student is currently at risk may require both an official threshold and a verified GPA. A general request for study strategies can be answered without private records, while a personalized improvement plan can use academic history when authorized. These distinctions explain why one retrieval path is not equally suitable for every advising query and why overlapping intents remain challenging.

The study does not establish that routing resolves every ambiguity. When a question is underspecified, the appropriate outcome may be to request clarification or state that a definitive eligibility decision cannot be made from the available evidence. This is particularly important for graduation and probation, where an unsupported answer could be consequential. The sufficiency check is an architectural attempt to distinguish relevant-looking text from adequate evidence; future experiments must measure whether it consistently makes that distinction.

A stronger follow-up experiment would create held-out advising questions with verified reference answers from the same student records and institutional rules. End-to-end answer accuracy could then be reported separately for policy-only, student-only, advice, and multi-source questions. A controlled comparison with and without sufficiency verification could record unsupported claims and abstentions. Such tests would help separate the value of structured-data access from that of routing and evidence checking.

7. Limitations and Future Work

The student database is synthetic and cannot establish reliability on real institutional records. End-to-end quality comparisons were qualitative and author-assessed, without blinded evaluation, independent raters, or inter-rater reliability. The RAG-only baseline did not have the same structured-data access as the hybrid, limiting causal attribution of performance differences. The sufficiency check was not evaluated through a separately quantified unsupported-answer rate. Future work should use a held-out set with ground-truth answers, explicit grounding and personalization metrics, robust error analysis, controlled ablations, and privacy-preserving real-world integration.

8. Conclusion

This paper presented an intent-aware academic advising architecture integrating RAG, SQL-based student records, direct model reasoning, and retrieval sufficiency verification. The routing component achieved 94% accuracy on 100 manually labeled questions. Qualitative comparisons showed that structured record access enabled more specific answers to personalized and multi-source advising requests than a document-only baseline, while policy answering still depended on appropriate retrieval and evidence checks. The results support hybrid knowledge access as a promising design direction, but controlled end-to-end evaluation is needed to verify the magnitude and generalizability of these benefits.

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Career Perceptions and Occupational Concerns of Information Technology Students in the Context of Developments in AI Technologies: A Qualitative Case Study

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Abstract

Rapid developments in artificial intelligence (AI) technologies are transforming career trajectories, professional competence expectations, and the transition from higher education to the labor market, particularly in the field of information technology (IT). This study aims to examine students' career perceptions and occupational concerns in IT-related programs in the context of recent developments in AI. More specifically, it focuses on how students evaluate AI as a career opportunity or risk and how they make sense of its possible effects on their future professional lives. The study was designed as a qualitative case study. The participants consisted of 67 students enrolled in IT-related undergraduate programs at a public university. Participants were selected through criterion-based purposive sampling. Data were collected using a printed semi-structured open-ended questionnaire developed by the researchers and reviewed by field experts. The collected written responses were transferred to a digital environment without changing their content and analyzed through inductive content analysis. The findings indicate that students perceive AI technologies both as career opportunities and as potential sources of occupational concern. While some students associate AI with new career opportunities, productivity, and professional development, others express concerns about job competition, automation, and the changing nature of entry-level positions. Overall, the study suggests that students view AI not as a force that eliminates IT professions, but rather as a transformative force that requires continuous adaptation and skill development.

Keywords: Artificial intelligence, information technology students, career perceptions, occupational concerns, qualitative case study, content analysis

Introduction

As one of the fundamental drivers of the Fourth Industrial Revolution, AI is radically transforming the labor market and employment dynamics (OECD, 2022). While automation and machine learning applications enhance productivity in production, the substitution of routine and rule-based tasks deepens unemployment concerns globally while simultaneously generating new domains of expertise (Acar & Güneş, 2022; Tekin Balcı & Demirel, 2025). This atmosphere of uncertainty directly shapes the occupational decisions and career planning of Generation Z, who encountered technology at an early age (Umar, 2020; Akay, 2024).

For students enrolled in IT programs, the sector is considered an attractive career field due to employment opportunities, global mobility, and flexible work models (Tekin Epik & Altay, 2026). However, capitalizing on this potential requires students to possess AI literacy and advanced technical competencies (Ceylan & Kirazcı, 2025). Indeed, the risk of task substitution, the pressure to adapt to technology, and dystopian discourses in the media can lead students to perceive AI as an occupational threat (Akçakanat, 2024; Kılıç, 2026; Sanguinetti & Palomo, 2024).

In university students' perceptions of post-graduation employment, there is a positive correlation between unemployment anxiety and AI-related anxiety (Surat & Ceran, 2020; Uçar et al., 2024). Rising employer expectations and the belief that theoretical education will fall short of meeting market practices exacerbate professional anxiety (Belber & Özmen, 2024). In contrast, the literature suggests that rather than eliminating professions, AI automates routine tasks, thereby transforming required skill sets and job descriptions (Pan & Froese, 2023; Eloundou et al., 2024). For instance, generative AI tools enhance productivity in software processes, whereas the ultimate output remains contingent upon expert supervision and level of experience (Cui et al., 2026). Accordingly, beyond the direct impact of AI on employment, it is critical to examine how students cognitively and affectively make sense of this transformation. While students receiving IT education encounter new career opportunities, they also experience professional ambiguity driven by the automation of entry-level roles and escalating competition.

This study aims to qualitatively examine the career perceptions and occupational concerns of IT students amid the proliferation of AI technologies. Within this scope, the study examines how AI is positioned across the opportunity

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and risk dimensions, post-graduation employment expectations, and the prospective implications of this technology for professional futures. The study sought to answer the following research questions:

RQ1: How do students in the field of IT view the impact of advancements in AI technologies on their career plans?

RQ2: Do computer science students view AI technologies as an opportunity or a risk for their careers?

RQ3: What kinds of concerns and expectations do computer science students have regarding AI technologies in their professional lives after graduation?

RQ4: How do computer science students think advancements in AI technologies will affect their professions in the future?

Methodology

Research Design

This qualitative study aims to examine the impacts of AI developments on IT students' career perceptions and occupational concerns. The research employs a case study design, which allows for an in-depth investigation of a bounded phenomenon within its real-world context (Creswell & Poth, 2016; Yin, 2018). Based on data collected through an open-ended questionnaire, students' positioning of AI as a career opportunity or a risk, their employment anxieties, and their future occupational expectations are analyzed holistically.

Study Group

The study group consisted of 67 university students selected through criterion sampling, a purposeful sampling method (Patton, 2015). The primary criteria for participation were that participants be enrolled in an undergraduate program related to IT, have at least some experience with AI tools, and volunteer for the study.

Table 1. Demographics of participants and frequency of AI use

Variable	Category	N	%
Gender	Female	35	52,2
	Male	32	47,8
Department	Computer Engineering	47	70,1
	Computer Technology & Information Systems	20	29,9
Grade	First	24	35,8
	Second	9	13,4
	Third	21	31,3
	Fourth	13	19,4
Frequency of AI use	Occasionally	10	14,9
	Often	36	53,7
	Frequently	21	31,3

Data Collection Tool

The data were collected using a printed open-ended questionnaire prepared by the researchers and validated through the input of experts in educational technology (n=3) and assessment and evaluation (n=2). In addition to demographic information, the questionnaire included four key questions examining the impact of AI on career plans, perceptions of opportunities and risks, concerns about post-graduation professional life, and the effects on the profession's future. The printed questionnaires were distributed to students in person; the data were digitized without any loss of content, and participants were anonymized by coding them as K1–K67.

Data Analysis and Reliability

The data were analyzed using an inductive content analysis approach (Yıldırım & Şimşek, 2018). Codes were developed from participants' responses, and common conceptual structures were then transformed into categories and main themes. To test coding reliability, the dataset was evaluated by six independent experts from the fields of educational technology (n=3) and engineering (n=3). Inter-coder reliability was calculated using Krippendorff's Alpha coefficient, yielding an alpha of 0.824. This value exceeded the 0.800 threshold, confirming that the analysis was highly reliable (Krippendorff, 2004).

Results

The Impact of AI on Career Plans

Students' views on the impact of AI on their career goals have been grouped under three themes (Table 2).

Table 2. Themes related to the impact of AI technologies on career plans

Theme	Sample participant opinion	f
Supporting career planning	"It helps me make my career plan more efficient and technology-focused; by accelerating my research and learning process, it makes it easier for me to achieve my goals." (K6) "Since it provides a general overview of every topic, it helps me figure out how to move forward." (K54)	33
Redefining career paths	"A junior developer cannot compete with AI tools in the software industry. I am trying to specialize in more specific areas." (K12) "I used to think only about becoming a software developer, but now I have goals like specializing in AI and becoming a machine learning engineer." (K29)	22
Not causing a noticeable change	"I wanted to pursue game design both before and after AI. That is why it did not really have much of an impact" (K10) "I do not think it had much of an impact" (K56)	12

Approximately half of the participants (n=33) view AI as a supportive tool that shortens the learning curve and increases individual productivity. A significant portion of the students (n=22), however, indicated that, in the face of AI competition, they have shifted their career goals toward niche fields such as machine learning engineering and data science.

Assessment of AI as Both an Opportunity and a Risk for Careers

The participants' assessments of opportunities and risks, based on the principle of multiple coding, are summarized in Table 3.

Table 3. Student perspectives on the assessment of AI technologies as career opportunities and risks

Theme	Sample participant opinion	f
Career opportunities that boost efficiency, learning, and productivity	"More opportunities in the field of IT, because it speeds up work, makes it easier to develop new projects, and increases productivity." (K23) "It is an opportunity because I think it makes learning easier and speeds up work." (K64)	24
New fields of work and opportunities for specialization	"It is definitely an opportunity because it creates new job opportunities and makes existing jobs more efficient. By delegating routine and tedious tasks to AI, we can focus on more creative and strategic work." (K29) "It is an opportunity because new job opportunities are emerging for those who specialize in AI, and different career options are opening up in the IT sector." (K35)	7
Job search, entry-level positions, and the risk of job loss	"With the advancement of AI, companies are thinking, Instead of hiring a junior, I will hire one person with 10–15 years of experience—they can handle it easily with an AI assistant, so career opportunities for recent graduates—that is, for us—are closing one by one." (K12) "I think it is a risk because, for example, before AI, a software team used to have a lot of people, but as a result of AI, it has been reduced to just one or two people, which, of course, means we have to compete with more people in terms of our careers." (K66)	27
The risk of declining basic skills and reliance on AI	"In my opinion, it is both an opportunity and a risk, but when used correctly, it is more of an opportunity. It boosts productivity, facilitates learning, and supports the development of new solutions. The risks, on the other hand, could include professional complacency, relying on misinformation, and a decline in basic skills." (K31) "It creates both opportunities and risks; how we use it determines the balance. It is best to use it to seek help without becoming overly dependent." (K61)	16

The findings indicate that students' greatest concern (f=27) is the shrinking number of entry-level (junior) positions and the restriction on hiring recent graduates due to experienced staff being paired with AI assistants. At the same

time, AI is recognized as a lever for learning and productivity (f=24); however, it is also emphasized that overuse carries the risk of cognitive laziness and weakening the fundamentals of coding (f=16).

Anxieties and Expectations Regarding the Professional Life After Graduation

Students' concerns and expectations regarding the post-graduation process have been grouped under four themes (Table 4).

Table 4. Student perspectives on concerns and expectations regarding professional life after graduation

Theme	Sample participant opinion	f
Concerns about finding a job, entry-level positions, and job loss	"I am feeling more anxious. As I mentioned before, companies are thinking in terms of 'senior + AI tools' rather than hiring juniors." (K2) "My biggest concern is that companies are scaling back entry-level job postings because they are thinking, 'Why should we hire recent graduates and train them from scratch when AI can do so much of the work?' My expectation, however, is that knowing how to use AI will no longer be a plus—it will become a requirement, just like knowing Git or English." (K30)	27
No particular concerns	"AI is not going to take over every job—it has its limits, so I am not very worried" (K9) "I am not worried about it for now" (K67)	18
Pressure regarding professional competence, competition, and adapting to AI	"The constantly rising expectations in job postings are creating a problem. Thanks to AI, one person can now do the work that used to be done by several people, so companies are looking for fewer but more qualified employees." (K27) "Especially in the IT and software sectors, AI is a formidable competitor for us, and for our colleagues who have not kept up with the times, AI—with its free and inexhaustible energy—is a threat to human performance. For this reason, when we graduate, we will be thrust into a struggle to find a job and hold onto the one we find, requiring extraordinary performance and advanced skills." (K35)	17
Expectations that AI will streamline work processes	"I believe it will improve my performance at work" (K16) "So, if I am in the workforce, it will not do any harm—it will actually be beneficial; it will help me do my job more accurately and quickly" (K66)	14

At the heart of students' employment concerns is companies' desire to avoid the costs of training new graduates (f=27). On the other hand, while some participants stated that they did not feel any significant concern, pointing to the limitations of AI's human-like reasoning (f=18), f=17 students noted that the bar for qualifications and competitive pressure in the job market has increased exponentially.

Views on the Impact of AI on the Future of IT Professions

The participants' views on the future evolution of their professions are presented in Table 5.

Table 5. Student perspectives on the future of IT careers

Theme	Sample participant opinion	f
Increased speed, ease, and efficiency in work processes	"It will make my job more efficient and faster, and it will automate some tasks, but human oversight and creativity will still be important." (K6) "I think it will save time and help solve difficult problems quickly." (K63)	22
Changes in professional roles and job responsibilities	"I believe that in the future, software development processes will be largely AI-driven. Tasks such as code generation, testing, and error detection will be completed more quickly. The role of computer engineers will shift from simply writing code to designing systems, evaluating the accuracy of AI outputs, and devising solutions to complex problems. For this reason, I believe the ability to work collaboratively with AI will become a fundamental professional competency." (K26) "In the future, traditional programming will largely disappear. Computer engineers will transition from being people who write code to becoming qualified professionals who tell AI agents what to do." (K30)	18

A decline in job opportunities and the risk of job loss	"In the future, everyone will start doing what we do thanks to AI, and our job opportunities will decrease. That is why our profession is at risk." (K10) "In the future, if a company has 100 computer engineers, it will hire only 10 engineers who are skilled in AI. As a result, there will still be plenty of computer engineers, but unemployment will rise." (K23)	17
The need to adapt to AI and pursue professional development	"It is hard to predict; even though I cannot directly point to the future in a system that's evolving every day, it is clear that those who adapt will succeed." (K36) "I think it will be beneficial for someone who has developed themselves sufficiently." (K54)	16
The view that the profession will be affected to a limited or neutral extent	"I do not think it will have an impact; I think things will continue as they are" (K44) "I do not think anything will change—technology is always changing and evolving, and changes like this always happen" (K62)	4

Participants predict that AI will accelerate routine coding processes (f=22) and transform the role of engineers from direct code writing to "system architecture, agent control, and prompt design" (f=18). Conversely, the possibility of handling the same workload with fewer staff triggers the risk of unemployment (f=17); it appears that professional viability is tied to the ability to adapt to technology (f=16).

Discussion and Conclusions

The research findings reveal that computer science students' attitudes toward AI are shaped by a multidimensional, pragmatic understanding centered on opportunities, risks, and the need for adaptation. A significant portion of the students view AI as a career lever that enhances productivity and cognitive acceleration, while shifting their career goals toward value-added fields such as machine learning and data science. This finding aligns with theoretical observations that AI is transforming professional profiles (Yavuz Aksakal & Ülgen, 2021; Pan & Froese, 2023).

In contrast, the primary point of tension regarding employment lies in the risk of job displacement in entry-level (junior) positions. As senior developers are equipped with generative AI tools and take on routine testing, documentation, and basic code blocks—tasks previously handled by junior staff—on their own, this raises barriers to entry for recent graduates. This dynamic aligns perfectly with findings in the literature regarding automation's potential for task substitution (Acemoglu et al., 2022; Eloundou et al., 2024) and AI-driven unemployment anxiety among university students (Akçakanat, 2024; Uçar et al., 2024). Furthermore, students' concerns that overreliance on AI assistants could dull fundamental algorithmic and software development skills are corroborated by experimental studies highlighting the importance of expert supervision in human-machine collaboration (Cui et al., 2026).

Projections regarding the future of the profession indicate that computer engineering will undergo a qualitative leap from operational coding tasks toward high-level architectural design, algorithmic orchestration, and AI agent supervision. In summary, while computer science students are aware that AI will not eliminate their profession, they acknowledge that the only way to remain employable is through continuous learning and the development of skills to collaborate with AI (co-piloting). In light of the research findings, the following are recommended:

- Courses on AI literacy, AI-assisted software engineering, large language model architecture, and AI ethics should be integrated into computer science programs.
- University career centers should implement programs that equip students with portfolio development, open-source contributions, and niche specialization strategies in line with the evolution of entry-level roles.
- Mentoring networks that connect students with industry professionals should be established; next-generation internship models that encourage companies to continue hiring junior staff should be implemented.
- While the use of generative AI tools is permitted in educational processes, independent assessment mechanisms that test the fundamentals of algorithmic thinking and problem-solving should be implemented.

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Enabling Social Coding Spaces to Enhance the Students' Learning Experience

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Abstract

The 21st century has seen significant technological progress, especially in Information and Communications Technology (ICT), with Artificial Intelligence (AI) among the most impactful innovations. Higher Education Institutions (HEIs) are quickly integrating AI into their curricula. A key milestone was the November 2022 release of ChatGPT 3.5 by OpenAI, based on the Generative Pretrained Transformer (GPT) model, which uses deep learning to produce human-like responses to various prompts. While AI presents many opportunities to improve learning and research, its misuse in academic settings raises concerns about integrity. A major challenge is students using AI tools in computer programming courses to complete coding assignments without truly engaging in problem-solving. On the other hand, when used responsibly, AI can be a valuable educational resource. Educators can utilise platforms like GitHub to foster collaboration, transparency, and accountability by observing emerging trends and best practices. Features such as version control, peer review, and open-source contributions encourage active participation and enhance learning. This study examines how Social Coding Spaces (SCSs) can boost student engagement and build computational thinking skills. The results highlight the advantages for educators in adopting innovative teaching strategies that incorporate social coding tools while safeguarding academic integrity.

Keywords: student engagement, Social Coding , Connectivism

Introduction

As software development evolves rapidly, it is essential to equip students with practical skills and promote ethical AI use. One effective approach is to introduce a nuanced model that combines peer-to-peer collaboration on social coding platforms such as GitHub with AI-generated code, creating a more balanced learning environment. These platforms can help students move from feeling isolated to becoming part of a community of practice, where they share and improve one another's code. This approach helps prevent over-reliance on AI by positioning it as a supplementary tool for strengthening coding abilities. Zagalsk et al. (2016) highlight GitHub's benefits for teamwork, communication, and problem-solving, making it well suited to developing software skills. Educators can also use GitHub's transparency and collaborative features to encourage participation in open-source projects and provide practical coding experience (Tushev et al., 2020). In addition to supporting collaboration, GitHub can help students develop critical thinking and problem-solving skills. Given the challenges in computer education, it is important to explore how emerging technologies such as Social Coding Spaces (e.g., GitHub) can transform traditional teaching methods and strengthen technical skills and teamwork. This study examines how social coding tools can increase student engagement and computational thinking, with the aim of developing a framework that enhances these skills while promoting ethical AI use.

Related Works

Software development skills have gained increasing importance in the industry over recent years (Istiyowati et al., 2021). Despite this, many students struggle to learn to code, leading to high dropout rates in introductory programming courses. To improve programming education, Glassey (2019) reviewed various version control tools, including GitHub Classroom, to help educators find optimal solutions. The study identified essential technical and pedagogical features, such as creating repositories, distributing materials, promoting team collaboration, engaging students on projects, and using student repositories for assessment.

Integrating Social Coding Platforms

Research has explored innovative tools and pedagogical approaches for teaching programming. For instance, Kroustalli and Xinogalos (2021) investigated the educational effectiveness of CodeCombat, a text-based serious game that uses Python to teach programming fundamentals, comparing it with conventional teaching approaches.

More recently, generative artificial intelligence (GenAI) tools, such as ChatGPT and GitHub Copilot, have introduced new opportunities to support code generation, debugging, code explanation and problem-solving in

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computer science education. However, these tools also present pedagogical challenges, particularly when students depend on AI-generated solutions without adequately engaging with the underlying programming concepts. Lau and Guo (2023), drawing on interviews with 20 introductory programming instructors across nine countries, identified differing approaches to this challenge, ranging from restricting AI use to integrating these tools into programming curricula.

Concerns about academic integrity further emphasise the need for clear institutional policies and guidance on the ethical and transparent use of generative AI in higher education. In this context, social coding platforms such as GitHub can complement AI-assisted programming with collaborative learning and the development of computational thinking. Through version control, peer collaboration, code review, debugging, and iterative problem-solving, students can make their programming processes more visible and develop skills in decomposition, algorithmic thinking, abstraction, and evaluation (Feliciano et al., 2016). Diehl and Brandt (2023) demonstrated GitHub Classroom's educational potential for teaching C++ and Git, showing how version-control practices can be integrated into programming education. GitHub can also help educators distribute learning activities, monitor student progress, and examine commit histories to understand how students develop and modify their code (Kalliamvakou et al., 2015).

In South Africa, educators are increasingly incorporating GitHub into programming courses to give students hands-on experience in coding and collaboration. This strategy aligns with industry standards, which require software developers to have skills beyond coding, such as version control, code review, and teamwork. Thus, rather than positioning generative AI and social coding as competing technologies, their integration can create opportunities for students to use AI critically while demonstrating their computational thinking, collaborative processes, and understanding of programming concepts. GitHub supports computer science education by fostering collaboration and peer learning, while also helping students develop soft skills valued in the industry (Patani et al., 2024). Patani et al., (2024) recommend integrating open-source projects and version control systems into curricula to align coursework with industry requirements and streamline assessment submissions. As technology advances rapidly, Higher Education Institutions (HEIs) must revise their curricula and teaching methods. With the rise of AI tools, HEIs need to establish ethical guidelines and best practices for their use in education. Combining Social Coding Spaces with generative AI offers a transformative opportunity for computer science education. When used effectively, these tools can increase student engagement, promote responsible AI use, enhance computational thinking, and prepare students for the workforce. Nonetheless, overcoming these challenges requires a structured approach within a Community of Practice that encourages ethical coding, boosts engagement, and develops the skills needed for future employment.

Benefits of GitHub for Students

GitHub is a web-based hosting service for version-controlled repositories that lets developers track changes, collaborate on code, and revert to previous versions when needed. Without version control, restoring previous versions can be time-consuming and may introduce errors. Patani et al. (2024), in a study of 319 undergraduate students, highlighted several benefits of integrating GitHub into software engineering education:

- Flexible access: Students can store repositories in the cloud and access their projects from anywhere.
- Collaboration: GitHub supports code sharing, change tracking, peer review and group project management.
- Professional portfolios: Students can showcase their projects, coding skills and development experience to potential employers.
- Authentic learning: Students can explore open-source projects and gain practical experience of real-world software development practices.
- Professional networking: Students can connect with peers, developers and open-source communities beyond the classroom.

Collectively, these affordances position GitHub as more than a repository for storing source code. It provides a social, collaborative environment where students can engage in authentic software development practices, document their learning, receive feedback, collaborate with peers and develop professional identities. Patani, Tiwari and Rathore (2024) found that integrating GitHub into a software engineering course improved teamwork, collaborative development and overall student learning.

Theoretical Framework

Downes (2006) stated that learning occurs within communities, where participation is central to the learning process. Siemens (2004) introduced Connectivism as a learning model that recognises technological shifts in society, emphasising that learning occurs within distributed, socially and technologically enhanced networks. He argues that emerging technologies enable learners and educators to move from isolated activities to interactive engagement and collaboration. According to Siemens, "learning is a process of connecting diverse nodes, knowledge sources, or accessing existing networks."

This connectivist approach supports the integration of GitHub into academic settings. While GitHub has gained significant traction in industry, its adoption in education remains limited. However, its collaborative features align with the principles of Connectivism, as learning is not solely about acquiring knowledge but also about networking and engaging with others. Kultawanich et al. (2015) further emphasise that online learning environments require technology to support interaction, sharing, and connection between various nodes, including students, lecturers, and experts. For this study, the lecturer and researcher proposed creating a social learning network using GitHub to foster collaboration and engagement in the learning process.

A case study using GitHub

This study adopts the case study research method, which is well suited to investigating contemporary phenomena in their real-world context (Crowe et al., 2011). For this study, a case study will allow the researcher to gather rich, detailed data in a reliable setting (Berg, 2004), making it ideal for examining how students engage with GitHub in a programming course. This approach enables the researcher to capture detailed insights into student experiences, challenges, and outcomes when using GitHub as a collaborative tool. According to Crowe et al. (2011), case study research is valuable in educational settings as it facilitates a holistic understanding of behaviours and contextual influences. By focusing on a specific group of students, this study provides rich qualitative data on their adaptation to GitHub, offering practical implications for educators seeking to integrate similar technologies into their teaching practices. Initially, students used the Learning Management System (Blackboard) to submit assessments and access course materials. However, due to the large file sizes of submitted assessments, lecturers opted for a more practical, work-based solution like GitHub. Despite initial uncertainty and scepticism, students became comfortable using GitHub within two weeks following a brief demonstration of its core functionalities. As part of this study, students were required to use GitHub to collaborate with the lecturer and their peers, developing computational skills while promoting the responsible use of AI-generated code. The researcher, a senior academic, presents key insights into integrating GitHub into a programming course, emphasising its influence on student engagement, peer collaboration, and enhanced computational thinking.

Methodology

This exploratory study used a qualitative, interpretive research design guided by Siemens's connectivism theory, a learning paradigm that emphasises the role of social and technological networks in constructing and disseminating knowledge (Siemens, 2005). Unlike traditional learning theories that focus on individual cognition, connectivism views learning as creating connections and developing a network. It recognises that learning can occur outside the individual, across digital platforms, among peers, and through tools that extend human capacity for knowledge acquisition and collaboration. The study aimed to explore academics' and students' conceptualisations and attitudes towards using social coding spaces, specifically GitHub, as collaborative and educational tools. Conducted over two semesters at a campus in Johannesburg, South Africa, the study began with exploratory engagement across various campuses to investigate why GitHub was preferred over the institutional Learning Management System (LMS) for portfolio submissions. Initial informal discussions with lecturers via Microsoft Teams, along with reflections on prior workshop sessions on social coding, informed the research direction. These conversations and observations revealed a growing need for platforms that support distributed, peer-driven learning environments, which are core tenets of both connectivism and Communities of Practice (Wenger, 1998).

The research involved conducting conversational interviews with five lecturers who co-facilitated the programming module alongside the researcher. With their permission, the researcher recorded the interviews on a mobile device and then transcribed them for analysis. The researcher applied thematic analysis to code and categorise the data, complemented by sentiment analysis through keyword counting. The researcher organised emerging themes under relevant headings and used supporting evidence to present the findings. This method enabled the researcher to explore how students engaged with GitHub. The 15–20-minute interview sessions served both as data collection activities and as reflective, co-constructive engagements.

Interview process:

The researcher explained the research aim to participants in the call for participation and at the start of the interviews. The following questions were posed to guide the interviews:

- Did you benefit from using a social coding tool such as GitHub in the classroom? Why or why not?
- Were you provided with adequate training to roll out GitHub in the classroom?
- If we could improve the way we use GitHub, what would you suggest?
- Do you think that GitHub can mitigate the unethical use of AI in the classroom?
- Do you think GitHub is preparing students for the world of work?
- What other social coding tools have you used?

Data Collection and Analysis

Merriam (2009) indicates that qualitative data provides researchers with information about participants' thoughts, opinions, and experiences. This research will use a two-phase approach. In the first phase, the researcher will conduct document analysis to gather information about how learners engage with GitHub in their courses. Analysis of lecture material, lesson plans, Git repositories, and learner e-portfolios is vital to gaining a rich understanding of learners' engagement with GitHub and its ability to encourage engagement. The second phase of this research process will involve direct contact through a focus group interview with the participants.

The data were anonymised as agreed with the participants, and the HEI previously granted ethical clearance for this study.

Findings and Discussion

The results of the thematic analysis revealed several themes within the responses:

i. Team Accountability
ii. Ongoing Collaboration
iii. Change Management

The following describes the main themes that emerged, including examples from participants' responses.

Team Accountability

A key theme that emerged from the study was enhanced accountability among team members, facilitated by GitHub's version control features. These tools enabled both students and instructors to monitor individual contributions to collaborative projects in real time, fostering a heightened sense of ownership, responsibility, and transparency within teams. This visibility supported more equitable participation and encouraged students to reflect on both their own learning processes and their peers' contributions. Importantly, the findings also point to the role of social coding environments in promoting ethical AI practices. As students increasingly use generative AI tools to support coding and problem-solving, contribution traceability can encourage greater accountability for how AI-generated code is produced, adapted, acknowledged, and integrated into collaborative work. GitHub's transparent development history can therefore support discussions around responsible AI use.

This finding aligns with existing research on social coding platforms in educational contexts, which emphasises their potential to promote accountability and collaborative engagement (Storey et al., 2016). It also resonates strongly with the principles of connectivism, which views learning as a process of building and navigating networks of information, relationships, and digital tools (Siemens, 2005). Lecturers concurred that GitHub could support a social learning environment in which learners become part of this networked learning process, requiring students not only to develop computational competence but also to exercise judgement and responsibility in their use of AI within their programming tasks.

Ongoing Collaboration

The study found that GitHub facilitated collaboration and allowed instructors to track individual contributions transparently. However, Lecturer 1 stated: "*Although we adopted Git, we used it more for assessments, so we need to encourage more collaboration and engagement outside the classroom, as now we are pushing only assessments*"

Two lecturers emphasised that more classroom time and GitHub training are needed to maximise the benefits of knowledge sharing and engagement beyond the classroom and to avoid repeated use of AI tools. However, for assessment submissions, it worked well because lecturers could comment on student code, provide constructive feedback, and help students identify and rectify errors more efficiently. All lecturers agreed that enforcing GitHub's role in fostering a supportive learning environment beyond traditional lecture-based instruction would be beneficial and hopefully encourage students not to rely on ChatGPT to complete assessments. However, it requires more training and time during lessons for further exploration.

Change Management

Introducing GitHub posed initial challenges, as many lecturers found the platform complex and unfamiliar. They expressed a need for structured onboarding, including foundational training on repository creation, file management, and commit processes. However, peer knowledge-sharing across campuses played a crucial role in accelerating the learning curve. Despite initial struggles, students recognised GitHub's relevance and the need to prepare for the workplace.
By introducing a detailed manual and additional workshops, including lectures and student sessions, participants will gain valuable insights into Git's benefits for managing projects from inception to completion. After initial deliberation, lecturers acknowledged the long-term value of GitHub in equipping students with industry-relevant skills. Exposure to version control and collaborative coding practices mirrors real-world software development workflows, preparing students for professional environments where such tools are standard. Lecturer 2 highlighted **: "***It was exciting to see students gain industry-level skills beyond the classroom. Watching them collaborate, problem-solve, and apply real-world tools like GitHub is truly rewarding. Closing the gap between academia and industry is important.*

Proposed Framework for using GitHub as a Social Learning Network.

Figure 1 presents the proposed Social Coding Framework, which conceptualises computing education as a socially connected learning process. The framework integrates five interrelated dimensions: building computational skills, fostering social learning, embedding ethical AI practice, applying knowledge through real-world projects, and continuously measuring and improving learning. Drawing on Connectivist principles, the framework positions learning as distributed across learners, peers, lecturers, digital platforms and communities. Social coding spaces therefore function not merely as repositories for code, but as networked environments through which learners develop computational competence, collaborate, engage with authentic challenges, and negotiate responsible and ethical uses of AI.



Figure 1. Social Coding Framework (AI-generated)

Conclusion

These findings align with Patani et al. (2024), who identified GitHub's potential to support participation, collaboration, and engagement in software engineering education. Building on this work, the proposed Social Coding Framework extends collaborative programming by explicitly integrating computational thinking, social learning, ethical AI awareness, and responsible technology use. Through activities such as collaborative coding, debugging, and peer feedback, social coding can support the development of both programming proficiency and broader computational competencies. Furthermore, the visibility and traceability of students' regular commits and commit messages afforded by GitHub can encourage greater accountability in collaborative work and create opportunities to address responsible AI practices, academic integrity, transparency, and critical evaluation of AI-generated code.

The Social Coding Framework therefore conceptualises GitHub not merely as a repository for storing and managing code, but as a social and networked learning environment in which students collaborate, exchange knowledge, negotiate meaning, receive feedback, and engage in authentic software development practices. By bringing together social coding, connectivist principles, and ethical AI education, the framework provides a holistic approach to computer education that recognises the interconnected technical, social, and ethical dimensions of contemporary computing. Such an approach can contribute to more collaborative, reflective, and contextually relevant programming learning while supporting students in developing the competencies and responsible practices required to participate meaningfully in an increasingly AI-enabled digital world.

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Human-in-the-Loop LLM-Based Assessment in LMS Environments: Developing an LTI-Compatible Tool for Rubric-Guided Evaluation

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Abstract

Open-ended questions can assess reasoning, interpretation, and written expression, but detailed rubric-based evaluation is difficult to scale in large, blended, and online courses. Large language models (LLMs) can generate score suggestions and feedback, yet direct automation raises concerns about rubric alignment, transparency, privacy, and instructor agency. This design study proposes an external assessment tool that connects to a learning management system (LMS) through Learning Tools Interoperability (LTI). In this paper, LLM-based assessment denotes a workflow in which an LLM produces an assessment draft and an instructor retains the release decision. Using a conceptual, requirements-driven design approach, the study translated requirements from formative feedback theory, evidence on feedback produced by LLMs, and LTI specifications into an architecture and workflow for a planned prototype. The proposed architecture comprises a task and rubric configuration interface, an LTI integration layer, a privacy-aware LLM scoring service, and an instructor review interface, with an audit layer spanning these components. The service would minimize or tokenize identifying data before sending a student response and instructor-defined rubric to the LLM. The assessment draft would contain criterion-level score suggestions, rationales, and student-facing feedback. The instructor could revise, approve, or withhold the assessment draft before release. This separation is intended to keep interoperability, LLM inference, pedagogical judgment, and release control distinct. The paper offers a design specification for LLM-based assessment in LMS environments; implementation, user testing, scoring agreement, workload effects, and cross-platform portability require subsequent evaluation.

Keywords: LLM-based assessment; Learning Tools Interoperability; rubric-guided feedback; human-in-the-loop assessment; learning management systems

1. Introduction

Open-ended questions are commonly used to elicit reasoning, evidence use, interpretation, and written expression. Their educational value, however, depends on evaluative judgments that are explicit and connected to standards. Sadler (1989) described formative assessment as a process in which learners understand a quality standard, compare their current performance with that standard, and take action to close the gap. Hattie and Timperley (2007) similarly emphasized that effective feedback clarifies the goal, indicates current progress, and identifies productive next steps. Detailed rubrics can make these relations explicit. Applying such rubrics across many responses is the practical problem motivating the proposed tool.

LLMs offer a possible means of supporting this work. They can interpret extended text, generate natural-language explanations, and respond to task-specific prompts. Early studies report fluent and detailed LLM-based feedback, although Dai et al. (2023) found limited agreement with instructor assessment. Prompt design also influences feedback specificity and usefulness (Jacobsen & Weber, 2025). However, quality is uneven. In a comparison of human and ChatGPT feedback on student writing, human feedback was stronger on several pedagogically important dimensions; fluency therefore did not ensure appropriate prioritization or accuracy (Steiss et al., 2024). Educational uses of LLMs also raise concerns involving transparency, privacy, bias, and insufficiently validated automation (Yan et al., 2024).

These concerns are especially relevant when an assessment draft is embedded in an LMS and may be perceived as institutionally authoritative. Khosravi et al. (2022) argue that educational explainable AI should provide explanations that are actionable for intended stakeholders and evaluated in context. In a study of EFL argumentative writing, Luo et al. (2025) found that combined teacher-AI feedback mitigated weaknesses of AI-only feedback in content selection, coherence, and cohesion. Accordingly, LLM-based assessment in this paper refers to a human-in-the-loop workflow: the LLM produces an assessment draft, and the instructor makes the release decision.

The study addressed the following design question: How can an LTI-based workflow for LLM-based assessment be specified to address rubric alignment, privacy-aware data handling, and instructor control before release? The

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aim was to specify an architecture and workflow for a planned prototype, not to establish system validity, effectiveness, interoperability, or workload reduction.

2. Method

This study used a conceptual, requirements-driven design approach. Its purpose was to translate pedagogical, responsible-AI, and interoperability requirements into a proposed technological architecture and workflow for later development and evaluation in an LMS context. The study comprised requirements analysis, architectural design, and prototype specification. Requirements were translated into component roles, data-flow rules, release conditions, and design checks. The study did not include software implementation, participant recruitment, student-response collection, automated scoring, expert review, user testing, or LTI conformance testing.

The source review was purposive rather than systematic. Sources were selected to inform four predefined design concerns: formative feedback, LLM-based feedback, responsible educational AI, and LTI interoperability. First, formative feedback theory indicated that feedback should be anchored to explicit criteria and identify a next action for improvement (Hattie & Timperley, 2007; Sadler, 1989). Second, empirical studies indicated that prompt design affects feedback quality and that LLM-based feedback requires instructor verification (Dai et al., 2023; Jacobsen & Weber, 2025; Steiss et al., 2024). On this basis, the design represented assessment drafts at the rubric-criterion level. Third, research on explainable and responsible educational AI informed requirements for actionable rationales, privacy-aware data handling, transparency, and human oversight (Khosravi et al., 2022; Yan et al., 2024). Logging was added as a design requirement for traceability. Latif and Zhai (2025), who evaluated federated learning, additionally supported the general principle of limiting raw educational-data transfer. Fourth, LTI defined the proposed interoperability boundary between the LMS and the external tool.

The technical specification assumed LTI 1.3 and the LTI Advantage service family. LTI permits an external tool to receive a secure launch and relevant course, role, and resource context. Depending on institutional configuration, Deep Linking may support task placement, Names and Role Provisioning Services may support roster-aware workflows, and Assignment and Grade Services may return a score to the LMS gradebook (1EdTech Consortium, n.d.). In the proposed workflow, score return would be invoked only for an instructor-approved score. TSUGI served as a precedent for separating LTI launch and context handling from tool-specific functions (Galanis et al., 2014). The specification did not require TSUGI, PHP, a particular LMS, an LLM provider, or an LLM version.

The author conducted a structured internal consistency review by mapping five design criteria to the corresponding architecture components and workflow steps: (a) each criterion-level score suggestion was linked to an instructor-defined rubric criterion; (b) identifying information was excluded from the LLM request unless required for the assessment transaction; (c) an assessment draft could not reach the student without an instructor-controlled release action; (d) the assessment draft, instructor edits, and release status were represented in the audit layer; and (e) LTI integration remained separate from LLM scoring. This procedure was a design self-check, not an expert review or empirical validation, and did not assess validity, usability, learning impact, security, or interoperability.

3. Results: Proposed Design

The principal output of the design process was a four-component architecture with a cross-cutting audit layer and a seven-step release workflow (Figure 1). The four components were the task and rubric configuration interface, LTI integration layer, privacy-aware LLM scoring service, and instructor review interface. In the configuration interface, the instructor would define the task, expected response conditions, rubric criteria, performance levels, weights, score range, and feedback guidance. The rubric would be stored as structured data so that the same criteria could be displayed during review and included in the LLM request. This arrangement was intended to limit divergence between configuration and review, but it was not tested in the present study.

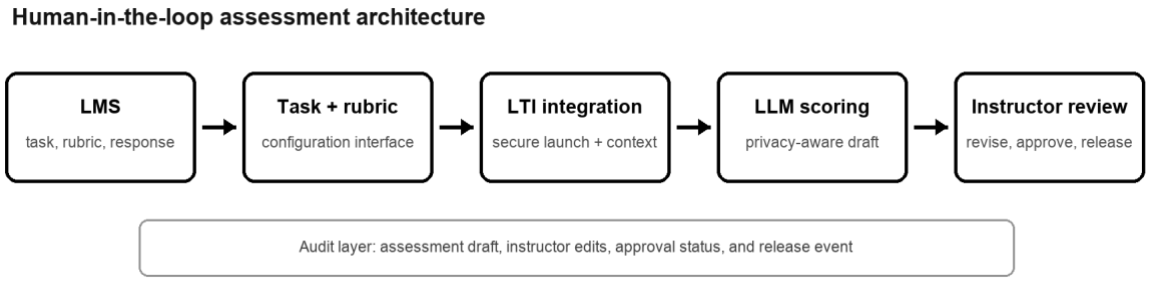


Figure 1. Proposed architecture for LLM-based assessment and instructor-controlled release.

The LTI integration layer would receive the context required for the assessment transaction after a student submitted a response through the LMS. The privacy-aware LLM scoring service would remove or replace direct identifiers, such as name, e-mail address, student number, and unnecessary course identifiers, with temporary tokens. It would then construct an LLM request containing the task, structured rubric, de-identified response, output schema, and constraints against unsupported claims. The expected response schema comprised criterion-level score suggestions, evidence-linked rationales, student-facing feedback, and a review flag. Together, these items formed the assessment draft and would not be posted directly to the gradebook.

The instructor review interface would display the original response, rubric criteria and levels, criterion-level score suggestions, rationales, and student-facing feedback draft in one view. The instructor could revise the feedback, change criterion or overall scores, request another draft, withhold the result, or approve release. Assignment and Grade Services would return an instructor-approved score only after approval. This release condition was the operational definition of instructor control in the proposed design.

The cross-cutting audit layer would record the rubric version, prompt template version, model identifier, timestamp, assessment draft, instructor edits, approval status, and release event. Token mappings would remain within the institutional environment or the external tool's controlled environment and would not be included in the LLM request. Retention periods, access permissions, and deletion procedures were identified as implementation requirements but were not specified or tested in the present study.

The proposed workflow comprised seven steps: (1) create the task and rubric; (2) launch the external tool and submit a response through the LMS; (3) establish the assessment context through LTI; (4) minimize or tokenize identifying data; (5) produce the assessment draft; (6) review, edit, and approve or reject the assessment draft; and (7) release approved feedback and, if configured, return the instructor-approved score. This separation was intended to keep an LLM inference request distinct from a release decision.

4. Discussion

The proposed design addressed responsibility by separating the assessment draft from the instructor's release decision. A structured rubric may focus the LLM request on explicit criteria, but neither the rubric nor instructor review establishes assessment validity without empirical evaluation. Displaying the evidence, rubric, and assessment draft in one interface may support reviewability. This interpretation is consistent with evidence from EFL argumentative writing that combined teacher-AI feedback may complement AI-only feedback on content and coherence (Luo et al., 2025), although the present study did not test that effect.

The proposed LTI integration may offer two practical advantages: access from the LMS and separation of interoperability functions from LLM scoring. These are design expectations, not observed benefits. LMS implementations vary in supported services, permissions, and score-return policies; implementation and conformance testing would therefore be required before claiming compatibility or portability across platforms.

Privacy by design requires more than removing a visible student name. Natural-language educational data may contain personal or sensitive information (Yan et al., 2024), and rubrics or task descriptions can include sensitive contextual data. Future development should therefore combine field-level minimization with detection of identifiers in response text, configurable data-retention periods, institutional LLM-provider agreements, access controls, and clear notices to instructors and students. The audit layer must also avoid becoming a secondary source of unnecessary personal data.

A structured rubric also provides a technical boundary. Criteria, level descriptors, weights, and score constraints should be stored independently from the natural-language prompt so that an implementation can validate totals, display the same standard during review, and check the assessment draft against an output schema. Versioning the rubric, prompt template, and model identifier would support later reconstruction of design changes. Because no prototype or inference configuration was implemented, the present study cannot provide executable prompts, LLM parameters, or replication results.

Instructor review should not be treated as a guarantee of safety. Because instructor behavior was not evaluated, whether score suggestions produce anchoring or automation bias remains an empirical question. The proposed interface would therefore foreground rubric-linked evidence, distinguish the assessment draft from instructor edits, and require an explicit release action. Institutions could also define review thresholds for low-confidence drafts, criterion inconsistencies, or possible prompt injection. The effect of these features on instructor behavior remains to be tested.

The study has several limitations. The prototype has not yet been implemented; consequently, no evidence is available regarding usability, scoring agreement, feedback quality, workload reduction, learning impact, latency, cost, or security performance. The design does not solve LLM bias, hallucination, prompt injection, or rubric

ambiguity. The review stage is intended to prevent direct release of LLM output, but its effect on instructor decisions has not been tested. Future evaluation should therefore examine both LLM performance and instructor behavior.

A staged evaluation is proposed. Technical testing should first verify LTI launches, role handling, tokenization, audit records, and conditional score return. An expert study could then assess rubric alignment, factual grounding, actionability, and revision effort by comparing assessment drafts with instructor decisions. A subsequent classroom pilot could examine review time, score agreement, instructor overrides, student perceptions, and revision quality. Fairness analyses should examine whether error patterns differ across response quality, language background, and other educationally relevant groups. These evaluations are required before the tool is considered for consequential summative use.

5. Conclusion

This paper presents a design specification for an LTI-based, human-in-the-loop assessment tool. Its proposed contribution is the separation of task and rubric configuration, LTI integration, privacy-aware LLM scoring, instructor review, and audit functions. Within this specification, the assessment draft cannot be released without instructor approval. The study does not establish assessment validity, system effectiveness, workload reduction, privacy protection, or cross-platform interoperability. Implementation and empirical evaluation are required to determine whether the proposed design can support reviewable pedagogical judgment in practice.

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Designing A Large Language Model–Supported Biostatistics Course to Ensure Statistical Literacy and Reduce Statistical Anxiety

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Abstract

Biostatistical literacy is essential for evidence-informed medical practice, yet statistics anxiety can hinder students' engagement with quantitative learning. Evidence on structured large language model (LLM)-supported biostatistics courses remains limited, particularly regarding validated learning-related outcomes and responsible use. This single-arm pilot study aimed to evaluate pre-to-post changes and satisfaction with an innovative biostatistics course supported by large language models (LLMs) targeted to enhance medical students' statistical literacy and reduce statistics-related anxiety. We conducted a thematic analysis to explore students' prior experiences with biostatistics education, perceived challenges, and expectations for an LLM-supported course model. We evaluated the effectiveness of the Moodle-based, eight-module LLM–supported biostatistics course in 33 students using pre-post measures of statistical literacy, self-efficacy, and statistics anxiety. Independent-samples t-test and Mann–Whitney U test were applied for between-group comparisons, and Spearman's rank correlation coefficient was used to examine relationships between continuous variables. We analyzed changes in scale-score differences between pre- and posttests among participants with and without LLM experience using the Brunner–Langer approach. Most participants (85.4%) reported having previously used LLM tools for learning purposes. Statistics anxiety decreased, while statistical literacy self-efficacy increased significantly ($p=0.040$ and $p<0.001$, respectively). Statistical literacy scores increased but not significantly ($p=0.247$). Students with prior experience using LLMs in education demonstrated a significantly greater increase in belief scores related to statistical reasoning compared with those without such experience ($p=0.024$). Confidence in statistical processes and belief in statistical reasoning were positively correlated with post-course self-efficacy scores ($r_s=0.446$, $p=0.009$; $r_s=0.504$, $p=0.003$). Overall course satisfaction was high; all students rated the use of LLMs as beneficial and indicated they intended to continue using them in future learning. An LLM–supported biostatistics course was feasible and acceptable for medical students and was associated with reduced statistics anxiety and notable gains in self-efficacy, particularly in reasoning and application-based interpretation domains. Based on these findings, LLM-supported biostatistics education should be integrated into medical curricula through structured, application-oriented, and interactive learning activities. LLM-based tools may serve as complementary educational aids that enhance conceptual learning, statistical literacy, and learner confidence through feedback-rich learning environments. Further multicenter and longitudinal studies with larger samples are needed to confirm the effectiveness and sustainability of this approach. Future research should compare different AI tools and instructional models to identify the most effective strategies for integrating AI-supported statistics education into medical training.

Keywords: large language models, biostatistics education, statistical literacy, statistical anxiety

Introduction

Biostatistics education plays an important role in enabling physicians to analyze and interpret data and to use statistical information effectively in clinical decision-making processes (Aggarwal, 2018). Statistical literacy is therefore essential for accessing and critically evaluating the best available evidence in diagnostic and treatment processes and for supporting evidence-based decision-making (Schmidt et al., 2021). However, statistical anxiety is highly prevalent among medical students and graduates and may negatively affect their engagement with biostatistics education (Beurze et al., 2013; Onwuegbuzie & Wilson, 2003). In this context, this study aimed to develop a large language model (LLM)-supported biostatistics course aligned with the level of statistical literacy required of physicians.

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Methodology

This single-arm pilot study used a pre-test/post-test intervention design. The intervention consisted of a biostatistics course enriched with application-based activities supported by an LLM. First, a qualitative analysis examined undergraduate students' experiences with biostatistics courses, the challenges they encountered, and their perceptions and expectations of an LLM-supported course model. We then developed a course design based on the qualitative analysis results and prepared and uploaded the course content to the Moodle learning management system of the Ege University Faculty of Medicine (https://okm.med.ege.edu.tr/login/index.php). All participants provided written informed consent before participation. The study was conducted in accordance with the Declaration of Helsinki, and the Ethics Committee of Ege University Health Sciences Scientific Research and Publication Ethics Board approved the protocol (Protocol No: 2738; February 7, 2025). We conducted an a priori power analysis using G*Power 3.1.9.7. For a paired-samples t-test comparing two dependent groups, assuming a medium effect size of 0.50, a power of 80%, and a Type I error rate of 0.05, the minimum required sample size was estimated as 27 participants. Allowing for potential difficulties in data collection, we increased the target sample size by approximately 10–12% and planned to recruit 30 participants. Forty-eight students voluntarily submitted the participant information form. A total of 33 students who attended the course completed the pre-test and post-test questions.

We collected responses to these items at the end of the course through the same Google Form link used for the post-test. The Statistical Literacy Scale developed by Şahin (2012) measured students' statistical knowledge levels. The Statistical Literacy Self-Efficacy Scale (Batur, Yiğit & Baki, 2019) assessed students' self-efficacy in statistical literacy. The Statistics Anxiety Scale, developed by Vigil-Colet, Lorenzo-Seva, and Condon (2008), and later validated in Turkish by Durak and Karagöz (2021), was used to assess statistical anxiety (Durak & Karagöz, 2021; Vigil-Colet, Lorenzo-Seva & Condon, 2008); higher scores indicate higher levels of anxiety. Accordingly, participants completed the statistical literacy, statistical literacy self-efficacy, and statistical anxiety scales twice, before and after the course. The course design was reviewed, and we made any necessary adjustments based on students' and experts' feedback.

We calculated descriptive statistics for continuous variables and reported frequencies and percentages for categorical variables. The Shapiro-Wilk normality test was performed to assess the normality assumption of continuous variables. To examine associations between total scale scores and student characteristics, we used the independent-samples t-test for normally distributed continuous variables and the Mann-Whitney U test for non-normally distributed continuous variables in two independent groups. We administered the statistical literacy, statistical literacy self-efficacy, and statistical anxiety scales twice, before and after the course. When comparing total scores, we used the paired-samples t-test if the continuous variables were normally distributed; otherwise, we used the Wilcoxon signed-rank test. Because the normality assumption was not met, non-parametric Spearman's rank-order correlation analysis was used to examine relationships between the continuous variables. We set the significance level for all hypothesis tests at 0.05. Statistical analyses were performed using IBM SPSS Statistics for Windows, Version 25.0 (IBM Corp., Armonk, NY, USA). When evaluating the changes in three scale scores and their factors over time between prior LLM users in education and non-user groups, the non-parametric Brunner–Langer method (F1-LD-F1 design) was employed, and analyses were conducted using R software version 4.5.1 (R Foundation for Statistical Computing, Vienna, Austria) with the nparLD package (Noguchi et al., 2012). Because interaction effects generally have lower statistical power than main effects, we adopted a more liberal significance threshold for the group-by-time interaction (Marshall, 2007). We used a significance threshold of $p<0.10$ to assess the interaction between group and time.

Results and Discussion

We conducted a formative qualitative needs assessment with 30 students using open-ended questions during May, 2025. One expert researcher in medical education independently coded the data and resolved disagreements through consensus. After the course announcement, 48 students completed the participant information form. However, 33 participants actively attended the course and completed both the pre-test and the post-test. Table 1 presents the descriptive statistics for both the initial participant group and the subset of students who completed all questionnaires. The mean age of the participants was 20.36±1.64 years. Almost all participants (97.9%) reported not having taken any biostatistics course outside their undergraduate education. Of the participants, 41 (85.4%) reported having previously used LLMs for educational purposes. Among these tools, 46 (95.83%) reported using ChatGPT, 15 (31.25%) Gemini, 3 (6.25%) DeepSeek, 2 (4.16%) Claude, and 2 (4.16%) Notebook LM. Supporting our findings, in a study conducted by McCoy et al. (2025), 77% of students also reported using artificial intelligence for educational purposes (McCoy et al., 2025). Among participants, ChatGPT was the most commonly used LLM, similar to findings from Fußhöller et al. (2025), who reported that it ranked first among medical students in Germany (Fußhöller et al., 2025). Participants who had used LLMs rated their competence at a mean of 6.39±1.64; their previous experiences with biostatistics courses were rated at a mean of 5.29±2.07 on a 0–10

scale. Among participants with complete pre- and post-test data, 18 (54.5%) were male, and 15 (45.5%) were female. Sixteen participants (48.5%) were third-year students. We present initial demographic characteristics for all enrolled participants (n=48), but all subsequent analyses used data from participants who completed both the pre- and post-test assessments (n=33).

Table 1. Descriptive Statistics of Initial Participation and Pre-Post Test Participants Participation

Variables	Descriptive Statistics	Initial Participation (n=48)	Pre-Post Test Participants (n=33)
Age (year)	Median (Min-Max)	20 (18-24)	20.00 (18.00-24.00)
	Mean± Standard Deviation	20.36±1.64	20.52±1.56
Gender n(%)	Male	23 (47.90)	18 (54.50)
	Female	24 (50.00)	15 (45.50)
	Missing	1 (2.10)	-
Academic Year Level n(%)	Year 1	5 (10.40)	3 (9.10)
	Year 2	11 (22.90)	2 (6.10)
	Year 3	16 (33.30)	16 (48.50)
	Year 4	13 (27.10)	9 (27.30)
	Year 5	2 (4.20)	2 (6.10)
	Year 6	1 (2.10)	1 (3.00)
Previous Biostatistics Training, n (%)	Yes	1 (2.10)	1 (3.00)
	No	47 (97.90)	32 (97.00)
Prior Use of AI-Based Tools in Education, n (%)	Yes	41 (85.40)	29 (87.90)
	No	7 (14.60)	4 (12.10)
Self-Reported Competency Score for Using AI-Based Tools in Education (1 = Lowest, 10 = Highest) (n = 41)	Median (Min-Max)	6 (3-10)	6 (3-9)
	Mean± Standard Deviation	6.39±1.64	6.00±1.28
Perceived Past Experience Score for Biostatistics Course (1 = Most Negative, 10 = Most Positive)	Median (Min-Max)	6 (1-10)	5 (1-10)
	Mean± Standard Deviation	5.29±2.07	5.18±2.31

In Table 2, the mean total score of the Statistical Literacy Scale was 7.30±2.74 prior to the course and 7.60±2.99 following the course. Although the total post-test score was higher than the pre-test score, the difference was not statistically significant (Median = 8 [0–11] vs. 9 [0–11], p=0.247). The total score for the examination anxiety factor was significantly lower after the intervention than at baseline (p=0.034). The overall anxiety total score was also significantly lower after the educational program than before (p=0.040). Because statistical anxiety can negatively affect students' learning and examination performance, innovative course-design interventions are recommended (Perchtold-Stefan et al., 2024). Educational programs that incorporate AI language models have been shown to reduce students' subject-related anxiety (He, Abbasi & He, 2025; Aydın-Yıldız, 2025). For the 38-item Statistical Literacy Self-Efficacy Scale, the mean factor score for the "confidence in statistical processes" factor increased from 32.30±8.29 at baseline to 38.93±10.23 at post-test (p<0.001). For the "beliefs in statistical reasoning" factor, the increase in the total score after the course was also statistically significant (p<0.001). Overall, the total score on the Statistical Literacy Self-Efficacy Scale was significantly higher at post-test than at pre-test (p<0.001). Practice-oriented statistics instruction models support statistical literacy, which encompasses the ability to make sense of, analyze, interpret, and communicate statistical information (Hariyanti, Budayasa & Setianingsih, 2025; Koparan & Güven, 2014).

Table 2. Results according to the analysis of the scales (n=33)

Scales		Pre-test n(%)	Post-test n(%)	p value
Statistical Literacy Scale				
Total Score	Median (Min-Max)	8 (0-11)	9 (0-11)	0.247[a]
	Mean± Standard Deviation	7.30±2.74	7.60±2.99	
	Cronbach's alpha coefficient (α)	0.774	0.829	
Statistics Anxiety Scale				
Examination anxiety	Median (Min-Max)	26 (8-40)	23 (8-37)	**0.034[b]**
	Mean± Standard Deviation	23.90±8.36	21.00±8.24	
	Cronbach's alpha coefficient (α)	0.936	0.940	
	Median (Min-Max)	13 (7-35)	14 (7-29)	0.463[a]

Interpretation Anxiety	Mean± Standard Deviation	14.57±7.88	13.42±6.44	
	Cronbach's alpha coefficient (α)	0.970	0.968	
Asking for help anxiety	Median (Min-Max)	10 (8-40)	11 (8-25)	0.252[a]
	Mean± Standard Deviation	14.96±8.30	13.18±5.87	
	Cronbach's alpha coefficient (α)	0.961	0.943	
Total Score	Median (Min-Max)	51 (23-115)	46 (23-75)	**0.040[a]**
	Mean± Standard Deviation	53.45±20.84	47.60±16.12	
	Cronbach's alpha coefficient (α)	0.963	0.944	
Statistical Literacy Self-Efficacy Scale				
Confidence in statistical processes	Median (Min-Max)	32 (13-54)	52 (37-65)	**<0.001[b]**
	Mean± Standard Deviation	32.30±8.29	51.81±5.71	
	Cronbach's alpha coefficient (α)	0.918	0.883	
Belief in Statistical Reasoning	Median (Min-Max)	39 (18-58)	48 (12-56)	**<0.001[a]**
	Mean± Standard Deviation	39.27±8.28	45.36±9.17	
	Cronbach's alpha coefficient (α)	0.939	0.970	
Proficiency in basic statistical concepts	Median (Min-Max)	39 (14-65)	52 (13-59)	**<0.001[a]**
	Mean± Standard Deviation	38.93±10.23	47.30±10.59	
	Cronbach's alpha coefficient (α)	0.937	0.963	
Total Score	Median (Min-Max)	112 (71-136)	152 (80-176)	**<0.001[a]**
	Mean± Standard Deviation	110.51±13.61	144.48±22.66	
	Cronbach's alpha coefficient (α)	0.838	0.971	

[a] Wilcoxon signed-rank test, [b] Paired samples t-test

We compared the three scales and their factors between participants who had previously used AI-supported tools in their education and those who had not; for the beliefs about statistical reasoning factor of the Statistical Literacy Self-Efficacy Scale, the group-by-time interaction was statistically significant ($p = 0.024$). Participants with prior experience using AI-supported tools showed a greater increase in their post-intervention beliefs about statistical reasoning scores than those without such experience. The correlation analyses examined previous biostatistics course experience (rated from 1 = most negative to 10 = most positive) and self-efficacy in using AI-supported language models for educational purposes (rated from 1 = lowest to 10 = highest), as well as the pre- and post-intervention scores of the three scales and their factors. A statistically significant positive correlation was observed between previous biostatistics course experience and the post-intervention total score on the Statistical Literacy Self-Efficacy Scale ($r_s = 0.438$, $p = 0.011$); the post-intervention scores of the "confidence in statistical procedures" factor and "beliefs about statistical reasoning" factor ($r_s = 0.446$, $p = 0.009$; $r_s = 0.504$, $p = 0.003$, respectively).

Table 3 summarizes levels of satisfaction with the course and students' suggestions. Overall, participants evaluated the use of LLM in the biostatistics course positively, with all students reporting it as useful or very useful. After the course, one student reported having no opinion regarding their competence in using LLMs for educational purposes, whereas 23 participants (69.7%) rated themselves as competent and 9 (27.3%) as highly competent. LLMs are increasingly recognized as supportive assistants in medical school education (Hu et al., 2025; Simoni et al., 2025). Regarding the perceived advantages of using LLMs in biostatistics education, 25 participants (75.8%) highlighted their contribution to the learning process, and 26 (78.8%) emphasized their benefits in speed and practicality. This aligns with the meta-analysis by Zhang, Jantakoon & Laoha (2025), which highlighted the contribution and practicality of AI in learning (Zhang, Jantakoon & Laoha, 2025). Regarding disadvantages, 8 students (24.2%) mentioned that it might encourage overreliance or superficial learning, while 22 (66.7%) expressed concerns about information security. Only one participant indicated dissatisfaction with the course and suggested that the content should be more comprehensive. Regarding overall course satisfaction, three students (9.1%) responded "no opinion", whereas 13 (39.4%) reported being "satisfied" and 16 (48.5%) reported being "very satisfied". After the course, all students expressed willingness to use LLMs in their future educational activities. To further improve the course, 7 students (21.2%) recommended expanding the content, 6 (18.2%) suggested increasing the number of practical activities, and 4 (12.1%) proposed incorporating different LLMs and providing free access to more advanced versions. LLMs are increasingly emerging as educational assistants that students can readily access whenever they have a computer and an internet connection (Lopez-Gazpio, 2025). In line with this evidence, our study also captured students' recommendations to further integrate different AI language models into medical education and to expand opportunities for free access.

Table 3. Course Feedback and Suggestions

Course Feedback and Suggestions (n=33)	Categories	n (%)
Evaluating the use of LLM in biostatistics education	Useful	13 (39.40)
	Very useful	20 (60.60)
Self-assessment of LLM competency after the training	No opinion	1 (3.0)
	Sufficient	23 (69.70)
	Very sufficient	9 (27.30)
Student satisfaction with the biostatistics course delivered via LLM	Dissatisfied	1 (3.0)
	No opinion	3 (9.10)
	Satisfied	13 (39.40)
	Very satisfied	16 (48.50)
Willingness to use LLMs in education after the training	Likely to use	13 (39.40)
	Very likely to use	20 (60.60)

Conclusions

LLM–supported biostatistics education enhanced medical students' statistical self-efficacy and reduced statistical anxiety. LLM-assisted activities supported conceptual understanding, practical application, and engagement through interactive and feedback-rich learning experiences. Students perceived LLMs as useful and accessible educational assistants in medical education. Findings support integrating LLM-supported learning designs to promote statistical literacy and technology-enabled learning skills. Future studies should explore larger, multi-institutional, and longitudinal LLM-enhanced education models.

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Challenge-Based and Gamified Learning in Energy Market Courses: Designing Engaging Experiences for Engineering Students

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Abstract

Energy market courses require engineering students to integrate mathematical reasoning, economic interpretation, and strategic decision-making, which can make it difficult to connect abstract market mechanisms to authentic professional situations. This paper presents the design of a challenge-based and gamified learning intervention intended for future implementation in the Energy Markets course of the Bachelor's Degree in Energy Engineering at Universitat Politècnica de València. Students will work in teams and assume rotating roles as generators, retailers, consumers, flexibility providers, and regulators in a simplified electricity market. A sequence of progressively complex challenges will address day-ahead bidding, renewable-generation uncertainty, imbalance settlement, scarcity situations, and flexibility mechanisms. Team points, mastery badges, optional missions, performance feedback, and multidimensional leaderboards will be aligned with learning outcomes rather than used only as rewards. Technical calculations, strategic decisions, written justifications, and reflection activities will form part of the assessment. The planned evaluation combines participation analytics, conceptual assessments, questionnaires, student artifacts, and reflection logs. The contribution is a transferable, evidence-informed design for integrating active learning and gamification into technically demanding energy-related courses. Because the intervention has not yet been implemented, the paper discusses anticipated benefits, design risks, and the evidence required to evaluate effectiveness.

Keywords: Gamification; learning; energy; engineering; motivation.

1. Introduction

Electricity markets combine engineering constraints, economic incentives, regulation, and uncertainty. Students must perform market-clearing and settlement calculations while explaining how bidding strategies, renewable variability, demand flexibility, and scarcity affect prices and participant behavior. Although lectures and deterministic exercises introduce formal procedures, they provide limited experience of the feedback between individual decisions and system-wide outcomes. Simulation can reduce this theory–practice gap by allowing students to act as market participants, test strategies, and observe their consequences in a controlled environment (Giraldo, Kok, & Paterakis, 2022). Interactive digital support can complement these activities by providing immediate guidance during modelling and simulation, although its outputs must be technically validated and supervised by instructors. Gamification can complement simulation by making progress visible, accelerating feedback, and encouraging participation. Its educational value, however, depends on aligning game mechanics with learning outcomes rather than relying solely on points, rewards, or competition. Meta-analytic evidence reports small positive cognitive, motivational, and behavioral effects, but also substantial variation across designs and educational contexts (Sailer & Homner, 2020). Long-term evidence from engineering courses similarly suggests that initial engagement may not necessarily result in durable learning or continued voluntary participation (Bueno, et al., 2024). Challenge-based learning (CBL) provides a complementary pedagogical structure by organizing learning around authentic, open-ended problems that require knowledge application, collaboration, student agency, and reflection. Because CBL implementations in engineering differ considerably in their objectives, assessment methods, resources, and teacher roles (Doulougeri, Vermunt, Bombaerts, & Bots, 2024), the proposed intervention explicitly aligns each market challenge and game mechanic with a learning outcome and a corresponding source of assessment evidence. The need for this alignment is particularly relevant in energy education. Gamification in higher education is generally associated with favorable motivational, engagement, and academic-performance outcomes, yet its implementation and evaluation remain uneven across disciplines (Montenegro-Rueda, Fernández-Cerero, Mena-Guacas, & Reyes-Rebollo, 2023). In electrical power and energy engineering, a review of 81 game-based learning applications found that fewer than half of the educational studies evaluated learning efficacy, and that post-activity perception surveys were the most frequently used assessment method (Giraldo, Kok, & Paterakis, 2024). Consequently, an enjoyable or highly rated activity cannot, by itself, be considered evidence of conceptual learning. The authors' previous work provides a local pedagogical basis for the present proposal. One study examined the incorporation of Kahoot! and Socrative activities into an Energy Management and Planning course, illustrating how short gamified tasks can support participation and knowledge

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practice in energy-engineering education (Oná-Ayécaba, Álvarez-Piñeiro, & Álvarez-Piñeiro, 2025). A related study explored the use of ChatGPT as an interactive assistant for OpenDSS-based modelling and simulation, while emphasising the need for technical validation and instructor supervision of AI-generated responses (Oná-Ayécaba, Rodríguez-García, Alcázar-Ortega, Álvarez-Piñeiro, & Berna-Escriche, 2025). These experiences inform the selection of interactive tools and feedback mechanisms in the present design, but they do not constitute evidence that the proposed electricity-market intervention will be effective. Accordingly, this paper presents a prospective instructional design that integrates authentic electricity market challenges, team roles, progressive complexity, rapid feedback, optional missions, and structured debriefing. It specifies the intended learning outcomes, the alignment between challenge phases and assessment evidence, and a mixed-method evaluation protocol for a future classroom pilot. Because the intervention has not yet been implemented, no learning gains, motivational effects, or student perceptions are claimed. The contribution is a transparent and replicable design that can be evaluated, revised, and compared with subsequent implementations in energy-market education.

2. Pedagogical Design and Course Context

The intervention is intended for the Energy Markets course in the Bachelor's Degree in Energy Engineering at Universitat Politècnica de València. The final implementation schedule, cohort size, and contact hours will be confirmed before the teaching period. The design assumes that students have introductory knowledge of power systems, basic optimization, and spreadsheet or programming tools. The activity will complement, not replace, instruction on market rules, offer construction, uniform-price clearing, balancing settlement, and economic interpretation.

Four principles guide the proposal. First, authenticity is created through recognizable market roles and uncertain operating conditions. Second, progressive complexity begins with transparent market clearing and later introduces renewable forecast errors, imbalance costs, scarcity, storage, and demand response. Third, constructive alignment links every game element to an observable learning outcome. Fourth, structured debriefing requires students to explain why a strategy succeeded or failed. The CBL design is intentionally bounded: the instructor defines datasets, constraints, milestones, and assessment criteria, while teams retain agency over bids, portfolios, risk positions, and proposed market improvements. Students will work in teams of three or four. Roles will rotate between challenges so that each student encounters both commercial and system perspectives. Possible roles include generator, retailer or aggregator, flexible consumer, storage operator, market operator, and regulator. Role rotation also limits persistent advantages caused by a favorable initial portfolio. The instructor acts as market facilitator and technical coach, releases scenario information, monitors participation, and leads the debriefing without prescribing a single optimal strategy.

2.1. Intended learning outcomes and alignment

By the end of the proposed sequence, students should be able to construct and interpret supply and demand offers; determine clearing price, dispatch, revenues, and settlement results; explain how strategic bids influence individual and system outcomes; quantify the consequences of renewable forecast error and imbalance exposure; compare storage and demand-response strategies; and defend a market-design recommendation using technical, economic, regulatory, and social criteria. These outcomes progress from understanding and application towards analysis, evaluation, and design. They also separate the ability to obtain a numerically correct result from the ability to explain its meaning and limitations. Constructive alignment is achieved at three levels. At the task level, each market event obliges students to use the concept targeted in that round. At the evidence level, bid files and market outputs demonstrate procedural competence, whereas reports, pitches, and reflections demonstrate reasoning. At the feedback level, simulator indicators reveal immediate consequences, and the instructor's rubric addresses the quality of the explanation. Team performance will therefore never be accepted as a proxy for individual learning: a profitable portfolio can coexist with weak reasoning, and an economically unsuccessful strategy can still reveal sophisticated diagnosis and adaptation.

3. Methodology

The procedure shown in Fig. 1 follows a repeated cycle of briefing, decision, simulation, feedback, reflection, and redesign. During each briefing, teams receive the market rules, role-specific information, available assets, and an explicit deliverable. They submit bids or market-design decisions, after which a simplified platform clears the market and returns prices, dispatch, revenues, imbalance costs, and selected system indicators. Teams then interpret the results and record changes for the next round. Recoverable failure is deliberate: an unsuccessful bid becomes evidence for revising the strategy rather than merely a low score.

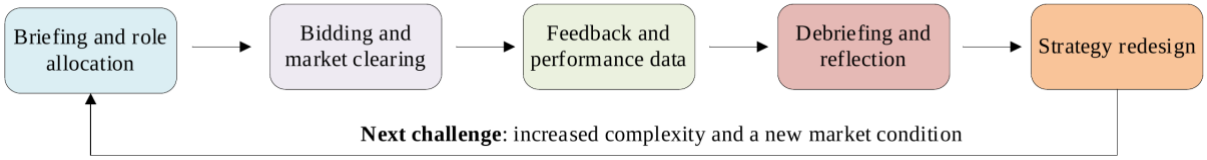


Figure 1. An iterative challenge-and-feedback cycle is proposed for the intervention.

To ensure constructive alignment, the learning activities are directly connected to observable student outputs. The evidence produced at each stage supports formative feedback and the subsequent evaluation of the proposed intervention. These relationships are summarized in Table 1.

Table 1. Proposed sequence of market challenges.

Stage	Market situation	Intended learning	Evidence
Onboarding	Tutorial market and baseline case	Interpret roles, rules, offers, and clearing	Individual diagnostic and first bid
Challenge 1	Day-ahead competition	Construct offers; calculate price, dispatch, and revenue	Bid file and annotated clearing results
Challenge 2	Renewable forecast error and balancing	Evaluate uncertainty, deviation exposure, and risk	Revised strategy and risk justification
Challenge 3	Scarcity, storage, and demand response	Compare flexibility options and distributional effects	Scenario comparison and team decision
Final challenge	Design a flexibility mechanism	Integrate technical, economic, regulatory, and social criteria	Market proposal, simulation, and short pitch
Debrief	Cross-team comparison	Explain causal links and transfer lessons	Individual reflection log

The onboarding round will establish a common technical baseline. Students will receive a small market with transparent marginal costs and no uncertainty, calculate the expected outcome manually, and then reproduce it in the simulation environment. Challenge 1 will introduce strategic offers while preserving a deterministic setting, enabling students to distinguish physical dispatch from commercial position. In Challenge 2, teams will use historical or instructor-provided data to produce a renewable energy forecast and observe how deviations are resolved. The debrief will compare aggressive and conservative bids and discuss whether revenue alone is an adequate measure of performance. Challenge 3 will add scarcity or a resource with constrained flexibility. Depending on the final course schedule, teams may operate storage, modify demand, or purchase flexibility, and will compare private benefits with system costs and reliability indicators. The final challenge will change perspective: instead of adapting to a fixed rule, teams will act as market designers. They will diagnose a limitation revealed in earlier rounds, propose a flexibility mechanism, state the expected behavioral response, and test at least one scenario. The final pitch must acknowledge trade-offs and unintended consequences. This transition from participant to designer is intended to integrate calculation, judgment, and sociotechnical reasoning.

3.1. Game mechanics and assessment logic

A shared narrative frames teams as market actors responding to an energy-system transition. The mechanics comprise immediate performance graphs, team points, mastery badges, optional bonus missions, and a multidimensional leaderboard. Points provide feedback but carry little direct weight in the course grade. The ranking will not depend exclusively on profit: it will also recognize technical correctness, risk management, quality of justification, improvement, and collaboration. Separate awards, such as best technical explanation or best risk-adjusted strategy, reduce the dominance of a single winner. Students may compare performance using anonymous team identifiers, and the instructor may suppress the public ranking if it produces counterproductive social comparison.

Table 2. Alignment of mechanics, learning purpose, and assessment evidence.

Mechanic	Pedagogical function	Safeguard	Evidence
Points and graphs	Rapid feedback on decisions	Combine profit with technical and risk criteria	Simulation logs
Mastery badges	Recognize demonstrated competence	Award only against explicit criteria	Calculation and rubric scores
Leaderboard	Support comparison and strategy discussion	Anonymous, multidimensional, and reviewable	Team indicators

Mechanic	Pedagogical function	Safeguard	Evidence
Optional missions	Encourage exploration and autonomy	Low-stakes; no grade penalty	Alternative analyses
Reflection log	Promote metacognition and transfer	Individual submission after team play	Causal explanation and redesign

Assessment will use a rubric rather than game position alone. A provisional weighting is 30% technical correctness, 25% market interpretation, 20% strategy and risk reasoning, 15% written or oral justification, and 10% individual reflection and collaboration. The rubric will be communicated before the first scored challenge. The design draws on electricity-market simulations that have successfully combined bidding, forecasting, portfolio decisions, and competitive feedback, while reporting programming experience and allocated time as practical constraints.

3.2. Implementation resources and instructor workflow

Implementation requires a market-clearing model, scenario datasets, team instructions, role cards, submission templates, the scoring rubric, and a dashboard or spreadsheet for feedback. The technical platform should export reproducible inputs and outputs to enable auditability of decisions. A low-technology spreadsheet version will be retained as a contingency for platform failure and as an accessibility option. Before the intervention, the instructor will test every scenario, define feasible strategy ranges, prepare an example calculation, and estimate the time required for submission, clearing, feedback, and debriefing.

During each round, the instructor will first confirm the relevant theory, disclose only the information appropriate to each role, and answer procedural rather than strategic questions. After clearing, teams will receive the same core indicators and a short prompt asking them to identify one expected and one unexpected outcome. The instructor will then compare representative strategies without identifying individual students, correct misconceptions, and connect observed behavior to the formal market model. A brief individual exit response will provide evidence from students who spoke less during the team discussion and will inform adjustments before the following round.

4. Planned Evaluation

The first implementation will be treated as a pilot evaluation. The research questions are: RQ1, how does the intervention affect behavioral engagement? RQ2, how do students perceive its effects on motivation, relevance, collaboration, and competition? RQ3: To what extent do student artifacts demonstrate technical understanding and higher-order reasoning? RQ4: Which design elements should be retained, modified, or removed? These questions avoid assuming effectiveness in advance. A mixed-method evidence plan will combine: (a) participation, submission, and simulator logs; (b) a short pre/post conceptual test covering price formation, settlement, uncertainty, and flexibility; (c) pre/post questionnaires using validated motivation or engagement constructs where feasible; (d) rubric-based analysis of bid files, calculations, reports, and pitches; (e) individual reflection logs; and (f) open-ended survey responses or a small focus group. Behavioral, affective, and cognitive outcomes will be analyzed separately. If historical-course data are sufficiently comparable, they may be used descriptively; they will not be treated as a causal control without equivalent teaching conditions and baseline measures.

Table 3. Planned evaluation matrix.

Question	Primary evidence	Indicator	Planned analysis
RQ1 Engagement	Attendance, submissions, platform logs	Participation, completion, punctuality, attempts	Descriptive trends across rounds
RQ2 Experience	Pre/post survey and open responses	Motivation, relevance, collaboration, competition	Change scores and thematic coding
RQ3 Learning	Concept test, bid files, reports, and reflections	Accuracy, interpretation, risk reasoning, transfer	Rubric scores, effect sizes, examples
RQ4 Revision	Focus group, teacher log, technical incidents	Useful mechanics, barriers, workload, accessibility	Triangulated design recommendations

Quantitative reporting will prioritize sample size, distributions, change scores, effect sizes, and uncertainty rather than statistical significance alone. Qualitative artifacts will be coded for the quality of causal explanation, the use of evidence, the treatment of uncertainty, and the recognition of technical-economic trade-offs. Student consent, data minimization, anonymization, and institutional requirements for educational research will be addressed prior to data collection. Participation in research instruments will be separated from grading where required. Longitudinal follow-up is desirable because engineering evidence suggests that voluntary participation and motivational effects may weaken over time, while retention benefits remain difficult to establish with small samples. The conceptual test will contain parallel pre- and post-items rather than reusing an identical sequence and

will include short explanations in addition to calculations. Two instructors will independently score a sample of artifacts to refine the rubric and examine agreement. Survey scales will be selected before implementation and reported with their sources, response formats, and internal consistency evidence. Missing survey responses will be reported rather than silently removed. Where cohort size prevents meaningful inferential analysis, the study will emphasize transparent descriptive evidence and representative student reasoning. This approach is consistent with the pilot's purpose: establishing feasibility, identifying mechanisms, and improving the design before testing stronger claims.

5. Contributions and Limitations

The expected contribution is a reusable alignment model for a technically demanding course: authentic energy-market challenges provide the task structure; gamification supplies feedback, progression, and optional competition; and debriefing connects performance with formal concepts. The proposal may promote experimentation, collaboration, and richer justification because teams must respond to uncertain outcomes rather than reproduce a predetermined solution. Evidence from higher education and engineering reports positive associations with motivation, engagement, creativity, hypothesis formation, and knowledge construction, but these findings justify hypotheses rather than claims about the present course. Several risks require active management. Prior programming or mathematical experience may produce unequal starting conditions. Market roles may have different strategic opportunities, and a profit-only ranking could reward advantageous portfolios or superficial gaming. Competition may demotivate some students, novelty may wane, self-reported enjoyment may not align with learning, and a small cohort will limit inference. The design addresses these risks through tutorials, rotating roles, common baseline datasets, multidimensional feedback, individual reflection, low-stakes mechanics, and triangulation of behavioral, affective, and cognitive evidence. Instructor workload, simulator reliability, accessibility, and the time required for debriefing must also be documented during the pilot. Transferability will depend on documenting the essential elements and those that may be adapted. The challenge cycle, alignment principles, role rotation, debriefing, and multidimensional assessment form the core design. Asset portfolios, market rules, software, session length, and the balance between competition and cooperation may be adjusted to different programs or regulatory contexts. Publishing the scenario assumptions, rubric, and evaluation instruments alongside future results would allow other instructors to judge whether the approach fits their own energy, power-system, or engineering-economics courses.

6. Conclusions

This paper has presented an evidence-informed design for combining challenge-based learning, electricity-market simulation, and carefully bounded gamification in an undergraduate Energy Markets course. The proposed sequence moves from transparent day-ahead clearing to uncertainty, balancing, scarcity, flexibility, and market redesign, while rotating professional roles and requiring technical justification after each simulation round. Its main design principle is that game mechanics should make learning progress and decision consequences visible, not replace disciplinary assessment. The intervention has not yet been implemented; consequently, its effects remain to be tested through the planned mixed-method evaluation. The pilot will provide evidence for revising the mechanics, workload, assessment rubric, and implementation protocol before wider adoption.

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Designing Micro-Credentials in Power and Energy Engineering: Short Learning Programs for Lifelong and Industry-Relevant Learning

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Abstract

Decarbonization, digitalization, and decentralization are changing the competence profile required in power and energy engineering. Degree programs provide essential foundations, but their curricular cycles may not accommodate every emerging, specialized, or practice-oriented topic at the speed required by students and working professionals. This design paper proposes a micro-credential framework for short learning programs in power and energy engineering. The framework has not yet been implemented; accordingly, the contribution reports a prospective educational design rather than learner outcomes. It combines stakeholder-informed needs analysis, constructive alignment, authentic assessment, and the European principles for transparent and quality-assured micro-credentials. Each proposed unit carries 2-3 ECTS, targets a small set of assessable learning outcomes, and uses a blended sequence of asynchronous preparation, an intensive workshop, and a workplace-relevant challenge. Three illustrative units address distribution-network modeling, energy-market fundamentals, and renewable integration in distribution grids. Units may be taken independently or stacked into a specialization. The paper specifies the intended learner profiles, credential metadata, assessment evidence, governance arrangements, and a staged evaluation protocol for a future pilot. The contribution is a transferable blueprint that energy-engineering departments can adapt while preserving institutional quality assurance and avoiding unsupported claims of employability impact before implementation.

Keywords: micro-credentials; learning; engineering; assessment; design; industry.

1. Introduction

Power and energy engineering is being reshaped by the integration of renewables, active distribution networks, flexibility, storage, electrification, and data-intensive operations. These developments create demand for professionals who can combine enduring electrical-engineering principles with knowledge of new market rules, digital tools, and operating practices. The International Energy Agency identifies the availability of skilled labor as a growing constraint on energy-system development, particularly in applied technical roles (IEA, 2025). Universities therefore face a dual responsibility: to maintain coherent degree programs and to provide timely opportunities for upskilling and reskilling. The challenge is not limited to the appearance of new technologies. Professional practice is also changing at the interfaces between traditionally separate areas. A distribution engineer may now need to interpret flexibility-market signals, evaluate the hosting capacity of a feeder, and communicate the operational implications of data-driven control. Similarly, an energy-market specialist may need sufficient network knowledge to understand why a commercially attractive schedule is not technically feasible. These combinations of competences evolve faster than the complete revision cycles of accredited degree programs. Adding every emerging topic to a compulsory curriculum would increase overload, fragment foundational learning, and risk embedding content that may soon change. The educational problem is therefore one of responsiveness without sacrificing coherence or academic depth. Conventional continuing-education courses already offer an important route for professional updating, but they do not always make the achieved competence sufficiently visible or comparable. A certificate of attendance confirms participation, whereas a micro-credential should certify that defined learning outcomes have been assessed against transparent criteria. This distinction is especially relevant in engineering, where being exposed to a software tool or technical concept does not demonstrate the ability to construct a valid model, diagnose an operating condition, or justify a decision under realistic constraints. The design of the assessment evidence is consequently as important as the selection of the subject matter. Micro-credentials are one possible response. In the European approach, learning outcomes achieved through a short learning experience are certified and should be transparent, assessed, quality-assured, portable, and, where appropriate, stackable (Council of the European Union, 2022). Their value is not simply that they are shorter than a conventional course. A credible micro-credential must communicate what the learner can do, the workload involved, how achievement was assessed, who issued the award, and how its quality can be verified (Varadarajan, Koh, & Daniel, 2023). Research, nevertheless, reports ongoing ambiguity in terminology, recognition, and implementation, as well as a need for stronger evidence of value to learners and employers (McGreal & Olcott, 2022). Short duration also creates a design constraint. A micro-credential cannot be produced

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simply by compressing a semester-long subject into fewer teaching hours. Its scope must be deliberately bounded around a professional capability that can be taught, practiced, and assessed within the advertised workload. Prerequisite knowledge must be explicit, learning activities must directly prepare learners for the required performance, and the final evidence must be meaningful outside the classroom. Stackability introduces a further requirement: independent units should connect through a coherent progression rather than form an arbitrary collection of digital badges. These conditions motivate a framework that integrates curriculum design, industry consultation, assessment, and institutional quality assurance from the outset.

This paper addresses the question: How can a university design short, stackable, and industry-relevant learning units in power and energy engineering prior to pilot implementation? Its contribution is a prospective design framework and an evaluation protocol, illustrated for three candidate units. No enrolment, completion, satisfaction, or learning-gain data are reported because delivery has not yet occurred. This boundary is important: expected benefits are design propositions to be tested, not findings.

2. Design Basis and Requirements

2.1. European and institutional basis

The design adopts the standard elements and principles of the 2022 Council Recommendation: identified learner, title, issuing body, learning outcomes, workload, level, assessment, form of participation, quality assurance, and, when relevant, stackability. The ETF(European Training Foundation) guidance further stresses the publication of assessment and quality-assurance arrangements, learner and employer feedback, accessibility, and periodic review (European Training Foundation, 2022). At UPV, micro-credentials are short university awards that certify specific competences and are generally worth fewer than 15 ECTS; they can serve students, employed professionals, and jobseekers (Universitat Politècnica de València, 2025). The proposed 2-3 ECTS size, therefore, represents a local design choice within this broader limit, not a universal definition.

2.2. Design requirements

Six requirements follow from the problem context. First, relevance must be traceable to job tasks rather than broad topic popularity. Second, outcomes must be few enough to be assessed credibly within the stated workload. Third, the learning design must accommodate heterogeneous professional experience without lowering technical expectations. Fourth, assessment must generate observable evidence of performance. Fifth, every unit must retain stand-alone value while using compatible metadata and prerequisites for stacking. Sixth, the design and subsequent claims must remain auditable through institutional quality assurance.

2.3. Intended users and value proposition

The framework distinguishes three intended learner profiles. Final-year students may use a unit to explore a specialized application that is not developed in depth within the degree. Recent graduates may use it to strengthen their transition into a particular professional role. Practicing engineers may use it to update or redirect their competence while remaining employed. The same credential can serve these groups only if the entry requirements are expressed in terms of prior capabilities rather than a single formal qualification. For example, the distribution-modeling unit would require basic three-phase power-flow concepts and spreadsheet literacy, while evidence of equivalent professional experience could satisfy the same entry condition. A short diagnostic activity would reveal gaps and recommend preparatory resources; it would not be used to unnecessarily exclude capable learners.

The value proposition also differs by stakeholder. Learners need a manageable workload, usable feedback, and evidence they can communicate to an employer. Employers need an interpretable statement of competence rather than a generic certificate of attendance. The university needs academic coherence, reliable assessment, and a sustainable review process. These interests can conflict: a highly customized company course may have immediate relevance but limited portability, whereas a broad academic course may be portable but insufficiently responsive. The proposed architecture addresses this tension by defining stable outcomes and quality criteria while allowing cases, data sets, and tool demonstrations to be updated more frequently.

3. Proposed Design Method

The proposed process is an iterative five-stage cycle shown in Figure 1. It begins with a needs diagnosis based on three sources: interviews or workshops with network operators, energy companies, and engineering consultancies; analysis of representative job tasks and professional standards; and review of gaps reported by prospective learners and teaching staff. Triangulation is intended to prevent a single employer or technology vendor from defining the curriculum.

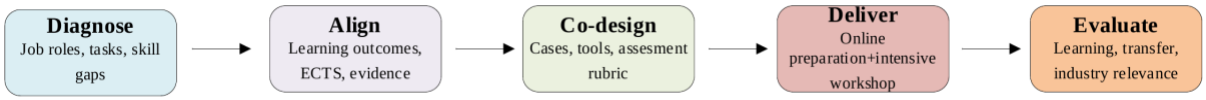


Figure 1. Prospective co-design and continuous-review cycle.

In Stage 2, each need is translated into two to four measurable learning outcomes and mapped to workload, prerequisite knowledge, and assessment evidence. Stage 3 brings instructors and industry advisers together to select realistic cases, data, and tools while preserving academic independence. Stage 4 uses a common blended pattern: guided online preparation, a short intensive workshop, and an assessed challenge. Stage 5 evaluates learning, experience, transfer, and continuing relevance. The evidence informs an annual decision on whether to retain, revise, suspend, or retire the unit. This cycle treats industry participation as an input to relevance and review, not as a substitute for academic quality assurance.

3.1. Competence-needs diagnosis

The diagnosis would use a structured workshop rather than an open request for topics. Participants would first identify job roles and recurring decisions, then describe the technical tasks and evidence of competent performance associated with those decisions. Proposed needs would be prioritised against four criteria: strategic relevance to the energy transition, frequency or consequence of the task, insufficiency of existing learning provision and feasibility within a short assessed unit. The output would be a ranked competence map with a short rationale and an identified review date. Teaching staff would then check whether each need is genuinely suitable for micro-credential delivery. Competences that require extensive mathematical foundations, long laboratory sequences, or supervised professional practice should remain in larger programs.

To reduce bias, the advisory group should include more than one type of organisation, for example a distribution system operator, an energy retailer or aggregator, an engineering consultancy and a technology provider. Learner representatives should also participate because scheduling, access to software and assumed prior knowledge influence feasibility. The university would document which recommendations were accepted, modified or rejected and why. This traceability is important when a course is marketed as industry-relevant: it provides evidence of consultation without implying that an external stakeholder controls academic content.

4. Micro-Credential Architecture

4.1. Common unit specification

Each unit is proposed as 2-3 ECTS (approximately 50-75 hours of learner workload under the conventional 25 hours per ECTS assumption). The target audience comprises final-year engineering students, recent graduates and practising engineers with the stated prerequisites. A diagnostic, ungraded entry task would direct learners to bridging resources. Delivery would combine short multimedia explanations, worked examples, tool-based exercises, live problem solving, and feedback. Accessibility would be supported through captions, downloadable materials, flexible asynchronous windows, and data sets that do not require proprietary workplace access.

A typical 2-ECTS unit could allocate approximately 14 hours to guided online preparation, 12 hours to synchronous workshops, 18 hours to the authentic challenge, and 6 hours to feedback, revision, and reflection. A 3-ECTS unit would extend the case complexity and independent analysis rather than add more recorded lectures. The intensive workshop would alternate brief explanations with model construction, interpretation, and peer critique. This distribution is provisional and would be tested through learner workload diaries. If median effort substantially exceeded the advertised workload, the design response would be to reduce scope or increase credit, not merely expect faster completion.

Table 1. Illustrative units and aligned assessment evidence.

Unit	Selected learning outcomes	Authentic evidence
Distribution Network Modelling (2 ECTS)	Build and validate a feeder model; interpret voltage and loading results; document assumptions.	Executable model, validation note, and five-minute technical briefing.
Energy Markets for Engineers (2 ECTS)	Explain market sequence; calculate settlement for a simplified portfolio; evaluate a bidding decision.	Spreadsheet or script, decision memo, and oral defense.

Renewable Integration in Distribution Grids (3 ECTS)	Assess hosting constraints, compare mitigation options, and justify a technically feasible recommendation.	Case report using a realistic feeder data set and rubric-based peer review.

The examples deliberately use accessible verbs and a tangible product. A multiple-choice quiz may assess prerequisite concepts, but it would not, by itself, demonstrate engineering performance. The final artifact should require interpretation, assumptions, uncertainty, and justification. A common analytic rubric would assess technical correctness, method selection, validation, interpretation, communication, and reproducibility. Identity verification, resubmission rules, and permitted collaboration should be specified before delivery.

4.2. Stackability and recognition

A unit should be useful independently. Stacking would add value only when the units form a coherent capability pathway. For example, the three units could contribute 7 ECTS toward a proposed specialization in Active Distribution Systems after completion of a cross-unit integration challenge. The stack would not automatically replace a degree-course component; any academic recognition would follow the applicable university rules and a documented equivalence decision. The digital record should include the EU standard metadata, a link to the assessment criteria and a verifiable issuer. These conditions reduce the risk that stackability becomes merely the accumulation of unrelated badges.

5. Planned Pilot and Evaluation

A future pilot should be staged. Phase 0 would validate the need and the prototype with an external advisory group and a small learner panel. Phase 1 would deliver one unit to a deliberately limited mixed cohort, followed by revision. Phase 2 would test the remaining units and the stack. The evaluation should answer four questions: whether the intended outcomes were achieved; whether the format was feasible and accessible; whether learners transferred the competence to a new problem or workplace task; and whether employers considered the evidence interpretable and relevant.

5.1 Pilot recruitment and delivery

The first cohort should be small enough to permit observation and detailed feedback, but recruitment should intentionally represent the proposed audiences. The call should state prerequisites, workload, delivery mode, assessment requirements, and the experimental status of the offer. Selection, if demand exceeds capacity, should use transparent criteria and avoid allowing a single partner company to dominate the cohort. Before teaching begins, assessors would calibrate the rubric by independently rating two sample artefacts and discussing discrepancies. Learners would receive the same rubric and an anonymized model extract so that quality expectations are visible without prescribing one solution.

During delivery, the teaching team would record participation, support incidents, software or data-access problems, and deviations from the planned schedule. A midpoint check would allow operational corrections that do not change the assessed outcomes. After submission, two assessors would double-mark a sample of artefacts to examine consistency. Learners not yet meeting the competence threshold would receive targeted feedback and one defined opportunity to revise. The credential would be issued only after the evidence met every essential rubric criterion; attendance alone would not be sufficient.

Table 2. Proposed evaluation matrix; all indicators are future measures.

Dimension	Indicator and evidence	Decision use
Reach and feasibility	Applications, learner profile, attendance, completion, workload diary, and support requests.	Adjust access, schedule, prerequisites, and workload.
Learning	Pre/post concept test; rubric scores; performance on an unseen transfer task; inter-rater agreement.	Revise outcomes, activities, rubric, and assessor calibration.
Experience and inclusion	Short survey plus interviews; accessibility issues; reasons for withdrawal.	Improve delivery, resources, and learner support.
Industry relevance	Structured review of artefacts and outcomes by advisers; 3-6 month learner/supervisor follow-up where feasible.	Retain, update or retire content; qualify claims about transfer.

Descriptive statistics would summarise participation, completion, and rubric performance. Pre/post comparisons should report effect estimates and uncertainty rather than rely only on statistical significance, particularly for a small pilot. Qualitative responses would be coded against predefined themes (relevance, usability, workload, transfer and barriers) while remaining open to emergent issues. Mixed-cohort results should be disaggregated cautiously by prior experience, with no inferential claims when group sizes are inadequate. Ethics review, informed

consent and data protection procedures would be confirmed before collecting research data. Course quality monitoring and research participation must be distinguishable so that declining research consent does not affect access to learning.

5.2 Success criteria and revision decisions

Before the pilot, the team should approve decision rules rather than interpret every result retrospectively. A unit would be considered ready for a broader second delivery only if the assessment evidence supports attainment of the core outcomes, observed workload is compatible with the assigned ECTS, no unresolved accessibility barrier prevents participation and external reviewers judge the resulting artefacts to be interpretable. These criteria need not be reduced to a single pass percentage. A unit might show strong learning but excessive workload, or feasible delivery but weak transfer to an unseen problem; each pattern implies a different revision. The review record should therefore link each finding to an action, an owner and a target date.

Claims would be released in stages. After the first pilot, defensible statements may concern feasibility, participant experience and demonstrated performance within the course. Evidence from an unseen task may support a cautious claim of near transfer. Claims about workplace application would require follow-up evidence, ideally from both learners and supervisors, while employability or career progression would require longer observation and a design capable of addressing alternative explanations. This hierarchy prevents marketing language from moving ahead of the evidence.

6. Discussion

The proposal offers three advantages. First, it links agility to explicit learning outcomes and assessment, so short duration does not mean low rigor. Second, it creates a common architecture while permitting fast revision of cases and data. Third, it embeds the evidence needed to decide whether a unit should scale. Previous engineering examples likewise position micro-credentials as complements to degree education and use industry input to shape practice-oriented learning (Richert, Marshall, & James, 2024), (Eager & Cook, 2020). The present framework complements semester-long education: foundational theory remains in degree programs, whereas bounded and changing applications can be addressed through short units.

Several risks require active management. Industry relevance can become vendor dependence or excessively narrow training; using multiple advisers and retaining academic control mitigates this risk. A heterogeneous cohort can enrich peer learning but may generate unequal starting points; transparent prerequisites and bridging resources are therefore necessary. Stackability may be misunderstood as automatic credit recognition, so the distinction must be communicated clearly. Workload estimates may also be optimistic until tested through diaries and completion data. Finally, neither enrolment nor satisfaction demonstrates employability. Claims about workplace transfer or career benefit require longitudinal evidence and appropriate comparisons, which may be beyond the scope of the first pilot.

The framework is intentionally transferable, but the illustrative units reflect the UPV and European context. Regulatory fit, credit conventions, labor-market needs, and available software may differ elsewhere. The paper also does not claim that the selected three topics are the highest-priority gaps; that judgment is reserved for the proposed stakeholder diagnosis. These limitations define the next empirical step rather than weaken the design contribution.

7. Conclusions

This paper has presented a prospective framework for designing micro-credentials in power and energy engineering. Its central proposition is that credible short learning depends on traceability: from an evidenced need for competence to measurable outcomes, aligned activities, authentic assessment, transparent metadata, and periodic review. Three illustrative 2-3 ECTS units show how the architecture could support stand-alone learning and a coherent stack. Because the proposal has not yet been implemented, the paper deliberately reports no learner or employer results. The next step is a staged pilot beginning with needs validation and one prototype unit, followed by evaluation of learning, feasibility, inclusion, transfer, and relevance. This approach allows future claims to be proportionate to evidence while offering universities a practical route to responsive lifelong learning.

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The Invisible Barrier in Educational Gamification: From Hand-Holding to Cognitive Mastery

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Abstract

Contemporary digital learning environments are frequently designed to keep learners moving forward without friction. Errors are corrected instantly, layered hints resolve every impasse, and retries carry no cost. This study argues that such excessive guidance, commonly described as hand-holding, removes the very cognitive effort in which learning takes place. Following the first phase of a design-based research cycle, namely analysis and exploration, the study pursues two questions: through which mechanisms do current gamification designs reduce learner effort, and on which principles should a design that preserves productive difficulty be built. Two data sources were used: a review of the core literature on help and help-seeking, and a document analysis of six widely used learning platforms along two criteria, learner decision latitude and cognitive demand. The review identifies four documented barriers: immediate correction, layered hints, gaming the system, and help dependency. The platform analysis shows that none of the six environments systematically withdraws support as competence grows, and that only one of them combines conventional gamification elements with medium-to-high learner decision latitude. Drawing on the zone of proximal development, desirable difficulties and flow theory, four design principles are proposed: fading guidance, a hint economy, error comfort with strategy-level feedback, and dynamic difficulty adjustment. The paper addresses the minimal-guidance critique, arguing for expertise-sensitive withdrawal rather than removal of guidance, and specifies safeguards and early-warning indicators for learners with low self-regulation capacity. Empirical validation is identified as the next phase.

Keywords: gamification, hand-holding, gaming the system, desirable difficulties, scaffolding and fading, self-regulated learning

Introduction

Gamification is commonly defined as the use of game design elements in non-game contexts (Deterding et al., 2011). Its adoption in education has been driven by the promise of sustained engagement, yet the empirical record is more qualified than the promise. Hamari et al. (2014) report predominantly positive but strongly context-dependent outcomes, and the meta-analysis by Sailer and Homner (2020) finds small but significant effects whose magnitude depends largely on design choices. The relevant question is therefore not whether gamification works, but which design choices make it work. This study focuses on one such choice: how much guidance the system provides, and whether that amount ever changes.

Many digital learning platforms are optimised for metrics that can be measured and reported, such as completion rates, daily active users and uninterrupted streaks. The most direct way to improve these metrics is to prevent the learner from becoming stuck. Errors are corrected before they can be reconsidered, hints resolve impasses on demand, and unlimited retries remove the cost of a decision. Each mechanism is defensible in isolation; taken together they absorb difficulty before it reaches the learner. This is a specific case of cognitive offloading, in which transferring mental work to an external tool can improve immediate performance while weakening the capability that the tool replaces (Risko & Gilbert, 2016). The learner reaches the goal without constructing the knowledge that leads to it.

The study addresses two research questions. RQ1: Through which mechanisms do current gamification designs reduce learner cognitive effort? RQ2: On which principles should a design that preserves productive difficulty be built? RQ1 is addressed through a review of the core literature and a document analysis of existing platforms; RQ2 through theoretical synthesis.

Methodology

The study adopts a design-based research (DBR) orientation. McKenney and Reeves (2018) describe the core processes of DBR as analysis and exploration, design and construction, and evaluation and reflection, with implementation and spread considered throughout. The present work is confined to the first of these phases: it analyses the problem and derives theoretically grounded design principles. Implementation and empirical testing

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lie outside its scope, and the study should therefore be read as a theoretical synthesis producing initial design propositions rather than as a completed DBR study.

Two data sources were used. The first was a review of theoretical and empirical work directly addressing the effects of help on learning. This review was not conducted according to systematic review criteria; it followed the core literature that defines the problem, and the four barriers summarised in Table 1 emerged from that reading. The second was a document analysis of the help flows offered by six widely used digital learning platforms, selected by criterion sampling on the basis of adoption, visibility of the help mechanism and diversity of learning domain. The platforms were examined between April and July 2026. Two criteria structured the analysis. Learner decision latitude refers to the freedom to determine task order, solution path and the timing of help. Cognitive demand refers to the number of inferences and decisions the learner must make independently in order to reach a correct solution. Each criterion was rated qualitatively as low, medium or high, with intermediate ratings (e.g. low to medium) used where a platform fell between two levels. The presence of competence-sensitive fading of support was recorded separately as none, partial or on request.

Results

Barriers Documented in the Literature

The effects of excessive guidance are not discussed in the literature under a single heading but across four separate lines of research. Table 1 brings them together, showing for each barrier its counterpart in the design, its effect on learning, and its principal source.

Table 1. Four documented barriers arising from excessive guidance.

Barrier	Counterpart in the design	Effect on learning	Key source
Immediate correction	The error is repaired before the learner can reconsider it	Retrieval practice is eliminated; desirable difficulty cannot arise	Bjork (1994); Bjork & Bjork (2011)
Layered hints	The final hint level discloses the solution directly	The system rewards clicking rather than cognitive effort	Aleven et al. (2016)
Gaming the system	The learner answers incorrectly on purpose or exhausts hints to reach the solution	Visible success becomes decoupled from actual learning	Baker et al. (2008)
Help dependency	The level of support does not decrease as competence grows	Overuse of help is linked to poorer learning; guidance no longer needed becomes counterproductive	Roll et al. (2014); Kalyuga et al. (2003)

Although the four barriers originate in different traditions, they converge on a single outcome: the learner completes the task without learning the path to its completion. Aleven et al. (2016) capture the underlying pattern in their review of help-seeking in intelligent tutoring systems, concluding that on-demand help supports learning, but only to a limited extent, and that its value depends on how and when learners use it. Koedinger and Aleven (2007) formalise the design tension as the assistance dilemma: the question of when a system should provide information and when it should require the learner to generate it. They argue that the dilemma has no universal solution, since the optimal level of assistance varies with prior knowledge. The position advanced here is not that the dilemma can be resolved, but that the balance must be renegotiated as competence grows.

Platform Analysis

Table 2 summarises the six platforms along the two criteria described above.

Table 2. Six digital learning platforms by learner decision latitude and cognitive demand.

Platform	Decision latitude	Cognitive demand	Fading of support
Duolingo	Low	Low	None
Khan Academy	Medium	Low to medium	Partial
Codecademy	Low	Low	None
Kahoot!	Low	Low	None
Brilliant	Medium to high	Medium to high	Partial
Scratch	High	High	On request

Note. Ratings reflect a qualitative assessment of the free learner-facing flows by a single rater and are not measured values. Platform interfaces are updated frequently, so the findings are specific to the period of analysis.

Three patterns are visible. First, four of the six platforms (Duolingo, Codecademy, Kahoot! and, to a lesser extent, Khan Academy) combine low decision latitude with low cognitive demand. This is consistent with, although it does not demonstrate, a design logic shaped by engagement and retention metrics rather than by pedagogy. Second, and most striking, none of the six environments contains a mechanism that systematically withdraws support as the learner becomes more competent; where partial fading occurs it is a by-product of content type rather than a designed progression. Third, an observation outside the two rating criteria concerns gamification elements. Scratch, the environment granting the most autonomy, offers no points, badges or levels, whereas Brilliant combines medium-to-high autonomy with experience points and weekly leagues earned by completing lessons and solving problems. Gamification and learner autonomy are therefore not mutually exclusive, yet even in Brilliant the reward structure tracks completed activity rather than growing independence from support. The framework proposed below addresses this gap.

Proposed Design Principles

Three theoretical positions converge on the same conclusion. Vygotsky (1978) locates learning in the zone of proximal development, where support is by definition temporary; Wood et al. (1976) describe scaffolding in the same terms. Bjork (1994) shows that certain conditions that depress immediate performance improve long-term retention and transfer. Csikszentmihalyi (1990) places learning in a narrow channel between challenge and skill. Taken together, difficulty appears not as a defect to be removed but as a design variable to be calibrated. Four principles follow.

Fading guidance. The system should offer progressively less direction as skill increases: hint levels, explanatory messages and feedback frequency are thinned over time. The rationale is not only theoretical. Kalyuga et al. (2003) demonstrate the expertise reversal effect, in which detailed guidance that benefits novices becomes actively detrimental as learners gain expertise, because comparing redundant explanations with an existing schema consumes resources. Renkl and Atkinson (2003) accordingly recommend a graduated rather than abrupt transition from worked examples to independent problem solving. Fading is thus a requirement derived from cognitive load theory itself, not a position against it.

A hint economy. Removing help entirely is not realistic for novices. Help is instead treated as a resource that is limited, costly and strategically allocated: each learner receives a finite number of hints, and once these are exhausted either independent work resumes or a time lock delays the next hint. The principal gain is not deterrence of gaming behaviour but the transfer of the help decision to the learner, which supports the basic need for autonomy described by Ryan and Deci (2000).

Error comfort and strategy-level feedback. Errors should be framed as a necessary part of the learning cycle rather than as a penalty. The type of feedback that follows an error is decisive here. Hattie and Timperley (2007) distinguish task-level feedback, which reports the correct answer, from process and self-regulation feedback, which addresses strategy, and argue that these differ in their effects on learning. Shute (2008) likewise recommends elaborated feedback that guides the learner over feedback that simply supplies the correct answer. The principle is therefore not the removal of feedback but the replacement of answer-disclosing feedback with feedback that redirects the learner towards a different strategy.

Dynamic difficulty adjustment. The system should monitor performance in real time and calibrate difficulty so that the learner remains in the challenging channel. Following Csikszentmihalyi (1990), difficulty exceeding skill produces anxiety while skill exceeding difficulty produces boredom; both reduce engagement. This principle should be read as the feasibility condition of the other three: reducing help is pedagogically defensible only where difficulty is calibrated to the individual learner.

Discussion

The contribution of this study is threefold. First, it brings together four lines of research that are usually treated separately (desirable difficulties, help-seeking in intelligent tutoring systems, gaming the system and the expertise reversal effect) and frames their common outcome as a design problem rather than a learner deficit. Second, it shifts the gamification debate from whether game elements work to how the level of support should change over time, a dimension that the platform analysis found to be largely absent from current practice. Third, it translates these positions into four design principles with explicit boundary conditions, which can serve as testable propositions in the subsequent phases of the DBR cycle.

The Minimal-Guidance Objection

The strongest objection to this framework was formulated by Kirschner et al. (2006), who argue that instruction based on minimal guidance produces weaker outcomes than direct instruction, particularly for novices. Their rationale rests on cognitive architecture: working memory is limited (Sweller, 1988), and a learner without the relevant schemas spends much of that capacity searching rather than learning. Two responses are offered. First, what is proposed here is not the removal of guidance but its expertise-sensitive withdrawal. Kirschner et al. defend strong guidance for novices; Kalyuga et al. (2003) show, within the same theoretical framework, that the same guidance becomes harmful as learners advance. Read together, the two positions produce precisely the fading principle. Second, the mechanisms criticised here are not instructional explanations but rescue mechanisms that substitute for the learner's cognitive effort. Explaining a concept supports schema formation; disclosing the answer after three failed attempts eliminates retrieval practice. Desirable difficulty does not require learners to invent what they do not know; it requires them to retrieve, effortfully, what they do (Bjork & Bjork, 2011).

Learners with Low Self-Regulation Capacity

Difficulty is not experienced uniformly. For learners with low prior knowledge, high anxiety or additional support needs, what is a desirable difficulty for an experienced learner may become an insurmountable barrier. Two boundary conditions are therefore stipulated. Accessibility provisions such as extended time, screen-reader compatibility and alternative input methods are not pedagogical hints and are never subject to the hint economy (Rose & Meyer, 2002). Beyond this, learners should be able to select their own difficulty level, which reframes making a task easier as a metacognitive decision rather than an admission of failure.

The most practically critical case is the learner with low self-regulation capacity. Zimmerman (2002) characterises self-regulated learning as a cyclical and teachable competence rather than a fixed trait; for a learner who lacks it, difficulty presents not as a problem to be solved but as an undefined starting point. The trajectory of this risk is documented. D'Mello and Graesser (2012) show that affective states during complex learning tend to follow a sequence in which unresolved confusion can turn into frustration and, if frustration persists, into boredom, a state associated with disengagement. Baker et al. (2010) similarly found boredom, rather than frustration, to be the more persistent state and the one associated with gaming the system. The design goal is therefore not to prevent frustration but to prevent it from turning into disengagement.

Three safeguards are added to the framework accordingly. The first is bidirectional calibration: dynamic difficulty adjustment must also operate downwards, suspending the hint restriction and lowering difficulty once consecutive failures exceed a threshold. The second is a consolidation phase following struggle. Kapur (2016) distinguishes productive failure, in which learners' own solution attempts are followed by a consolidation phase with structured instruction, from unproductive failure, in which struggle does not lead to learning. The third is the explicit teaching of self-regulation. Aleven et al. (2003) show that help-seeking is a skill requiring deliberate support rather than an ability that develops spontaneously, and Roll et al. (2011) show that metacognitive feedback can improve help-seeking behaviour, with gains that persisted after the support was removed. The hint economy should therefore be presented together with visible guidance on when and why to seek help, and the number of hints should vary with the learner's current competence rather than being fixed. In addition, early-warning indicators such as consecutive failed attempts, unusually long time on a single task, task abandonment and shortening session length can trigger an increase in support before disengagement occurs.

Conclusions

The invisible barrier in educational gamification is neither a technical shortcoming nor a deficit of learner motivation. It arises from the designer's reflex to protect learners from difficulty, trading long-term cognitive growth for short-term satisfaction. The framework proposed here, comprising fading guidance, a hint economy, error comfort with strategy-level feedback and dynamic difficulty adjustment, treats learning as the construction of capability rather than the transfer of content.

For the framework to become testable, measurable indicators are required. The next phases of the DBR cycle will examine change over time in hint usage frequency, mean latency before a help request, the incidence of gaming behaviour, delayed post-test performance and transfer to a different context, together with the disengagement indicators noted above. Process and outcome measures must be tracked jointly, since evaluation based on immediate performance alone systematically conceals the benefit of desirable difficulties (Bjork & Bjork, 2011).

Several limitations should be noted. The study contains no empirical data; the effects of the four principles on learning outcomes have not been tested. The comparative analysis is qualitative and based on a single rater, so inter-rater agreement is required to establish reliability. The platforms were examined through their learner-facing

flows; teacher-mediated classroom use, the typical setting for Kahoot!, was not examined. Finally, how the proposed mechanics should vary by learner age and subject domain was not addressed.

Declaration of Generative AI Use: Generative AI and research assistance tools (Claude and Google NotebookLM) were used to assist with language editing, text fluency, translation, and identifying supplementary literature following the initial drafting to enrich the references. All candidate references suggested through these tools were subsequently accessed in their original form, critically reviewed, and evaluated for relevance by the author prior to inclusion. The author takes full responsibility for the content and academic integrity of the final manuscript.

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A Comparative Conceptual Analysis of AI Literacy Frameworks and Their Synthesis in the Context of Teacher Education

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Abstract

Artificial intelligence (AI) literacy is now defined in several parallel documents produced on different institutional and epistemological grounds. This study compares six such documents through descriptive-analytical document analysis: three constitutive frameworks (UNESCO, 2024; DigComp 3.0, Cosgrove & Cachia, 2025; Long & Magerko, 2020), two regulatory and policy texts (European Union, 2024; OECD & European Union, 2026) and one national guideline (Council of Higher Education, 2024). Units of meaning were coded deductively against four analytical axes adapted from Ng et al. (2021), and four literature-informed needs were then checked against every document. The documents converge strongly on ethics and critical thinking but diverge sharply by addressee, and pedagogical integration is central in only one of them. A gap matrix intersecting the six documents with these four needs shows that only five of twenty-four cells are partially filled: domain-specific integration, real-time classroom decision-making, affective readiness and cultural adaptation remain largely unaddressed. The gap stems not from the documents being outdated but from the divergence of their addressees and their level of abstraction. A three-layer structure for teacher education is proposed as an implication.

Keywords: AI literacy, teacher education, competency frameworks, document analysis, TPACK

Introduction

AI literacy has matured rapidly. Long and Magerko (2020) produced the first systematic conceptualisation, defining it as a set of competencies enabling individuals to critically evaluate AI, communicate with it and use it as a tool online, at home and at work. Ng et al. (2021) then made the concept educationally operational through a four-dimensional classification. Since 2024, however, the field has moved beyond academic conceptualisation onto regulatory ground: Article 4 of the EU AI Act required organisations to ensure a sufficient level of AI literacy among staff using AI systems on their behalf (European Union, 2024), a duty recast in 2026 as an obligation to take supporting measures (European Union, 2026), and the AILit Framework was developed jointly by the European Commission and the OECD to inform the innovative domain of PISA 2029 (OECD & European Union, 2026).

The concept matured further through measurement work. Wang et al. (2023) developed a scale around awareness, use, evaluation and ethics; Carolus et al. (2023) added psychological meta-competencies such as emotion regulation and self-management. With the spread of generative systems, Bozkurt (2024) placed generative AI literacy on the agenda as a distinct requirement and opened it to discussion from a critical pedagogy perspective. In the Turkish literature, however, the effort has concentrated on adapting international scales (Polatgil & Güler, 2023; Balıkçı & Yıldız Durak, 2025) and on describing proficiency levels, rather than on comparing the defining documents themselves.

This plurality enriches the field conceptually but produces a fragmentation problem for curriculum developers (Ng et al., 2021). The argument of this paper is that the source of that fragmentation is not the number of definitions but their addressees. Each document speaks to a different subject and therefore answers a different question; consequently the documents are not alternatives to one another, yet none can substitute for another.

This matters most in teacher education. The teacher is both a user of these tools and the actor who shapes learners' AI literacy; as UNESCO (2024) notes, the classical teacher-student relation is becoming a teacher-AI-student dynamic. Evidence from Türkiye further shows that AI anxiety is a salient variable among pre-service teachers (Ayduğ & Altınpulluk, 2025; Demir & Çelebi, 2025), indicating that readiness is affective as well as cognitive. Comparative work exists, but it has typically consolidated frameworks into a single comprehensive model (e.g., Chiu et al., 2024) rather than asking whom each document addresses; syntheses linking the documents to teacher education, and analyses that include both the final AILit Framework and the amended Article 4, remain scarce. Accordingly, this study asks: (1) On which dimensions do the documents converge and diverge? (2) Which needs are left unmet by all of them? (3) What structure for teacher education follows from these answers?

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Methodology

The study was designed as a descriptive-analytical document analysis within the qualitative tradition. Six documents were selected purposively against three criteria: global or national recognition, diversity of institutional and academic representation, and relevance to teacher education. DigCompEdu (Redecker, 2017) was excluded because it is a general digital competence framework containing no dedicated AI competence area; the DigComp family is therefore represented by version 3.0, in which AI competence is integrated transversally (Cosgrove & Cachia, 2025). UNESCO's companion framework for students was also excluded, since the learner addressee is already represented by AILit, which additionally anchors an international assessment.

Because the six texts differ in kind, treating them as equivalent units would compromise comparative validity. They were therefore sorted into three groups: constitutive frameworks (UNESCO, 2024; DigComp 3.0; Long & Magerko, 2020), regulatory and policy texts (EU AI Act; AILit) and the national context (Council of Higher Education, 2024). The first group carries the comparison; the other two serve as reference points against which it is assessed.

Primary full texts were read holistically and segmented into units of meaning. Coding proceeded in two stages. Deductively, units were assigned to four analytical axes adapted from Ng et al. (2021), who distinguish knowing and understanding, using and applying, evaluating and creating, and ethics: the first two were merged into technical competence, evaluating and creating was operationalised as critical thinking, ethics was retained, and pedagogical integration was added because the study concerns teacher education. In the second stage, four needs were drawn from the teacher education literature (Mishra & Koehler, 2006; Carolus et al., 2023; Demir & Çelebi, 2025), since an absence cannot be coded directly from document units, and each document was searched for units addressing them. Cells were coded as met, partially met or unmet, where *partially* denotes that a need is named but not tied to a functional architecture. Only primary texts were used and coding was repeated at intervals; as the analysis was conducted by a single coder, intercoder reliability could not be computed.

Results

Profiles of the Six Documents

Each document is summarised below in terms of why it emerged and what it argues, since these two questions account for most of the divergence reported in the following sections.

UNESCO (2024). The framework continues a position held since the 2019 Beijing Consensus and made operational by the spread of generative AI. Its diagnosis is that few countries had defined the competencies teachers need or built national programmes to develop them. Its deeper concern, however, is not that teachers cannot use AI but that they may use it excessively, delegating data-informed pedagogical decisions to the system and losing professional competence. Structurally it crosses five competence areas with three developmental levels (acquire, deepen, create), yielding fifteen competence blocks.

DigComp 3.0 (2025). Digital literacy a decade ago was largely defined by operational skills such as searching, handling files and sending e-mail. As algorithmic systems entered everyday decision-making, that definition became insufficient. Version 2.2 accommodated AI mainly through added examples (Vuorikari & Holmes, 2022), whereas version 3.0 retains the overall structure while integrating AI competence transversally across the framework and adding a learning outcomes section (Cosgrove & Cachia, 2025). Its addressee, however, remains the citizen.

Long and Magerko (2020). Before 2020, AI education was largely equated with programming and advanced mathematics, which formed an entry barrier for non-technical audiences. Synthesising a literature scattered across disciplines, the authors removed that barrier and defined the concept functionally through seventeen core competencies under five themes, together with design considerations for educators. Their definition explicitly covers everyday life, so the addressee is the non-technical public rather than the learner alone; what distinguishes the text from DigComp is not its audience but its genre, being a conceptual definition rather than a policy instrument.

EU AI Act (2024). The Act responds to two gaps: AI systems had entered organisational processes without any obligation regarding the competence of the staff operating them, and individuals had no protected right to know the origin of the text or image before them. Article 4, applicable since February 2025, originally required providers and deployers to ensure a sufficient level of AI literacy among staff acting on their behalf. The Digital Omnibus on AI, in force since July 2026, rewrote the article as a duty to take measures supporting the development of AI literacy and removed any guaranteed level (European Union, 2026). The transparency obligations of Article 50

became applicable in August 2026, requiring machine-readable marking of AI-generated content. The Act has thus moved further away from, rather than closer to, defining what AI literacy means for teaching.

AILit (2026). Use had outpaced guidance: a large share of young people were already using AI tools without any guidance on how these systems work or where they fail, and the innovative domain of PISA 2029 required the construct to be defined before it could be assessed. The framework defines nineteen competencies across four domains (engaging with AI, creating with AI, managing AI and shaping AI), relating each to knowledge, skills and attitudes. Positioning attitude on a par with knowledge and skills is notable for the affective gap reported below, yet the addressee is the school student.

CoHE Guideline (2024). Generative AI entered academic production rapidly, placing research integrity at risk. The guideline, distributed to higher education institutions in May 2024, rests on transparency, honesty, diligence, fairness, confidentiality and accountability. Its position is that AI may be used but responsibility remains human and use must be declared. Its scope is deliberately limited to research and publication; the teaching dimension is left to institutions to regulate themselves.

Divergence by Addressee

Table 1 shows that differences among the documents derive largely from a single variable. The same concept is defined for six different subjects, and what each document seeks to protect follows from that choice. All six protect something legitimate; none protects the same thing.

Table 1. Addressee, protected value and pedagogical integration across the six documents

Document	Addressee	What it seeks to protect	Pedagogical integration
UNESCO (2024)	Teacher	Professional competence and pedagogical judgement	Explicit and central
DigComp 3.0 (2025)	Citizen	Citizens' awareness and control over their data	Absent (deferred to DigCompEdu)
Long & Magerko (2020)	Non-technical public	The concept itself; opening the black box	General, learner-centred
EU AI Act (2024)	Organisation	The right to know the source; accountability	Out of scope
AILit (2026)	School student	The move from passive consumer to agent	Scenario level
CoHE Guideline (2024)	Researcher	Research integrity; responsibility remaining human	Out of scope

Note. CoHE = Council of Higher Education (Türkiye).

The decisive column is the last. Pedagogical integration is central in UNESCO (2024) alone. DigComp defers it explicitly, the AI Act and the national guideline place it out of scope, AILit addresses it at the level of learning scenarios, and Long and Magerko treat pedagogy as learner-centred design rather than as a professional matter. No document takes as its primary concern how a teacher is to teach this content.

Convergence and Divergence on Four Axes

On technical competence all six require an understanding of how AI operates, but depth diverges, and it does so in a striking inversion: the most detailed technical treatment is found in Long and Magerko (2020), the document furthest from the teacher, while UNESCO (2024) keeps technical knowledge instrumental to pedagogical purpose. On ethics convergence is strong, yet the grounding differs: human rights and agency in UNESCO, citizen safety in DigComp, individual critical appraisal in Long and Magerko, legal compliance in the AI Act, responsibility and agency in AILit, and research integrity in the national guideline. Critical thinking is the most consistently shared axis: it appears in all six documents and, unlike ethics, is not grounded in divergent rationales. Pedagogical integration, as shown above, is the sharpest divergence.

One observation is worth emphasising. DigComp 3.0 integrates AI competence transversally across the whole framework, and AILit was shaped by consultation with more than 2,000 stakeholders; yet neither alters the pattern, because both retain addressees other than the teacher. The gap therefore does not stem from the documents being outdated.

The Gap Matrix

Intersecting the four literature-informed needs with the six documents yields the matrix in Table 2. Of twenty-four analytical cells, only five are partially filled and none is fully met.

Table 2. Gap matrix: distribution of unmet needs across the six documents

Need	UNESCO	DigComp	Long & M.	AI Act	AILit	CoHE
Domain-specific integration (TPACK)	Partial	Absent	Absent	Absent	Absent	Absent
Real-time classroom decision-making	Partial	Absent	Absent	Absent	Absent	Absent
Affective readiness and AI anxiety	Absent	Absent	Absent	Absent	Partial	Absent
Cultural and local adaptation	Partial	Absent	Absent	Absent	Absent	Partial

Note. Partial = the need is named but not tied to a functional architecture; Absent = the need is not addressed.

The first need concerns technological pedagogical content knowledge (Mishra & Koehler, 2006). The documents treat AI in a largely content-agnostic manner, whereas the way a mathematics teacher integrates AI differs epistemologically from the way a literature teacher does. UNESCO includes pedagogy but offers no detailed architecture for domain-specific use, hence the partial code. The second concerns the moment of decision: competence lists exist, but functional guidance for how a teacher responds to an erroneous output mid-lesson does not. The third is affective. Carolus et al. (2023) show that psychological meta-competencies such as emotion regulation are critical, and Turkish evidence identifies AI anxiety among pre-service teachers (Demir & Çelebi, 2025); the sole partial response comes from AILit, and at student level. The fourth concerns cultural adaptation: the five international texts were produced in Western institutional contexts, and the national guideline, while local, is confined to research ethics.

Discussion

Six documents, six different concerns, and none centred on the pedagogical task of the teacher. Addressee explains most of this pattern but not all of it: UNESCO (2024) does take the teacher as its subject and still meets three of the four needs only partially. A second factor is level of abstraction, since a global framework written for very different education systems cannot specify subject-level practice, real-time decisions or local adaptation without ceasing to be global. Because the gap follows from addressee and abstraction rather than from obsolescence, it cannot be closed by merging definitions into a single comprehensive model (cf. Chiu et al., 2024); it requires a synthesis that takes the teacher as its subject and operates at programme level.

The implication for teacher education is that the documents should be treated as complementary rather than competing, each functional at a different stage of preparation. Foundational AI literacy, drawing on Long and Magerko (2020) and DigComp 3.0, belongs in a faculty-wide course, built by redesigning the existing instructional technology course rather than adding a new one; pedagogical integration, combining UNESCO (2024) with TPACK, belongs in subject-specific methods courses, since where AI helps and where it does not can only be answered within a discipline's own epistemology; and critical, affective and cultural adaptation belongs in the teaching practicum. Such a structure therefore rearranges existing provision rather than adding new course load.

The scalability of such a structure depends on a constraint that is easily overlooked: the readiness of the teacher educators expected to deliver it. Uerz et al. (2018) show that the competences of teacher educators in teaching with technology are underdeveloped in many contexts, and Foulger et al. (2017) responded by defining a dedicated set of technology competencies for this group. Ertmer and Ottenbreit-Leftwich (2010) further indicate that the principal barrier is self-efficacy, beliefs and institutional culture rather than knowledge, which suggests that the affective dimension identified above applies recursively to faculty. The constraint is manageable if readiness expectations are differentiated by layer: expertise at the creation level is required only of the small specialist group delivering the first layer, whereas subject educators need pedagogical judgement within their own field, supported through paired work with a technology specialist. Because one-off seminars do not meet the content focus, duration and collective participation features of effective professional development (Desimone, 2009; Tondeur et al., 2012), a cross-disciplinary community of practice is the more appropriate vehicle. Specifying these requirements and a phased implementation pathway is left to further work.

Conclusions

AI literacy documents diverge chiefly by addressee, pedagogical integration is central in only one of them, and domain-specific integration, real-time classroom decision-making, affective readiness and cultural adaptation remain largely unmet. Reading the frameworks as complementary layers of teacher preparation, rather than as competing definitions, allows teacher education to use them now instead of waiting for a single teacher-specific standard.

Two limitations should be noted. The analysis rests on six purposively selected documents and was conducted by a single coder, so the partial codes in Table 2 are interpretive; legal texts may also change, as Article 4 did during the study. The proposed structure is conceptual and has not been empirically validated; testing it with teacher educators across subject areas is the next step.

Declaration of Generative AI Use: Generative AI tools (Anthropic Claude) were utilized to identify updated framework versions and supplementary regulatory texts beyond the initial scope of the study, and to assist with English translation and stylistic refinement. All primary documents were independently retrieved, examined, analyzed, and synthesized by the author, who retains full intellectual and scientific responsibility for the entire manuscript.

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The Transition from Simulation to Physical Computing: Examining Middle School Robotics Coding Research Through the SAMR Model

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Abstract

Simulation-based environments have become widespread in middle school robotics coding education, yet transferring simulation-acquired skills to physical hardware is less seamless than assumed. This study identifies the difficulties in the transition to Arduino-based physical computing, analyzes them through the SAMR model, and discusses how hardware awareness scaffolds can elevate learning toward Modification and Redefinition. Twenty studies meeting the inclusion criteria were examined through document and content analysis. Difficulties cluster around pin identification, breadboard logic, wiring and hardware-related debugging, which may increase cognitive load and weaken self-efficacy. The studies concentrate at the Substitution and Augmentation levels. We argue that this ceiling stems from the systematic abstraction of physical uncertainty in simulation, which therefore functions as a partial substitution rather than a full digital equivalent. A design framework linking each difficulty to a classroom activity and a SAMR level is proposed.

Keywords: Robotics coding, Arduino, Tinkercad, simulation-based learning, SAMR model, scaffolding.

Introduction

Robotics coding applications have become widespread at the middle school level because they support problem-solving and algorithmic thinking skills (Anwar et al., 2019; F. Erdoğan, 2023). These applications are carried out both in simulation environments, where the circuit is modeled on screen, and in physical computing environments, where students work with real components. Physical computing is an approach that turns abstract programming concepts into tangible products and is rooted in Papert's (1980) constructionism (Przybylla & Romeike, 2014). In the literature, the two environments are often treated as seamless alternatives to each other, and skills are assumed to transfer automatically; the starting point of this study is that the empirical basis for this assumption is weak.

Simulation tools are widely used because they reduce hardware costs and make activities repeatable (R. Erdoğan et al., 2023). Tinkercad allows circuits to be built and tested in a virtual environment (Dağlı et al., 2022), and positive changes in student attitudes have been reported after activities conducted in this environment (Güleryüz, 2023). In physical applications, however, students struggle to identify the 5V and GND pins (Atila et al., 2023), to make wire connections, and to get sensors working (Yener & Yay, 2025). R. Erdoğan et al. (2023) reported that some of the 12 information technology teachers who found Tinkercad usable could not complete all ten circuit tasks.

Three theoretical foundations explain why transfer does not occur automatically. Barnett and Ceci (2002) defined transfer distance along dimensions such as knowledge domain, physical context, functional context, and modality; in the transition from simulation to a physical circuit, several of these dimensions change at the same time. According to cognitive load theory, circuit topology, polarity, wiring, and code logic are highly interactive elements, and operations such as getting the computer to recognize the board create extraneous load (Sweller et al., 2019). Repeated failed attempts, in turn, weaken self-efficacy beliefs (Bandura, 1997). Taken together, these foundations suggest that transition difficulties are a predictable consequence of instructional design; indeed, designs that blend virtual and physical laboratories have been reported to be more effective in science education (de Jong et al., 2013; Jaakkola & Nurmi, 2008; Olympiou & Zacharia, 2012).

Existing national reviews rely mainly on descriptive content analysis and do not interpret their findings through a theory of technology integration (Soypak & Eskici, 2023; Turhal & Bektaş, 2024). To address this gap, the SAMR model was used as the analytical framework (Puentedura, 2006); the model asks not whether technology is present but to what extent it transforms the learning task. The model has been criticized for its weak theoretical grounding, its disregard for context, and its rigid hierarchy (Hamilton et al., 2016); here, therefore, it is used not as a ladder to be climbed but as an analytical tool operationalized through observable indicators.

Accordingly, three research questions were addressed: (1) What technical difficulties arise during the transition, and how are they reflected in the learning process? (2) At which levels of the SAMR model are the studies

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positioned, and how do transition difficulties limit progression to higher levels? (3) How can scaffolds that build hardware awareness move learning to the Modification and Redefinition levels?

Method

Document analysis, a qualitative research design, was adopted, and content analysis was used to analyze the data (Yıldırım & Şimşek, 2018). Criterion sampling, a purposeful sampling technique, was used to select the documents to be examined (Patton, 2014).

The search was conducted in Google Scholar, the Council of Higher Education (YÖK) National Thesis Center, and DergiPark, and institutional repositories were used to access full texts. Keyword combinations were formed from the Turkish equivalents of the terms "robotics coding," "educational robotics," "Arduino," "physical computing," "Tinkercad," and "middle school." The inclusion criteria were as follows: the study was conducted at the middle school level or involved middle school teachers; it addressed Arduino-based robotics coding, simulation environments, or physical computing applications; and it was published in the field of educational sciences as a peer-reviewed article, thesis, or conference paper between 2017 and 2026 in the Turkish context. Twenty studies that met all criteria were included in the analysis through criterion sampling.

A standard data extraction form covering publication type, sample, method, tool used, reported difficulties, and practices supporting the transition was used for each study. In the first stage, the data were coded inductively and grouped under the themes of technical difficulties, pedagogical difficulties, and approaches supporting the transition; in the second stage, each study was coded deductively to SAMR levels using the observable indicators in Table 1. Coding was consensus-based: each study was read jointly by the two researchers, assignments were decided by mutual agreement, and the rationale for each decision was recorded. This choice precludes the calculation of an agreement coefficient but keeps the decisions traceable.

Table 1. Observable indicators of the SAMR levels used in this study

Level	Observable indicator	Example in the robotics coding context
Substitution	The environment is digitized while the structure and output of the task and student autonomy remain unchanged	Building a ready-made circuit provided by the teacher in Tinkercad instead of on a real breadboard
Augmentation	The task remains the same, and technology provides a measurable functional improvement	Testing the same circuit at no cost and without limit; observing the code-circuit correspondence instantly
Modification	The task is redesigned; the student contributes to the problem definition and criteria	Measuring and justifying the difference between the ideal behavior in the simulation and the behavior of the physical circuit
Redefinition	A task emerges that could not be designed without technology	Collecting long-term sensor data and sharing it with a real audience outside the school

Findings

Technical Difficulties and Their Pedagogical Implications

Technical difficulties in the reviewed studies fall under four headings. **Pin and component identification:** Atila et al. (2023) state that students struggle to distinguish the 5V and GND pins; this is not a label-reading problem but a conceptual difficulty with the distinction between the power and ground lines. **Breadboard logic and wiring:** Yener and Yay (2025) reported wire connections, LED applications, and getting sensors to work as the most frequent problems. The internal conduction layout of the breadboard is visible on screen but hidden on the physical board. **Board recognition and code uploading:** Kasalak (2017) and Koç (2024) note that operations such as getting the computer to recognize the board complicate the process; because these operations are unrelated to the learning objective, they constitute extraneous load. **Hardware-related debugging:** In a physical circuit, the source of an error can lie in at least four layers: code, circuit topology, components, and connection quality. In simulation, components are assumed to be ideal and connections flawless, so only the first two layers are involved.

The effects of these difficulties on the learning process were observed in three dimensions. First, students who lack a systematic elimination strategy resort to random trial and error and spend much of their time on operations unrelated to the learning objective (F. Erdoğan, 2023; Yener & Yay, 2025). Second, students who cannot get their circuits working need intensive teacher guidance (Atila et al., 2023; Turhal et al., 2026); this dependence limits scalability in crowded classrooms. Third, Kasalak (2017) reported that students did not find ready-made materials sufficiently challenging and that participation remained low; this can be interpreted as step-by-step instructional

materials leaving no room for design decisions. Durak et al. (2019) report the relationship between computational thinking and programming self-efficacy, and Meço and Görgülü Arı (2021) report difficulties with task sharing in group work; opinion-based studies are also consistent with this picture (Gökçe et al., 2024; Göksoy & Yılmaz, 2018).

SAMR Positioning and Partial Substitution

Most of the reviewed studies are concentrated in the Enhancement category of the SAMR model, that is, at the Substitution and Augmentation levels. Tinkercad moves circuit building into a safe environment by offering digital representations of the board and components (R. Erdoğan et al., 2023), while functions such as programming support, sharing, and IDE integration raise applications to the Augmentation level (Dağlı et al., 2022; Güleryüz, 2023). In studies targeting the Modification level, much of the reported process is devoted to getting the circuit to work. Based on the indicator in Table 1, no study fully meets the Redefinition level.

Reading this distribution as a verdict of inadequacy would be misleading; as Hamilton et al. (2016) point out, SAMR is not a ladder of achievement, and in a school with limited access to hardware, an activity carried out in simulation is better than a physical application that never takes place. The key finding is the reason for the distribution: simulation is not a full digital equivalent of the physical circuit, as contact resistance, loose connections, supply fluctuations, component tolerances, and mechanical wear are not modeled. This is referred to here as **partial substitution**. Most of the technical difficulties correspond to features that the simulation leaves out or represents differently (the hidden conduction layout of the breadboard, board recognition, connection quality); transfer difficulties are therefore largely predictable, and the solution is to make these features visible through instructional design.

Discussion and Conclusion

Elevating Hardware Awareness Scaffolds to Higher Levels

The third research question asks whether scaffolds can do more than resolve transition difficulties and move learning to higher SAMR levels. The supports proposed in the studies cluster under gradual progression, contextualization, and teacher professional development (Başgül & Coştu, 2024; Cansız, 2026; Fatsa & Turan, 2022; Taşmış & Doğru, 2024; Taylan Koparan et al., 2021), but they do not specify which support addresses which difficulty or when it should be withdrawn. Yet intensive support that is held constant can lower the performance of more advanced learners (Kalyuga, 2007).

Table 2, offered as a proposal derived from the findings in the literature and not yet empirically tested, links each type of difficulty to a scaffold, a classroom activity, and a target SAMR level. The core claim is that hardware awareness scaffolds can enable progression to higher levels not to the extent that they spare students from troubleshooting, but **to the extent that they are turned into shareable products created by the students themselves**.

For example, when the four-step diagnostic protocol is modeled by the teacher in the first week, it merely shortens troubleshooting time (Augmentation); when students update the protocol with their own error patterns, they move on to generating criteria (Modification); and when the protocol becomes a shared school resource at the end of the term, a product with real users outside the classroom emerges (Redefinition).

Phased Transition Framework

The solutions in Table 2 can be integrated into a four-phase instructional sequence. **In the first phase (Guided Simulation),** students build a given circuit in Tinkercad and grasp the relationship between code and behavior; support is high. **In the second phase (Paired Construction),** the same circuit is built simultaneously on screen and on a breadboard. **In the third phase (Difference Analysis and Debugging),** students repair a circuit deliberately broken by the teacher and explain the difference in behavior between the two environments; support is limited to the protocol and peers. **In the fourth phase (Open-Ended Physical Design),** students define their own problem, select components, and present their solution to an audience outside the classroom.

The distinctive feature of the framework is that the second phase uses the two environments simultaneously rather than sequentially, which is consistent with findings on blended manipulatives (Jaakkola & Nurmi, 2008; Olympiou & Zacharia, 2012). The planned fading of support takes the expertise reversal effect into account (Kalyuga, 2007), and distributing support among the teacher, materials, and peers may make the framework more feasible in crowded classrooms (Puntambekar & Kolodner, 2005). It is also recommended that in-service training focus on typical hardware errors.

Table 2. Difficulties, scaffolds, their transformation into classroom activities, and corresponding SAMR levels

Difficulty	Hardware awareness scaffold	Transformation into a classroom activity	SAMR
Distinguishing 5V/GND	Color-coded pin diagram; "power first, then signal" rule	Students draw their own pin maps and use them to check each other's circuits	Augmentation → Modification
Internal logic of the breadboard	Locating and marking the conduction lines with a multimeter	Matching the virtual and physical boards side by side and mapping the differences as a class	Modification
Four-layer error space	Four-step diagnostic protocol: power, connection, polarity, code	Writing and testing the protocol as a class and turning it into a shared school resource	Modification → Redefinition
Dependence on the teacher	Distributed support: peer mentors, checklist cards, QR-coded troubleshooting videos	Students produce and share their own archive of video solutions to common errors	Redefinition
Overly prescriptive materials	Gradual fading of support: full instructions, partial instructions, criteria only	A project in which students select components, collect data, and present their solution to an audience outside the school	Redefinition

Situating the Findings in the Literature and Contribution

The findings are consistent with international results indicating that virtual and physical laboratories should be used as complements rather than substitutes for each other (de Jong et al., 2013; Olympiou & Zacharia, 2012). This study extends that conclusion to middle school robotics coding. Going beyond the descriptive classifications of national reviews (Soypak & Eskici, 2023; Turhal & Bektaş, 2024), it interprets the findings through a framework based on observable indicators and, taking critiques of SAMR into account (Hamilton et al., 2016), locates the cause of the ceiling in the abstraction inherent in simulation. The contribution lies in the concept of partial substitution and the mapping in Table 2; both require empirical testing.

Limitations and Future Research

The study is limited to the 20 studies that met the criteria and to the Turkish context; Web of Science, Scopus, and ERIC were outside its scope. SAMR coding is based on how the applications were reported rather than on the applications themselves, and no agreement coefficient can be reported. The priority need is for experimental studies that compare simulation, physical, and blended conditions within the same design; this design, well established in science education, was not found in the reviewed pool. The proposed framework should also be tested with controlled designs, and the cognitive load experienced during the transition should be measured using eye tracking.

Generative AI Statement: Generative AI technologies (Anthropic Claude and Google Gemini) were used during the research process to identify potential additional sources and to edit the language, style, and flow of the text. The suggested sources were independently verified by the authors; all analysis, synthesis, and scientific responsibility rest with the authors.

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Approaches to Learning and Collaboration Patterns in Flipped Classrooms

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Abstract

This study investigates how students' learning approaches shape collaboration configurations and the subsequent collaboration quality in flipped classrooms. Integrating self-reported surveys with digital trace data collected from 432 first-year undergraduates, latent profile analysis identified two distinct profiles of learning approaches: Deep-Active and Surface-Disengaged. Based on students' learning approach profiles and their choice of collaborators, three collaboration configurations were identified: homogeneous Deep-Active, homogeneous Surface-Disengaged, and heterogeneous Mixed Configurations. One-way ANOVAs showed that students in the three configurations differed significantly on indegree, outdegree, and inward harmonic closeness centrality. Students in the Deep-Active and Mixed Configurations experienced more reciprocal and sustained interactions and occupied positions that made them more easily reachable by peers than their Surface-Disengaged peers.

Keywords: collaboration quality; learning approaches; social network analysis; flipped classrooms; self-reported measures; digital trace measures

Introduction

Many traditional large lecture-focused courses have been transformed into flipped classrooms (McLean & Attardi, 2023), in which direct instruction is moved outside class, typically via video lectures or digital materials, while in-class time is devoted to active and interactive activities such as problem solving, discussion, and collaboration (Algarni & Lortie-Forgues, 2023). Rooted in constructivist and social learning theories, the flipped classroom model emphasises learner engagement, peer interaction, and knowledge co-construction (Vygotsky, 1978). Collaboration is therefore not an ancillary feature but a central pedagogical mechanism through which flipped learning aims to enhance understanding and higher-order thinking, creating opportunities for structured peer collaboration including group discussions, collaborative problem solving, peer instruction, and project-based learning (Cho et al., 2021).

Collaboration supports deeper conceptual understanding, critical thinking, and knowledge transfer by enabling students to articulate reasoning, negotiate meaning, and receive immediate peer feedback, and meta-analytic evidence indicates that flipped classrooms generally outperform traditional lecture-based instruction, particularly when active and collaborative learning strategies are implemented (van Alten et al., 2019).

Despite these generally positive findings, students' experiences of collaborative learning in flipped classrooms are not uniformly effective or of high quality (Han, 2025). Most existing studies measure collaboration quality solely through self-reported perceptions on Likert scales rather than more objective measures of collaborative processes, limiting insight into how collaboration actually unfolds (Han et al., 2022a). Moreover, there is limited research examining how individual differences shape the configuration of collaboration networks, or whether different configurations differ in collaboration quality.

To address these gaps, the present study adopts Student Approaches to Learning (SAL) research (Trigwell & Prosser, 2020) as a theoretical framework to examine (1) how collaboration configurations vary according to an important individual difference, students' learning approaches, and (2) how collaboration quality differs across these configurations, integrating social network analysis to provide more objective indicators of collaboration quality than students' self-reported perceptions.

Methods

Research context and sample

The research was conducted in a national Chinese university with a sample of 432 Chinese first-year undergraduates. The flipped course consisted of both face-to-face and online components. Each week the face-to-face part comprised a 60-minute lecture and a 60-minute student-directed tutorial; as the tutorials were learner-centred, teaching assistants only supported collaborative work, facilitated discussion, encouraged evidence-based

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reasoning, ensured respectful academic discourse, and responded to students' questions. As a core component of the course, online learning required mandatory weekly participation both before and after lectures and peer-led tutorials. Six types of online events were generated from the LMS: pre-class readings, pre-class videos, pre-class quizzes, announcements, post-class consolidation tasks, and learning analytics feedback.

Instruments

Students' learning approaches were measured in two ways. The close-ended questionnaire comprised four scales using five-point anchors: two on approaches to learning and two on approaches to using online learning technologies. Digital trace measures were collected via the learning analytics functions in the LMS and comprised seven measures: the frequencies of students' interactions with the six types of online learning events, and the total duration.

Collaboration was measured with a social networking questionnaire adopting a peer nomination approach (McLevey et al., 2023). Each student could nominate up to three students enrolled in the course as their collaborators; self-nomination and nomination outside the course were not allowed.

Data analysis

To answer the first research question, a latent profile analysis (LPA) was conducted in Mplus. To address the second, a directed unweighted collaboration network was constructed and five commonly used network centrality measures were calculated in R 4.5.1 (R Core Team, 2025) using the network package (version 1.19.0; Butts, 2008) and the igraph package (version 2.2.1; Csardi & Nepusz, 2006). A series of one-way ANOVAs and post-hoc analyses were then conducted, using SNA centrality measures as dependent variables and types of collaboration configuration as between-subjects independent variables.

Results

Profiling students' learning approaches

Both the VLMR and BLRT were significant for the two-profile model compared with the one-profile model ($ps < .001$), but not significant when comparing the three-profile with the two-profile model. Taken together, these results supported the two-profile solution as the most parsimonious and interpretable model. Students in Profile 1 employed a Deep-Active learning approach, whereas students in Profile 2 used a Surface-Disengaged learning approach.

RQ1: Variations of collaboration configurations

On the basis of students' profiles of learning approaches and their choices as to with whom to collaborate, students were categorized into one of three mutually exclusive collaboration configurations: Deep-Active, Surface-Disengaged, and Mixed Collaboration Configurations. The majority of students ($n = 310$) were embedded in heterogeneous Mixed Configurations rather than in the two configurations consisting of students with homogeneous learning approaches.

RQ2: Comparison of collaboration quality across configurations

The students in the three collaboration configurations differed significantly on three centrality measures: indegree centrality, outdegree centrality, and inward harmonic centrality. The post-hoc analyses showed a similar pattern for all three: students in the Deep-Active and Mixed Collaboration Configurations had significantly higher indegree, outdegree, and inward harmonic centrality values than those in the Surface-Disengaged Configuration, while the Deep-Active and Mixed Configurations did not differ significantly from each other.

Discussion

This study examined variations of Chinese university students' collaboration configurations based on their self-reported and observed learning approaches in a large first-year flipped classroom course, and investigated how collaboration quality, represented by SNA centrality measures, differed across those configurations. The identification of two distinct latent profiles validates the utility of integrating digital trace measures with self-reported data and extends prior SAL literature on deep and surface approaches across disciplines and instructional contexts (Ellis et al., 2025; Trigwell & Prosser, 2020). Students in the Deep-Active profile self-reported using deep approaches to online technologies more frequently, which was also manifested in significantly higher engagement across all online learning events and greater time spent studying online, whereas their Surface-Disengaged peers

showed significantly lower interaction frequencies. This convergence supports the argument that integrating multiple data sources provides a more comprehensive representation and triangulation of learning processes in blended and flipped learning environments (Gašević et al., 2017; Han, 2025; Han & Yang, 2025).

Critically, the statistical separation between the two profiles was most pronounced in video viewing ($\eta^2 = .405$) and total duration ($\eta^2 = .302$), suggesting that in flipped learning contexts engagement with preparatory content and time online were the primary behavioural differentiators between the two groups. That the majority of students were embedded in heterogeneous Mixed Configurations suggests that the learning design of the flipped classroom supported heterogeneous collaboration, which aligns with social constructivist perspectives emphasising learning as a socially mediated process shaped by the interactional opportunities afforded by the learning environment (Vygotsky, 1978).

Students in the Deep-Active and Mixed Configurations experienced more reciprocal and sustained interactions (higher indegree and outdegree) and occupied positions that made them more easily reachable by peers within the collaboration network (higher inward harmonic closeness) (Marchiori & Latora, 2000; Wasserman & Faust, 1994) than their Surface-Disengaged peers. This is consistent with prior research showing that students who participate more actively and are more centrally embedded in collaboration networks engage in more effective collaborative learning processes (Saqr & Alamro, 2019). The absence of significant differences between the Deep-Active and Mixed Configurations suggests that collaboration across different learning approaches does not necessarily diminish collaboration quality. Rather than showing the reduced participation commonly found in mixed-ability groups (Karau & Wilhau, 2020; Zambrano et al., 2019), participants with a Deep-Active learning approach appeared to maintain a high level of interaction frequency and active positions even when collaborating with Surface-Disengaged peers, consistent with research showing that well-designed mixed-ability groups can support learning (Scager et al., 2016; Sevnarayan & Vaughan, 2024).

In contrast, the significantly lower centrality measures of the Surface-Disengaged Collaboration Configuration seem to reflect a poor-get-poorer dynamic: when students adopting a Surface-Disengaged learning approach worked only with one another, it appeared difficult for them to sustain collaboration and maintain high-quality interactions. These findings extend existing research on learner-related factors in collaborative learning in higher education (Han et al., 2022a; Rojas et al., 2022; Scager et al., 2016) by offering new insights into how students' learning approaches may affect collaboration patterns and quality.

Conclusion

Collaboration in flipped classrooms is an important and complex phenomenon which requires actionable evidence to help the quality of student learning. This study provides evidence that students' learning approaches strongly shape their online engagement and collaboration patterns in flipped classrooms. Deep, active learners engage more and collaborate more effectively, whether they work with similar peers or in mixed groups, whereas surface learners struggle most when isolated together. Ultimately, both how students learn and how they position themselves socially contribute to the quality of collaboration.

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What Influences Early Childhood Teachers' Adoption of Artificial Intelligence in Teaching?

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Abstract

Artificial intelligence (AI) is increasingly used in early childhood education (ECE) for teaching, assessment, and administration, yet little is known about what drives teachers' adoption. This study applied the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to examine factors associated with Chinese early childhood (EC) teachers' behavioural intention (BI) and use behaviour (UB) concerning AI in teaching. Survey data from Chinese EC teachers were analysed using partial least squares structural equation modelling. Habit was the strongest positive predictor of BI, followed by Personal Innovativeness, Performance Expectancy, and Hedonic Motivation. Effort Expectancy negatively predicted BI, while Social Influence and Facilitating Conditions did not significantly affect intention. For actual use, only BI and Facilitating Conditions had significant positive effects; Habit did not directly predict UB. These findings indicate that internal factors, particularly established AI-use habits, innovativeness, perceived usefulness, and enjoyment, shape teachers' intentions, whereas contextual resources and support help translate intention into practice. ECE centres should provide systematic professional development, opportunities to experiment with AI tools, reliable infrastructure, practical resources, and accessible technical support. By strengthening both teachers' motivation and enabling conditions, ECE institutions can promote confident, effective, and sustained AI integration in educational practice over the longer term.

Keywords: early childhood teachers, artificial intelligence, behavioural intention, use behaviour

Introduction

AI is increasingly used across education to support personalised learning, classroom instruction, assessment, and administrative work (Chen et al., 2020; Choi et al., 2023; Su & Zhong, 2022). Teachers nevertheless differ in their willingness to adopt it. Existing research has examined AI acceptance among pre-service, school, and university teachers (Chocarro et al., 2023; Strzelecki et al., 2024; Zhang et al., 2023), but early childhood teachers remain understudied. This study used the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to examine factors associated with Chinese early childhood teachers' Behavioural Intention (BI) and Use Behaviour (UB) concerning AI in teaching.

The UTAUT2 model

UTAUT2 integrates major technology-adoption theories and distinguishes BI, a person's intention to use a technology, from UB, actual use (Venkatesh et al., 2003, 2012). Its seven factors are Performance Expectation, Effort Expectation, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit. The model has been applied to emerging educational technologies, including ChatGPT (Strzelecki, 2024).

Because participating teachers used AI tools provided by their ECE centres, Price Value was excluded. Personal Innovativeness was added because willingness to experiment may shape adoption of new technologies (Agarwal & Prasad, 1998; Strzelecki et al., 2024).

Hypothesis development

H1: Personal Innovativeness has a significant positive effect on Chinese early childhood teachers' BI toward using AI in teaching.

H2: Performance Expectation has a significant positive effect on Chinese early childhood teachers' BI toward using AI in teaching.

H3: Effort Expectation has a significant positive effect on Chinese early childhood teachers' BI toward using AI in teaching.

H4: Social Influence has a significant positive effect on Chinese early childhood teachers' BI toward using AI in teaching.

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H5: Hedonic Motivation has a significant positive effect on Chinese early childhood teachers' BI toward using AI in teaching.

H6: Habit has a significant positive effect on Chinese early childhood teachers' BI toward using AI in teaching.

H7: Habit has a significant positive effect on Chinese early childhood teachers' UB of AI in teaching.

H8: Facilitating Conditions have a significant positive effect on Chinese early childhood teachers' BI toward using AI in teaching.

H9: Facilitating Conditions have a significant positive effect on Chinese early childhood teachers' UB of AI in teaching.

H10: BI has a significant positive effect on Chinese early childhood teachers' UB of AI in teaching.

Methods

Sample

Invitations were sent to 732 in-service teachers from public and private ECE centres in several locations; 77.19% completed the online survey.

Instruments

The 7-point questionnaire used established scales. Performance Expectation, Effort Expectation, Social Influence, Facilitating Conditions, and BI were adapted from Venkatesh et al. (2003); Hedonic Motivation and Habit were adapted from Venkatesh et al. (2012). References to the original technologies were replaced with 'AI'. Personal Innovativeness used Agarwal and Prasad's (1998) scale. UB was adapted from studies of ChatGPT adoption (Strzelecki, 2024; Strzelecki et al., 2024).

Data analysis

Data were analysed in SmartPLS 4 using partial least squares structural equation modelling (PLS-SEM), which is suitable for prediction-oriented models and does not require multivariate normality (Gefen et al., 2000). Following Hair et al. (2017), we first assessed the measurement model. Convergent validity required Cronbach' s alpha and composite reliability above .700 and average variance extracted (AVE) above .500. Discriminant validity required each construct's square root of AVE to exceed its correlations with other constructs (Fornell & Larcker, 1981). We then tested the structural paths using standardised coefficients (β).

Results

The measurement model

All Cronbach's alpha, composite reliability, and AVE values exceeded the recommended thresholds. Each construct's square root of AVE also exceeded its correlations with other constructs, supporting convergent and discriminant validity.

The structural model

The results of the structural model regarding the 10 hypotheses were presented in Table 1.

hypothesis	path	coefficient	*p*	f^2	confirmation
H1	PI→BI	.242	**.000**	0.090	Y
H2	PE→BI	.194	**.004**	0.058	Y
H3	EE→BI	-.106	**.011**	0.021	Y
H4	SI→BI	-.025	.537	0.001	N
H5	HM→BI	.176	**.006**	0.037	Y
H6	HA→BI	.486	**.000**	0.387	Y
H7	HA→UB	.127	.124	0.004	N
H8	FC→BI	.036	.441	0.002	N
H9	FC→UB	.149	**.028**	0.008	Y
H10	BI→UB	.283	**.000**	0.026	Y

Table 1 presents the results of the structural model for the ten hypothesised paths, including the standardised path coefficients (β), their significance levels (p), the effect sizes (f^2), and whether each hypothesis was supported. Following Cohen (1988), f^2 values of .02, .15, and .35 were interpreted as small, medium, and large effects, respectively.

Of the ten hypotheses, seven paths were statistically significant and three were not. Habit was by far the strongest predictor of BI (β = .486, p < .001), and it was the only construct with a large effect size (f^2 = .387). Personal Innovativeness was the second strongest predictor (β = .242, p < .001, f^2 = .090), followed by Performance Expectation (β = .194, p = .004, f^2 = .058) and Hedonic Motivation (β = .176, p = .006, f^2 = .037). All three had small effects on BI. These results indicate that users' intention is driven mainly by established usage routines, and to a lesser extent by their openness to new technology, the perceived usefulness of the technology, and the enjoyment they derive from it.

Effort Expectation was significantly related to BI (β = −.106, p = .011), but in the opposite direction to the one hypothesised, and its effect size was small (f^2 = .021). H3 was therefore not supported. Social Influence (β = −.025, p = .537, f^2 = .001) and Facilitating Conditions (β = .036, p = .441, f^2 = .002) had no significant relationship with BI, so H4 and H8 were not supported. This suggests that the opinions of important others and the availability of resources and support did not meaningfully shape users' intentions.

For UB, BI was the strongest predictor (β = .283, p < .001), although its effect size was small (f^2 = .026), supporting H10. Facilitating Conditions also positively predicted UB (β = .149, p = .028), supporting H9, but its effect size (f^2 = .008) fell below the threshold for a small effect, so its practical contribution is limited. In contrast, Habit did not significantly predict UB (β = .127, p = .124, f^2 = .004), so H7 was not supported. Taken together, Habit appears to influence actual use indirectly through BI rather than directly. In total, six of the ten hypotheses (H1, H2, H5, H6, H9, and H10) were supported.

Discussion

Factors associated with Behavioural Intention

Six of the ten hypotheses were supported. Habit was the strongest predictor of BI, suggesting that established use may be especially important for sustained intention. This result is consistent with research on teachers' adoption of digital resources and ChatGPT (Avci, 2022; Strzelecki et al., 2024).

Personal Innovativeness, Performance Expectation, and Hedonic Motivation also positively predicted BI. Teachers were more inclined to continue using AI when they were willing to experiment, regarded it as useful, and enjoyed using it. These results align with prior research on teachers' adoption of emerging technologies (Boel et al., 2023; Strzelecki et al., 2024).

Effort Expectation was negatively related to BI, contrary to the hypothesis and earlier findings (García-Murillo et al., 2023). One possible explanation is that as AI becomes easier to use, its novelty and the motivation to explore it may decline. Because this interpretation was not directly tested, future research should examine the mechanisms underlying the negative path.

Social Influence and Facilitating Conditions did not predict BI. In this sample, intention therefore depended more on teachers' routines, dispositions, expected usefulness, and enjoyment than on others' views or organisational support.

Factors associated with Use Behaviour

BI was the strongest direct predictor of UB, supporting the UTAUT2 proposition that intention precedes use (Venkatesh et al., 2003, 2012). Teachers who intended to use AI reported more frequent use, consistent with findings in other educational contexts (Rad et al., 2023; Strzelecki et al., 2024).

Facilitating Conditions predicted UB but not BI, whereas Habit predicted BI but not UB. Organisational resources and support may therefore enable actual use even when they do not shape intention, while habitual use may strengthen intention without independently predicting behaviour after BI and Facilitating Conditions are considered. Similar patterns have been reported for virtual laboratories and ChatGPT (Kolil & Achuthan, 2023; Strzelecki et al., 2024).

Conclusion

Contributions and practical implications

This study extends UTAUT2 research to early childhood teachers, an understudied group in the literature on AI adoption. It also distinguishes factors associated with intention from those associated with reported use.

ECE centres can support adoption by giving teachers regular opportunities to use and experiment with AI in authentic teaching tasks. Because Facilitating Conditions predicted UB, centres should also provide reliable infrastructure, practical integration resources, and accessible technical assistance. These supports should help teachers use AI purposefully rather than simply increase exposure.

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Chinese University EFL Learners' Essay Revision and Perceptions of The Feedback: A Comparison Between Teacher Versus Chatgpt Feedback

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Abstract

Using a mixed-methods, within-subject design, this study compared the effects of teacher feedback and ChatGPT feedback on the English essay revision of 35 Chinese university students, together with their perceptions of the two feedback sources. Participants wrote two descriptive essays, revising one using teacher feedback and the other using ChatGPT feedback, and then rated the Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) of each source on a five-point Likert scale. Fifteen students were subsequently interviewed. Essays revised with ChatGPT feedback received significantly higher scores, yet students rated teacher feedback as significantly more useful and easier to use. Thematic analysis produced five themes capturing the perceived strengths and limitations of each source. The findings suggest that students recognise the complementary affordances of teacher and ChatGPT feedback, holding nuanced rather than uniformly favourable views of the role of either in English essay revision.

Keywords: Chinese university students, teacher feedback, ChatGPT feedback, revision in writing, Perceived Usefulness, Perceived Ease of Use

Introduction

Developing strong English writing skills is a fundamental objective for learners of English as a Foreign Language (EFL), and high-quality feedback plays a central role in supporting this process. Providing individualized feedback, however, is among the most time-consuming and demanding aspects of EFL instruction. The rapid emergence of generative artificial intelligence (GenAI), particularly ChatGPT, offers a potential solution by providing immediate, automated feedback on students' writing. Before such tools can be integrated into routine EFL teaching and learning, it is necessary to determine how their effectiveness compares with that of traditional teacher feedback. Accordingly, this study investigates three issues: (a) the relative effects of teacher feedback and ChatGPT feedback on the quality of Chinese university students' English essay revisions; (b) students' perceptions of the usefulness and ease of use of the two feedback sources; and (c) students' views of the respective strengths and limitations of teacher-generated and ChatGPT-generated feedback.

Literature review

ChatGPT and feedback on writing

ChatGPT is a conversational application built on large language model (LLM) technology developed by OpenAI. One reason for its rapid adoption is accessibility: unlike earlier AI systems that often required programming knowledge, it provides a natural-language conversational interface and maintains context across exchanges. Writing has emerged as one of its most prominent application areas, and beyond automated assessment ChatGPT has attracted considerable attention as a feedback provider. It can generate rapid, individualized comments addressing multiple dimensions of writing, including organization, content development, grammar, vocabulary, and mechanics, and has therefore been viewed as a potential writing assistant capable of supporting EFL learners throughout the revision process.

Effects of ChatGPT feedback on writing performance

Comparative studies have examined ChatGPT against no feedback, teacher feedback, and peer feedback. Meyer et al. (2023) found that EFL learners who received ChatGPT feedback produced significantly better revisions than learners who received no feedback, although the two groups did not differ on a subsequent independent writing task; because the comparison excluded teacher feedback, the relative effectiveness of the two sources remained unclear. Song and Song (2023) reported greater improvements in writing competence for students learning with ChatGPT than for those taught by English teachers over 12 weeks, but participants also engaged in multiple

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language-learning activities throughout the intervention, making it difficult to attribute the gains to feedback itself. To minimise this confound, Escalante et al. (2023) compared teacher and ChatGPT feedback during a six-week intervention without extensive supplementary activities. No significant differences emerged in post-test writing proficiency, although the short intervention period may have limited measurable improvement and the study focused on overall writing development rather than revision quality. Evidence comparing the two feedback sources specifically for essay revision therefore remains limited, and addressing this gap constitutes the first objective of the present study.

Effects of ChatGPT feedback on learners' perceptions

Research on students' affective responses has produced mixed findings. Meyer et al. (2023) reported stronger task value and more positive emotions among students receiving ChatGPT feedback than among those receiving none, and Teng (2024) found higher motivation, self-efficacy, and engagement among students supported by ChatGPT than by teacher feedback. In contrast, Escalante et al. (2023) found comparable satisfaction ratings for the two sources, with students almost equally divided in their preferences: teacher feedback was appreciated for its personal interaction and human support, whereas ChatGPT feedback was valued for its clarity, consistency, and detailed language-related suggestions.

The present study examines students' perceptions through the Technology Acceptance Model by comparing the perceived usefulness (PU) and perceived ease of use (PEOU) of the two feedback sources. PU refers to the extent to which individuals believe that using a technology enhances task performance, whereas PEOU reflects the degree to which they perceive it as easy to use with minimal effort. Both constructs are established determinants of technology acceptance across educational contexts, including AI-supported learning, and comparing teacher and ChatGPT feedback along these dimensions provides insight into students' willingness to adopt AI-assisted writing support. The study addresses the following research questions:

1. How do teacher feedback and ChatGPT feedback differ in their effects on Chinese university students' English essay revision?

2. How do students' perceived usefulness and perceived ease of use differ between teacher feedback and ChatGPT feedback?

3. How do Chinese university students perceive the respective strengths and limitations of teacher feedback and ChatGPT feedback?

Methods

Research design, participants, and study context

This research employed a mixed-methods, within-subject design to investigate the comparative effects of teacher-generated and ChatGPT-generated feedback on English essay revision. Participants were 35 first-year undergraduate students at a public university in northwestern China, enrolled in a compulsory English language course designed to develop integrated English skills, including speaking, listening, reading, and writing.

Writing tasks

Two descriptive essay-writing tasks were developed in consultation with the course instructor to ensure their suitability for the participants. Both topics were aligned with units that students had recently completed in their English textbook, so participants had already been exposed to the relevant vocabulary, expressions, grammatical structures, and content. Students first completed both essays and subsequently revised each one using a different feedback source: *An Unpleasant Experience* received feedback from the course instructor, whereas *A Person I Admire* was revised using feedback generated by ChatGPT.

Questionnaire and interviews

Students' perceptions were measured using a 16-item questionnaire with responses recorded on a five-point Likert scale, adapted from the validated Technology Acceptance Model scales developed by Venkatesh and Davis (2000). The instrument comprised four subscales: PU of teacher feedback (4 items; Cronbach's $\alpha = .870$), PU of ChatGPT feedback (4 items; $\alpha = .895$), PEOU of teacher feedback (4 items; $\alpha = .758$), and PEOU of ChatGPT feedback (4 items; $\alpha = .786$).

To complement the survey findings, semi-structured interviews were conducted with 15 participants, guided by two questions: (1) *What advantages and disadvantages did you experience when revising your essay using teacher feedback?* and (2) *What advantages and disadvantages did you experience when revising your essay using*

ChatGPT feedback? Follow-up prompts were used to clarify and expand participants' responses. All interviews were audio-recorded with participants' permission and transcribed verbatim.

Research ethics and procedure

Ethical approval was granted by the Human Research Ethics Committee of XXX University before recruitment commenced. All students received an information sheet and consent form, were informed that participation was entirely voluntary and would have no influence on their course results, and that they could withdraw at any stage without penalty. Written informed consent was obtained from every participant before data collection began.

Data collection was conducted over two consecutive weeks during regular English classes. During the first week, participants wrote two approximately 200-word descriptive essays; the instructor provided feedback on the former and ChatGPT generated feedback for the latter. To ensure comparability, both feedback sources addressed the same dimensions of writing, namely organization, content development, language use (including grammar, vocabulary, and collocations), and writing mechanics (including spelling, punctuation, and capitalization). During the second week, students revised each essay using the assigned feedback source and then completed the questionnaire. To minimise potential rater bias, both the original drafts and revised essays were evaluated using Pigaiwang, a web-based automated English writing assessment system widely adopted by Chinese universities whose reliability and validity have been demonstrated through comparisons with large corpora of human-rated English compositions (Wang, 2016; Yang & Dai, 2015).

Data analysis

Quantitative analyses were conducted using SPSS Version 29. Assumptions of normality were assessed using Shapiro–Wilk tests together with visual inspection of Q–Q plots, while Levene's tests were employed to examine homogeneity of variance. Repeated-measures analyses of variance (ANOVAs) were performed to compare revision performance and students' perceptions across the two feedback conditions. Qualitative interview data were analysed using reflexive thematic analysis within an interpretive research framework (Braun et al., 2019; Thorne, 2008). Analysis began with repeated readings of the transcripts, after which meaningful segments describing students' perceived advantages and disadvantages of each feedback source were coded. Similar codes were grouped into preliminary themes, which were reviewed by comparing similarities and differences across participants' accounts and iteratively refined until each represented a coherent and conceptually distinct pattern.

Results

RQ1: Differences in essay revision quality

Repeated-measures ANOVAs revealed no statistically significant difference between the initial draft scores for the two writing tasks ($F(1, 34) = 0.018$, $p = .895$, partial $\eta^2 = .001$), indicating that students began the two revision tasks with comparable levels of writing performance. Following revision, however, a significant difference emerged: essays revised using ChatGPT-generated feedback received significantly higher scores than those revised using teacher feedback ($F(1, 34) = 18.560$, $p < .001$, partial $\eta^2 = .353$). Given the equivalent quality of the initial drafts, these findings indicate that ChatGPT feedback was more effective than teacher feedback in facilitating improvements during the essay revision process.

RQ2: Differences in perceived usefulness and perceived ease of use

Repeated-measures ANOVAs revealed significant differences for both constructs. Participants assigned higher usefulness ratings to teacher feedback than to ChatGPT feedback ($F(1, 34) = 4.238$, $p = .047$, partial $\eta^2 = .111$), and teacher feedback was perceived as significantly easier to use ($F(1, 34) = 5.338$, $p = .027$, partial $\eta^2 = .136$). These findings suggest that although ChatGPT produced stronger revision outcomes, students regarded teacher feedback as both more beneficial and more user-friendly.

RQ3: Perceived strengths and limitations of the two feedback sources

The qualitative analysis generated five overarching themes. Collectively, the findings revealed that participants did not view either feedback source as uniformly superior; instead, they identified complementary strengths and weaknesses in both.

Theme 1: Human encouragement versus the impersonal nature of ChatGPT feedback

Participants described teacher feedback as encouraging and motivating, emphasizing that the teacher's comments conveyed care, support, and personal attention. By contrast, ChatGPT feedback was frequently described as

emotionally neutral or impersonal: "The teacher's red-pen markings on my essay gave me a sense of human connection. In contrast, the tone of ChatGPT feedback was rather cold, which reduced my motivation to revise."

Theme 2: Focused teacher feedback versus comprehensive ChatGPT feedback

Teacher feedback was viewed as concise and selective, concentrating on the most important issues in the essay. Conversely, ChatGPT was praised for providing extensive comments addressing a wide range of writing aspects, including issues that students believed teachers occasionally overlooked: "While my teacher focused on clarity in my essay, ChatGPT caught subtle issues that teacher overlooked, from word choice to mechanic errors."

Theme 3: Simple teacher feedback versus linguistically demanding ChatGPT feedback

Participants generally found teacher feedback straightforward and easy to interpret. In comparison, ChatGPT feedback was often considered excessively long and written in relatively sophisticated English, requiring considerable effort to read and understand: "Reading ChatGPT feedback was just like reading a long English article. Processing the language was quite tedious and effortful for me. I just prefer teacher feedback which is much shorter."

Theme 4: Individualized teacher feedback versus standardized ChatGPT feedback

Participants appreciated the personalized nature of teacher feedback, believing that their instructor understood their ideas, writing style, and individual learning needs. In contrast, ChatGPT was perceived as producing feedback according to a fixed template, allocating comments across organization, content, language, and mechanics regardless of the characteristics of the individual essay. Some students felt this standardized approach generated unnecessary comments and made it more difficult to identify revision priorities: "ChatGPT provides feedback by equally distributing the comments on the four aspects: content, structure, language, and punctuation. I felt that it was unnecessary to focus on every aspect in details as this generic format created difficulties for me to see the key points."

Theme 5: Teachers' understanding of implicit meaning versus ChatGPT's difficulty with cultural nuance

Participants believed that their English teacher was able to understand culturally embedded messages and implied intentions in their writing, whereas ChatGPT occasionally misinterpreted these indirect expressions because it focused primarily on literal meanings: "When I wrote about my grandmother's silence suggesting her disapproval of the proposal, ChatGPT treated it as ambiguity and suggested deleting this part as it failed to recognise the cultural practice of conveying dissent through silence. However, my teacher always understands the implied meaning I want to express."

Discussion

Effects of teacher and ChatGPT feedback on essay revision

Essays revised with ChatGPT-generated feedback received significantly higher scores than those revised using teacher feedback. This result extends earlier research showing that ChatGPT feedback produces better revision outcomes than either no feedback (Meyer et al., 2023) or peer feedback (Mun, 2024), and provides direct evidence that AI-generated feedback can also outperform traditional teacher feedback in supporting immediate improvements during revision. A plausible explanation lies in the breadth and richness of ChatGPT's output: compared with teacher feedback, it typically offers more extensive suggestions covering text organization, content development, lexical choice, collocations, grammar, and stylistic refinement simultaneously, and rather than merely identifying problems it frequently proposes alternative expressions, additional supporting ideas, and ways to restructure paragraphs. This interpretation is consistent with Dai et al. (2023), who reported that ChatGPT generated substantially more detailed comments than instructors, frequently expanding upon ideas and providing explanatory information beyond simple error correction. Similar patterns emerged in the present interviews, where many students highlighted ChatGPT's detailed suggestions for reorganizing their essays and strengthening logical flow.

Students' perceptions of usefulness and ease of use

Despite achieving better revision outcomes with ChatGPT, participants perceived teacher feedback as significantly more useful and easier to use. This discrepancy between objective performance and subjective perceptions suggests that instructional effectiveness and learner acceptance do not necessarily coincide. Comparable findings have been reported by Nazaretsky et al. (2024), who observed that students preferred feedback attributed to teachers rather

than AI systems even when the content was comparable, and by Solovey (2024), who found that teacher feedback remained students' preferred source of writing guidance.

Several factors may account for these perceptions. First, in Chinese higher education teachers traditionally occupy positions of authority and expertise, and students are generally socialized to trust their professional judgement, which may strengthen confidence in teacher feedback and increase its perceived usefulness. Second, as first-year university students who had completed secondary education in predominantly face-to-face classrooms, most participants had limited exposure to AI-assisted learning and little experience interpreting AI-generated feedback, which may have lowered their evaluations of its usefulness and usability. Third, ChatGPT often produces substantially longer feedback than human instructors (Tzirides et al., 2023); although detailed feedback may offer more opportunities for revision, it also requires greater reading comprehension and cognitive processing, and for learners with relatively modest English proficiency lengthy explanations and sophisticated language may increase cognitive load (Barrot, 2023). Finally, participants received AI-generated comments in a static format and could neither request clarification nor ask ChatGPT to simplify or elaborate on its suggestions. Such passive use differs substantially from the interactive nature of contemporary conversational AI, and earlier research suggests that opportunities for iterative dialogue can improve learners' satisfaction, confidence, and willingness to adopt AI-assisted tools (Escalante et al., 2023).

Students' perceptions of the strengths and limitations of the two feedback sources

Students did not regard either feedback source as universally superior, instead viewing them as offering complementary strengths. Teacher feedback was consistently valued for its interpersonal qualities: participants appreciated teachers' encouragement, empathy, and awareness of their learning needs, viewing these human elements as important sources of motivation during revision. These findings support earlier work demonstrating that teacher-student interaction plays a central role in shaping engagement with feedback (Lee & Schallert, 2008), and suggest that although AI can support cognitive aspects of writing improvement, human instructors remain indispensable for providing emotional support and maintaining motivation. At the same time, participants acknowledged ChatGPT's ability to deliver comprehensive, detailed, and systematic feedback, characteristics that likely contributed to the superior revision performance observed. Nevertheless, the volume and complexity of AI-generated comments could become overwhelming, a perceived difficulty corresponding closely with the lower ratings of perceived ease of use obtained for ChatGPT feedback and particularly relevant for learners with limited English proficiency. An additional finding that has received limited attention in previous research concerns ChatGPT's occasional difficulty in interpreting culturally embedded meanings, including indirect ways of expressing disagreement that are common in Chinese communication. This suggests that future development of educational GenAI systems may benefit from incorporating greater sensitivity to culturally specific linguistic practices and discourse conventions.

Conclusions

The findings indicate that AI-generated feedback and teacher feedback should be viewed as complementary rather than competing instructional resources. Although ChatGPT produced stronger improvements in students' revised essays, teacher feedback remained more highly valued because of its clarity, accessibility, credibility, and interpersonal support.

Accordingly, EFL teachers may achieve better learning outcomes by combining both forms of feedback. ChatGPT can efficiently identify grammatical, lexical, organizational, and mechanical issues, allowing teachers to devote more time to higher-order concerns such as argument development, critical thinking, audience awareness, and individualized guidance, capitalizing on the respective strengths of AI and human instructors while reducing teachers' marking workload. Students should also receive explicit guidance on how to interpret and effectively use AI-generated feedback, as developing AI literacy may improve their confidence in evaluating AI recommendations. Finally, teachers should encourage students to interact actively with conversational AI by asking follow-up questions, requesting explanations, and seeking alternative suggestions. Transforming AI feedback from a one-way delivery mechanism into an interactive dialogue may enhance engagement, increase perceived usefulness and ease of use, and ultimately promote more effective revision practices.

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Using GeoGebra to Visualize the Bisection and Newton Methods in the Teaching of Nonlinear Equations

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Abstract

Nonlinear equations arise in numerous mathematical models and applications, making numerical methods essential for obtaining approximate solutions. However, students often encounter difficulties in developing an intuitive understanding of iterative procedures and the convergence process when numerical methods are presented solely through formulas and numerical computations. Dynamic mathematics software can help overcome these difficulties by providing visual representations and connecting analytical procedures with their geometric interpretation. In this context, visualization can play an important role in supporting conceptual understanding and promoting meaningful learning. This paper presents the use of GeoGebra for the visualization and teaching of two classical numerical methods for solving nonlinear equations: the Bisection Method and Newton's Method. The theoretical background of both methods is briefly reviewed, including the conditions required for their application, stopping criteria, and convergence properties. Particular attention is devoted to the graphical representation of the iterative process and to illustrating the geometric ideas underlying each method. Interactive GeoGebra visualizations were developed to provide students with a dynamic representation of successive approximations and to enable them to observe the convergence process in real time. The developed visualizations were incorporated into the teaching process as a supplement to traditional instruction. By combining analytical procedures with graphical representations, students are able to relate symbolic calculations to their geometric meaning more effectively and to explore numerical methods through active interaction. Such an approach encourages active learning and supports the development of a deeper conceptual understanding of convergence and approximation processes. Furthermore, dynamic visualizations make abstract mathematical concepts more accessible and facilitate the interpretation of iterative procedures, which are often difficult to understand through numerical calculations alone. Preliminary classroom observations suggest that the activities may encourage student engagement and support the interpretation of iterative procedures. Although these observations have not been evaluated through a formal study, the developed activities demonstrate how interactive visualization can complement traditional instruction in numerical mathematics.

Keywords: numerical methods, GeoGebra, mathematics education

1. Introduction

Numerical methods play an important role in solving nonlinear equations and are an essential component of numerical mathematics education. However, teaching these methods presents certain challenges. Students may learn to apply numerical algorithms and obtain correct results without fully understanding the iterative process or the mathematical principles underlying convergence. When instruction relies primarily on formulas, numerical calculations, and tables, the geometric meaning of successive approximations may remain unclear.

This challenge was observed in the Numerical Mathematics course at Aspira University of Applied Sciences, where students often found it difficult to explain how new approximations are generated and how they approach the solution. These classroom experiences motivated the introduction of dynamic visualizations as a complement to traditional instruction. GeoGebra was selected because it enables numerical procedures to be represented graphically and allows students to interact with mathematical concepts rather than merely follow predefined computational steps.

The Bisection and Newton methods were chosen because they illustrate two different approaches to solving nonlinear equations. The Bisection Method progressively reduces an interval containing a root, whereas Newton's Method generates new approximations using tangent lines (Burden & Faires, 2011). Their distinct geometric interpretations provide opportunities for students to explore the relationship between numerical calculations and the convergence process.

The aim of this paper is to present the development and classroom integration of interactive GeoGebra activities for these two methods. The activities were incorporated into the Numerical Mathematics course to supplement lectures and tutorial exercises. Particular attention is given to their interactive features, their application in teaching, and the initial observations arising from classroom implementation.

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2. Methodology: Activity Design and Classroom Integration

This work adopted a practice-based approach focused on the development and classroom implementation of interactive GeoGebra activities. Two visualizations were designed for the Bisection and Newton methods and incorporated into the Numerical Mathematics course at Aspira University of Applied Sciences during the 2025/2026 academic year.

The activities were integrated into the existing teaching process as a supplement to lectures and tutorial exercises. Students were first introduced to the theoretical foundations of each method and worked through numerical examples manually. They subsequently used GeoGebra to examine the same procedures through dynamic graphical representations. By progressing through individual iterations and modifying input parameters, students could explore how the methods behave under different conditions while relating their calculations to the corresponding geometric constructions.

The activities were designed to encourage active participation and independent exploration. The Bisection visualization enables students to investigate how successive iterations reduce an interval containing a root, while the Newton visualization illustrates the construction of tangent lines and the influence of the initial approximation on convergence (Burden & Faires, 2011). Both activities combine graphical representations with numerical information, allowing students to follow the iterative process from complementary perspectives.

The implementation was evaluated informally through the instructors' classroom observations, focusing on student participation, discussions, explanations of numerical procedures, and performance on related exercises. As no formal assessment instruments, comparison groups, or statistical analyses were employed, these observations are presented as preliminary teaching experiences rather than evidence of measurable learning gains.

3. Interactive GeoGebra Activities

3.1. Bisection Method

The interactive GeoGebra activity developed for the Bisection Method allows students to explore the iterative process through a combination of graphical representations and numerical calculations. The activity is designed to present the algorithm step by step, enabling students to observe how successive approximations are generated and how the interval containing the root gradually decreases.

At the beginning of the activity, students specify a nonlinear equation f(x)=0, an initial interval [a,b], and a prescribed tolerance ε. The interval is selected so that the continuous function takes values of opposite signs at its endpoints, ensuring that at least one root lies within the interval. The GeoGebra interface displays the graph of the function, the endpoints of the selected interval, and a spreadsheet prepared to record the successive approximations and corresponding error estimates.

Figure 1 presents the initial state of the developed activity. The interface contains input fields for the function, interval endpoints, and tolerance, together with the *Start* and *Next Iteration* buttons. At this stage, the initial interval is visible on the graph, while the spreadsheet has not yet been populated with numerical results.



Figure 1. Initial state of the interactive GeoGebra activity for the Bisection Method.

After starting the procedure, students can advance the algorithm using the *Next Iteration* button. At each step, the midpoint of the current interval is calculated, and the half-interval in which the function changes sign is retained. The graphical representation is updated to display the new interval, while the spreadsheet records the current approximation and its error estimate. This process continues until the prescribed stopping criterion is satisfied. The step-by-step execution allows students to examine how the interval is reduced and how the numerical approximations approach the root. The simultaneous display of graphical and numerical information helps them relate the changes observed on the graph to the values recorded in the spreadsheet. Students can also modify the initial interval and tolerance to investigate how these choices influence the iterative process and the number of iterations required. In the example illustrated in Figures 1 and 2, the function $f(x)=\sin(x)-x^3+1$ is considered on the interval [0.1,1.5], with a prescribed tolerance of $\varepsilon=0.01$. After seven iterations, the method produces the approximation $x\approx1.2539$, with an error estimate of approximately 0.0055, satisfying the stopping criterion. Figure 2 presents the final state of the activity. The graphical display shows the considerably reduced interval containing the root, while the spreadsheet provides a record of the successive approximations and decreasing error estimates. The message *"Stopping Criterion Satisfied"* confirms that the required accuracy has been achieved and the iterative procedure has terminated.



Figure 2. Final state of the Bisection Method after several iterations, showing the approximate root and the satisfied stopping criterion.

From an educational perspective, the two figures illustrate how the developed activity transforms a numerical algorithm into an interactive learning experience. By comparing the initial and final states and examining the intermediate iterations, students can explore the relationship between interval reduction, error estimates, and convergence. The activity therefore complements manual calculations by providing a visual representation of the mathematical process and encouraging students to investigate the method through direct interaction.

3.2. Newton's Method

The interactive GeoGebra activity developed for Newton's Method enables students to investigate the geometric interpretation of the iterative procedure through the construction of tangent lines. Unlike the Bisection Method, which progressively reduces an interval containing a root, Newton's Method generates successive approximations from a selected initial value. The visualization allows students to follow this process step by step and examine how the choice of the initial approximation influences the behaviour of the method.

At the beginning of the activity, students specify a nonlinear equation $f(x)=0$, an initial approximation x_0, and a prescribed tolerance ε. The interface displays the graph of the function, the selected starting point, and a spreadsheet prepared to record the numerical values obtained during the iterative process. Figure 3 presents the initial state of the activity for $x_0=1.3$ and $\varepsilon=0.01$.



Figure 3. Initial state of the interactive GeoGebra activity for Newton's Method with $x_0=1.3$.

After starting the procedure, students use the *Next Iteration* button to advance the algorithm. At each step, GeoGebra constructs the tangent to the graph at the current approximation. The intersection of this tangent with the x-axis determines the next approximation, while the spreadsheet records the numerical results. The process continues until the prescribed stopping criterion is satisfied.

The activity allows students to investigate how the initial approximation affects the sequence of iterations. For the function $f(x)=\sin(x)-x^3+1$, the starting value $x_0=1.3$ leads to rapid convergence, whereas choosing $x_0=3$ requires more iterations to achieve the prescribed tolerance. Students can observe these differences directly by changing the initial value and repeating the procedure.

To illustrate the influence of the initial approximation, two separate runs of the activity are presented, starting from $x_0 = 1.3$ and $x_0 = 3$, respectively. Figure 4 presents the final state of a separate run of the activity, starting from $x_0 = 3$ with $\varepsilon = 0.01$. The spreadsheet shows five successive iterations, with the approximation approaching $x\approx1.2491$. The graphical representation displays the tangent constructed at the final approximation, while the message *"Stopping Criterion Satisfied"* indicates that the iterative procedure has terminated.

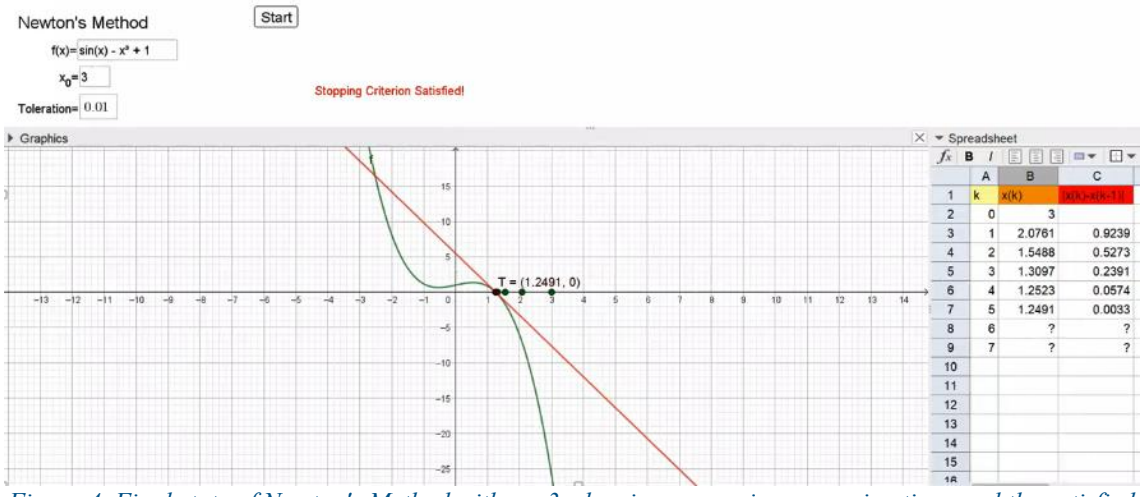


Figure 4. Final state of Newton's Method with $x_0=3$, showing successive approximations and the satisfied stopping criterion.

By comparing the two starting values, students can explore the sensitivity of Newton's Method to the initial approximation. The activity also provides opportunities to investigate the influence of tolerance on the number of iterations and to discuss situations in which the method may converge slowly or fail to converge. In particular, students can examine why the next iteration cannot be calculated when the derivative at the current approximation is zero.

4. Classroom Observations and Discussion

The implementation of the GeoGebra activities during the 2025/2026 academic year provided encouraging classroom experiences. During tutorial sessions, students participated more actively in discussions and showed greater interest in exploring how numerical methods approach a solution. They also appeared more confident in relating numerical calculations to their graphical representations and explaining the convergence process.

We additionally noticed improvements in students' performance on classroom problems involving the Bisection and Newton methods. In particular, students appeared better able to explain how successive approximations are generated and interpret the results of individual iterations. These impressions suggest that interactive visualization may support conceptual understanding by helping students connect computational procedures with their mathematical meaning.

An important educational feature of the activities is the opportunity for students to investigate the consequences of their choices. By modifying input parameters, they can formulate predictions, observe the resulting changes, and discuss their mathematical meaning. This creates opportunities for classroom discussion and encourages students to explore numerical methods actively rather than simply memorize computational procedures.

However, these findings are based on informal observations made by the instructors rather than systematically measured learning outcomes. No formal assessment instruments or controlled comparisons were used, and the observed improvements therefore cannot be attributed exclusively to GeoGebra. A future evaluation should incorporate structured assessments and student feedback to examine the activities' educational impact more systematically.

5. Conclusions

This paper presented the development and classroom integration of interactive GeoGebra activities for teaching the Bisection and Newton methods in the Numerical Mathematics course. The main contribution of this work is the practical integration of dynamic visualization into an existing teaching approach, enabling students to explore numerical procedures and examine their geometric interpretation.

The activities were designed to complement theoretical instruction and manual calculations rather than replace them. Their interactive features allow students to follow individual iterations, modify input parameters, and investigate the behaviour of numerical methods under different conditions. In this way, the developed activities provide an additional teaching resource that connects computational procedures with visual exploration.

The classroom implementation provided encouraging initial experiences, although the impact on student learning requires further evaluation. Future work will focus on systematically assessing the educational effectiveness of the activities and extending the approach to other topics in Numerical Mathematics.

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What Do Graduates Say? A Five-Year Satisfaction Trend in Applied Education within Higher Education

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Abstract

The uncertainty produced by globalisation, rapid technological change and successive crises is shifting the outcomes expected of higher education beyond the transmission of theoretical knowledge, increasingly prioritising the continuity of learning, adaptability and ethical responsibility. Within this framework, monitoring graduate outcomes constitutes a key indicator for institutional quality assurance and strategic planning. This study aims to examine, through secondary analysis, the publicly shared graduate satisfaction survey results (2021–2025) of Sakarya University of Applied Sciences, in order to reveal how the learning, adaptation/resilience and responsibility gains targeted by the "+1 Applied Education Model"—which devotes the final semester to workplace-based applied training—are reflected in satisfaction indicators. The study addresses the following questions: (1) what trend do graduate satisfaction perceptions show between 2021 and 2025; (2) how do satisfaction indicators differ across years and academic units; (3) what changes are observed across years in areas such as foreign-language proficiency and employment opportunities? A repeated cross-sectional (trend) survey design within a quantitative approach was adopted; because data obtained from different graduate groups in different years using the same instrument are compared, change is examined at the cohort rather than the individual level. The data source is the annual results of a 22-item, 5-point Likert-type survey developed by a team of the university's academic staff. Descriptive statistics and—to the extent permitted by the granularity of the data—comparative analyses across years and units are employed, with attention to the cross-year comparability and reliability of the indicators. Because the data consist of voluntary, publicly available responses, limitations regarding representativeness and response rate are explicitly addressed. The study's original contribution lies in combining a five-year trend dimension with a transparent, reproducible secondary-analysis approach to present a situation and needs analysis of sustainable learning and institutional responsibility in applied higher education.

Keywords: Applied higher education, graduate satisfaction, repeated cross-sectional (trend) analysis, secondary analysis, quality assurance

Introduction

The rapid transformation of technology driven by globalization and the uncertainties arising from the successive crises are fundamentally changing the outcomes expected from institutions of higher education. Today's approach to higher education has evolved from a model focused on equipping students with theoretical knowledge to a dynamic process that enhances their capacity for lifelong learning, enables rapid and flexible adaptation to crises and uncertainties, and instills a sense of ethical and social responsibility (Barnett, 2012; Yorke, 2006). In this transformation process, higher education institutions' ability to evaluate their own performance and monitor the real-world impact of the educational models they offer serves as a vital indicator in terms of institutional quality assurance and strategic planning. Education possesses fundamental characteristics that enable the socio-economic development, progress, and improved quality of life of a nation's people. Universities, which undertake this mission, lead the way in scientific inquiry, social engagement, and the advancement of technological developments. At the same time, they have assumed the responsibility of serving society by fostering the professional skill development of young adults (Scott, 2002; Şahin et al., 2011).

Monitoring the satisfaction levels of relevant stakeholders has become crucial for improving the quality of education and ensuring its sustainability at higher education institutions (Ulusoy et al., 2010). Satisfaction data collected from students—the most important stakeholders of higher education institutions—reveal findings regarding universities' services, the quality of their physical infrastructure, social amenities, the competence of faculty members, and the effectiveness of administration (Mark, 2013; Altaş, 2014). Students' satisfaction with their educational experiences directly affects their academic success, motivation, and commitment to their education (İyigün et al., 2023). When university students' expectations are not met and their satisfaction is affected—particularly in cases of low satisfaction—universities must promptly implement improvements tailored to address that specific area of dissatisfaction (Noel-Levitz, 2005). In addition to social, cultural, and intellectual opportunities, students view universities as vocational schools primarily due to the expectation of career preparation, which has become more prominent due to high unemployment and the difficulty of finding

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employment (Şahin et al., 2011). For this reason, students' satisfaction with their academic field is determined by whether they voluntarily chose their major, their strong sense of belonging, and their hopes for employment (Gerçek, 2020; Şahin et al., 2011).

The provision of applied vocational training opportunities at universities serves as a bridge, enabling students to apply their theoretical education in the workplace. At the same time, the high-quality delivery of applied courses at universities and vocational training at businesses helps meet the business world's need for qualified personnel after graduation and increases the rate of employment (Altaş, 2014; İyigün et al., 2023). The literature emphasizes that, to increase satisfaction levels, curricula must include practical courses and maintain close ties with the business world (Arslanhan & Yaman, 2020). Conversely, students graduating from departments and programs where the educational process is conducted solely on a theoretical basis face greater difficulty adapting to the professional world, which increases dissatisfaction (Uçar, 2017; Arslanhan & Yaman, 2020). In higher education, "Alumni Tracking Systems"—a requirement of accreditation processes—have become a cornerstone (Taşcı and Lapçın, 2023). By utilizing these tracking systems, universities support their graduates not only through education but also by enhancing their reputation and social connections to a respectable level. At the same time, graduates also provide universities with experience and feedback from the business world. From this perspective, a review of the literature reveals that while alumni loyalty influences the university's success (Iskhakova et al., 2017), another study describes alumni as mentors who loyally support and evaluate their university (Rodriguez, 1991). In yet another study, the alumni tracking system used at the university is of such importance that it goes beyond being a mere administrative practice to play a key role in guiding the university's strategic success in the long term. Based on data from this system, employer feedback is used to improve and develop academic programs, strengthen foreign language skills, foster graduate-mentor relationships, and implement university-industry collaboration (Ürün et al., 2026).

This study aims to examine data from public graduate satisfaction surveys collected by the SUBÜ Quality Coordination Office between the 2020–2021 and 2024–2025 academic years (a 5-year period) using secondary analysis and a repeated cross-sectional (trend) survey design. Sakarya University of Applied Sciences (SUBÜ) has established a unique institutional model with the "+1 Applied Education Model," which requires students in both undergraduate and associate degree programs to spend their final semester entirely in businesses or in the field. This study aims to make a unique contribution to the literature by revealing how the dimensions of learning, resilience/adaptation, and responsibility—which the "+1 Applied Education Model" aims to instill in graduates—are reflected in satisfaction indicators.

In line with this primary objective, the study seeks to answer the following questions:

1. What trend do graduate satisfaction perceptions exhibit between 2021 and 2025?

2. How do indicators of overall satisfaction, satisfaction by gender, and satisfaction by academic unit vary across years and academic units?

3. What changes have been observed over the years in critical areas such as foreign language proficiency and post-graduation employment status?

Methodology

Research Design

This study was conducted using a repeated cross-sectional survey design, one of the quantitative research methods. This design aims to identify trends among data collected from different groups sharing the same characteristics at different time intervals (Lebo & Weber, 2015). In this design, data are collected by administering the same measurement tool to participants representing a specific population at different time intervals. These data allow for the identification of intergenerational temporal trends—known as cohorts—rather than individual trends (Büyüköztürk et al., 2020). The objective of this study was to identify longitudinal trends in graduate satisfaction over a five-year period spanning 2021–2025.

Data Source for the Study

The data source for this study consists of the official graduate satisfaction survey reports, which were conducted annually between 2021 and 2025 by the Quality Coordination Office at Sakarya University of Applied Sciences, and whose analysis results were shared with the public. Since this study utilized secondary data analyzed by the institution, no sampling method was applied; all data made public were included in the analysis.

Table 1: Participant and Gender Indicators by Year

Year	Number of Participants	Female	Male
2020-2021 Academic Year	929	%58	%42
2021-2022 Academic Year	943	%52	%48
2022-2023 Academic Year	217	%63	%37
2023-2024 Academic Year	918	%61	%39
2024-2025 Academic Year	872	%52,6	%47,4

The dataset includes all academic units of the university—namely, vocational schools, colleges, and institutes—which represent the university's levels of student education. To ensure the consistency of the data over time, data from previous years have been reported under the new name, as Karasu Vocational School was renamed the Information Technologies Vocational School in the 2024–2025 academic year.

Data Collection Tool and Process

The data collection tool used by the university to gather satisfaction data was developed by the university's expert academic staff and the Quality Coordination Office as a 22-item, 5-point Likert-scale survey titled the "Graduate Satisfaction Survey." The rating scale used was as follows: 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree Nor Disagree, 4 = Agree, 5 = Strongly Agree. The questions in the graduate satisfaction survey, which was used as the data collection tool, are as follows.

Graduate Satisfaction Survey

1. I made a conscious decision when choosing my university.
2. Before making my university choice, I had knowledge about the profession in which I was being trained.
3. I am able to apply the knowledge I gained in my field of study in my professional life.
4. The educational standards of the department/program from which I graduated are adequate.
5. The education I received in the department/program from which I graduated met my expectations.
6. The faculty members in my department provided me with advice regarding the requirements of my profession and the business world.
7. I possess a sufficient level of foreign language proficiency related to my profession/field.
8. Throughout my university education, I acquired the skills to research and obtain the information I needed.
9. Thanks to my education, I was able to develop my communication skills.
10. Thanks to the education I received, I have developed an understanding of professional ethics and responsibility.
11. I would recommend my university to people in my circle and to prospective students.
12. I am proud to be a graduate of this university.
13. If I had to choose again, I would select the same university and the same department/program.
14. I believe the opportunities provided to me by my university throughout my education were sufficient.
15. +1 I believe that through hands-on education, I will be able to contribute to the industry.
16. +1 Thanks to hands-on education, I will enter the workforce with more experience.
17. My university supports me in my job search after graduation.
18. The events held at my university throughout my education help me with my career development.
19. I can easily communicate with my university.
20. I would like to participate in events organized for alumni (career days, alumni association, etc.).
21. I do not want to lose my connection with my university.
22. I feel a sense of belonging to my university.

Data Analysis

In this study, the secondary data analysis method was used to analyze the dataset. This method aims to reanalyze data that was previously collected and analyzed for different purposes in light of new scientific questions and objectives (Johnston, 2014). In accordance with secondary data analysis, a descriptive analysis of the existing results was conducted, and by comparing percentage or frequency values, trends, differences, and changes were identified.

Findings

The study's findings are organized under three headings derived from secondary analyses conducted in line with the research questions. These are presented as follows: overall satisfaction and the distribution of satisfaction by gender; a comparison of satisfaction trends by year at the academic unit level; and notable changes—both positive and negative—identified on a question-by-question basis.

The distribution of the total N=3,879 graduates who participated in the satisfaction survey over a five-year longitudinal period, along with the distribution trends reflecting overall satisfaction and satisfaction by gender, are presented in Table 2.

Table 2: Number of participants by year, overall satisfaction, and distribution of satisfaction by gender

Academic Year	Number of Participants (N)	Overall Satisfaction Rate (%)	Satisfaction by Gender	
			Famale	Male
2020-2021	929	%78,9	%79,8	%78,3
2021-2022	943	%78,1	%77,9	%78,4
2022-2023	217	%79	%79	%80
2023-2024	918	%78	%78	%78
2024-2025	872	%77	-*	-*

** Note: Since satisfaction rates by gender were not published in the institutional data for the 2024–2025 academic year, the relevant fields are indicated with "-".*

An examination of Table 2 reveals that participant numbers followed a stable trend in all years except the 2022–2023 academic year. The decline in participant numbers during the 2022–2023 academic year was due to the transition to online education under extraordinary circumstances resulting from the earthquake disaster that struck the country. The overall satisfaction rate is seen to follow a stable trend within the 77–79% range. When examining the breakdown by gender, it is observed that the satisfaction levels of female and male graduates are parallel to one another, averaging within the 78–79% range.

Table 3: Five-year satisfaction trends by academic unit

Unit Name	2020-2021	2021-2022	2022-2023	2023-2024	2024-2025
Akyazı Vocational School of Health Services	86,36	73	76	77	80
Arifiye Vocational School	81,29	80	-	82	86
Information Technologies Vocational School	78,84	81	75	75	85
Denizcilik Vocational School	-	78	84	79	79
Ferizli Vocational School	88,70	78	55	79	79
Geyve Vocational School	75,91	79	80	75	71
Hendek Vocational School	82,26	76	92	76	81
Kaynarca S. S. Vocational School	77,11	79	77	76	68
Pamukova Vocational School	80,43	79	80	78	70
Sakarya Vocational School	80,35	80	75	83	80
Sapanca Vocational School	82,82	81	83	83	84
Sapanca Tourism Vocational School	78,93	76	-	78	84
Faculty of Health Sciences	-	-	-	-	71
Faculty of Sports Sciences	80,55	80	49	82	79
Faculty of Technology	75,49	78	73	76	74
Faculty of Tourism	80,19	74	75	78	79
Faculty of Applied Sciences	75,45	72	81	78	82
Faculty of Agriculture	-	-	-	77	89
Institute of Graduate Studies	90,39	84	81	90	87

An examination of Table 3 reveals that during the 2020–2021 academic year, graduate satisfaction levels across all departments ranged from 75% to 90% and averaged around 80%. In the 2021–2022 academic year, these levels varied between 72% and 84%, with the average dropping to 78%. This trend was followed by a decline in satisfaction to an average of 75% during the 2022–2023 academic year, with satisfaction levels ranging from 49% to 92%. It is believed that this year's decline was influenced by the low satisfaction rates of 49% and 55% observed at the Faculty of Sports Sciences and Ferizli Vocational School, respectively. In the 2023–2024 and 2024–2025 academic years, satisfaction rates ranged from 75–90% and 68–89%, respectively, resulting in an average satisfaction rate of 79% in both years. Overall, satisfaction levels at academic units ranging from 75% to 80% show a trend that is generally consistent with overall satisfaction levels and satisfaction levels by gender.

Table 4: Five-Year Average Satisfaction Trends by Type of Academic Unit

Unit Level	2020-2021	2021-2022	2022-2023	2023-2024	2024-2025
Satisfaction with Vocational Schools	81,18	78,33	77,7	78,41	78,91
Faculty Satisfaction	77,92	76	69,5	78,2	79
Institute of Graduate Studies Satisfaction	80,94	78,11	75,73	79	79,36

An examination of Table 4 reveals that satisfaction averages vary across different types of academic units. While the satisfaction averages for all unit types were relatively close to one another, the highest level of satisfaction was observed among graduates of vocational colleges offering associate's degrees. This was followed by graduate degree holders, while the lowest satisfaction was reported among bachelor's degree holders. In particular, during the 2021–2022 and 2022–2023 academic years, a decline in satisfaction levels was observed across all types of academic units compared to previous years. However, in contrast to this decline, an increase in satisfaction levels was observed during the 2023–2024 and 2024–2025 academic years.

Table 5: Question-Based Satisfaction Level Analysis

Level of Satisfaction	2020-2021	2021-2022	2022-2023	2023-2024	2024-2025
	15	10	16	10	10
	16	16	15	16	16
Areas Where High Satisfaction Was Reported	10	15	10	9	15
	9	6	3	6	6
	1	9	21	15	9
	7	7	7	7	7
	17	14	17	17	17
Points of Uncertainty	13	17	13	18	4
	14	13	14	14	14
	18	18	5	17	5
	7	7	7	7	7
	17	17	17	14	17
Areas for Improvement	2	13	2	13	13
	13	2	14	2	14
	18	14	13	17	2

An examination of Table 5 reveals that the 5-year longitudinal analysis of the 22-item survey questions was conducted under three headings: "High Satisfaction," "Indecision," and "Areas for Improvement." Question-based trend analyses reveal the organization's strengths as well as areas where it falls short strategically and requires improvement. The responses to questions 10, 15, and 16—which consistently indicated high satisfaction throughout the entire five-year period—constitute the key indicators of sustainable satisfaction levels. These are followed by questions 9 and 6. Based on Question 10, high satisfaction indicates that sufficient gains have been achieved in the areas of responsibility and ethics, and further demonstrates the existence of a structure that prioritizes ethical values in addition to professional development. Furthermore, based on Questions 15 and 16, the fact that the university's +1 Applied Education Model has consistently ranked at the top over the five-year period validates the model's effectiveness. Certain crises and uncertainties that provide experience in applied education help graduates develop adaptability and resilience. Question 9 reveals high satisfaction with the effectiveness of the education in developing communication skills. This level of satisfaction indicates that the education is effective in fostering the acquisition of social skills.

An analysis of Table 5 in terms of areas of uncertainty and those requiring improvement has revealed critical findings. Longitudinally, across all years, questions 7, 13, 14, and 17 consistently ranked among the lowest. With regard to question 7, the question's content reveals low satisfaction among graduates regarding foreign language

proficiency. From this perspective, it indicates that the university needs to update its foreign language education curriculum at a reform level as part of its commitment to lifelong learning. Question 17, meanwhile, reveals that the low satisfaction expressed by graduates regarding employment points to proactive shortcomings in the university's graduate tracking systems and career center activities. Questions 13 and 14, meanwhile, reveal that graduates' indecision regarding the university's adequacy in terms of physical and social facilities and its re-enrollment appeal indicates a need to foster a sense of belonging and enhance campus life.

Conclusions

In this study, the results of institutional data collected by Sakarya University of Applied Sciences from its graduates were reanalyzed at a 5-year longitudinal level using a secondary analysis method. Based on the analysis results shared by the university with the public, which included data from a total of 3,879 graduates, several key findings were derived within the framework of the university's unique educational model, the +1 Applied Education Model. Accordingly, the study aimed to reveal the temporal changes in perceptions and satisfaction following graduation. The results obtained based on the research questions are as follows:

It was determined that graduates' overall satisfaction rates showed consistent and high stability in the 77–79% range over a five-year longitudinal period from 2020 to 2025. However, while studies in the literature indicate that students' overall satisfaction with their university or department is at moderate levels, ranging from 47% to 50%, this study differs in that its overall satisfaction results are at a high level (Şahin et al., 2011; Ulusoy et al., 2010). Although there was a decline in the number of participants due to universities switching to online education following the earthquake disaster in Turkey during the 2022–2023 academic year, no significant change was observed in the overall satisfaction perceptions of the graduates who participated. However, a similar study in the literature emphasizes that technical issues during the educational process, changes in automation, or disengagement from the educational environment for any reason can lead to a decline in students' expectations and satisfaction levels (Yangın & Kırca, 2013). This situation can be clearly explained by the university's institutional structure, its resilience during crisis periods, and its ability to adapt quickly to solutions. In another study, efforts to increase student satisfaction by continuously updating the curriculum in the Physical Therapy and Rehabilitation (FTR) department at Acıbadem Mehmet Ali Aydınlar University through continuous improvement show similarities to the results obtained in this study regarding increased satisfaction (Alaca & Kaba, 2022). Graduates' high level of satisfaction is clearly reflected in their confidence that they will contribute to the business world through the +1 Applied Education Model and in their belief that the experience they have gained will have a positive impact on their lives.

The gender factor examined in the second question of the study did not reveal any differences in overall satisfaction. It was found that the satisfaction levels of female and male graduates showed parallel results over a five-year period. Ebulum & Chidiboi's (2016) study, which examined satisfaction with academic disciplines, also concluded that there were no differences based on gender. However, this study's findings differ from those of Gerçek (2020), who found that women's satisfaction with their academic field was higher, and from Baltacı et al. (2012), who found that male students' satisfaction with education was lower. Furthermore, to ensure the rigorous presentation of scientific reporting, the lack of gender-disaggregated data for the 2024–2025 academic year was reported as an institutional limitation.

Comparisons among academic units, however, showed that vocational school graduates had the highest level of satisfaction. Graduate students followed them, while undergraduate students had a relatively low level of satisfaction compared to other levels in terms of overall satisfaction. While the studies by Ekinci & Burgaz (2007) concluded that overall satisfaction regarding expectations and satisfaction was moderate, the findings show some similarity in that satisfaction was low in certain faculties—such as Science, Medicine, and Dentistry—and moderate in others. It is believed that the decline in overall satisfaction observed during the 2022–2023 academic year—which coincided with the year of the earthquake disaster—was due to online instruction. In certain units where in-person instruction is particularly important—such as the Faculty of Sports Sciences (49%), Ferizli Vocational School (55%), Arifiye Vocational School (–), and Sapanca Tourism Vocational School (–)—a decline in satisfaction or a complete lack of participation has contributed to periodic drops in satisfaction levels. An examination of some studies supporting this finding revealed that physical infrastructure, the duration of practical courses, and the adequacy of course materials and equipment all influence satisfaction levels. In this regard, the present study is consistent with previous research (Bakır et al., 2016; Uzgören and Uzgören, 2015). Nevertheless, the fact that satisfaction levels among the first graduates of the Faculty of Agriculture were accurately assessed and that satisfaction is trending upward among the second cohort indicates that institutional improvements are being effectively reflected in the field.

In the question-based analyses of the study's third question, the concepts of professional ethics, responsibility, and communication skills—which the university instills in its graduates—were the skills with the highest satisfaction

ratings. At the same time, the fact that the questions regarding the +1 Applied Education Model (questions 15 and 16) have consistently ranked highest in satisfaction among all survey questions over the past five years demonstrates that the model has achieved sustainable success and fostered a sense of institutional belonging among graduates. These findings are consistent with the following studies in the literature. In his study, Altaş (2006) found that the dimensions of "applied courses" and "proximity to the business world" were the dimensions that contributed most to the applicability of theoretical education in professional life. İyigün et al. (2023) concluded that graduates of the FTR department reported the highest level of satisfaction regarding the "opportunity to apply their theoretical knowledge in practice during internships," Arslanhan & Yaman (2020) concluded that the failure of theoretical courses in the field of gastronomy to translate into practice and the lack of coordination with the industry constituted the greatest source of dissatisfaction.

However, while there has not been a consistent decline in foreign language proficiency and post-graduation employment support, it has been determined that these are areas requiring improvement, as they consistently show the lowest satisfaction levels across all years in the longitudinal analysis. There are studies highlighting the chronic problem regarding foreign language proficiency. These include the findings from the Alaca & Kaba (2022) FTR graduate survey, in which the "English language proficiency" program outcome received the lowest score, and the study by Ürün et al. (2026), which examined employer opinions in the evaluation of BTÜ graduates and found that the lowest score was given for foreign language skills—both of which concretely demonstrate similarities with this study. Additionally, Uçar's (2017) study on theology departments revealed that students' high demand for foreign language courses indicates the need for reforms in the development of foreign language skills. Another area where a decline has been observed is post-graduation job placement support, and there are many studies showing similarities in this regard. For example, Ekinci & Burgaz (2007) found that among Hacettepe University students, the highest expectations—and consequently the lowest satisfaction—were related to the lack of adequate promotion and guidance regarding post-graduation employment. İyigün et al. (2023) found that FTR graduates expressed the lowest level of satisfaction with the faculty's role in helping them find employment. Zeydan & Gürbüz (2019), in a study where students at Zonguldak Bülent Ecevit University mentioned that graduation was meaningless when there were no job opportunities, emphasized the lack of employment-related services. Another finding was that graduates remained undecided regarding the university's re-enrollment appeal due to physical and social facilities. This situation indicates the need for measures to improve the quality of life on campus.

In conclusion, the university's mission regarding the +1 Applied Education Model has been a key area that graduates strongly endorse. However, in terms of institutional development, the university needs to focus on areas such as supporting employment and implementing language education reforms.

Suggestions

To address the areas where graduates reported the lowest levels of satisfaction, it is recommended to move away from traditional theoretical language instruction and design sector-specific, practice-oriented professional foreign language teaching programs.

At the same time, to increase the low level of satisfaction with post-graduation job placement support, it is recommended that career planning activities be restructured and that a system be implemented to track graduates' employment and, consequently, provide mentoring support.

It is recommended that researchers conduct similar studies at this level using graduate satisfaction survey results from different universities, compare these universities across various dimensions, and repeat these studies at specific intervals—such as every 5, 10, or 15 years.

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Generative AI in Visual Design Education: Insights from Students' Lived Experiences

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Abstract

Generative artificial intelligence (GenAI) has rapidly become part of visual design practice, accelerating production, providing alternative solutions, and raising questions about creativity, originality, and ownership. This study examines graphic design students' lived experiences of using GenAI-assisted tools in visual design. A phenomenological qualitative design was employed with 23 second-year students who had used GenAI tools in visual design courses. Data were collected through a semi-structured interview form containing seven open-ended questions and analyzed through content analysis. Seven themes emerged: purposes of AI use, effects on learning, changes in design thinking, creativity and originality, contributions to the design process, perceptions of inspiration versus ready-made solutions, and design ownership. Most participants used GenAI for idea generation, inspiration, visual editing, and developing alternatives. They emphasized learning support, new perspectives, and substantial time savings, particularly in drafting and technical operations. However, some students warned that excessive reliance on AI could weaken originality and creativity. Views on ownership were also divided: some students regarded AI as a tool and considered the final work their own, whereas others felt that AI-generated works could not be fully claimed as personal creations. The findings suggest that GenAI can support learning and design processes, but its pedagogical integration should also address originality, creative agency, and ethical ownership.

Keywords: Generative artificial intelligence, visual design, graphic design education, phenomenology

1. Introduction

Rapid developments in digital technologies continue to transform the tools and production practices used in design. Beyond conventional graphic design software and online design platforms, the widespread adoption of generative artificial intelligence (GenAI) has introduced a new stage in this transformation. GenAI systems can generate text and images in response to user prompts and support idea development, visualization, alternative generation, and editing. In design education, this is important because learning is not limited to software operation; students are also expected to define problems, generate ideas, compare alternatives, make aesthetic decisions, communicate visually, and develop original solutions. Recent research indicates that GenAI can accelerate early-stage ideation and diversify creative options, while concerns remain that extensive technological support may weaken individual expression or perceived originality (Lee, 2025).

GenAI may also alter how students think and make decisions during design. Unlike conventional digital tools that mainly help users execute an already formed idea, GenAI can propose new visual directions. Students therefore shift partly from direct producers to evaluators, selecting, redirecting, and refining machine-generated alternatives. Fleischmann (2026) describes this shift as moving from AI as a tool to AI as a 'thinking partner.' Such use requires new competencies, including prompt literacy, critical evaluation, and curatorial decision-making. Evidence further suggests that GenAI may be more educationally effective when embedded in structured pedagogical approaches rather than introduced as a stand-alone technology (Hatef Jalil & Abdullah, 2026; Song & Xu, 2026).

Another major contribution of GenAI is the rapid testing and comparison of alternatives. Students can explore color, composition, form, and content options in a fraction of the time required by conventional workflows. Wagler (2025) found that advertising design students valued GenAI for idea development and alternative workflows, while also stressing the need to consider its implications for originality and strategic creativity. The relationship between GenAI and creativity is therefore not unidirectional. AI may expand the space of possible ideas, yet overreliance on ready-made outputs may reduce independent ideation or lead to convergent aesthetics. Baltà-Salvador et al. (2026) similarly found that AI support did not directly reduce ideational fluency, flexibility, or originality, although AI-assisted ideas could become more similar and students often interacted with the system in a directive but relatively passive way.

Questions of originality are closely related to creative ownership. In design education, originality involves not only visual difference but also the student's ability to justify decisions, express an individual aesthetic position, and develop a distinctive response to a design problem. Because GenAI outputs are derived from patterns in existing data, students may adopt similar aesthetic solutions or use outputs without sufficient transformation.

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Bartlett and Camba (2024) therefore emphasize originality, ethics, copyright, and the quality of creative labor when GenAI is integrated into design education. These issues also complicate authorship: when a student develops the concept and directs the process but the system generates much of the visual output, the boundary between human contribution and algorithmic production becomes less clear.

Research Purpose

This study examines graphic design students' experiences using GenAI-assisted tools in visual design and the meanings they attribute to these experiences. The study focuses on purposes of use, learning and design thinking, creativity and originality, the role assigned to GenAI during design, perceptions of inspiration versus ready-made solutions, and ownership of AI-assisted designs.

The research questions were:

1. How do visual design students experience GenAI-assisted design, and what roles do they assign to GenAI in this process?

2. How do students make sense of GenAI's effects on their learning and design-thinking processes?

3. How do students experience the role of GenAI in creativity and design originality?

4. How do students perceive GenAI as a source of inspiration or as a provider of ready-made solutions?

5. How do students make sense of ownership and creative belonging in designs produced with GenAI support?

2. Method

2.1. Research Design and Participants

This study employed a phenomenological qualitative design. Phenomenological research aims to reveal how individuals experience a particular phenomenon and the meanings they attribute to those lived experiences (Moustakas, 1994). This study examined students' experiences using GenAI-assisted tools in visual design. The study group consisted of 23 second-year students (13 male, 10 female; ages 18-23) enrolled in the Graphic Design Department of a higher education institution. The study used criterion sampling; participants were required to have taken visual design courses and directly used GenAI tools in their design processes.

2.2. Data Collection

Data were collected through a semi-structured interview form comprising seven open-ended questions developed with reference to the literature and reviewed by two experts. The questions addressed learning experiences, positive and negative aspects of GenAI use, changes in design thinking, newly acquired skills, creativity and originality, and perceptions of ownership. Before the interviews, students had used GenAI throughout one semester in a second-year Packaging Design course. Using chatbots and tools such as Leonardo, they completed 10 assignments over 10 weeks. Participants were informed about the study and participated voluntarily. To protect confidentiality, they were coded as S1-S23.

2.3. Data Analysis

The qualitative data were analyzed using content analysis. Responses were first reviewed holistically, then meaningful statements were coded and related codes were grouped into higher-order categories and themes. Seven themes were identified: purposes of AI use, effects on learning, changes in design thinking, creativity and originality, effects on the design process, inspiration versus ready-made solutions, and design ownership. We used frequencies to summarize recurring codes, and we supported findings with participant quotations. Two researchers independently coded the data. Inter-coder agreement was calculated using Miles and Huberman's (1994) formula, Reliability = Agreement / (Agreement + Disagreement) x 100, and was 87%.

3. Findings

3.1. Purposes of Using GenAI

Table 1. Purposes of Using GenAI Tools

Code	f
Idea generation	18

Inspiration	15
Visual generation	11
Visual editing	9
Color and composition suggestions	7
Learning support	6

Idea generation (f=18) and inspiration (f=15) were the most frequent purposes, followed by visual generation and editing. This indicates that students used GenAI not only for final production but also as an early-stage exploratory aid. S6 stated, "I use it to generate ideas, conduct visual research, and try different compositions."

3.2. Effects on the Learning Process

Table 2. Effects of GenAI Tools on the Learning Process

Code	f
Facilitating learning	17
Developing technical skills	12
Accelerating software use	11
Generating alternatives	10
May negatively affect learning	4

Most students reported that GenAI facilitated learning (f=17), supported technical skill development (f=12), and accelerated software use (f=11). Four participants also noted possible negative effects. S3 explained, "It helps me use design software more efficiently and makes it easier to discover new techniques during learning."

3.3. Changes in Design Thinking

Table 3. Effects of GenAI Tools on Design Thinking

Code	f
Developing different perspectives	16
Acquiring new design skills	14
Thinking more strategically	8
Developing prompt-writing skills	6
No perceived change	3

Developing different perspectives (f=16) and acquiring new design skills (f=14) were the most common changes. Students also referred to more strategic thinking and prompt-writing skills. S12 summarized this shift as follows: "I started to think more analytically and strategically."

3.4. Creativity and Originality

Table 4. Effects of GenAI Tools on Creativity and Originality

View	Code	f
Positive view	Increases creativity	14
Positive view	Offers new perspectives	11
Positive view	Supports originality	8
Negative view	May reduce originality	6
Negative view	May weaken design skills	3

Views were mixed. Many participants believed GenAI increased creativity and exposed them to new perspectives, while others worried about reduced originality or weakened design skills. S15 noted, "It affected my creativity positively; seeing different design examples made it easier to generate new ideas." In contrast, S14 warned that consuming too much simple content could reduce creativity and originality.

3.5. Effects on the Design Process

Table 5. Effects of GenAI Tools on the Design Process

Code	f

Saves time	19
Accelerates drafting	13
Facilitates editing	10
Increases alternative generation	9
Can sometimes slow the process	1

Time saving was the strongest finding (f=19), followed by faster drafting and easier editing. S1 stated that tasks such as background removal, lighting correction, and resolution enhancement were reduced from time-consuming operations to seconds. However, one student noted that greater speed could also reduce attention to design detail and meaning.

3.6. Inspiration or Ready-Made Solution?

Thirteen participants described GenAI primarily as a source of inspiration, seven viewed it as providing both inspiration and solutions, and three saw it mainly as a ready-made solution. Students generally positioned AI as a starting point rather than a replacement for their own creative process. As S16 stated, "AI is a starting point for me, not the final result."

3.7. Design Ownership

Table 6. Responses on Design Ownership

Code	f
The design belongs to me	11
It partly belongs to me	6
It does not belong to me	5
Undecided	1

Ownership produced clear disagreement. Eleven students considered the design their own, six viewed it as partly their own, five did not consider it theirs, and one was undecided. For students who claimed ownership, the decisive factor was that the core idea, direction, and decisions came from them. S15 stated, "The idea comes from me; AI is only a tool." In contrast, S22 said, "I only give the command; it produces it, so I have no labor in it."

4. Discussion and Conclusion

The findings show that students generally experienced GenAI not as an autonomous system replacing the designer but as a supporting resource for idea development, inspiration, technical operations, alternative generation, and learning. This is consistent with research showing that design students use GenAI to support ideation and alternative workflows and are willing to learn how to use it effectively and ethically (Fleischmann, 2024; Wagler, 2025). Students also emphasized easier learning, technical skill development, faster software use, and substantial time savings. These outcomes support the view that GenAI can lower technical barriers and enable faster experimentation. Song and Xu (2026) similarly found that GenAI integrated with a structured design-thinking strategy supported design achievement, creative self-efficacy, and problem solving, highlighting the importance of pedagogical structure.

Changes in design thinking were also evident in students' reports of broader perspectives, new design skills, strategic thinking, and prompt writing. The fact that most students described GenAI as an inspiration source or starting point rather than a ready-made answer aligns with the idea of AI shifting from a conventional tool toward a thinking partner (Fleischmann, 2026). At the same time, creativity and originality presented a more complex picture. Lee (2025) reported stronger perceived contributions to ideational fluency and flexibility than to visual originality. Lin and Xie (2026) likewise found strong gains in elaboration and fluency without a significant originality effect, describing an efficiency-originality divergence. Xianwen et al. (2026) further argue that GenAI may both support and constrain creativity depending on students' independence, cognitive engagement, and motivation.

These concerns are particularly relevant to design education because originality, creative labor, and authorship are closely connected. Bartlett and Camba (2024) recommend using visual GenAI as a process-support tool while explicitly addressing originality, ethics, and copyright; Wagler (2025) similarly advocates a process-oriented approach that gives students opportunities to reflect critically on their use of AI. The divided ownership responses in the present study reinforce this need: some students regarded ideation, direction, and selection as sufficient creative contribution, whereas others did not feel ownership when AI performed most of the visual production.

In conclusion, GenAI has substantial potential to support learning, ideation, and efficiency in visual design education, but its value depends on how it is pedagogically structured and how actively students remain involved in creative decision-making. Design education should therefore emphasize critical evaluation of AI outputs, prompt and curatorial skills, transformation rather than passive adoption of generated content, and explicit discussion of originality and ownership. Future qualitative and mixed-method studies may further examine how these experiences change across design disciplines, different levels of AI literacy, and longer-term learning contexts.

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Preparing Future Information Professionals for AI-Enabled Library Services: An Assessment of Turkish LIS Curricula

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Abstract

Artificial intelligence is increasingly embedded in library and information services, raising questions about how Library and Information Science (LIS) education prepares future professionals. This study assesses AI preparedness across six undergraduate LIS programs in Türkiye using a five-dimensional framework developed from 20 LIS-relevant studies retrieved from the Web of Science Core Collection. The framework covers foundational AI knowledge, information and data competencies, ethical and critical AI competencies, AI-enabled service and management competencies, and professional and societal dimensions. Curriculum evidence was coded as either AI-enabling or explicit AI. The results show that all six programs provide substantial AI-enabling foundations through areas such as information retrieval, information organization, databases, digital systems, and information services. Explicit AI content is also present, most clearly in foundational AI knowledge, but its integration across ethical, professional, and societal dimensions is uneven. The main curricular issue is therefore not the absence of AI-related preparation, but the need to connect existing LIS foundations more explicitly with AI concepts, applications, limitations, and responsibilities.

Keywords: artificial intelligence, AI literacy, LIS education, curriculum analysis, Türkiye

Introduction

Artificial intelligence is becoming part of everyday library and information services, influencing how information is organized, retrieved, evaluated, and delivered to users. AI applications increasingly appear in information discovery, metadata creation and enrichment, reference services, research support, recommendation, and information summarization (Chiang & James, 2025; International Federation of Library Associations and Institutions [IFLA], 2026). As these applications become embedded in established areas of library work, they also change the competencies expected of information professionals.

Recent AI-literacy literature emphasizes that preparedness involves more than the ability to use particular tools. It includes technical understanding, critical evaluation, ethical awareness, and consideration of the wider social implications of AI (Lo, 2025). The Association of College and Research Libraries (ACRL, 2025) similarly organizes AI competencies for academic library workers around ethical considerations, knowledge and understanding, analysis and evaluation, and use and application. These dimensions are closely connected with long-standing LIS responsibilities concerning authority, accuracy, relevance, privacy, access, and responsible information use.

The implications for LIS education are therefore broader than adding a single AI course. A database course is not an AI course. Neither are courses in metadata, bibliometrics, digital libraries, or information retrieval. Such subjects may provide important foundations for working with AI-supported information systems, but their presence does not demonstrate that students are learning about machine learning, generative AI, algorithmic bias, AI governance, or other AI-specific issues. A useful assessment must distinguish competencies that enable AI-related professional practice from those that explicitly address AI.

Recent international curriculum research reinforces this need. Bridges et al. (2025), combining a scoping review with an analysis of LIS syllabi, found substantial variation in how AI literacy is incorporated into LIS education and highlighted differences between technical and critical approaches. Their findings show that the presence of AI-related content alone does not indicate balanced preparation across technical, ethical, and sociotechnical dimensions. The present study builds on this concern but examines the Turkish undergraduate context through a framework that distinguishes AI-enabling disciplinary foundations from explicit AI competencies.

This distinction is particularly relevant in Türkiye, where undergraduate LIS programs, generally organized under the title Bilgi ve Belge Yönetimi (Information and Records Management), retain established areas such as information organization, cataloging, classification, information retrieval, archives, information technologies, digital libraries, and information management. These areas can support AI-enabled practice, but the extent to which curricula explicitly address AI knowledge, applications, critical evaluation, ethics, and professional implications remains less clear.

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Against this background, the study assesses AI preparedness across six undergraduate LIS programs in Türkiye. AI preparedness is treated as a curricular capacity that may be distributed across different areas of LIS education rather than confined to courses labeled AI. The study addresses the following research questions:

RQ1. To what extent do Turkish LIS curricula incorporate competencies required for AI-enabled library services?

RQ2. Which dimensions of AI preparedness are most strongly and least strongly represented within the curricula examined?

By separating AI-enabling foundations from explicit AI competencies, the study aims to identify both existing curricular strengths and areas requiring more direct AI-related development.

AI Preparedness Framework

AI preparedness in LIS education cannot be assessed solely through courses explicitly labeled artificial intelligence. Recent competency models treat AI literacy as multidimensional, combining knowledge of AI technologies with information and data skills, critical evaluation, ethical awareness, and responsible professional application (ACRL, 2025; Lo, 2025). The framework used here therefore accommodates both emerging AI competencies and established areas of LIS practice.

To operationalize this concept, 20 LIS-relevant studies retained from the literature search were examined through their keywords, abstracts, and conceptual frameworks. Five recurring dimensions were identified: D1 – Foundational AI Knowledge; D2 – Information and Data Competencies; D3 – Ethical and Critical AI Competencies; D4 – AI-enabled Service and Management Competencies; and D5 – Professional and Societal Dimensions. Together, these dimensions cover AI concepts and technologies, information and data work, critical and ethical issues, professional applications, and the broader organizational and societal context of AI.

The framework also distinguishes AI-enabling competencies from explicit AI competencies. AI-enabling competencies are established LIS knowledge and skills that can support work in AI-mediated environments. Explicit AI competencies directly address AI concepts, applications, or implications. Information retrieval, metadata, databases, or bibliometrics were therefore not treated as evidence of explicit AI education unless the curriculum directly connected them to AI. This distinction formed the basis for the curriculum coding.

Methodology

The study was conducted in two stages. First, a literature-based framework was developed to identify the competencies associated with AI preparedness in Library and Information Science (LIS) education. The Web of Science Core Collection was searched using the topic query TS=("AI" AND "Library Science"). At the time of the original retrieval, the search yielded 30 records. The records were screened for relevance, and 10 studies outside the LIS context were excluded. The remaining 20 studies formed the literature base for framework development. Their keywords, abstracts, and conceptual frameworks were examined to identify recurring AI-related competencies, which were organized into the five dimensions presented in the AI Preparedness Framework section.

In the second stage, the framework was applied to the undergraduate curricula of six Turkish LIS programs: Hacettepe University, Ankara University, İstanbul University, Marmara University, Kastamonu University, and Çankırı Karatekin University. Official university curricula, course descriptions, program information, and available learning outcomes were examined. Course titles alone were not treated as sufficient evidence when more detailed course information was available. Official institutional sources were consulted for all six programs (Ankara University, 2024; Çankırı Karatekin University, n.d.; Hacettepe University, n.d.; İstanbul University, n.d.-a, n.d.-b; Kastamonu University, n.d.; Marmara University, n.d.).

Curriculum evidence was classified as either AI-enabling or explicit AI. AI-enabling competencies were defined as established LIS knowledge and skills that could support professional practice in AI-mediated environments. Explicit AI competencies required direct reference to AI or identifiable AI-related concepts, applications, or issues. A course could contribute to more than one dimension when its content or learning outcomes provided sufficient evidence. Where the evidence was unclear, the course was not classified as providing explicit AI preparation.

A single researcher conducted coding; therefore, an inter-rater reliability statistic was not calculated. To maintain consistency, the same predefined dimensions and classification criteria were applied across all six programs. The coded material was reviewed a second time, and ambiguous cases were reconsidered using the same criteria before the coding was finalized.

Results

The analysis revealed an uneven pattern of AI preparedness across the six LIS curricula. All programs contained established LIS competencies relevant to AI-mediated information work, particularly in information retrieval, information organization, databases, digital information environments, research methods, and information services. Explicit AI content was also identified, but its breadth and integration across the five dimensions varied among the programs.

D1 – Foundational AI Knowledge showed the clearest evidence of explicit AI education. Marmara University includes the compulsory course *Artificial Intelligence Technologies in Information Sciences* (Marmara University, n.d.), while İstanbul University offers two compulsory courses, *Web Ecosystem and Artificial Intelligence* and *Digital Technologies and Artificial Intelligence in Archives* (İstanbul University, n.d.-a, n.d.-b). At Çankırı Karatekin University, the course Algorithms and Data Structures provides a potential computational foundation for AI-related learning (Çankırı Karatekin University, n.d.). Kastamonu University explicitly identifies artificial intelligence, machine learning, and data analytics among the areas covered by its undergraduate program (Kastamonu University, n.d.). The depth of documented coverage nevertheless differed. Marmara's detailed course content, for example, extends from basic AI concepts to neural networks, deep learning, natural language processing, recommender systems, and supervised and unsupervised learning (Marmara University, n.d.).

D2 – Information and Data Competencies was the most broadly represented dimension when AI-enabling competencies were considered. Across the programs, courses addressing databases, information retrieval, metadata and knowledge organization, information technologies, statistics, data-related methods, and digital information systems provided a disciplinary foundation for AI-supported information work. Explicit connections to AI were less consistently visible. Where such connections were documented—as in AI-supported search, recommendation, classification, data analysis, or data-mining applications—they were coded as explicit AI evidence rather than simply as general information or data competencies.

The distinction was more pronounced in **D3 – Ethical and Critical AI Competencies**. General curricular coverage of professional ethics, privacy, copyright, and responsible information practice provided an enabling foundation, but explicit attention to AI-specific concerns was less consistently identified. Marmara provided clear evidence of explicit coverage through algorithmic bias, responsibility, and data privacy in its AI course (Marmara University, n.d.). İstanbul's Web Ecosystem and Artificial Intelligence also addresses algorithmic responsibility, while Digital Technologies and Artificial Intelligence in Archives includes digital security and ethical issues (İstanbul University, n.d.-a, n.d.-b). General ethics courses were not treated as explicit AI ethics unless their available descriptions established a direct connection to AI.

For **D4 – AI-enabled Service and Management Competencies**, the curricula provided relevant foundations through subjects such as information services, cataloging, automation, digital libraries, information retrieval, and information-center management. Explicit AI applications were identifiable in a smaller number of programs. Marmara directly connects AI with information management, recommendation, classification, and AI-supported search (Marmara University, n.d.). İstanbul connects AI with web-based information environments, archival systems, automated document processing, AI-supported access and classification, and decision-support systems (İstanbul University, n.d.-a, n.d.-b). Kastamonu's program description also explicitly links AI and data analytics with information services (Kastamonu University, n.d.). The professional foundations for AI-enabled services are therefore broadly present, while their explicit connection with AI remains uneven across programs.

D5 – Professional and Societal Dimensions was represented primarily through broader LIS competencies, including professional responsibility, information access, lifelong learning, and interdisciplinary perspectives. Compared with the other dimensions, explicit curricular evidence concerning human-centered AI, organizational readiness for AI, AI policy, or the wider societal implications of AI was less consistently identifiable in the available documentation.

Overall, the results show that AI preparedness cannot be reduced to whether a program offers a course labeled "artificial intelligence." The six curricula contain a broad base of AI-enabling competencies, particularly within D2 and D4, while explicit AI preparation is more visible in D1 and in selected courses and programs. Explicit coverage of the critical, ethical, professional, and societal dimensions of AI is less consistently documented. The principal curricular gap, therefore, is not the complete absence of AI-related preparation, but the uneven integration of explicit AI competencies across the different dimensions of LIS education.

Discussion

The findings show that AI preparedness in LIS education is better understood as a matter of curricular integration than as the simple presence or absence of AI courses. The programs examined already contain substantial

disciplinary foundations that can support work in AI-mediated environments, particularly through information retrieval, data and database work, information organization, digital systems, and information services. At the same time, these foundations should not be treated as equivalent to explicit AI preparation. Maintaining this distinction prevents established LIS technology courses from being retrospectively relabeled as AI education and provides a more realistic view of current curricular readiness.

This pattern is consistent with the broader fragmentation identified by Bridges et al. (2025), whose international analysis found considerable variation in how AI literacy is incorporated into LIS education and warned against separating technical preparation from critical approaches. The Turkish curricula examined here show a related pattern. Explicit AI knowledge is becoming visible, particularly through AI-focused courses and applications, but its integration with ethics, governance, professional judgment, and societal concerns is less systematic. The issue, therefore, is not simply whether students encounter AI, but whether they encounter it across the range of competencies needed for professional practice.

This broader interpretation is also consistent with current AI-literacy frameworks. Lo (2025) treats AI literacy as extending beyond technical knowledge to include ethical awareness, critical thinking, practical application, and societal impact. Similarly, the ACRL competencies organize professional AI preparedness around ethical considerations, knowledge and understanding, analysis and evaluation, and use and application (ACRL, 2025). Viewed against these frameworks, introducing an AI-focused course is an important development, but it does not by itself ensure balanced preparation.

For LIS curriculum development, this suggests that the next step need not be the wholesale replacement of established disciplinary content. Many existing competencies remain directly relevant to AI-enabled professional work. A more practical approach is to build explicit AI learning into these foundations. Information retrieval can address AI-supported search and evaluation; metadata courses can examine automated description and classification; information ethics can incorporate algorithmic bias, privacy, and accountability; and information services can consider appropriate uses and limitations of generative AI. Such integration would preserve core LIS knowledge while making its relationship to contemporary AI environments explicit.

The findings should be interpreted within the study's scope. The analysis covers six Turkish undergraduate programs and relies on publicly available curricula, course descriptions, and learning outcomes; topics discussed informally within individual courses may therefore not be visible in the documentation. Nevertheless, the distinction between AI-enabling and explicit AI competencies offers a useful way to identify where curricular foundations already exist and where more deliberate integration is needed.

Conclusions

This study examined how six Turkish undergraduate LIS programs prepare students for work in increasingly AI-enabled information environments. The analysis shows that the curricula already contain many competencies that can support such work, particularly in information retrieval, information organization, databases, digital systems, and information services. Explicit AI content is also present, but it is not yet integrated evenly across the different dimensions of preparedness.

The distinction between AI-enabling and explicit AI competencies proved useful in showing this difference. Established LIS courses remain important, but they should not automatically be treated as evidence of AI education. What matters is whether students are also introduced directly to AI concepts, applications, limitations, ethical concerns, and professional implications.

For curriculum development, the findings point toward greater integration rather than wholesale replacement of existing content. AI-related learning can be incorporated into established LIS subjects while preserving the field's disciplinary foundations. Future studies could extend the analysis to a larger international sample and examine course-level implementation in greater depth.

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Bridging Theory and Practice in Robotics: A Pilot Study of a Shared Hardware Loan System

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Abstract

The integration of advanced automation and robotics into industrial practices necessitates a corresponding shift in vocational education and training (VET) curricula. However, VET institutions frequently encounter substantial resource constraints when attempting to provide hands-on experience with contemporary hardware. To address this challenge within the Moravian-Silesian Region of the Czech Republic, the Moravian-Silesian Technological Academy (MTA) developed a framework of teaching materials that prioritizes industry-standard equipment to ensure graduates' labour market relevance. Recognizing the prohibitive costs of such hardware relative to basic educational alternatives, the MTA paired its "EduBoxes"—open-access digital learning modules—with a shared physical loan system.

This pilot study evaluates the deployment of mobile and service robotics using the Festo Robotino platform. Preliminary curriculum analysis indicates that this domain remains underrepresented in current VET programs compared to traditional industrial robotics. Evaluating the initiative's initial rollout, this pilot study involved 7 of the 44 eligible secondary vocational schools in the region, operating with an anticipated expansion of three additional schools annually. Data was collected via a mixed-methods survey from technical teachers (N = 11) who utilized the robots during a trial loan period. The survey measured parameters including lesson preparation efficiency, perceived material utility, and student engagement.

Results demonstrate that the introduction of physical, industry-grade robots into the classroom environment positively influenced student motivation and active participation. Concurrently, the standardized EduBox materials streamlined lesson preparation tasks, particularly for experienced instructors. However, the study identified specific areas for systemic refinement. Educators with lower baseline experience in mobile robotics reported requiring extended, hands-on training to effectively operate the equipment. Furthermore, logistical feedback indicated that initial trial loan periods were occasionally insufficient, with several teachers requesting extensions of up to three months to facilitate optimal curricular integration. Moving forward, the project will systematically track longitudinal impact metrics, such as student placements in technical competitions, to formally assess the framework's ongoing educational efficacy and the broader viability of shared-hardware models paired with standardized teaching materials in VET environments.

Keywords: Robotics Education, Resource Sharing, Service Robotics

Introduction

Industry 4.0, characterized by the increasing integration of cyber-physical systems, automation, and robotics into manufacturing, is associated with changing qualification requirements and new demands on workers (Kuper, 2020; Oks et al., 2024). The increasing adoption of Industry 4.0 technologies changes the technological and organizational conditions of manufacturing work and creates new requirements for vocational preparation (Frank et al., 2019; Kuper, 2020). Consequently, VET curricula are increasingly expected to incorporate technological and transversal competencies associated with Industry 4.0, including emerging digital and automation technologies (Chou et al., 2018; Klement & Domanský, 2024).

In the context of VET, the integration of theoretical and practical knowledge is an important component of vocational learning (Orozco et al., 2021). In robotics education, hands-on approaches involving physical devices have been widely investigated as a means of supporting student engagement and the development of technical and transferable skills. Systematic mapping research suggests that robotics and physical devices can support student engagement and the development of technical and transferable skills, particularly when combined with active and collaborative learning approaches (Conde et al., 2021). Educational robotics has also been associated with positive learner perceptions and with opportunities to develop affective, cognitive, and transferable skills (Alimisis, 2013; Darmawansah et al., 2023). Furthermore, a meta-analysis of studies in vocational education found positive effects of robotic technology on learning outcomes and reported benefits related to computational thinking, creativity, innovation, communication, and teamwork (Sukardi et al., 2024). While educational simulators can increase accessibility to robotics and provide opportunities for safe experimentation (Tselegkaridis & Sapounidis, 2021),

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research comparing virtual-physical robot combinations with physical-robot-only approaches suggests that such combinations can affect cognitive load and engineering design ability, although effects may vary across learning outcomes (Zhong et al., 2023).

Despite the undeniable benefits of hands-on robotics, VET institutions face significant barriers to implementation. The implementation of advanced technologies can also create organizational and resource challenges for educational institutions, particularly in contexts characterized by rapid technological change (Kuper, 2020). The integration of these technologies also places additional demands on vocational teachers, who need to develop and update their technological and pedagogical competencies. Professional development can therefore play an important role in strengthening teachers' knowledge and competencies related to Industry 4.0 and STEM technologies (Akgunduz & Mesutoglu, 2021). Systematic reviews identify lack of time, insufficient professional training, limited technical support, and inadequate resources as major barriers to technology integration (Akram et al., 2022; Chen et al., 2026). Time, access to technology, professional development, and teachers' beliefs can constitute important barriers to technology integration (Kopcha, 2012). Successful integration requires not just technical operation, but the complex combination of technological, pedagogical, and content knowledge, known as the TPACK framework (Mishra & Koehler, 2006).

One possible approach to mitigating these constraints is the shared use of technological resources. Research on shared technological environments suggests that shared digital resources can support resource sharing and collaborative project work (Nicol & MacLeod, 2005). Building on this principle, the present pilot study explores whether a shared hardware-loan model can improve access to specialized robotics equipment in VET. An important component of this approach is standardized methodological support that can reduce the amount of basic lesson preparation required from teachers. This pilot study explores one such solution through the implementation of "Eduboxes" (learning materials developed and used as a tool to raise the level of teaching vocational subjects in secondary schools and to facilitate the preparation of teachers so that they can more easily respond to the increasing demands and requirements of employers in the context of constantly modernizing technologies). By combining a shared physical platform Festo Robotino (see Figure 1) with comprehensive, pre-prepared didactic materials, this approach aims to make practical robotics education accessible while supporting the critical role of the teacher.

Methodology

This pilot study utilizes a mixed-method survey to evaluate the deployment of a shared hardware loan system in vocational education with its primary objective of determining feasibility of this version of a system, reception of teachers, focusing on the subjective preparation time and professional demands placed on teachers, the didactic utility of standardized materials, and what impact having physical industry-grade robot in the classroom has on students.

The study targeted Vocational Education and Training (VET) schools in the Moravian-Silesian Region (MSK) of the Czech Republic. The initial phase involved 7 out of 44 eligible secondary vocational institutions in the region during a first wave of loans conducted between December 4, 2025, and June 25, 2026. This number is expected to grow by 3 each year. The research sample was made of teachers of technical subjects (N = 11), both vocational and practical training instructors, who used the option to introduce robots in their schools during the trial period. The participating teachers possessed varying levels of prior experience with mobile robotics, as detailed in Table 1.

Table 1. Participant breakdown based on prior experience with mobile robotics.

Experience Level	No experience	Basic exposure	Advanced skill	Total
Number of Teachers (n)	3	7	1	11
Percentage of Sample	27.3%	63.6%	9.1%	100%

Out of 11 involved educators, a subset of 8 actively used the robot in the classrooms and as such, this subset will serve as the core group for evaluating student-related variables.

As a physical hardware for this study was chosen the educational platform Robotino, which represents contemporary mobile and service robotics. This equipment was provided for schools together with corresponding Edubox modules containing standardized digital learning materials and lesson plans. The hardware loan system provided organized rotation of the mobile robots between the involved schools. The whole process involved providing the logistics of transportation of the robots to the schools and back, foundation training provided to teachers before the deployment to classrooms and the option of technical support during the whole time of the loan of the hardware.

The research data were collected after the trial via the online questionnaire, which was distributed to the involved teachers. This questionnaire was designed to evaluate key operational and educational parameters. These parameters included time demands and effectivity of lesson preparation, perception of usefulness of corresponding learning materials, level of student interest and involvement and overall satisfaction with the logistics, for example the length of the loan or the lector evaluation. Following analysis of acquired responses was used to assess the educational effectiveness of the whole concept of loans and to identify specific areas, that will require system improvements for the future implementations.

Results

The results of this pilot study are derived from the data collected from the initial group of 11 vocational teachers. However, to ensure the methodological validity of findings related to direct pedagogical impact, the analysis of didactic variables, such as student engagement, material utility, and lesson preparation, focuses exclusively on the core subset of 8 educators who actively deployed the Robotino platform during their direct teaching hours. The remaining respondents provided baseline logistical feedback but are excluded from the classroom impact metrics to prevent data distortion. An overview of the core findings, including student engagement, material utility, and logistical satisfaction, is provided in Figure 1.

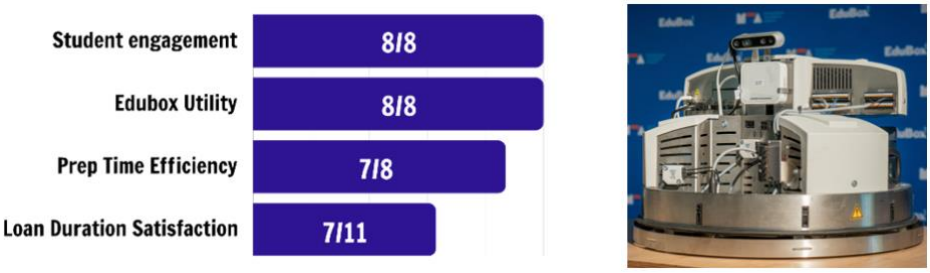


Figure 1. Teacher evaluation of the pilot shared hardware loan system parameters, illustrating evaluated didactic variables along with a view of the Robotino mobile robot. Photograph by Moravian-Silesian Technological Academy, 2026. Reprinted with permission.

Teacher Preparation and Professional Self-Efficacy

The integration of complex robotic systems into teaching practice traditionally imposes significant time and cognitive demands on educators, creating a major barrier to the adoption of Industry 4.0 technologies. This subsection evaluates how the provision of standardized EduBox materials and initial foundation training influenced the teachers' subjective sense of professional readiness and their actual time invested in lesson preparation. The findings address the core research assumption that pre-prepared didactic materials reduce the technical barrier to entry, theoretically freeing the teacher to focus on the pedagogical delivery of the content.

Qualitative Observations on Preparation Strategies

An initial assumption regarding the deployment of shared technological systems was that a higher sense of professional readiness would lead to a reduction in the time required to prepare for a lesson. It was naturally expected that as teachers gained technical confidence, their preparation workload would decrease.

While the sample size of this pilot study is too small for broad statistical generalizations, analysis of the active user subset revealed an unexpected divergence in preparation strategies. The educators who reported feeling "rather unprepared" for independent work with the robot (n = 2) declared the shortest preparation times, spending less than 30 minutes per lesson. Conversely, educators who felt "rather prepared" or "completely prepared" dedicated significantly more time to preparation, most frequently reporting between 30 to 60 minutes, or even 1 to 2 hours per lesson.

Open-ended survey responses were essential for contextualizing this phenomenon. Qualitative feedback indicated a shift in how preparation time was utilized. Because standardized EduBox modules reduced the cognitive load by eliminating the need to develop basic technical operations and introductory presentations from scratch, confident educators reported reinvesting this saved capacity into deeper didactic planning. Their open responses detailed activities such as designing more complex, time-consuming tasks or differentiating assignments for students with varying skill levels.

In contrast, qualitative data from educators lacking technical confidence suggested a tendency to minimize interaction with the technology or to rely heavily on the provided baseline materials without further expansion, resulting in shorter preparation times.

Therefore, the preliminary qualitative evidence suggests that standardized materials do not necessarily eliminate teacher preparation; rather, they enable technically confident teachers to elevate the pedagogical quality of their lessons. This observation forms a key hypothesis that will be tracked as the project expands to additional schools.

The Impact of Standardized Theoretical Materials

A critical barrier to technology integration in vocational education is the teacher's fear of insufficient technical or didactic expertise. The provision of standardized theoretical materials within the EduBoxes is intended to serve as a methodological safety net, reducing this cognitive burden.

Survey data from the active user group confirmed the importance of this support. Among the five respondents who evaluated the theoretical presentations as "rather beneficial," two still reported feeling "rather unprepared" for independent work with the robot. Conversely, out of the three educators who perceived the theoretical support as "highly beneficial," none reported feeling unprepared for independent teaching.

This trend underscores that the technical functionality of the loaned hardware represents only one facet of successful integration. Comprehensive, high-quality theoretical materials are equally essential, as they directly increase teachers' professional self-efficacy, providing them with the confidence to experiment with new technologies in the classroom.

Student Engagement and Didactic Implementation

While the physical presence of an industry-grade robot is known to stimulate intrinsic motivation, research suggests that hardware alone does not guarantee sustained student engagement; the pedagogical implementation is equally critical.

The survey results demonstrated a positive correlation between the perceived clarity of the practical assignments and the level of student activity, with 8 out of 8 respondents reporting high student engagement (Figure 1). Among the educators who utilized the pre-prepared task assignments, all four who rated the tasks as "rather beneficial" observed "sufficient engagement" from their students. Notably, all three educators who rated the assignments as "highly beneficial" reported the highest possible level of student activity, noting that students were "highly engaged."

Since the EduBox scenarios were identical across all schools, these results highlight the critical role of the teacher as a facilitator. When educators fully understand, align with, and appreciate the didactic value of the provided methodology, they can successfully transfer that potential into the classroom, maximizing student participation. This emphasizes that initial foundation training must not be limited to technical operation but must extensively cover methodological execution to ensure teachers can utilize the materials to their full potential.

Logistics and Operational Feedback

Beyond pedagogical variables, the broader operational feedback (N = 11) provided valuable insights into the shared hardware model's logistics. While the rotation system effectively bypasses the financial barriers of purchasing and maintaining hardware, certain logistical limitations were identified, which is reflected in a lower satisfaction rate of 7 out of 11 regarding the loan duration (Figure 1).

Educators with no prior robotics experience indicated that a standard introductory training session was occasionally insufficient, highlighting a need for more extensive, hands-on methodological preparation. Furthermore, some teachers found the initial trial loan periods too brief for seamless curricular integration, with respondents suggesting that extended loan periods of up to three months would facilitate optimal educational outcomes.

Conclusions

The integration of Industry 4.0 technologies into vocational education is frequently hindered by financial constraints and the overwhelming didactic burden placed on educators. This pilot study indicates that a shared hardware loan system, supported by standardized EduBox modules, presents a promising and potentially sustainable solution for VET institutions. By providing schools with coordinated access to industry-grade platforms like the Festo Robotino, educational institutions can mitigate the barriers of high procurement costs and rapid technological obsolescence while delivering critical hands-on experience to students.

A central observation of this study is that the physical presence of advanced technology in the classroom is insufficient on its own to guarantee educational success; the educator's role as a didactic facilitator remains paramount. Furthermore, initial qualitative feedback suggests a nuanced reality regarding teacher workload: rather than entirely eliminating lesson preparation time, standardized theoretical and practical resources appear to act as

a cognitive safety net. They relieve confident teachers from the burden of designing foundational technical content, allowing them to reinvest their time into complex didactic planning, task differentiation, and active classroom facilitation. Consequently, it is recommended that future teacher training programs go beyond mere technical operation to heavily emphasize methodological execution and pedagogical integration.

While the initial rollout indicated high student engagement and positive teacher reception within the pilot group, specific systemic refinements were identified to optimize the framework. To maximize curricular integration and reduce scheduling pressure, the trial loan durations should be extended, ideally up to three months, as requested by the participants. Additionally, educators with minimal prior robotics experience require more intensive, hands-on introductory training to build the necessary professional self-efficacy before entering the classroom.

Moving forward, the project aims to expand the shared loan system by incorporating three additional regional schools annually. Future research and project phases will focus on systematically tracking longitudinal impact metrics, such as student placements in technical competitions, and validating these preliminary qualitative observations on a larger dataset to further evaluate the long-term efficiency of the shared-hardware model in vocational education.

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Analysis of Faculty Perceptions of the Use of Artificial Intelligence Tools in Higher Education: The Case of the Adventist University of Bolivia

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Abstract

Introduction: Artificial intelligence (AI) is transforming higher education; however, evidence on its adoption from the perspective of university faculty in Bolivia remains limited. This study aimed to analyze faculty perceptions and use of AI tools, as well as the opportunities and challenges associated with their integration into teaching. **Method:** A convergent mixed-methods design was employed with 106 faculty members from the Adventist University of Bolivia. Quantitative and qualitative data were collected simultaneously through a survey with closed- and open-ended questions and were analyzed independently before integration. **Results:** Faculty reported favorable perceptions of AI: 82.1% highlighted its usefulness for planning and developing materials and 75.5% for improving teaching. A positive Spearman's rank correlation was found between AI knowledge and perceived opportunities ($r_s = .468$, $p < .001$), as well as significant differences in the frequency of ChatGPT use according to knowledge level, $H(3) = 13.727$, $p = .003$, $\eta^2H = .104$. Qualitative findings highlighted benefits related to access to information and time savings, together with challenges such as faculty training, plagiarism, and technological dependence. **Discussion:** The findings show a favorable perception of AI and indicate that greater knowledge is associated with a more favorable assessment of its opportunities and with more frequent use of ChatGPT. Nevertheless, sustainable integration requires faculty training, clear institutional policies, and ethical criteria to promote responsible pedagogical use.

Keywords: Artificial intelligence; higher education; university faculty; technology adoption; faculty perceptions.

Introduction

Artificial intelligence (AI) is transforming multiple areas of society and, particularly, higher education by expanding possibilities for teaching, learning, and research (Bond et al., 2024; Castillo-Martínez et al., 2024). Its rapid development has encouraged the incorporation of tools capable of supporting content generation, academic planning, feedback, personalized learning, and various teaching and research activities (Qian, 2025). However, this expansion also raises pedagogical, ethical, and technological challenges related to its effective integration into educational practices (Giannakos et al., 2025; Al-Zahrani & Alasmari, 2024; Qian, 2025).

In this process, faculty play a fundamental role, as their knowledge, perceptions, and practices can facilitate or limit the adoption and pedagogical use of AI. Faculty are not only users of these technologies but also key agents in their educational and institutional integration, since their attitudes, competencies, and decisions influence how AI is incorporated into teaching and learning processes (Mah & Groß, 2024; Najjar et al., 2026; Ofosu-Ampong, 2024).

Although research on AI in higher education has increased considerably worldwide (Bond et al., 2024), a substantial part of the literature has focused on students, while faculty perspectives and teaching practices have received less attention (Liang et al., 2025). In Latin America, research on AI in higher education has also grown, although scholarly output remains uneven and the evidence is still fragmented (De La Torre & Baldeon-Calisto, 2024; Manrique Gallegos et al., 2025). In Bolivia, research is still emerging, and several recent studies have focused primarily on the student perspective (Fernández Calle et al., 2025; Martínez Cruz et al., 2026; Rodríguez Chávez & Galindo Céspedes, 2026). Consequently, there is a need to expand the evidence on how Bolivian university faculty perceive and use these technologies, as well as the opportunities and challenges they identify for their integration into teaching practice.

Understanding these processes can be supported by technology acceptance models. Davis's (1989) Technology Acceptance Model (TAM) explains technology acceptance primarily through perceived usefulness and perceived ease of use. However, TAM addresses only to a limited extent the social and institutional factors that may also influence technology adoption. It can therefore be complemented by the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003), which incorporates factors such as social influence

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and facilitating conditions. The complementarity of both approaches was recently supported by Gao and Yang (2026), who applied an integrated UTAUT2–TAM model to analyze university faculty adoption of AI tools. Together, these models provide a broader understanding of the individual, social, and institutional factors associated with AI adoption and use in higher education.

In this context, it is necessary to understand university faculty perceptions and use of AI, as well as the opportunities and challenges they identify for its integration into teaching practice. Accordingly, this study addresses the following research question: How do university faculty perceive and use artificial intelligence, and what opportunities and challenges do they identify for its integration into teaching practice? In line with this question, the objective of the study is to analyze how university faculty perceive and use artificial intelligence tools, as well as the opportunities and challenges associated with their integration into teaching practice in the Bolivian context.

Methodology

A convergent mixed-methods design was employed (Creswell & Plano Clark, 2018), also referred to as a parallel or concurrent mixed-methods design (Thierbach et al., 2020). After approval was obtained from the Research Directorate, quantitative and qualitative data were collected simultaneously, analyzed independently, and subsequently integrated to identify convergence, divergence, and complementarity across the findings. Convenience sampling was used. The invitation was distributed to 193 faculty members at the Adventist University of Bolivia, of whom 116 responded to the survey. Ten responses were excluded because of missing data, resulting in a final sample of 106 participants.

The questionnaire was developed based on the literature and the authors' contributions, incorporating conceptual elements from TAM (Davis, 1989) and, complementarily, UTAUT (Venkatesh et al., 2003). Its organization into sections on sociodemographic characteristics, AI knowledge and use, perceived opportunities and challenges, and open-ended questions drew on Kankeviciene et al. (2026), while its format was guided by Pari et al. (2020). The items were adapted to the context and objectives of the study. A pilot test was conducted with the first 40 participating faculty members, leading to minor adjustments in terminology and item sequence. Because no substantial changes were made, these participants remained eligible for inclusion in the final sample. The Likert-scale items on frequency of AI use, perceived opportunities, and identified challenges showed high overall internal consistency (Cronbach's $\alpha = .947$).

Quantitative data were analyzed using SPSS version 27 through descriptive and inferential statistics, including frequencies, percentages, Spearman's rank correlation, and the nonparametric Kruskal–Wallis test. Qualitative data from the open-ended questions were analyzed through manual coding in Microsoft Excel, following an inductive approach that included repeated reading, identification of thematic patterns, development of a codebook, and systematic classification. The three authors categorized the responses independently and resolved discrepancies by consensus. Each response could be assigned to more than one thematic category. Finally, integration of both components provided a broader understanding of the phenomenon under study.

Results

Quantitative Results

Sociodemographic Characteristics

The sample ($n = 106$) showed a balanced gender distribution: 50.9% were women and 49.1% were men. Regarding disciplinary area, Health Sciences predominated (30.2%), followed by Economics and Administrative Sciences (27.4%), Humanities and Social Sciences (21.7%), and Engineering (20.8%). With respect to artificial intelligence training received during the previous year, 73.6% of participants reported having received formal training, 15.1% indicated that they were self-taught, and 11.3% reported having received no training.

Level of AI Knowledge, Access, and Use

Regarding AI knowledge, the intermediate level predominated (51.9%), followed by the basic (31.1%) and advanced (10.4%) levels, while 6.6% of participants reported no knowledge. In terms of access to the internet and technological devices, 84.0% indicated having sufficient access, 8.5% reported partial access, and 7.5% reported having no such access. Regarding the use of AI in teaching, 85.8% stated that they had used these tools, while 8.5% indicated that they had not used them and 5.7% were unsure.

Most Frequently Used AI Tools

ChatGPT was the most frequently used tool, with 50.0% of participants reporting its use as 'frequent' or 'always,' followed by Gemini (47.2%), NotebookLM (46.2%), and Canva AI (33.0%). Frequent use was reported to a lesser extent for image-generation tools (31.1%), data analysis tools (23.6%), Copilot (20.8%), Grammarly (13.2%), DeepL (10.4%), and other tools (8.5%).

Faculty Perceptions of the Impact of AI in Higher Education

Regarding perceptions of the impact of AI in higher education, favorable views predominated: 50.0% of faculty considered its effects more positive than negative, while 38.7% expressed a balanced assessment. A smaller proportion (4.7%) perceived predominantly negative effects, and 6.6% expressed uncertainty about its impact. In addition, 70.8% of participants reported feeling prepared to integrate AI tools into their courses.

Perceived Opportunities and Challenges of Artificial Intelligence in Higher Education

Table 1. Perceived Opportunities Associated with Artificial Intelligence in Higher Education.

Opportunities (perceived usefulness)	Frequency	%
AI facilitates the planning and development of educational materials.	87	82.1%
AI improves the quality of university teaching.	80	75.5%
AI facilitates the incorporation of new teaching strategies into my courses.	75	70.8%
AI improves feedback to students.	73	68.9%
AI supports personalized learning.	69	65.1%

Note. Frequencies represent the number of participants who selected "agree" or "strongly agree" for each item. Percentages were calculated using the total sample of 106 participants. Because items were assessed independently, frequencies are not cumulative, and percentages do not necessarily sum to 100%.

The results show a favorable perception of the usefulness of AI in teaching practice. The main opportunity identified was its contribution to planning and developing educational materials (82.1%), followed by improving teaching quality (75.5%). In addition, more than 65.0% of faculty recognized benefits related to new teaching strategies, feedback, and personalized learning.

Table 2. Perceived Challenges Associated with Artificial Intelligence in Higher Education.

Challenges associated with AI implementation	Frequency	%
It is important to establish institutional guidelines for AI use.	74	69.8%
AI-assisted plagiarism represents a real risk.	63	59.4%
Lack of faculty training.	56	52.8%
Technological dependence.	50	47.2%
The use of AI tools may compromise students' privacy and data protection.	45	42.5%
Incorrect or unreliable information.	34	32.1%
Resistance to change.	33	31.1%
The use of AI raises ethical dilemmas related to authorship and academic responsibility.	32	30.2%

Note. Frequencies represent the number of participants who selected "agree" or "strongly agree" for each item. Percentages were calculated using the total sample of 106 participants. Because items were assessed independently, frequencies are not cumulative, and percentages do not necessarily sum to 100%.

The results indicate that the main perceived challenges concern the need to establish institutional guidelines for AI use (69.8%), followed by the risk of academic plagiarism (59.4%) and lack of faculty training (52.8%). Concerns were also identified regarding technological dependence, privacy, information reliability, and ethical issues, highlighting the need for responsible and regulated integration of AI in higher education.

Level of AI Knowledge and Frequency of ChatGPT Use

ChatGPT was the most frequently used AI tool among those evaluated. To determine whether its frequency of use differed according to the level of AI knowledge, the nonparametric Kruskal–Wallis test was applied. The results showed statistically significant differences among the four knowledge levels, $H(3) = 13.727$, $p = .003$, $\eta^2H = .104$. Mean ranks were 19.07 for no knowledge, 48.21 for basic, 58.55 for intermediate, and 66.00 for advanced knowledge. Pairwise comparisons with Bonferroni correction showed significant differences between the no-

knowledge and intermediate levels (p = .006) and between the no-knowledge and advanced levels (p = .007), with no significant differences among the remaining pairs (p > .05). Overall, the results indicate a higher frequency of ChatGPT use among faculty with intermediate and advanced levels of knowledge than among those with no knowledge.

Qualitative Results

The thematic analysis of faculty responses to the open-ended questions (n = 106) identified several recurring themes related to the perceived benefits of AI use. The most frequently mentioned themes were access to information and up-to-date information (37.7%), the development of educational materials, planning, and assessment (33.0%), and time savings and optimization (30.2%). Other themes included active teaching methodologies and instructional strategies (20.8%), research and knowledge production (12.3%), and personalization and learning support (12.3%).

Regarding challenges, eight recurring themes were identified. The most frequently mentioned was lack of faculty training (57.5%), followed by technological dependence (47.2%), risk of academic plagiarism (46.2%), lack of access to up-to-date tools (45.3%), absence of clear institutional policies (36.8%), resistance to change (35.8%), generation of incorrect or unreliable information (32.1%), and ethical and privacy concerns (30.2%). In both cases, the percentages represent the proportion of faculty who mentioned each theme. Because each participant could mention more than one benefit or challenge, the categories were not mutually exclusive and, therefore, the percentages may sum to more than 100%.

Integration of Quantitative and Qualitative Results

The quantitative and qualitative results converged in their favorable assessment of AI opportunities. Quantitatively, faculty highlighted its usefulness for planning and developing educational materials (82.1%), improving teaching quality (75.5%), and incorporating new teaching strategies (70.8%). These findings were consistent with the qualitative results, in which access to up-to-date information, development of materials, time savings, and active teaching methodologies emerged as the main benefits. In addition, a moderate positive correlation was found between the level of AI knowledge and perceived opportunities (r_s = .468, p < .001), indicating that greater AI knowledge is associated with a more favorable assessment of AI's educational potential.

Regarding challenges, both components showed convergence and complementarity. The quantitative results highlighted the need to establish institutional guidelines (69.8%), the risk of AI-assisted plagiarism (59.4%), and lack of faculty training (52.8%). Consistently, the open-ended responses identified lack of training (57.5%), technological dependence (47.2%), risk of plagiarism (46.2%), lack of access to up-to-date tools (45.3%), and absence of clear institutional policies (36.8%). Overall, the findings show that faculty recognize the pedagogical opportunities of AI while also identifying training-related, ethical, technological, and institutional barriers that may limit its effective integration.

Discussion

The results indicate a favorable assessment of AI among faculty, particularly regarding its usefulness for planning, developing educational materials, and improving teaching. These findings are consistent with TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) and align with Gao and Yang (2026), who identified perceived usefulness, performance expectancy, and institutional support as relevant factors in university faculty adoption of AI tools. Similar patterns have been reported by Mah and Groß (2024) and Najjar et al. (2026).

A relevant finding was the positive relationship between AI knowledge and perceived opportunities (r_s = .468, p < .001). In addition, the frequency of ChatGPT use differed significantly according to knowledge level, $H(3)$ = 13.727, p = .003, η^2H = .104, with higher use among faculty with intermediate and advanced levels than among those with no knowledge. These findings suggest that greater AI knowledge may reduce uncertainty regarding the technology and enable faculty to identify more concrete pedagogical applications, thereby strengthening perceived usefulness and facilitating adoption. This interpretation is consistent with TAM (Davis, 1989), which emphasizes perceived usefulness as a key determinant of technology acceptance, and with Najjar et al. (2026), who found a positive association between familiarity and AI adoption among university faculty.

The integration of quantitative and qualitative results showed convergence between perceived opportunities and benefits such as time savings, access to information, and material generation. At the same time, challenges emerged related to faculty training, plagiarism, technological dependence, privacy, and the absence of clear institutional policies. Overall, these findings suggest that AI integration should be understood as a process shaped by both individual factors, such as knowledge and perceived usefulness, and contextual and institutional conditions that may facilitate or limit its use. A favorable perception of AI, therefore, does not imply uncritical acceptance but

rather the simultaneous recognition of its benefits and risks. In the Bolivian context, where recent studies have focused primarily on students (Fernández Calle et al., 2025; Martínez Cruz et al., 2026; Rodríguez Chávez & Galindo Céspedes, 2026), this study expands the evidence from the faculty perspective. Consequently, sustainable AI integration requires strengthening faculty training, establishing clear institutional policies, and promoting ethical criteria for responsible use.

The study has limitations associated with its cross-sectional design, convenience sampling, and implementation at a single institution, which restrict causal inference and the generalizability of the results. In addition, reliance on self-reported data and the rapid development of AI may have influenced the findings. Future research should consider longitudinal designs and multicenter samples to examine changes in AI acceptance and use over time.

Conclusions

The results show that participating faculty generally perceive AI favorably and report meaningful engagement with AI tools, particularly recognizing their usefulness for supporting planning, improving teaching, and expanding pedagogical strategies. Greater AI knowledge was also associated with a more favorable assessment of the opportunities offered by AI and with more frequent use of ChatGPT. However, AI integration also poses challenges related to faculty training, plagiarism, technological dependence, privacy, and the absence of clear institutional policies. Taken together, these findings suggest that sustainable AI adoption requires moving beyond instrumental use toward pedagogical, ethical, and institutional integration, supported by continuous faculty training, clear institutional policies, and criteria for the critical and responsible use of AI in higher education.

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Implications of AI-Induced Lexical Creativity for Digital Language Tools

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Abstract

The availability of advanced generative artificial intelligence systems to the general public in November 2022 created an important turning point in human-computer language interaction. Particularly after the public release of ChatGPT, the rapid integration of AI technologies into daily communication, education, media, and professional activities has also caused noticeable changes in the digital lexicon of English. These changes can be observed both in the emergence of new words and expressions and in the acquisition of new technological meanings by existing lexical items. The current article investigates the implications of lexical creativity observed in post-2022 AI discourse for digital language tools. Within a corpus-based approach, lexical items which have acquired high relevance in modern AI discourse are compared with a reference corpus, and their contextual behavior is analyzed. Items such as "prompt injection" and "AI-generated" are considered as new lexical formations, whereas "hallucinate," "train," "agent," and "alignment" are examined as examples of new or newly activated technological meanings. The research shows that automated translation systems, automated writing evaluation programs, language learning applications, and online dictionaries which rely on static or slowly updated lexical resources may face difficulties in processing rapidly changing digital lexis. The article emphasizes the importance of discriminating between an unknown word and a new meaning of a known word in such systems and suggests dynamic updating mechanisms based on continuous corpus monitoring, domain-sensitive lexical models, and human expertise.

Keywords: artificial intelligence, neologism, semantic change, lexical creativity, digital language tools, corpus linguistics, automated writing evaluation

Introduction

Language is like a living organism because it constantly reacts to changes occurring in society and technology. The emergence of new technologies does not only create new notions and fields, but it also leads to the need to name those notions and explain them. Therefore, the link between technological advancements and lexical change is not a new phenomenon. For example, the word "broadcast" used to refer to seeding in agriculture, but then it acquired a new sense related to radio transmission. Similarly, the word "surf" used to refer to moving on sea waves, but it is now used in internet-related fields (Fortson, 2003; Li & Siew, 2022). In modern times, the rapid integration of technology into daily life has made these processes much quicker. Rudnicka (2023) also noted that AI-based technologies may influence linguistic change, and the entrance of new technology into language may assign new meanings to existing vocabulary. The public release of generative artificial intelligence since the end of 2022 has shaped a new and more intensive stage of the interrelationship between technology and language. The entrance of AI systems into daily technological conversations has necessitated the need to name new processes, products, and different forms of human-machine interaction. The English language in general responds to these needs in two directions. On the one hand, new lexical items, namely neologisms, emerge; on the other hand, words that have been present in the language for decades acquire new shades of meaning. These two processes are interrelated, but they are discriminated in the present research. For the purposes of the present article, a neologism is defined as a newly coined lemma, whereas semantic change is described as the phenomenon whereby existing vocabulary acquires new meaning or new shades of meaning. This kind of distinction allows for a more pristine examination of how artificial intelligence impacts the lexicon of English.

The notion of neologism is not absolute by itself; it is also dependent on time and context. According to some scholars, we should take four points into consideration when we define new lemmas. The first one is when it entered the lexicon; the second one is whether or not it has been documented in dictionaries; the third one is to what extent its form and meaning have been stabilized; and the last one is how much speakers of the language perceive it as new. This approach is particularly important for fast-changing technological discourse because words which used to be employed in narrowly specialized environments can spread to wide public usage in a very short period, thereby extending beyond their terminological boundaries. Rehman et al. (2025) also noted that new words can enter professional and academic usage much faster in digital communicational environments.

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The second major direction of AI-induced lexical creativity is semantic change. The change of meaning of words is a natural characteristic feature of the evolution of any language (Campbell, 1999). Semantic change can be described from a semasiological point of view as the acquisition of different or new meanings by the same lexical form (Baghana et al., 2019; Traugott, 2006). In modern linguistics, distributional approaches are widely used in order to research this process. The main principle behind that methodology is that profound changes in the usage context of a word are accompanied by semantic change. In other words, the comparison of the semantic environment of a certain word across different time periods allows researchers to follow changes occurring in its meaning. This principle has been widely implemented in studies devoted to learning semantic change with computer technology (Hamilton et al., 2016; Kim et al., 2014; Sagi et al., 2009).

AI-related modern vocabulary lets individuals observe two processes simultaneously: the coinage of new terms and the acquisition of technological meaning by existing words. Recent research regarding computer-related lexis noted different forms of word-formation, including compounding, affixation, blending, and prefixation (Chyrvonyi, 2024, 2025). In a similar vein, semantic extension stands as a major lexical mechanism in AI discourse. For example, Chyrvonyi (2025) showed that words like “hallucination” and “slop” in English have acquired new meanings. Chyrvonyi (2024) also noted that words like “hallucinate” and p(doom) can reflect social concerns and anthropomorphic approaches towards automation. Such examples show that it is not always necessary to generate brand-new lexical items to talk about new technological notions; languages can also respond to communicative needs by adapting their existing lexical resources to new domains.

The fast-paced improvement of AI technology has also drawn attention to the issue of the sufficiency of existing lexical resources. Hewitt et al. (2025) claim that the current English lexicon is not enough to describe AI processes; therefore, there is a great need to coin new terms. In their approach, the extension of the lexicon of English is not only an issue of naming, but also explaining and understanding of AI-related processes. Therefore, lexical creativity in the age of AI can be characterized by the emergence of new terms and the existing lexicon’s acquisition of new shades of meaning.

The importance of this process is not only limited to theoretical linguistics. AI-related lexical creativity, which has entered our lives since 2022, can also pose problems for digital language systems. If automated language technologies rely on static lexical databases, their usage can entail inconsistencies between current digital discourse and language use. A newly introduced word can be considered a mistake in writing, and a new technological meaning of an existing word may be interpreted based on its traditional meaning. Such kinds of inconsistencies may directly impact automated translation systems, language learning applications, automated writing evaluation systems, online dictionaries, and other digital language tools.

In light of this view, it is not enough to learn modern lexical creativity based on the emergence of new terms or semantic change instances. At the same time, researchers should consider what those changes mean for the operation of language technologies. The current research unites these two directions. Using a corpus-based research design, it examines neologisms coined after 2022 and semantic change instances. Consequently, it analyzes possible implications of these changes for digital language tools. So, the main objective of the current study is to investigate to what extent language translation, evaluation, teaching, explanation, and processing systems adapt to these lexical changes.

Methodology

The research is based on a corpus-based comparative approach. The main objective is to identify lexical items which demonstrate unusually high relevance in modern AI-related discourse and compare their usage with earlier and more general English language material.

Two data sources are used in the current research. The first source is the self-compiled AI corpus, which represents modern artificial intelligence discourse after 2022. The second source is the general reference corpus, which functions as a basis for comparison.

The analysis consists of four main stages. At the first stage, the frequency profile of words and expressions in the target corpus is identified. At the second stage, this profile is compared with the reference corpus in order to select candidate items which demonstrate disproportionately high frequency in AI discourse. At the third stage, those items are examined through concordance lines and broader contexts. At the final stage, they are classified based on the type of lexical change.

An important methodological principle in this process is that high frequency does not automatically mean neologism. The frequent usage of a certain word in AI-related texts can simply originate from the characteristics of the topic. Therefore, the collocations, grammatical behavior, discourse functions, and concordance contexts of candidate items should be analyzed in order to determine whether or not they represent genuine lexical innovation.

Three main criteria are applied in the current research in order to identify post-2022 lexical innovation: the emergence or noticeable stabilization of the item in modern AI discourse; its significantly higher visibility in this discourse compared with the reference material; and the presence of a stable, contextually confirmed specific meaning related to the field of artificial intelligence.

Semantic change, on the other hand, is considered as the systematic usage of an existing lexical form in a new AI-related meaning. This category may be particularly complicated for digital systems. A completely new word can be marked by the system as unknown, but a new meaning of a word which already exists in the dictionary can create a more serious mistake: the system recognizes the form but assigns the wrong meaning to it.

Results and Discussion

The analysis shows that lexical creativity in AI discourse occurs through different mechanisms. The first group consists of multi-word lexical items which are new or have acquired a new communicative status.

“Prompt injection” is a specific security term formed through the combination of two already existing words. Here, the previous technical meanings of “injection” are adapted to a new artificial intelligence security context. It is not possible to determine the meaning of the expression simply as the sum of the general dictionary meanings of its components; its correct interpretation requires specific domain knowledge.

“AI-generated” also draws attention as a productive morpho-syntactic model. In combinations such as AI-generated text, AI-generated image, AI-generated essay, AI-generated music, and AI-generated content, the same structure can be combined with numerous nouns and allows for the emergence of new nominative items. In light of this view, the lexical impact of artificial intelligence should be considered not only at the level of individual words, but also at the level of productive word- and expression-formation patterns.

The second group covers new or more widely spread technological meanings of existing words. One of the clearest examples is the verb “hallucinate.” In its traditional usage, the word is related to a person seeing, hearing, or feeling things which are not real. In AI discourse, however, constructions such as “the model hallucinated” refer to a system generating incorrect, invented, or unsupported information. This meaning is already documented as a separate AI-related meaning in dictionaries.

An important characteristic feature of this example is that the previous meaning of the word does not disappear. Human-related and artificial intelligence-related meanings exist in parallel, and correct interpretation depends on the context. In the sentences “The patient hallucinated during the night” and “the model hallucinated a citation,” the same verb belongs to completely different semantic fields. Therefore, the main issue for a digital system is not the recognition of the word form, but the selection of the appropriate meaning based on the context.

“AI slop” represents a clearer example of metaphorical semantic extension. The evaluative meaning of “slop,” which is associated with low quality and worthlessness, is transferred to low-quality digital content generated by artificial intelligence on a massive scale. The widespread usage of this item shows that lexical innovation does not occur only through technical terminology, but also as a result of evaluative and metaphorical creativity of internet users. The fact that modern dictionaries have already documented “slop” as a separate item indicates that it is developing towards lexical stabilization.

A similar terminological specialization can also be observed in the word “train.” One of its traditional meanings is teaching a certain skill to a person or an animal. In the context of machine learning, however, to train a model refers to the process of determining and optimizing model parameters based on data. This technical meaning existed before 2022 as well; however, the widespread use of generative artificial intelligence has increased its visibility and communicative relevance in non-specialist discourse.

The same nuance applies to the word “agent.” In traditional usage, “agent” can refer to a person who acts on behalf of another person or organization. In modern generative AI discourse, however, the term refers to a software system which can make plans, make decisions, and perform certain actions towards the objective of the user.

“Alignment” can refer to physical arrangement, correspondence, or agreement in general language, but in AI discourse it acquires a specific terminological meaning related to bringing system behavior into correspondence with intended objectives, human preferences, values, and limitations. Here again, the main issue is not the novelty of the word form itself, but the strengthening of a particular semantic profile in technological discourse.

These findings show that lexical development in the age of AI should not only be learned as a list of neologisms. The broader problem is the change of word meanings, collocations, discourse fields, and their spread among different user groups over time.

Implications for Digital Language Tools

Automated Translation Systems

Semantic change can create a direct problem for automated translation. For example, in the sentence "The model hallucinated a citation," translating the verb "hallucinated" in its traditional meaning related to human perception would distort the main content of the sentence. Here, knowing only the dictionary equivalent of the word is not enough; the system should process collocational and domain-related signals such as "model + hallucinate + citation" together.

A similar problem also exists with new terms. Translating each component of "prompt injection" separately and literally may fail to transfer its terminological meaning in the context of cybersecurity and large language models. In such cases, successful translation requires the identification of the domain, recognition of the multi-word item as a term, and selection of its current equivalent in the target language.

Automated Writing Evaluation Systems

Automated Writing Evaluation (AWE) and automated essay evaluation systems can use lexical and grammatical features in order to evaluate the quality of writing. The main risk here is that the normative basis of the system may fall behind modern language usage. When writing an essay about artificial intelligence, a student can use contextually appropriate expressions such as "AI slop," "prompt engineering," or "the model hallucinated." If the evaluation system does not recognize these items, there is a possibility that it can mark them as non-standard, excessively informal, or lexical mistakes.

In such a case, the technological system rewards lexical conservatism instead of measuring language proficiency. In other words, a student who follows modern discourse and correctly uses current terminology can be unfairly penalized by a system based on an older lexical database. Therefore, AWE systems should discriminate between a language error, stylistic choice, domain-specific term, and a legitimate lexical item which is still in the process of formation.

Language Learning Applications

Digital language learning systems traditionally rely on word-meaning correspondences, stable dictionary explanations, and level-based lexical lists. However, modern digital literacy requires students not only to know the dictionary meaning of a word, but also to understand in which field and in which period the word carries a certain meaning.

For example, presenting the word "agent" only as "representative," the verb "train" only as "teach/practise," and the verb "hallucinate" only in the meaning of a person seeing unreal things creates incomplete lexical knowledge for modern digital English. Therefore, domain information, new collocations, and modern authentic contextual examples should be presented more systematically in language learning applications.

Online Dictionaries and Lexical Databases

Although online dictionaries have more flexible updating opportunities compared with printed dictionaries in the digital age, a certain time gap still remains between the emergence of new usage and its documentation in the dictionary. The process generally includes the emergence of a new form, its spread, observation by lexicographers, collection of sufficient linguistic evidence, and only after that its transformation into a dictionary entry.

The fact that the AI-related meaning of the verb "hallucinate" and the expression "AI slop" have already been documented in major online dictionaries shows that these resources react to changes. Nevertheless, the main issue is not simply that dictionaries should contain more words, but that they should become systems which detect lexical changes more quickly and prioritize them based on context.

Recommendations

Based on the findings of the research, several principles can be suggested in order to strengthen the adaptation of digital language technologies to lexical change.

First of all, continuous lexical monitoring should be implemented. The lexical database of systems should not only be manually updated at certain intervals, but new usage tendencies should also be automatically followed in modern news, social media, popular-scientific, and technological corpora. Corpora are particularly important in terms of showing changes in usage over time, and methods based on contextualized language models already provide practical opportunities for the automatic identification of semantic change.

Secondly, the system should discriminate between an unknown form and a new meaning of a known form. In the first case, the problem is the incompleteness of lexical inventory; in the second case, a more complicated problem of semantic interpretation exists. The presence of a word like "hallucinate" in the system's dictionary does not guarantee that it will be understood correctly.

Thirdly, domain-sensitive lexical representations should be developed. The system should not include "hallucinate + patient" and "hallucinate + model" contexts within the same semantic profile. The same principle also applies to "agent," "alignment," "train," and other items demonstrating polysemy.

Fourthly, automatic detection should be complemented by human expertise. Not every item whose frequency suddenly increases in a corpus represents a genuine neologism or new meaning. A change in contextual distribution can sometimes reflect a change in topic, and it would not be correct to directly consider it as lexicographical semantic change. Therefore, linguists, lexicographers, and experts from the relevant field should participate in the validation of automatically identified candidates.

Finally, in educational evaluation systems, innovation should not automatically be considered a mistake. Technical terminology, new legitimate words, and expressions specific to a particular communicative field should be evaluated within their context. The objective of digital evaluation should not be to adapt a student to a previous state of language, but to measure their meaningful and correct language use within current communicative norms.

Conclusion

Generative artificial intelligence does not only create new technologies; it also changes the language used to describe, discuss, and evaluate those technologies. New items or items which have acquired a new status, such as "prompt injection," "AI slop," and "AI-generated," as well as the rapid spread of technological meanings of words such as "hallucinate," "train," "agent," and "alignment," demonstrate the highly dynamic nature of lexical creativity in modern English.

From the perspective of theoretical linguistics, this process provides suitable material for studying phenomena such as neologization, semantic extension, specialization, and terminological repurposing. However, its importance is not only limited to the theoretical level. Lexical change can directly impact the operation of numerous digital systems, ranging from automated translation and online dictionaries to language learning applications and automated writing evaluation.

The main problem is that language is dynamic, whereas many digital resources are relatively static. As the distance between these two processes increases, the possibility that systems will provide interpretations which are not compatible with modern usage also increases. Semantic change is particularly critical in this respect because even if the system formally recognizes a word, it may fail to recognize its new meaning.

Therefore, future digital language tools need not only larger dictionaries, but also dynamic and corpus-based semantic monitoring. The automatic detection of new words and new meanings, their discrimination based on context and domain, and their subsequent confirmation by human experts can significantly increase the adaptability of digital language systems.

Such an approach is particularly important for educational technologies. The evaluation of a language learner's modern and contextually appropriate lexical choices as mistakes by an outdated digital resource weakens the reliability of measurement and creates an artificial difference between real communicative competence and the correct language accepted by the system. Consequently, the main objective of digital language tools should not be to limit language change, but to follow and represent it as accurately as possible.

Considering the speed of language change in the age of artificial intelligence, the continuous updating of lexical resources is no longer an additional advantage; it has become one of the major conditions for the functional reliability of digital language technologies.

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STEM Education for an Unpredictable Digital World: Competencies and Responsible Innovation

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Abstract

In a deeply unpredictable digital world, this study examines how STEM education can support the development of the competencies required to adapt to accelerated technological transformations. The aim of the research is to understand which STEM competencies become essential within an unstable digital ecosystem and how they can be cultivated through innovative pedagogical practices oriented toward responsible innovation. The study formulates three main objectives: (1) identifying STEM competencies relevant for effective functioning in an unpredictable digital world; (2) exploring innovative pedagogical practices that can facilitate the development of these competencies; (3) clarifying how technological responsibility can be explicitly integrated into STEM education. The methodology is qualitatively interpretive, based on literature review, educational case studies, and critical evaluation of emerging pedagogical models. The study formulates three central questions: what STEM competencies are needed to function effectively in an unpredictable digital world; how can innovative pedagogical practices facilitate their development; and how can technological responsibility be integrated into STEM education. The analysis highlights three major results. The first shows that, in the context of technological acceleration, relevant STEM competencies include not only technical skills, but also cognitive and metacognitive dimensions such as critical thinking, cognitive flexibility, and the ability to operate with uncertainty. The second result concerns the role of innovative pedagogical practices: project-based learning, technology-assisted exploration, and interdisciplinary activities facilitate the transfer of skills and the development of student autonomy, although uncritical integration of technology can generate algorithmic dependence and educational inequalities. The third result highlights the importance of the ethical dimension of innovation, with European documents on the ethics of artificial intelligence stressing the need for technological responsibility as an explicit part of STEM education. Overall, the study shows that STEM education can provide a solid framework for preparing students for digital uncertainty, provided that the integration of technology is accompanied by a pedagogy oriented towards autonomy, reflexivity and responsibility. The conclusions highlight the need for a flexible, ethical, and discernment-oriented pedagogy capable of preparing students for a continuously evolving digital future.

Keywords: STEM Education, unpredictable digital world, responsible innovation, ethics, digital pedagogy.

Introduction

The accelerated transformations of the digital world have profoundly reshaped how we understand education, competencies, and technological responsibility. In an ecosystem marked by uncertainty, volatility, and the continuous emergence of intelligent technologies, STEM education becomes a strategic space for developing students' adaptability, critical thinking, and autonomy. The literature emphasizes that scientific and technological literacy can no longer be conceived as a stable body of knowledge, but rather as a dynamic process oriented toward problem-solving and understanding the complexity of the digital world. Bybee (2013) describes STEM as "an integrated approach to learning that prepares students for the real challenges of contemporary society," a perspective that is even more relevant in a context defined by unpredictability.

At the same time, critical scholarship highlights the risks associated with the digitalization of education. Holmes (2022) argues that the use of artificial intelligence in schools may reduce student autonomy, excessively standardize learning processes, and amplify inequalities if not accompanied by robust ethical reflection. This position aligns with the European Union's analysis in *The Ethics of Artificial Intelligence: Issues and Initiatives* (European Commission, 2020), which stresses that AI integration in education must be governed by principles such as transparency, accountability, data protection, and respect for fundamental rights. Selwyn (2019) underscores that the digitalization of education is a process laden with social and political implications, while Floridi (2020) contends that responsibility in the use of emerging technologies becomes a fundamental competency in a world where algorithmic decisions increasingly shape human experience.

Recent studies on the relationship between writing, thinking, and cognitive processes in STEM contexts (Bostan, 2026) show that the ways in which students interact with technology directly influence the quality of reasoning

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and conceptual understanding. These preliminary findings suggest that effective pedagogy must integrate both technological and reflexive dimensions, avoiding algorithmic dependence and promoting cognitive autonomy.

Against this backdrop, the present study investigates how STEM education can contribute to developing the competencies required for effective functioning in an unpredictable digital world. The aim is to clarify both the technical and cognitive dimensions of these competencies and the ethical component essential for the responsible use of emerging technologies. The analysis highlights three major directions: the importance of cognitive and metacognitive competencies in managing uncertainty, the role of innovative pedagogical practices in fostering student autonomy, and the need for the explicit integration of technological responsibility into the curriculum. The study's conclusions outline the need for a flexible, ethical, and discernment-oriented pedagogy capable of preparing students for a rapidly changing digital future.

Building on these premises, the research formulates three central objectives: (1) identifying STEM competencies relevant for effective functioning in an unpredictable digital world; (2) exploring innovative pedagogical practices that can facilitate the development of these competencies; and (3) clarifying how technological responsibility can be explicitly integrated into STEM education.

In line with these objectives, the study addresses three research questions: What STEM competencies are necessary for effective functioning in an unpredictable digital ecosystem? How can innovative pedagogical practices support the development of these competencies? In what ways can technological responsibility be integrated into STEM education?

Thus, in an era in which uncertainty becomes the norm and technology profoundly shapes human experience, STEM education is no longer merely a curricular domain but a formative framework for autonomy, discernment, and creativity.

Theoretical background

Over the past two decades, STEM education has become a central conceptual framework for understanding how students can develop relevant competencies in a rapidly evolving digital society. Bybee (2013) argues that STEM is not merely a curricular integration of science, technology, engineering, and mathematics, but a way of cultivating the capacity to operate in complex, uncertain, and interdisciplinary situations. In an unpredictable digital world, this perspective becomes essential, as competencies can no longer be reduced to declarative knowledge but must be understood as dynamic, transferable structures oriented toward solving real-world problems.

Recent literature emphasizes that the digitalization of education is not a neutral process and introduces significant new challenges. Selwyn (2019) highlights the risks associated with technological dependence, showing that digital technologies can generate novel forms of control, mediation, and dependency in learning, which require a critical and reflexive approach to their integration in schools. Similarly, Floridi (2020) argues that artificial intelligence and algorithmic systems reshape the individual's decision-making space, and education must cultivate the ability to understand and evaluate these processes. The ethical dimension is reinforced by the European Union's analysis in *The Ethics of Artificial Intelligence: Issues and Initiatives* (European Commission, 2020), which insists on transparency, accountability, and the protection of fundamental rights in the use of AI in education.

Holmes (2022) offers an important critical contribution, showing that the use of artificial intelligence in schools may amplify inequalities, reduce student autonomy, and transform educational processes into opaque mechanisms if not accompanied by a pedagogy grounded in responsibility. This perspective is further developed in subsequent work (Holmes, Persson, Chounta et al., 2022; Holmes, 2026), which emphasizes that AI integration in education must be examined through the lenses of human rights, democracy, and social responsibility.

Another relevant theoretical pillar concerns the relationship between thinking, writing, and cognitive processes in STEM contexts. Bostan (2026) demonstrates that the ways in which students interact with technology—whether through handwriting, typing, or digital interfaces—directly influence reasoning structures, abstraction capacity, and conceptual understanding. This perspective is supported by earlier research on the role of science in the curriculum (Bostan, 2013) and by analyses of the effects of the digital revolution on teaching, learning, and assessment in physics (Bostan, 2025), which show that technology is not merely a tool but a cognitive environment that shapes learning processes.

Taken together, the theoretical foundation indicates that STEM education, in the context of an unpredictable digital world, must simultaneously foster technical competencies, critical thinking, and ethical responsibility. STEM is no longer simply a curricular domain but a formative framework for autonomy, discernment, and responsible innovation—one capable of preparing students for a future in which uncertainty becomes the norm and technology becomes a pervasive environment of life.

Methodology

The methodology of this study is situated within the qualitative–interpretive paradigm, which is well suited for research aimed at understanding educational processes in complex and dynamic contexts. Given the unpredictable nature of the digital ecosystem and the emergent character of STEM competencies, a qualitative approach enables a nuanced investigation of the relationships among technology, learning, and responsibility. The study draws on a critical analysis of the scholarly literature, an examination of relevant educational case studies, and a comparative evaluation of emerging pedagogical models, with particular emphasis on the integration of digital technologies and artificial intelligence into teaching and learning processes.

The literature review included foundational works on STEM education (Bybee, 2013), the role of science in the curriculum (Bostan, 2013), the impact of the digital revolution on teaching, learning, and assessment in physics (Bostan, 2025), the digitalization of education (Selwyn, 2019), the ethics of emerging technologies (Floridi, 2020; European Commission, 2020), and the effects of artificial intelligence on student autonomy (Holmes, 2022; Holmes, Persson, Chounta et al., 2022; Holmes, 2026). Recent contributions on the relationship between writing, cognitive processes, and STEM thinking (Bostan, 2026) were also integrated, offering valuable insights into how digital interaction shapes reasoning and conceptual understanding. These sources were selected based on their theoretical relevance and their contribution to understanding the interplay among competencies, technology, and responsibility.

The case studies analyzed originate from educational contexts in which digital technologies have been integrated in innovative ways, providing concrete examples of how STEM competencies can be cultivated in real learning situations. These cases include educational scenarios where digital tools, interactive platforms, or AI-based applications were used to support exploration, modeling, and problem-solving, allowing observation of how student autonomy is influenced by pedagogical design.

The methodological approach follows three main directions aligned with the research objectives. The first direction focuses on identifying the STEM competencies required in an unstable digital world through a conceptual analysis of the literature and the European framework for digital competencies. The second direction examines how innovative pedagogical practices—such as project-based learning, AI-supported exploratory activities, and interactive technologies—can foster the development of these competencies. The third direction investigates the ethical dimension of innovation, analyzing how technological responsibility can be integrated into STEM education in accordance with European recommendations on the ethical use of artificial intelligence.

Overall, the methodological design aims to formulate a coherent perspective on how STEM education can contribute to preparing students for an unpredictable digital future in which adaptability, discernment, and responsibility become essential competencies.

Results and discussions

The analysis of the scholarly literature, combined with an in-depth examination of educational case studies, reveals three major findings regarding the role of STEM education in an unpredictable digital world.

The first finding shows that, in the context of accelerated technological change, relevant STEM competencies are no longer strictly technical but encompass cognitive and metacognitive dimensions such as critical thinking, cognitive flexibility, and the ability to operate under uncertainty. These insights confirm Bybee's (2013) perspective that STEM should be understood as an integrated framework for preparing learners to navigate complex situations, rather than as a simple disciplinary aggregation. The case study examining the relationship between writing, cognitive processes, and STEM thinking (Bostan, 2026) reinforces this conclusion. In this study, students engaged in tasks requiring transitions between handwriting, typing, and digital modeling; the results showed that each mode of interaction activated distinct reasoning patterns. Handwriting supported conceptual structuring, typing facilitated rapid hypothesis testing, and digital interfaces enhanced abstraction and visualization. These findings demonstrate that technological interaction directly shapes reasoning structures and abstraction capacity—elements essential for functioning in unpredictable digital environments.

The second finding concerns the ways in which innovative pedagogical practices can support the development of these competencies. The analyzed case studies indicate that project-based learning, technology-assisted exploration, and interdisciplinary activities facilitate competency transfer and foster student autonomy. One case study drawn from physics education (Bostan, 2025) illustrates this particularly well: students used digital simulations to manipulate variables in complex physical systems, which enabled them to visualize dynamic processes that would otherwise remain abstract. Interactive tools such as real-time graphing applications and AI-supported modeling environments allowed learners to test multiple solution paths, compare outcomes, and justify decisions autonomously. Another case study involving interdisciplinary STEM projects showed that when

students collaborated on real-world problems—such as environmental monitoring or data-driven design—they demonstrated increased capacity to transfer knowledge across domains. However, critical literature emphasizes that technology integration does not automatically guarantee high-quality learning. Selwyn (2019) and Holmes (2022) warn that uncritical use of digital tools may lead to algorithmic over-dependence, reduced autonomy, and amplified educational inequalities. The findings of this study confirm these risks, showing that technology becomes a catalyst for learning only when embedded within a reflective and meaning-oriented pedagogical framework.

The third finding addresses the ethical dimension of innovation. The analysis of European policy documents on AI ethics (European Commission, 2020) and the broader scholarly literature (Floridi, 2020) indicates that technological responsibility must become an explicit component of STEM education. The case studies examined show that students develop a "technological consciousness" when they engage in activities that problematize algorithmic functioning, data implications, and the social impact of emerging technologies. For example, in one case study, students analyzed how AI-based recommendation systems filter information and discussed the ethical consequences of biased data sets. In another, learners explored the functioning of machine-learning models by manipulating training data and observing how small changes produced disproportionate effects—an exercise that strengthened their understanding of algorithmic opacity and ethical risk. This direction is further supported by research on the role of science in the curriculum (Bostan, 2013), which shows that competency formation cannot be separated from the development of ethical discernment and critical evaluation of technology. In this sense, STEM education becomes a formative space for responsibility, not merely for technical proficiency.

Overall, the findings indicate that STEM education can provide a robust framework for preparing students to navigate digital uncertainty, provided that technology integration is accompanied by a pedagogy oriented toward autonomy, reflexivity, and responsibility. The discussion suggests that the future of education depends not only on access to technology but on the system's capacity to cultivate flexible, ethical, and adaptive competencies capable of responding to the challenges of a continuously evolving digital world.

Conceptual Model

The conceptual model proposed in this study is grounded in the premise that STEM education constitutes an integrative framework capable of responding to the challenges of a profoundly unpredictable digital world, in which emerging technologies, artificial intelligence, and informational dynamics continuously reshape learning processes. At the center of the model lies the interdependence among three essential dimensions: STEM competencies, innovative pedagogical practices, and technological responsibility. These dimensions do not operate as autonomous entities but form a dynamic educational ecosystem in which each component influences and reinforces the others.

The first dimension, STEM competencies, is conceptualized as a set of technical, cognitive, and metacognitive abilities required to navigate an unstable digital environment. These competencies encompass not only scientific and technological knowledge but also the capacity to operate under uncertainty, critically analyze information, and transfer knowledge to new situations. Within the model, STEM competencies are directly shaped by the ways in which technology influences cognitive processes, aligning with Bostan's (2026) findings on the relationship between digital tools, reasoning structures, and abstraction processes.

The second dimension, innovative pedagogical practices, represents the mechanism through which STEM competencies are cultivated, strengthened, and transferred into authentic learning contexts. The model integrates approaches such as project-based learning, technology-assisted exploration, interdisciplinarity, and the use of artificial intelligence as a cognitive tool. These practices are considered catalysts for student autonomy; however, the model emphasizes—consistent with Holmes (2022) and Selwyn (2019)—that their effectiveness depends on the presence of a reflective pedagogical framework capable of preventing algorithmic dependence, over-standardization, and the erosion of students' critical capacities.

The third dimension, technological responsibility, functions as a transversal principle regulating the use of emerging technologies in education. Inspired by Floridi's (2020) ethical analysis and the European Union's recommendations (2020), the conceptual model asserts that STEM education must explicitly include the development of ethical discernment, understanding of algorithmic functioning, awareness of data-related risks, and the ability to evaluate the social impact of technology. Technological responsibility is not an additional element but a fundamental condition for ensuring that innovation is oriented toward individual and collective well-being.

Taken together, the conceptual model describes a dynamic triangle in which STEM competencies, innovative pedagogical practices, and technological responsibility mutually sustain one another, generating an educational framework capable of preparing students for an unpredictable digital future. In this ecosystem, technology

becomes a formative environment, competencies are evolving processes, and responsibility constitutes the foundation of autonomy and authentic innovation.

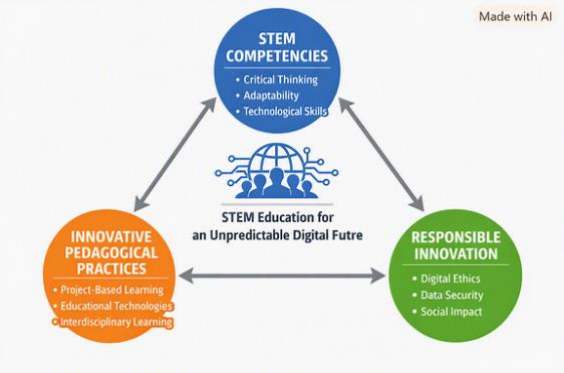


Figure 1. Conceptual Model of STEM Education for an Unpredictable Digital World

Conclusions

The study confirms that STEM education constitutes a fundamental framework for developing the competencies required in an unpredictable digital world, in which technology functions not merely as an operational tool but as an environment for living, thinking, and learning. The theoretical and methodological analysis shows that the development of STEM competencies must be understood as a complex and evolving process that integrates technical, cognitive, and metacognitive abilities such as critical thinking, adaptability, and ethical discernment. In line with the perspectives of Bybee (2013) and Floridi (2020), STEM education becomes a space for cultivating the capacity to operate under uncertainty, to evaluate the social impact of emerging technologies, and to navigate responsibly within a continuously transforming digital ecosystem.

The findings indicate that innovative pedagogical practices—project-based learning, interdisciplinarity, technology-assisted exploration, and the responsible integration of artificial intelligence—can support the development of transferable competencies and student autonomy. However, the effectiveness of these practices depends on the presence of a reflective pedagogical framework capable of preventing algorithmic dependence, over-standardization, and the erosion of critical capacity. In this regard, the European Union's recommendations (2020) and Holmes's analyses (2022) highlight the need for a pedagogy that balances innovation with responsibility, transparency, and data protection, guiding technology integration toward the formation of an active technological consciousness.

The overall conclusion is that STEM education must evolve from a model predominantly centered on technical performance toward one oriented toward responsible innovation, capable of forming reflective, autonomous, and ethical citizens. In an unpredictable digital world, STEM competencies cannot be dissociated from the moral dimension of technological action, and preparing for the future requires the coherent articulation of science, technology, and responsibility. The future of education depends on the system's ability to integrate these dimensions into a unified conceptual and pedagogical framework that cultivates discernment, sustainable creativity, and the capacity to act responsibly within a constantly changing digital environment.

Implications for Practice

The findings of this study suggest that integrating STEM education into an unpredictable digital world requires a profound reconfiguration of pedagogical practices. First, teachers must adopt a competency-oriented approach in which the focus shifts from content transmission to the development of critical thinking, adaptability, and the ability to operate under uncertainty. This shift entails designing learning activities that stimulate exploration, hypothesis formulation, solution testing, and reflection on the learning process rather than solely on the final outcome.

Second, the use of digital technologies and artificial intelligence must be guided by clear pedagogical principles. Technology becomes genuinely formative only when embedded within an instructional framework that encourages student autonomy, collaboration, and responsibility. In this regard, teachers require continuous professional development to understand both the potential and the limitations of digital tools, avoiding algorithmic dependence and the over-standardization of learning processes.

Another important implication concerns the explicit introduction of the ethical dimension into STEM activities. Students need to become familiar with how algorithms function, the risks associated with data, and the social

impact of emerging technologies. This approach not only strengthens STEM competencies but also contributes to the development of technological consciousness, which is essential for responsible participation in the digital society.

Finally, schools and policymakers must create an educational ecosystem that supports responsible innovation: adequate infrastructure, robust data-protection policies, equitable access to technology, and spaces for pedagogical experimentation. Only within such a framework can STEM education become a meaningful instrument for preparing students for an unstable yet opportunity-rich digital future.

Limitations of the Study

This study has several important limitations. First, the analysis is predominantly conceptual and relies on scholarly literature and documented case studies, without incorporating empirical data collected directly from educational contexts. This limits the ability to evaluate the actual impact of pedagogical practices on the development of STEM competencies. Second, the sources used reflect primarily European and Anglo-Saxon perspectives, which reduces the generalizability of the conclusions to diverse global educational contexts. Third, the socio-economic dimension of access to technology is not examined empirically, even though the literature indicates that digital inequalities strongly influence the development of STEM competencies. Finally, the proposed conceptual model requires empirical validation to confirm its applicability across varied educational settings.

Future Research Directions

Future research should include empirical studies that investigate the development of STEM competencies across diverse educational contexts and test the applicability of the proposed conceptual model. It is essential to examine the impact of digital inequalities on students' autonomy and critical thinking. Additionally, there is a need to design pedagogical tools that explicitly integrate the ethical dimension of technology, in line with European recommendations on the responsible use of artificial intelligence. Furthermore, the relationship between writing, visual representation, and digital interaction in shaping cognitive processes in STEM warrants in-depth exploration, building on the directions opened by Bostan (2026). Such an approach would contribute to a deeper understanding of the relationship between technology, thinking, and learning, providing a solid foundation for designing innovative and responsible pedagogical practices.

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The Ecology of AI in Education: Between Technological Promise and Epistemic Responsibility

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Abstract

Education is undergoing an accelerated transformation driven by the integration of adaptive systems, intelligent tutoring technologies, conversational agents, learning analytics, and immersive environments. Within this dynamic context, the paper offers a critical examination of artificial intelligence (AI) applications in education, assessing their benefits, emerging risks, and the ethical responsibilities of the actors involved. The analysis is grounded in a systematic review of recent literature across educational AI, technology ethics, and educational policy. The aim of the study is to critically analyze AI applications in education, relating them simultaneously to pedagogical opportunities, ethical and cognitive risks, and to the responsibilities of the actors involved in designing and implementing educational technologies. The research is theoretical and analytical in nature, grounded in a critical review of recent literature. The study formulates four main objectives: (1) identifying and classifying the main applications of AI in education; (2) analyzing the pedagogical opportunities associated with these applications; (3) examining the ethical, pedagogical, and cognitive risks; and (4) formulating a framework of responsibilities for teachers, institutions, developers, and policy makers. In line with these objectives, four research questions are articulated: (1) what are the main applications of AI in education and how are they evaluated in the specialized literature; (2) how does AI contribute to personalization, inclusion, and the efficiency of teaching activities; (3) what risks are associated with the use of AI and how are they problematized in recent research; and (4) what responsibilities lie with educational actors in the ethical integration of AI. The conclusions highlight that AI represents one of the most promising yet complex transformations in contemporary education. Its potential to amplify learning outcomes can be realized only through pedagogical approaches that cultivate autonomy, reflexivity, and epistemic responsibility—ensuring that the student, the teacher, and the learning process remain central within the educational ecology.

Keywords: adaptive systems, intelligent tutors, conversational agents, learning analytics, immersive environments, simulations.

Introduction

Artificial intelligence (AI) is profoundly reshaping contemporary education, transforming how students construct knowledge and how teachers design learning experiences. Technologies such as adaptive systems, intelligent tutors, conversational agents, learning analytics, and immersive environments generate a paradigm shift that affects cognitive processes, educational interactions, and the structure of pedagogical ecosystems. Recent literature highlights both major opportunities—personalized learning, increased inclusion, and the optimization of teaching activities—and significant ethical, pedagogical, and social risks, including algorithmic bias, cognitive overload, deprofessionalization, and data vulnerabilities (Holmes, Bialik & Fadel, 2019; OECD, 2021; UNESCO, 2021).

In this context, the present study critically examines AI applications in education, assessing their pedagogical benefits, emerging risks, and the responsibilities of the actors involved. The analysis is grounded in a systematic review of recent literature across educational AI, technology ethics, and educational policy. The study formulates four objectives: (1) identifying and classifying the main applications of AI in education; (2) analyzing the pedagogical opportunities associated with these applications; (3) examining the ethical, pedagogical, and cognitive risks; and (4) outlining a framework of responsibilities for teachers, institutions, developers, and policy makers. Correspondingly, four research questions address the evaluation of AI applications, their contribution to personalization and inclusion, the risks highlighted in recent research, and the responsibilities required for ethical integration.

Theoretical Framework

The transformations generated by artificial intelligence (AI) in education must be understood within a complex ecology, where technologies, cognitive processes, educational actors, and institutional structures interact dynamically. AI is not merely a technological tool, but a transformative agent that reconfigures how knowledge is produced, mediated, and evaluated. The specialized literature emphasizes that AI produces an epistemic mutation,

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affecting both the cognitive architecture of learning and the professional roles of educational actors (Bostan, 2026; Mayer, 2021).

Core Theoretical Pillars of Educational AI. A first theoretical pillar is represented by adaptive systems and intelligent tutors, which are based on algorithmic models capable of analyzing student performance and adjusting content in real time. Classic studies by Kulik and Fletcher (2016) show that intelligent tutors can replicate, in certain contexts, the effectiveness of a human teacher by providing individualized feedback and scaffolding. Baker and Inventado (2014) highlight that learning analytics and educational data mining allow for the early identification of difficulties, the optimization of learning trajectories, and the grounding of pedagogical decisions in data. These technologies introduce a new paradigm of "algorithmic pedagogy," wherein learning processes are modeled through predictive and adaptive mechanisms.

A second theoretical pillar is represented by conversational agents and generative models, such as ChatGPT, which open up the possibility of AI-mediated dialogic learning. Kasneci et al. (2023) show that these models can support concept explanation, example generation, problem-solving, and metacognitive development; however, they can also induce cognitive overload, automation bias, and a reduction in mental effort. Zhai (2023) emphasizes that the effectiveness of these agents depends on how they are integrated into instructional activities, requiring careful moderation by the teacher to prevent the substitution of deep cognitive processes with rapid, automatically generated answers.

A third theoretical pillar consists of immersive environments and intelligent simulations, which enable experiential learning through multimodal interaction. Mayer (2021) demonstrates that multimodal learning, when well-designed, can reinforce conceptual understanding and support the transfer of knowledge to new contexts. At the same time, the literature draws attention to the risk of cognitive overload and the necessity of calibrating immersion levels to avoid distraction (Chen et al., 2020).

Anticipatory Systems and Cognitive Reconfiguration. Within the AI ecology, an essential contribution is represented by the perspective of Mihai Nadin, one of the most prominent theorists of anticipatory systems. Nadin argues that any intelligent system—whether biological or artificial—functions not merely through reaction, but through anticipation, by its capacity to prefigure actions and model future behaviors. In education, this idea is crucial: AI does not just respond to student performance; it influences, shapes, and directs it, becoming an anticipatory actor in the cognitive ecology of learning.

In his works on anticipation, Nadin emphasizes that digital technologies can alter how we think, how we perceive information, and how we construct meaning, which implies a major epistemic responsibility in the design and use of AI in education (Nadin, 2014; Nadin, 2018). Nadin's perspective aligns with recent research showing that AI influences the cognitive processes involved in STEM learning, mental representation formation, and the development of intellectual autonomy. In this regard, Bostan's (2026) work on the relationship between writing, thinking, and cognitive processes in STEM complements Nadin's anticipatory vision, suggesting that integrating AI into writing and problem-solving activities can modify the cognitive architecture of learning. More specifically, by anticipating the student's problem-solving behavior, AI reconfigures the very sequence of logical steps required for abstraction. Therefore, AI must be analyzed not merely as a technological tool, but as an element that fundamentally reconfigures the cognitive ecology of education.

Ethical, Socio-Political, and Institutional Dimensions. Beyond these technological and cognitive dimensions, the AI ecology includes an ethical and political dimension. Floridi and Cowls (2019) propose a unified framework of ethical principles for AI—beneficence, non-maleficence, autonomy, justice, and explicability—which must be adapted to the educational context. Jobin, Ienca, and Vayena (2019) show that the global landscape of AI ethical guidelines is fragmented, and their implementation in education is often superficial. Recent European documents, such as the Ethical Guidelines for AI in Education (European Commission, 2022) and the AI Act (European Commission, 2023), underscore the need for clear regulation, algorithmic transparency, and data protection, particularly regarding AI use by minors.

The social and political dimension of AI is analyzed in depth by Crawford (2021), who argues that AI is not just a technology, but a socio-economic infrastructure that redistributes power, resources, and responsibilities. In education, this redistribution manifests through tensions surrounding the teacher's role, which risks deprofessionalization if AI is utilized as a substitute rather than an augmentation tool (Selwyn, 2019). Williamson, Eynon, and Potter (2020) show that AI introduces new forms of data-driven, predictive, and automated educational governance, which can undermine the autonomy of both institutions and teachers.

Concurrently, the literature highlights significant opportunities. Holmes, Bialik, and Fadel (2019) demonstrate that AI can support the development of 21st-century skills, such as critical thinking, problem-solving, and digital literacy. Luckin et al. (2016) emphasize that AI can expand teachers' capacity to personalize learning, monitor

student progress, and intervene effectively. The OECD (2021) further highlights that AI can contribute to inclusion by providing tailored resources for students with diverse needs.

In conclusion, the theoretical framework demonstrates that AI produces a profound transformation of the educational ecology, simultaneously affecting technological, cognitive, pedagogical, ethical, and institutional dimensions. Integrating Mihai Nadin's perspective brings additional depth, highlighting that AI is not just an automation tool, but an anticipatory actor that influences the future of cognitive processes and intellectual development. Understanding this ecology is essential for the responsible integration of AI in education and for safeguarding the epistemic processes that underpin students' autonomous development.

Conceptual model of AI ecology in education

To synthesize the theoretical dimensions discussed previously, the figure below illustrates the conceptual model of the AI ecology in education. This model is constructed based on recent literature and the epistemic frameworks proposed by Mihai Nadin (2014, 2018), Floridi and Cowls (2019), Luckin (2017), Mayer (2021), and Bostan (2026). The model reflects the interdependence among four major domains—cognitive, pedagogical, technological, and ethical-social—which define how AI integrates into educational processes.

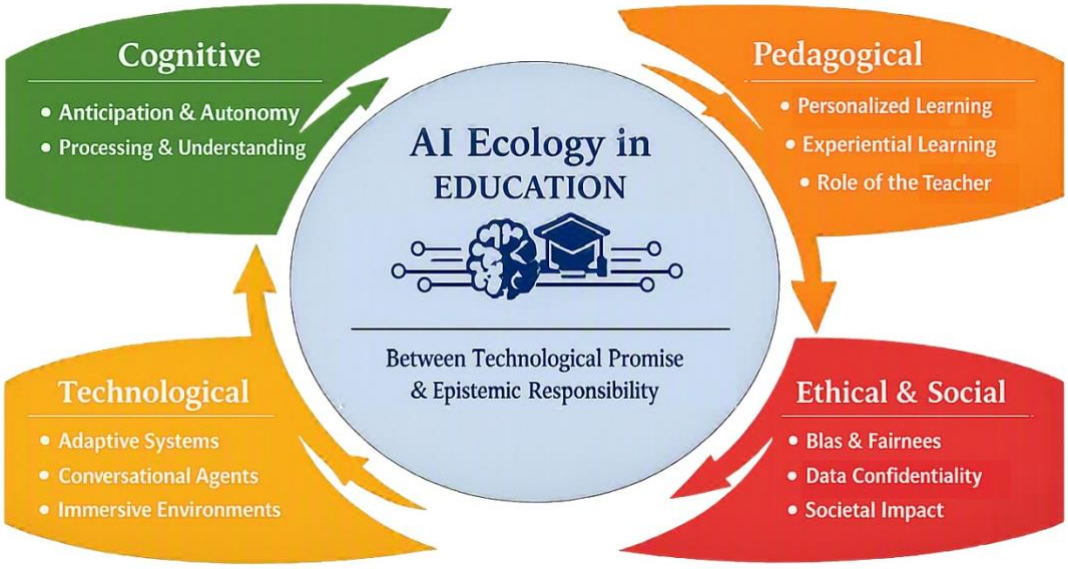


Figure 1. The conceptual model of the AI ecology in education. (Made with AI)

At the core of the model lies the concept of the educational ecology of AI, understood as an anticipatory, reflexive, and responsible system situated ***between technological promise and epistemic responsibility***. In this context, *technological promise* denotes the techno-optimistic discourse that frames AI as an absolute solution for educational efficiency. Conversely, *epistemic responsibility* represents the ethical and cognitive duty of both educators and students to safeguard intellectual autonomy, ensure truth validation, and prevent the uncritical outsourcing of deep thinking to automated systems.

The *Cognitive Dimension* describes the processes of anticipation, autonomy, and understanding inspired by Nadin's theory of anticipatory systems, according to which AI does not merely react to student performance but actively shapes and prefigures it. The *Pedagogical Dimension* highlights learning personalization, experiential learning, and the role of the teacher as a mediator between the algorithm and knowledge acquisition. The *Technological Dimension* includes adaptive systems, conversational agents, and immersive environments, which provide the digital infrastructure of this ecology. The *Ethical and Social Dimension* integrates the principles of equity, data protection, and societal responsibility, in alignment with UNESCO (2021) and European Commission (2022, 2023) guidelines.

Ultimately, this conceptual model proposes an integrated vision of AI in education, where technology, pedagogy, cognition, and ethics form an interdependent system. Within this ecology, AI becomes an anticipatory actor capable of amplifying educational potential only when paired with a pedagogy oriented toward autonomy, reflexivity, and epistemic responsibility.

Methodology

The study is theoretical and analytical, situated within the interpretive paradigm aimed at understanding educational phenomena in the context of contemporary digital transformations. The methodology follows a theoretical meta-synthesis designed to articulate an integrated conceptual framework describing the ecology of artificial intelligence (AI) in education. The research employs conceptual, comparative, and interpretive analysis to identify convergences and divergences in recent literature and to construct a coherent theoretical model.

The documentation process involved a systematic review of literature published between 2014 and 2026, including conceptual papers, empirical studies, international reports, and policy documents from major academic publishers and institutions such as UNESCO, OECD, and the European Commission. Sources were selected based on thematic relevance, methodological consistency, and their contribution to understanding AI's pedagogical opportunities, risks, and responsibilities.

The analysis unfolded across three stages: (1) identifying key AI applications in education—adaptive systems, intelligent tutors, conversational agents, learning analytics, and immersive environments; (2) correlating these technologies with ethical and cognitive risks such as algorithmic bias, deprofessionalization, and data vulnerabilities; and (3) integrating the findings into the "AI Ecology in Education" model, structured around cognitive, pedagogical, technological, and ethical-social dimensions. Foundational studies (Luckin, 2017; Mayer, 2021; Floridi & Cowls, 2019) were contextualized through Nadin's theory of anticipatory systems and complemented by recent research on cognitive architecture and data governance.

Through this reflexive approach, AI is analyzed not merely as a technological tool but as an epistemic and anticipatory actor, providing a robust conceptual foundation for understanding its role in the future of education.

Results and Discussion

The results of this study derive from a theoretical meta-synthesis and an integrated analysis of the specialized literature. In the absence of an empirical, quantitative approach, the "results" presented herein constitute the conceptual conclusions of the analysis, formulated in relation to the developed AI Ecology in Education model and the examined epistemic, pedagogical, and ethical tensions. The synthesis of the literature allowed for the extraction of five major results:

1. Systemic reconfiguration of the educational ecology. The analysis confirms that AI produces a profound mutation within learning systems, simultaneously affecting cognitive processes, pedagogical dynamics, and technological infrastructure. The literature demonstrates that adaptive systems and intelligent tutors contribute directly to learning personalization by offering individualized trajectories and immediate feedback, which enhances self-regulation and intrinsic motivation. Foundational studies (Kulik & Fletcher, 2016; Baker & Inventado, 2014) confirm the efficacy of these systems in optimizing performance, yet they underscore the imperative for strict pedagogical calibration to prevent over-reliance on the algorithm.

2. Cognitive ambivalence of generative models and conversational agents. A central contribution of this analysis is highlighting the deeply ambivalent role of LLM-type technologies (e.g., ChatGPT). On the one hand, they facilitate concept explanation, example generation, and metacognitive support, thereby democratizing access to resources. On the other hand, critical literature (Kasneci et al., 2023; Zhai, 2023) draws urgent attention to the risks of cognitive overload, the diminution of mental effort, and the emergence of subtle forms of automation bias. Consequently, AI can either amplify or inhibit deep cognitive processes, depending entirely on the instructional design of the learning activity.

3. Anticipatory agency of artificial intelligence. The analysis validates the crucial importance of the anticipatory dimension within the AI ecology, grounded in the theoretical theses of Mihai Nadin (2014, 2018). AI can no longer be viewed as a merely reactive tool, but rather as an anticipatory actor that shapes behaviors, prefigures actions, and influences how students construct mental representations and value judgments. This perspective becomes vital for safeguarding cognitive autonomy and epistemic responsibility at points where the algorithm tends to preempt the sequence of logical steps required for abstraction (Bostan, 2026).

4. Ethical and socio-political polarization. The results indicate a major fragmentation within the landscape of global ethical guidelines, identifying structural risks such as algorithmic bias, digital surveillance, and the inequitable redistribution of power within school infrastructures (Floridi & Cowls, 2019; Crawford, 2021). Crucially, critical ethical frameworks (Holmes, Bialik, & Fadel, 2019; Holmes et al., 2022) emphasize that when AI ethics are treated superficially or reduced to mere checklists, the technology risks exacerbating educational inequalities and commercializing public education. In this regard, recent European frameworks, such as the AI Act (European Commission, 2023), confirm the necessity for clear standards of algorithmic transparency and data protection, formally classifying educational AI systems as high-risk.

5. The teacher as an epistemic mediator in augmented pedagogy. The analysis demonstrates that AI cannot substitute fundamental human pedagogical functions, including interpretation, contextualization, critical evaluation, and mentorship. Instead of an automated pedagogy, the literature (Luckin, 2017; Williamson, Eynon, & Potter, 2020) supports a transition toward an augmented pedagogy. Within this framework, the teacher utilizes AI to extend personalization capabilities but retains sovereign control over the epistemic processes and the overall classroom ecology.

Discussion and theoretical implications. The synthesis of these results indicates that AI should not be viewed as a universal solution—a technological panacea—but rather as a disruptive force that can amplify educational potential only when integrated in a reflexive, ethical, and pedagogical manner. In the absence of a responsible architecture, AI risks fragmenting cognitive processes, accelerating the deprofessionalization of educators (Selwyn, 2019), and eroding the intellectual autonomy of minors.

The conceptual model proposed in this study provides precisely an interpretive map of these interdependencies. It demonstrates that the success of digital transformation does not depend on the computational power of algorithms, but on the preservation of the human ecology of learning. Ultimately, this shifts AI from being a cognitive risk factor to an anticipatory dialogue partner oriented toward critical thinking tailored for the 21st century.

Conclusions

This study shows that artificial intelligence fundamentally reconfigures the educational ecology, influencing cognitive processes, pedagogical dynamics, and ethical responsibilities. AI acts not only as a technological tool but as an anticipatory agent that shapes learning trajectories, requiring pedagogical approaches that safeguard intellectual autonomy and epistemic responsibility. While AI can enhance personalization, access to resources, and the development of higher-order skills, its benefits depend on reflective instructional design and responsible integration. The teacher remains an essential epistemic mediator, contextualizing algorithmic outputs and ensuring that deep learning processes are preserved. Overall, the study argues that AI can amplify educational potential only within a pedagogical framework oriented toward autonomy, reflexivity, and ethical responsibility.

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Exploring AI-Integrated Assessment Competencies in Teacher Education: A Case Study

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Abstract

The rapid integration of artificial intelligence (AI) into educational environments has reshaped teaching, learning, and assessment. Consequently, it has expanded the competencies expected from teachers. This qualitative case study examines how a preservice teacher demonstrates AI-integrated assessment competencies after participating in a six-week learning module embedded in a required educational technology course at a major public university in Türkiye. The module was informed by the European Framework for the Digital Competence of Educators (DigCompEdu) and its AI Supplement (Redecker, 2017; Bekiaridis & Attwell, 2023). The case participant was selected through typical sampling based on completion of all assignments, regular attendance, and voluntary participation in an interview. Data were gathered through a semi-structured interview and pre- and post-opinion forms and analyzed using the constant comparative method (Glaser, 1965; Glaser & Strauss, 1967). Preliminary analysis has identified five themes: purposes of AI use, decision-making in AI-integrated assessment design, pedagogical considerations, ethical considerations, and limitations and challenges of AI use in education. Initial findings suggest that the participant positions AI as a supportive tool rather than a decision-maker, places human judgment before AI assistance, emphasizes students' responsible AI use and visible thinking processes, and considers privacy, accuracy, and fair scoring when designing assessment. As analysis is ongoing, these themes are presented as preliminary patterns rather than final findings. The study is expected to contribute to teacher education research by illustrating how structured learning experiences may support the development of reflective and human-centered AI-integrated assessment competencies.

Keywords: Teacher education; AI competencies; Assessment competencies; Case study

Introduction

Artificial intelligence (AI) has become increasingly visible in educational practice, developing from earlier intelligent tutoring and automated feedback systems toward generative tools that can support more complex educational tasks (Luckin & Holmes, 2016; Kasneci et al., 2023). AI-supported and generative AI tools can assist teachers with content creation, lesson planning, personalized feedback, question generation, and assessment design (Chen et al., 2022; Hwang et al., 2020; Kasneci et al., 2023). These possibilities expand what teachers can do with digital technologies, but they also increase the importance of professional judgment. Teachers need to evaluate the accuracy of AI-generated content, its alignment with pedagogical objectives, and the extent to which its implementation remains transparent, equitable, and responsible. Therefore, competence in the age of AI involves not only knowing how to use a tool but also making pedagogical and ethical decisions about its use (Bekiaridis & Attwell, 2023; Holmes & Tuomi, 2022).

Assessment-related competencies are particularly important for these decisions. Generative AI can produce or support traditional assessment products such as homework, essays, explanations, and quiz answers. As a result, a final product may not always show what a student independently knows or can do (Kasneci et al., 2023). At the same time, AI can support assessment by helping teachers generate questions, develop rubrics, provide feedback, and analyze learning-related information (Chen et al., 2022; Hwang et al., 2020). The central issue is therefore not simply whether AI should be allowed or avoided. Teachers need to make context-sensitive decisions about when, why, and how AI should be integrated into assessment.

One response to these changes is to distinguish between AI-adapted and AI-resilient assessment. In AI-adapted assessment, AI use is incorporated into the task and can support activities such as brainstorming, feedback, or revision. In AI-resilient assessment, the task is designed so that meaningful completion depends on evidence of the learner's own process, experience, or performance rather than only on an AI-generated product (Bekiaridis & Attwell, 2023). Both approaches require teachers to consider the learning objective, task characteristics, student needs, and possible risks of AI use.

The present study is informed by the European Framework for the Digital Competence of Educators (DigCompEdu), which describes educators' digital competence across professional engagement, digital resources, teaching and learning, assessment, empowering learners, and facilitating learners' digital competence (Redecker,

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2017). Although DigCompEdu provides a strong foundation for digital competence, it was not originally designed to address the specific challenges introduced by AI. The AI Supplement extends the framework by highlighting competencies such as evaluating AI-generated content, recognizing potential bias, understanding relevant AI processes, and integrating AI responsibly into teaching, learning, and assessment (Bekiaridis & Attwell, 2023). Together, the two frameworks provide a useful basis for examining how preservice teachers reason about AI-supported assessment.

Preservice teachers are an important group in this transition because they are entering a profession in which AI tools are likely to be routinely available. Earlier reviews of AI in higher education have noted that research has often focused more strongly on technologies and systems than on educators and pedagogical perspectives (Zawacki-Richter et al., 2019). Structured teacher education can provide opportunities to examine the benefits and limitations of AI before preservice teachers take full classroom responsibility. However, there is still a need for close qualitative accounts of how AI-related assessment competencies appear in the reasoning of an individual preservice teacher after structured learning. Accordingly, this study explores how one preservice teacher demonstrates competencies in the process of designing AI-integrated assessment practices after completing a six-week learning module.

Method

This study employed a case study design (Yin, 2018) to provide an in-depth exploration of one preservice teacher's experience. The case was bounded by the participant's involvement in a six-week learning module within a required educational technology course offered in the fall 2025 semester at a major public university in Türkiye. The case participant was an undergraduate preservice teacher from the Foreign Language Education Department. She was selected using typical sampling (Creswell, 2013) based on completion of all module assignments, regular class attendance, and voluntary participation in the interview. The case participant is referred to as P1 to preserve anonymity.

The six-week module was informed by DigCompEdu and its AI Supplement (Bekiaridis & Attwell, 2023; Redecker, 2017) and moved from foundational concepts toward assessment design. The first three weeks addressed AI in education, educator digital competencies, AI literacy, evaluation of example lesson plans, AI ethics, and practical strategies for teaching with AI. In Week 4, the module introduced AI tools and the distinction between AI-resilient and AI-adapted assessment. Week 5 focused on assessment design through an AI studio, adaptation of traditional assessments, analysis of institutional strategies, and work on participants' own AI-integrated lesson designs. Week 6 concluded with peer feedback on these lesson designs. In this way, assessment was connected to earlier work on AI literacy, pedagogy, and ethics rather than treated only as a tool-use topic.

Three types of qualitative data sources were used: a semi-structured interview, pre- and post-opinion forms, and an interview conducted after the module that lasted approximately 20-30 minutes. The interview protocol was developed with reference to the Assessment Area of the AI Supplement to DigCompEdu and addressed purposes of AI use, decisions about where and how to integrate AI, pedagogical considerations, ethical considerations, preferred tools, and anticipated or experienced challenges. The pre- and post-opinion forms each included five open-ended questions about assessment in the AI era.

Data are being analyzed using the constant comparative method (Glaser, 1965; Glaser & Strauss, 1967). The analysis involves breaking the data into meaningful units, assigning labels to key ideas and actions, comparing similar labels, and organizing them into a codebook. Codes are then compared across the interview and opinion forms and grouped into broader themes. At the current stage of analysis, five preliminary themes have been identified: (1) purposes of AI use, (2) decision-making in AI-integrated assessment design, (3) pedagogical considerations, (4) ethical considerations, and (5) limitations and challenges of AI use in education. Because analysis is ongoing, the results below represent preliminary patterns and may be refined as coding and interpretation continue.

Several strategies are used to support credibility and transparency. The interview and pre/post opinion forms provide source triangulation. Coding decisions, theme development, and analytic reflections are documented in an audit trail. Preliminary codes and themes have also been discussed through peer debriefing in a qualitative research course. The first author was involved in the instructional context as a teaching assistant and contributed to the module, which provides close familiarity with the learning experience but also creates a potential for bias and social desirability. To reduce this risk, interview prompts were framed in neutral language, participation was voluntary, and analysis focused on the participant's own statements. Institutional ethics procedures were followed, informed consent was obtained, and data were anonymized and stored securely.

Preliminary Results

The ongoing analysis currently points to five themes describing P1's engagement with AI-integrated assessment design. Across these preliminary themes, a consistent pattern is emerging: P1 tends to position AI as a resource that can support assessment design while keeping human judgment central. At the same time, her account shows continuing uncertainty about accuracy, the quality of AI suggestions, and fair scoring.

Purposes of AI Use

P1 primarily describes AI as an assistant rather than a decision-maker. Two initial purposes are especially visible: brainstorming and checking. When she does not have an initial idea, she uses AI to generate possibilities, but she expects to revise rather than directly accept them. She also uses AI as a second source of feedback after producing or considering something herself. This preliminary pattern suggests that AI is used to extend or review her thinking while ownership of the assessment idea remains with the teacher.

Decision-Making in AI-Integrated Assessment Design

A human-centered ordering is visible in P1's decision-making. She reports relying first on her own judgment, then on experienced peers, and only afterward on AI. When AI is used, she describes providing context, learning objectives, and instructional goals rather than asking the tool to determine the assessment independently. She also notes that the decision to use AI depends on the type and purpose of the assessment. These responses suggest that AI integration is conditional rather than automatic.

Pedagogical Considerations

Two pedagogical concerns are prominent in the preliminary analysis: teaching students to use AI appropriately and making students' own thinking visible. P1 does not view prohibition as the only response to students' use of AI. Instead, she considers responsible use something that students should learn. At the same time, she emphasizes process-focused evidence. For example, in a writing task, discussing how a student produced the text may help the teacher understand the student's contribution and reasoning. This shifts attention from the final product alone toward evidence of the learning process.

Ethical Considerations

P1's account also includes ethical considerations that influence tool use. Data privacy is one example: she reports stopping use of a tool after learning that uploaded content could be reused or published. Environmental responsibility also appears in her reasoning, with AI use described as something that should occur when it is necessary rather than automatically. These concerns reflect the broader importance of privacy, responsible use, and human-centered decision-making in guidance on generative AI in education (UNESCO, 2023). These preliminary findings suggest that ethical awareness is connected to practical decisions about whether and how to use an AI tool.

Limitations and Challenges of AI Use in Education

P1 identifies several continuing challenges. First, AI can provide incorrect information, which makes verification necessary. Second, some AI suggestions are described as superficial or traditional and therefore require adaptation. The most unresolved issue concerns fair scoring when students use AI. Although process visibility may help teachers understand student-AI interaction, P1 remains uncertain about how to determine the student's contribution and how AI assistance should be considered in grading. This issue appears to require more than general awareness and may call for explicit criteria for acceptable AI contribution and process evidence.

Conclusions

The preliminary findings suggest a pattern of AI-integrated assessment reasoning in which AI use is treated as supportive rather than authoritative. P1's reported practices combine the use of AI for brainstorming and checking with human-first decision-making, attention to learning objectives, and verification of AI output. Her emphasis on making students' thinking processes visible also suggests that assessment design in the AI era may need to focus more directly on evidence of process, reasoning, and contribution rather than relying only on final products.

The preliminary analysis also indicates that AI-adapted and AI-resilient approaches may coexist in practice. P1 supports teaching students to use AI responsibly, which is compatible with integrating AI into learning and assessment, while also emphasizing the need to preserve evidence of students' own thinking. Rather than treating

these approaches as strict opposites, her reasoning appears to depend on the purpose of the assessment and the evidence needed for a fair judgment.

At the same time, the current results should not be treated as final conclusions. The study examines a single case participant, and the analysis is still in progress. The available data show how P1 describes her reasoning rather than how every stated principle would necessarily be enacted in classroom practice. As analysis continues, the preliminary themes and their relationships may be refined. Nevertheless, the current patterns point to the importance of assessment-specific AI competencies in teacher education. Future work can examine preservice teachers from different backgrounds, compare subject areas, and explore the unresolved challenge of developing fair and transparent criteria for student-AI collaboration in assessment.

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Mapping Sustainable and Responsible Artificial Intelligence Research in Education: A Bibliometric and BERTopic-Based Analysis

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Abstract

This study aimed to examine current developments in sustainable and responsible artificial intelligence research in education through bibliometric analysis of Web of Science Core Collection data and BERTopic-based topic modelling. The widespread adoption of artificial intelligence (AI)-based tools in educational technologies and online learning ecosystems requires a multidimensional evaluation that considers pedagogical effectiveness, efficiency and innovation alongside ethics, data privacy, academic integrity, accessibility, equity, environmental sustainability and institutional governance. In this context, the study sought to identify the bibliometric and thematic patterns shaping the literature on sustainable and responsible artificial intelligence in education. A Topic search was conducted in the Web of Science Core Collection by combining terms related to sustainable, responsible, ethical and environmentally efficient AI with terms related to education and digital learning. The search was limited to Article, Review Article, and Proceeding Paper document types. Two BibTeX files were merged, duplicate records were checked, and a total of 887 records were analysed. Within the bibliometric analysis, annual publication trends, leading countries, publication sources, author keyword frequencies and keyword co-occurrence relationships were examined. The thematic structure of the field was modelled using BERTopic on text bodies created from titles and abstracts. The findings indicate that publication output on sustainable and responsible artificial intelligence in education increased sharply after 2024. The number of publications reached 387 in 2025, while 330 records had been indexed in 2026 by the data collection date of 25 June. The most frequent author keywords were artificial intelligence, generative AI, higher education, responsible AI, ethical AI, ChatGPT, ethics, and AI literacy. The strongest co-occurrence relationships linked artificial intelligence with higher education and ChatGPT, and generative AI with higher education. BERTopic assigned 882 of the 887 records to eight topic clusters: responsible and ethical AI development, educational data privacy, generative AI in education, teachers and AI literacy, AI assessment and fairness in education, ethical AI in healthcare, AI adoption intentions in higher education, and AI in medical and nursing education; five records were excluded during quality control. The keyword co-occurrence network and BERTopic results indicate that the literature is primarily organised around generative AI, higher education, ethics, data privacy, responsible use, academic integrity and AI literacy. No distinct BERTopic cluster was primarily focused on environmental sustainability, suggesting that energy consumption, computational efficiency and the carbon footprint of AI remain comparatively peripheral concerns. The findings highlight the need to address AI integration in online learning and educational technology research in conjunction with sustainability, accountability and human-centred governance principles.

Keywords: Artificial intelligence in education, sustainable artificial intelligence, responsible artificial intelligence, educational technologies, BERTopic, bibliometric analysis.

Introduction

Artificial intelligence (AI) has taken on an increasingly prominent role in educational technology and online learning, supporting processes such as content creation, personalised learning, learning analytics, adaptive learning systems, automated assessment and feedback. Zawacki-Richter et al. (2019) found that research in this field had been dominated by computer science and STEM perspectives, while educators, pedagogical perspectives and critical discussion of the risks of AI remained comparatively under-represented. Research on AI in higher education increased markedly in 2021 and 2022 (Crompton & Burke, 2023). The subsequent emergence of widely accessible generative AI tools further intensified attention to the educational uses of large language models (Kasneci et al., 2023).

While this transformation highlights the instrumental benefits and learning outcomes associated with educational technologies, it also calls for these technologies to be examined in relation to values, governance and sustainability. Ouyang and Jiao (2021) conceptualise three paradigms of AI in education: AI-directed learning, in which the learner is primarily positioned as a recipient; AI-supported learning, in which learners collaborate with AI systems;

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and AI-empowered learning, in which learner agency becomes more prominent. These paradigms have potential implications for teachers' roles, student autonomy, assessment practices and the technology policies of educational institutions.

Generative AI (GenAI) has made these debates more complex. Large language models offer capabilities for creating teaching materials, supporting writing and coding, generating examination questions, providing automated feedback and personalising learning processes (Kasneci et al., 2023). In the specific context of large language models, concerns have been raised about academic integrity, attribution, inaccurate or fabricated outputs, bias, assessment validity and student data privacy (Kasneci et al., 2023). Broader research on responsible AI in education similarly emphasises privacy, autonomy, well-being, fairness and accountability (Akgun & Greenhow, 2022; Dignum, 2021; Fu & Weng, 2024).

Sustainability in educational AI can also be considered in environmental and computational terms. The Green AI approach argues that AI models should be evaluated not only in terms of accuracy and performance but also in relation to energy consumption, computational cost and carbon emissions (Schwartz et al., 2020). The training of large-scale natural language processing models can entail substantial computational, financial and environmental costs (Luccioni et al., 2023; Strubell et al., 2019). Across the wider AI system lifecycle, environmental impacts may also arise from model inference and deployment, data-centre operations and hardware-related resource use (Patterson et al., 2021; Verdecchia et al., 2023). At the socio-technical level, responsible AI frameworks foreground human agency, fairness, transparency, privacy and accountability (Floridi et al., 2018; Jobin et al., 2019).

The aim of this study is to examine the development of sustainable and responsible AI research in education during the period 2020–2026 using bibliometric analysis based on Web of Science (WoS) data and a BERTopic-based topic modelling approach. By identifying publication trends, productive actors, key concepts and thematic clusters in this field, the study aims to highlight research orientations regarding the sustainable, ethical and responsible use of AI in the context of educational technologies and online learning. In this context, four research questions have been identified:

- Q1. How did publication output on sustainable and responsible artificial intelligence in education evolve between 2020 and 2026?
- Q2. Which countries or regions and publication sources contributed the largest numbers of publications in this field?
- Q3. Which author keywords occurred most frequently, and how were the leading keywords connected within the co-occurrence network?
- Q4. Which topic clusters were identified through BERTopic-based topic modelling?

Methodology

The study adopted a quantitative and exploratory literature-mapping design combining descriptive bibliometric analysis with BERTopic-based topic modelling. Bibliometric analysis uses quantitative indicators to examine publication output, research contributors and conceptual patterns within a defined body of literature. It is particularly useful for identifying publication trends and mapping the development of a research field across large volumes of scientific data (Donthu et al., 2021). Author keywords were normalised for capitalisation and redundant spacing, clearly equivalent variants were consolidated, and the nine most frequent terms were visualised using a document-level co-occurrence network; only links occurring in at least seven records were displayed. Topic modelling, by contrast, is a computational approach used to identify recurring thematic patterns within large text collections. In this study, topic modelling was conducted using BERTopic on a text corpus comprising the titles and abstracts of the retrieved records. BERTopic generates interpretable topic representations by combining pre-trained transformer-based document embeddings, clustering and class-based term frequency-inverse document frequency (c-TF-IDF) (Grootendorst, 2022).

The search was conducted in the Web of Science Core Collection using the Topic field. The following Boolean search query was applied: TS = ("sustainable artificial intelligence" OR "sustainable AI" OR "responsible artificial intelligence" OR "responsible AI" OR "ethical artificial intelligence" OR "ethical AI" OR "green artificial intelligence" OR "green AI" OR "energy-efficient AI" OR "carbon footprint of AI") AND TS = ("education" OR "educational technology" OR "online learning" OR "e-learning" OR "digital learning" OR "distance education" OR "higher education" OR "AI in education" OR "generative AI in education" OR "learning analytics" OR "adaptive learning"). The database, timespan and eligibility criteria applied in the search are summarised in Table 1.

Table 1. Search criteria.

Criterion	Description
Database	Web of Science Core Collection
Search scope	Topic (TS): title, abstract, author keywords and Keywords Plus
Time range	2020-2026
Document types	Article, Review Article and Proceeding Paper; during data checking, 5 records were found with an 'other/mixed' document type label
Number of raw records	887 records
Export format	Two BibTeX files were merged
Core Scope	Sustainable AI, responsible AI, ethical AI, Green AI and the intersection of educational technologies and online learning

Results

Publication trends by year

The annual distribution of publications shows that the literature on sustainable and responsible AI in education grew slowly but steadily after 2020, before experiencing a sharp acceleration after 2024 (Figure 1). Whilst there was only one record in the dataset for 2020, this number rose to 6 in 2021, 16 in 2022, 34 in 2023 and 113 in 2024. The highest number of publications was recorded in 2025, with 387 entries. By 25 June 2026, 330 records had been indexed. This indicates that discussions on generative AI and responsible/ethical AI have gained momentum very rapidly within the educational technology literature.

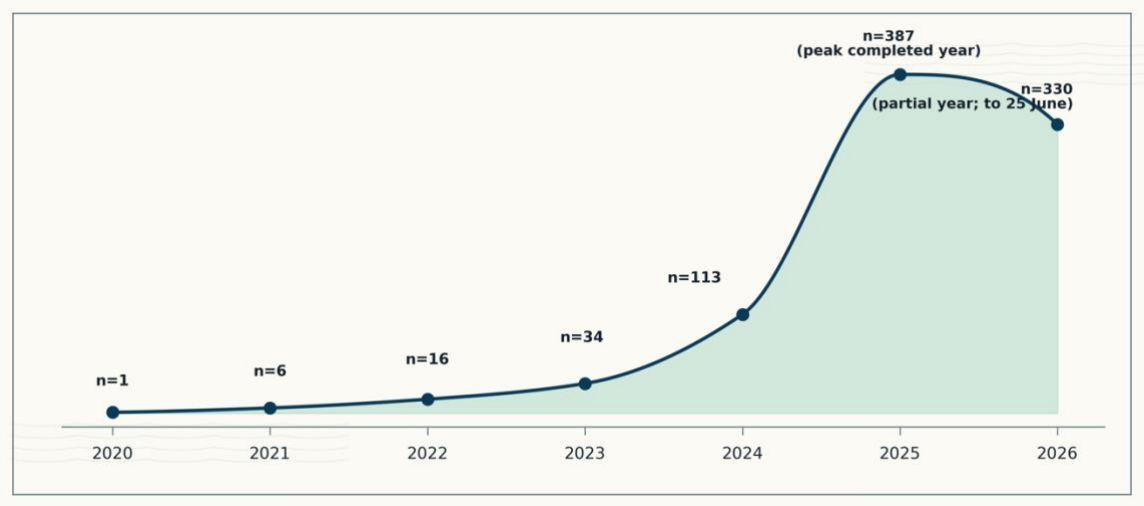


Figure 1. Annual distribution of publications on sustainable and responsible AI in education.

Countries of publication and sources

In terms of country/region distribution, the US clearly ranks first (n=220). The US is followed by China (n=85), the United Kingdom (n=70), Saudi Arabia (n=49), India (n=48), Australia (n=41), Türkiye (n=37) and Canada (n=37) (Figure 2). This indicates that the themes of artificial intelligence, ethics and sustainability in education have come to the fore on the international research agenda.



Figure 2. Countries and sources of sustainable and responsible AI publications in education.

The number of sources across which the publications in the dataset are distributed is quite high; this demonstrates the interdisciplinary nature of the subject. Among the most prolific sources, Sustainability (n=28), Education Sciences (n=25), Computers and Education: Artificial Intelligence (n=14), Frontiers in Education (n=13) and Education and Information Technologies (n=12) stand out (Figure 2). This distribution indicates that the literature is published in journals focusing on educational technology, AI and sustainability.

Author Keyword Patterns and Co-occurrence Network

The author keyword analysis and co-occurrence network provide an overview of the principal concepts and relationships within the literature (Figure 3). The network visualised nine prominent author keywords: artificial intelligence (n=358), generative AI (n=136), higher education (n=107), responsible AI (n=88), ethical AI (n=73), ChatGPT (n=70), AI literacy (n=61), large language models (n=47) and academic integrity (n=46). The strongest co-occurrence was observed between artificial intelligence and higher education (n=47), followed by artificial intelligence and ChatGPT (n=35), generative AI and higher education (n=31), artificial intelligence and ethical AI (n=30), and artificial intelligence and generative AI (n=25). These relationships indicate that discussions of generative AI and higher education are closely connected with ethical, governance-related and literacy-oriented concerns.

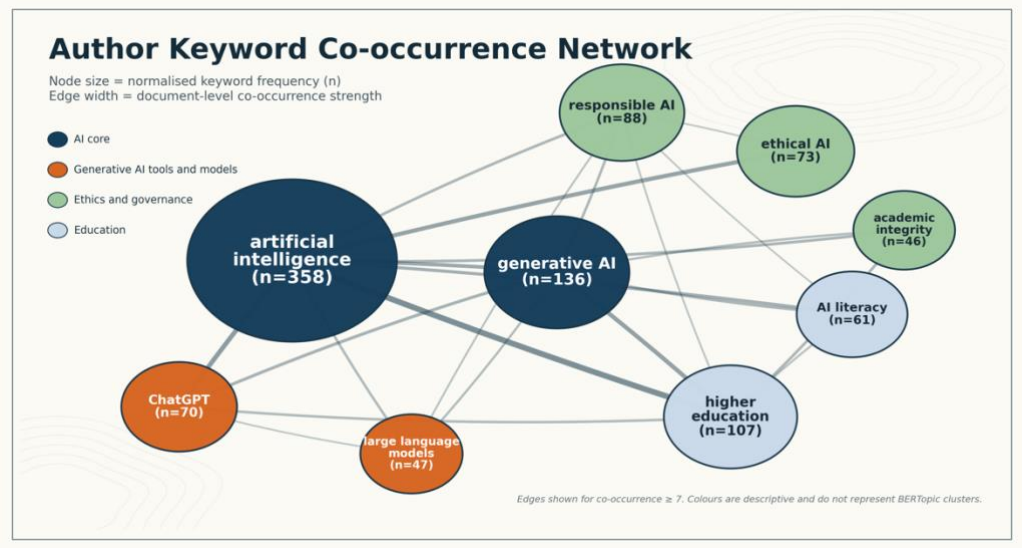


Figure 3. Co-occurrence network of the leading author keywords.

BERTopic-derived topic clusters

To determine the thematic structure of the literature on sustainable and responsible AI in education, topic modelling was carried out using the BERTopic algorithm on a dataset comprising 887 records. As a result of the modelling, 882 records (99.4 per cent) were assigned to eight topic clusters. Five records were excluded from the topic distribution as they were identified during quality control as being of a different document type or of a note-like nature. Figure 4 shows the sizes of the identified topic clusters and the main terms representing these clusters. The percentages shown in the figure were calculated based on the 882 records assigned to the topic clusters.

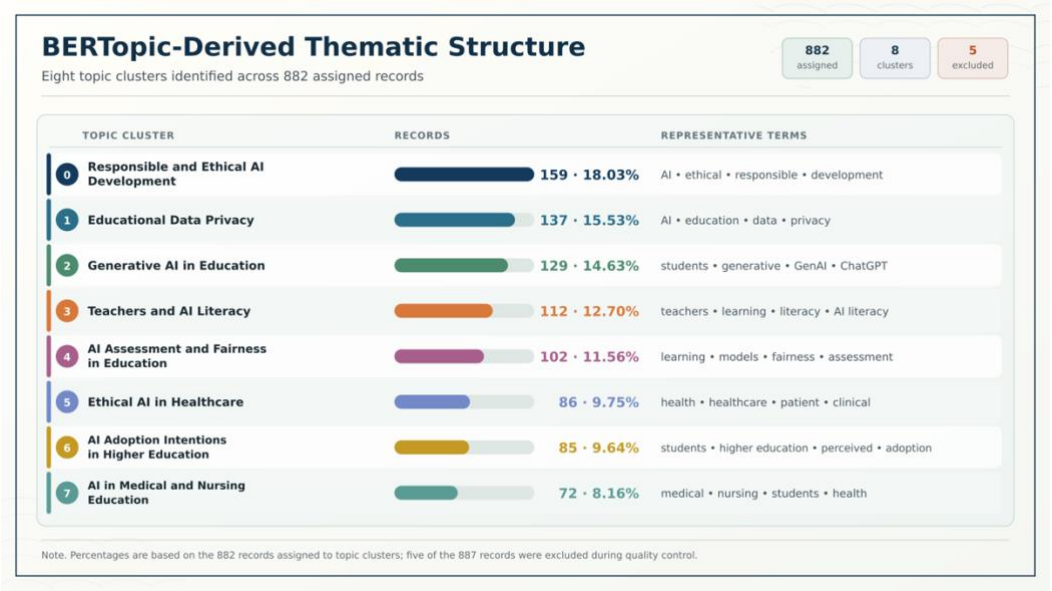


Figure 4. Distribution and representative terms of the BERTopic-derived topic clusters.

The largest cluster of topics was ‘Responsible and Ethical AI Development’ (n=159; 18.03 per cent), followed by ‘Educational Data Privacy’ (n=137; 15.53 per cent) and ‘Generative AI in Education’ (n=129; 14.63 per cent). The clusters ‘Teachers and AI Literacy’ (n=112; 12.70 per cent) and ‘AI Assessment and Fairness in Education’ (n=102; 11.56 per cent) also feature among the literature’s key thematic areas. Ethical AI in healthcare, the adoption of AI in higher education, and AI in medical and nursing education, however, formed relatively smaller clusters. Overall, the distribution of topics indicates that the development of ethical and responsible AI, data privacy and the applications of generative AI constitute the central themes of the literature.

Conclusions

This study has revealed the current structure of the literature on sustainable and responsible AI in education by analysing 887 records obtained from the WoS through bibliometric analysis and BERTopic-based topic modelling. The findings indicate that the field grew rapidly after 2024, reached its highest publication volume in 2025, and had already reached 330 records by 25 June 2026. The distributions by country and publication source, meanwhile, suggest that the topic has evolved into an international and interdisciplinary research field bringing together the disciplines of educational sciences, educational technologies, AI and sustainability.

The author keyword analysis showed that the literature was concentrated around artificial intelligence, generative AI and higher education. The co-occurrence network further demonstrated that these central concepts were closely connected with ethical AI, responsible AI, academic integrity and AI literacy. The BERTopic results complemented this pattern by identifying responsible and ethical AI development, educational data privacy and generative AI in education as the largest thematic clusters. The absence of a distinct environmentally focused cluster suggests that environmental sustainability remains a comparatively peripheral concern within the current literature.

The findings highlight the need to evaluate AI applications in education not only in terms of their pedagogical value and technical performance but also with regard to data privacy, algorithmic fairness, academic integrity, AI literacy and accountable governance. These findings should, however, be interpreted in light of several limitations. The analysis was restricted to publications indexed in the Web of Science Core Collection, and the 2026 publication count covers only records available up to 25 June 2026. Moreover, the BERTopic results are sensitive to the selected text fields, preprocessing procedures and modelling decisions. Future research should devote greater

attention to environmental sustainability, particularly energy consumption, computational efficiency and the carbon footprint of AI systems.

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Cognitive Risks in Generative AI-Supported Learning: A Literature Mapping

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Abstract

Generative artificial intelligence (GenAI) tools have spread into learning environments at an extraordinary pace; students' delegation of core cognitive tasks such as writing, problem solving, summarizing, and exam preparation to these tools has raised a set of cognitive risks, most notably cognitive offloading, over-reliance/dependence, and deskilling. Because these concepts are used in a scattered and often disconnected manner across disciplines, the overall conceptual structure of the field remains unclear. Existing reviews address specific cognitive risks or educational outcomes; this study complements them by jointly mapping related concepts. This study aims to map, using computational methods, the scholarly literature on cognitive risks in GenAI-supported learning published between 2023 and 2026. The research was guided by four research questions concerning publication volume and influential sources/works, the conceptual structure of the field, temporal change in latent topics, and comparatively underrepresented contexts. A corpus of 1,412 documents (812 sources) retrieved from Web of Science and Scopus and deduplicated by DOI/title was analyzed through descriptive bibliometrics, keyword co-occurrence (co-word) network analysis, thematic mapping/evolution, and Latent Dirichlet Allocation (LDA). Co-occurrence analyses used author keywords, which were far more complete in the combined corpus than Keywords Plus. For LDA, the 10-topic solution was retained by considering c_v coherence together with topic interpretability (c_v ≈ 0.374; k = 7 was a close alternative). The findings show rapid growth from 2023 onward and an interdisciplinary distribution across education, psychology, and medical-education journals. The 2026 figures represent a partial year ending on June 17. Annual output was 30 documents in 2023, 181 in 2024, 704 in 2025, and 497 by June 17, 2026. The co-word network and LDA jointly suggest that cognitive-risk concepts-including cognitive offloading, AI dependency, deskilling, critical thinking, metacognition, and self-regulated learning-do not constitute an isolated domain; rather, they form a central but still underdeveloped substream embedded within the broader GenAI-higher education discourse. On the thematic map, the 'generative ai' cluster showed the highest centrality (0.746) but comparatively low density, positioning it as a basic theme containing the study's core concepts. Thematic evolution indicates that emerging concepts such as cognitive debt have begun to enter the field. Open and distance education, preventive/intervention-oriented designs, K-12 contexts, and disadvantaged groups show comparatively limited visibility in the science maps. The study proposes a future research agenda based on these exploratory gap indicators.

Keywords: generative artificial intelligence, cognitive offloading, cognitive risks, literature mapping, topic modeling

Introduction

Generative artificial intelligence (GenAI) tools have entered learning environments much faster than expected since late 2022. Students widely use these tools for core cognitive tasks such as writing, problem solving, summarizing, and exam preparation. This rapid diffusion is particularly important for open and distance education, where learning depends heavily on self-regulation and students often work on their own.

Early literature emphasized efficiency and learning support alongside academic integrity. More recent debate concerns learners' thinking, self-regulation, and skills when cognitive work is delegated to tools. Related concepts span three levels: cognitive offloading as the mechanism of delegating cognitive work to an external tool (Risko & Gilbert, 2016); over-reliance and AI dependence at the attitude/behavior level; and deskilling or cognitive atrophy at the outcome level. Metacognitive laziness has been discussed as a possible bridge between these processes (Fan et al., 2025), while cognitive debt is an emerging construct concerning the cumulative, longer-term consequences of repeated delegation (Watts, 2025). Recent work also examines AI reliance and critical thinking (Gerlich, 2025). Definitions and measures vary across cognitive psychology, human-computer interaction, and education, leaving conceptual boundaries and overlaps unclear. Existing reviews examine over-reliance on AI dialogue systems and student engagement with ChatGPT (Lo et al., 2024; Zhai et al., 2024). Joint field-level mappings of these risk concepts appear limited; dominant and neglected themes, conceptual clustering, and the visibility of open/distance education and self-regulation therefore remain unclear.

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To address this gap, this study computationally maps the 2023-2026 literature on cognitive risks of delegating cognition to GenAI in learning contexts and derives a future research agenda. Four research questions (RQs) guide the analysis:

RQ1. What trend does publication volume show in the field; which sources are most productive, and which studies are most cited?

RQ2. What is the conceptual structure of the field; which clusters stand out in the keyword co-occurrence network and thematic map, and do related sub-constructs (cognitive offloading, over-reliance/dependence, deskilling) form distinct or overlapping clusters?

RQ3. Which latent topics emerge in the literature, and how does their relative weight change between 2023 and 2026?

RQ4. Which contexts and themes (e.g., open and distance education, self-regulated learning, preventive/solution-oriented designs) are comparatively underrepresented, and what future research agenda can be derived from these gaps?

Methodology

Research Design

This quantitative computational literature-mapping/science-mapping study analyzed exported bibliographic metadata without collecting human-participant data. Four complementary layers addressed RQ1-RQ4, respectively: descriptive bibliometrics, co-word analysis with thematic mapping/evolution, LDA topic modeling, and integration of findings in a gap analysis.

Data Sources and Corpus

Web of Science Core Collection and Scopus searches, completed on June 17, 2026, covered English-language articles, reviews, and conference/proceedings papers from 2023-2026, yielding 884 and 1,311 records, respectively. DOI/title deduplication removed 782 duplicates, leaving 1,413 unique records; excluding one out-of-scope book chapter yielded 1,412 documents: 863 articles (96 early access), 406 conference/proceedings papers, and 143 reviews (8 early access).

Search Strings

The search combined three conceptual blocks (cognitive-risk terms, GenAI/related-tool terms, and education/learning terms) with AND in Web of Science TS and Scopus TITLE-ABS-KEY:

(("cognitive offload" OR "metacognitive laziness" OR "metacognitive offload*" OR "cognitive debt" OR "cognitive outsourcing" OR "outsourcing of cognition" OR "cognitive deskilling" OR "intellectual deskilling" OR deskilling OR "cognitive atrophy" OR "skill atrophy" OR "skill decay" OR "skill erosion" OR "over-reliance" OR overreliance OR "over reliance" OR "AI dependence" OR "AI dependency" OR "chatbot dependence" OR "technology dependence" OR "automation complacency" OR "automation bias") AND ("generative AI" OR GenAI OR "generative artificial intelligence" OR ChatGPT OR "large language model*" OR LLM* OR chatbot* OR "conversational agent*" OR "AI tool*") AND (educat* OR learn* OR student* OR teach* OR "self-regulat*" OR "critical thinking" OR academic*))*

Analysis

Descriptive bibliometrics and science mapping used R/bibliometrix/biblioshiny (Aria & Cuccurullo, 2017): annual production, source productivity, and most cited studies (RQ1); author-keyword co-occurrence (clustering and centrality), Callon centrality-density mapping, and thematic evolution (RQ2). All co-word analyses used author keywords because missingness was 6.5%, versus 48.8% for Keywords Plus.

LDA topic modeling (RQ3) used Python/gensim (Blei et al., 2003) on titles, abstracts, and author keywords after lowercasing, stop-word removal, lemmatization, and bigram construction. Topic numbers k = 2-12 were compared using c_v coherence (Röder et al., 2015); k = 10 was retained based on coherence and interpretability (c_v ≈ 0.374), with k = 7 a close alternative. Topic overlap was examined using pyLDAvis, and annual weights were based on each document's dominant topic.

Different cited-reference formats prevented a reliable common citation space, precluding co-citation and bibliographic coupling. Influence used total-citation (TC) metadata at retrieval. No record-level title-and-abstract

relevance screening followed merging and deduplication of the broad-search corpus; this exploratory, high-sensitivity approach broadens coverage but may retain peripheral records.

Results

Descriptive Landscape (RQ1)

The corpus comprised 1,412 documents from 812 sources and was very young (mean document age: 0.82 years). Annual production was 30 documents in 2023, 181 in 2024, 704 in 2025, and 497 by June 17, 2026 (partial year). The corpus involved 4,283 authors, averaging 3.64 authors per document; 222 documents were single-authored. Mean citations per document were 7.87. Tables 1-2 present the most productive sources and most cited studies, respectively.

Table 1. Most productive sources (top 10).

Source	Documents
Education Sciences	25
Frontiers in Education	22
Computers and Education: Artificial Intelligence	20
International Journal of Learning, Teaching and Educational Research	16
Discover Education	13
Frontiers in Psychology	12
Interactive Learning Environments	11
Education and Information Technologies	10
JMIR Medical Education	10
Journal of Medical Internet Research	10

Table 2. Most cited documents (top 8).

Document	DOI	Citations
Zhai C. (2024), Smart Learn. Environ.	10.1186/s40561-024-00316-7	596
Abd-Alrazaq A. (2023), JMIR Med. Educ.	10.2196/48291	419
Gerlich M. (2025), Societies	10.3390/soc15010006	360
Song C. (2023), Front. Psychol.	10.3389/fpsyg.2023.1260843	332
Chan C. (2023), Smart Learn. Environ.	10.1186/s40561-023-00269-3	307
Fan Y. (2025), Brit. J. Educ. Technol.	10.1111/bjet.13544	286
Meng X. (2024), iScience	10.1016/j.isci.2024.109713	245
Lo C. (2024), Comput. Educ.	10.1016/j.compedu.2024.105100	222

Conceptual Structure (RQ2)

The keyword co-occurrence network revealed three main clusters (Figure 1): (1) general AI and technical/clinical applications (artificial intelligence, ChatGPT, large language models, machine learning, medical and nursing education, natural language processing, automation bias, trust); (2) generative AI, higher education, and cognitive risks (generative AI, higher education, critical thinking, academic integrity, AI literacy, cognitive offloading, AI dependency, self-regulated learning, academic writing); and (3) educational technology (educational technology, AI in education, personalized/adaptive learning, intelligent tutoring systems, systematic review).

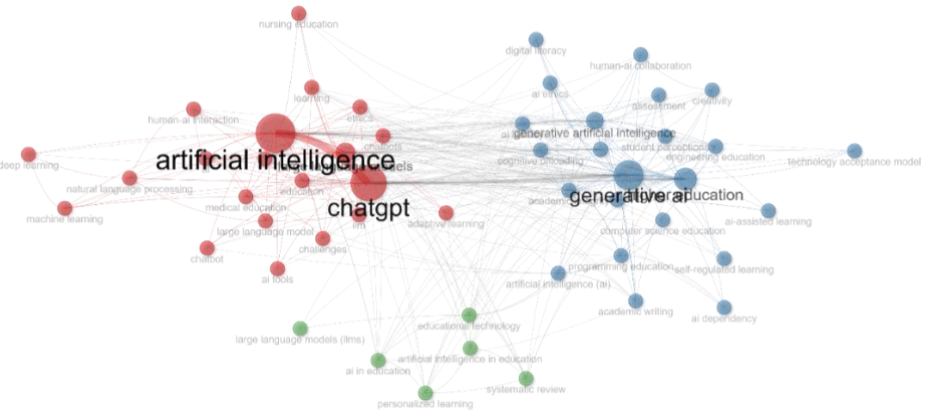


Figure 1. Keyword co-occurrence (co-word) network (three clusters).

The thematic map (Callon centrality-density plane) produced five clusters (Figure 2). The “generative ai” cluster had the highest centrality (0.746) but comparatively low density, placing it in the basic-theme quadrant; it contained the study’s core concepts: cognitive offloading (42), critical thinking (80), academic integrity (59), AI literacy (51), self-regulated learning (21), AI dependency (14), metacognition (12), cognitive load (8), and deskilling (7). The “artificial intelligence” cluster represented broad AI discourse and medical/clinical/technical diffusion. The “educational technology” cluster was comparatively developed (high density). The “artificial intelligence (ai)” cluster focused on academic writing and EFL, while the “digital literacy” cluster represented a niche theme involving language teaching, teacher education, and digital pedagogy.

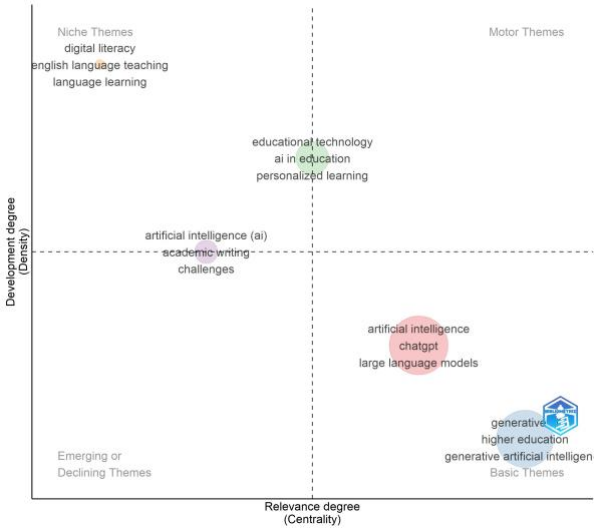


Figure 2. Thematic map (Callon centrality-density plane).

Cognitive-risk sub-constructs (cognitive offloading, over-reliance/dependence, deskilling) thus form a central but underdeveloped stream within the generative-AI cluster, not an isolated domain.

Latent Themes and Temporal Change (RQ3)

The retained ten-topic LDA solution comprised: (1) GenAI and academic writing (especially English/EFL); (2) GenAI in higher education, cognitive engagement, and human-centered design; (3) assessment, skills, and ethical frameworks; (4) adoption/perceptions and integration of GenAI; (5) cognitive dependence/over-reliance, trust, and critical thinking; (6) ChatGPT's impact and ethical debate in higher education; (7) technical and clinical applications of large language models; (8) GenAI in medical education; (9) chatbots in programming and nursing education; and (10) teachers, language teaching, feedback, and AI literacy. The core cognitive-risk discourse is particularly visible in Topic 5. Inspection of the pyLDAvis visualization indicated some overlap among topics, alongside interpretable subthemes.

Annual dominant-topic shares tended to increase for Topic 2 and the comparatively small Topic 5, whereas Topic 6 declined relatively (Figure 3), suggesting an emerging cognitive-risk research stream. These temporal patterns remain exploratory because only dominant topics were counted and 2026 covers the period through June 17.

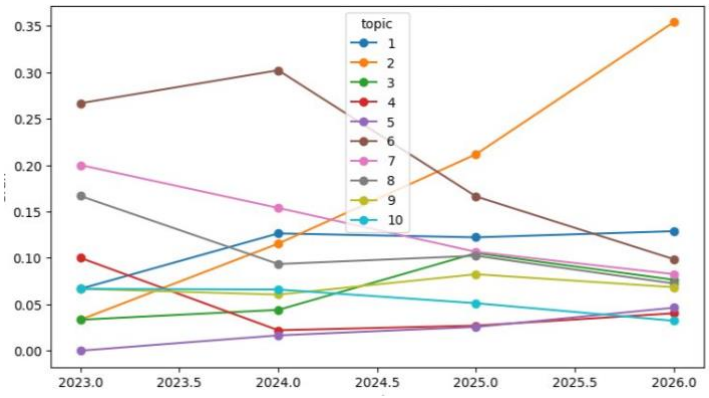


Figure 3. Annual dominant-topic shares (2023-2026; 2026 through June 17).

Exploratory thematic evolution compared 2023-2025 with 2026 through June 17 (Figure 4). Cognitive debt shifted from a separate theme to artificial intelligence; critical thinking moved toward higher education with cognitive offloading and AI literacy. AI dependency and cognitive load flowed from generative AI toward higher education, while deskilling flowed toward motivation. Trend-term analysis placed automation bias among the newest terms (median year 2026). Because 2026 is partial, these flows indicate thematic direction rather than definitive growth. Convergence with LDA reflects similar cognitive-risk structures identified through complementary analyses of the same corpus.

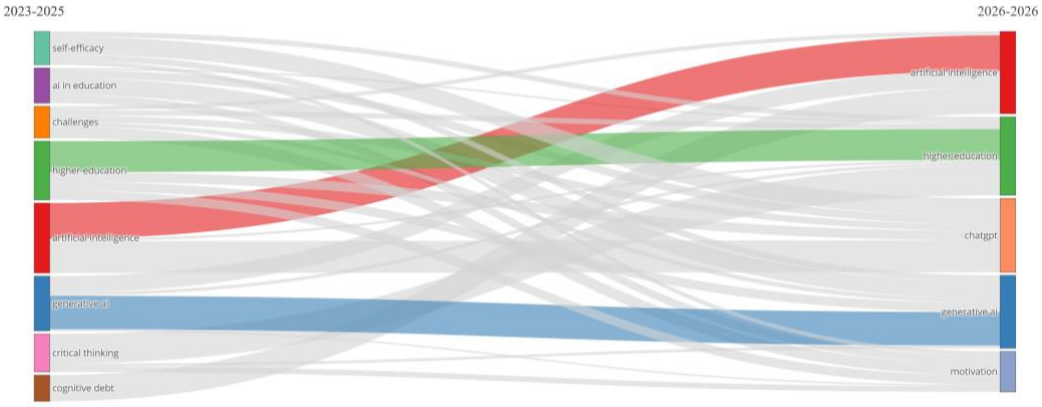


Figure 4. Thematic evolution (2023-2025 → 2026; 2026 through June 17).

Underrepresented Contexts and Themes (RQ4)

Open and distance education, where self-regulation is important, showed limited visibility as a main theme. Preventive and intervention-oriented designs, including scaffolding and mitigation strategies, were less visible than risk descriptions. K-12 and disadvantaged groups were also comparatively less visible; the prevalence of longitudinal and causal research designs was not assessed in this mapping. These are exploratory gap indicators derived from science-map visibility, not formal record-level context or method coding.

Discussion

The findings position cognitive risks as a developing substream within the broader GenAI-higher education discourse, rather than a mature specialty. This young, rapidly growing literature spans disciplinary applications and several LDA topics.

The fragmented concept family indicates a need for conceptual integration. Cognitive debt's emergence and incorporation into broader themes suggest that a shared theoretical framework remains undeveloped. In this corpus, cognitive debt is a new, low-frequency construct, not an established long-term outcome. Clustering with critical thinking, academic integrity, AI literacy, and self-regulated learning suggests examining cognitive risks alongside learning design and assessment (Fan et al., 2025; Gerlich, 2025; Watts, 2025).

The mapping does not establish a causal chain; however, it suggests a testable integrative hypothesis for future research: habitual cognitive offloading may, under some conditions, be accompanied by reduced metacognitive engagement and verification, which may strengthen patterns of over-reliance or dependence; over longer periods,

such patterns may in turn be associated with risks of deskilling or cognitive debt. This sequence should be treated not as a causal model demonstrated by the present study but as a research agenda derived from relationships among the mapped concepts.

Conclusion and Future Research Agenda

Cognitive risks form a developing, conceptually fragmented stream within the broader GenAI-higher education discourse. The RQ4 gaps suggest five research priorities: (a) examining cognitive risks in open, distance, and self-regulated learning; (b) developing and testing instructional-design and assessment interventions to mitigate cognitive offloading and over-reliance; (c) theoretical and empirical testing of possible relationships among cognitive offloading, metacognitive engagement, over-reliance/dependence, deskilling, and cognitive debt within an integrated framework; (d) comparisons across educational levels and disadvantaged groups; and (e) longitudinal and, where feasible, experimental/quasi-experimental designs tracking effects over time.

Limitations

Coverage is limited to Web of Science and Scopus and English-language publications. Crucially, no record-level title-and-abstract relevance screening followed database merging and deduplication. Broad terms such as learn*, chatbot*, 'AI tool*', and over-reliance may therefore have retained peripheral technical, clinical, or non-GenAI-learning records. Findings represent an exploratory field-level map of broadly retrieved literature, not a record-level validated systematic corpus exclusively addressing GenAI-supported learning. Author keywords were not comprehensively harmonized for synonyms/format variants; terms such as 'artificial intelligence' and 'artificial intelligence (ai)' may have fragmented co-word and thematic-map structures. Citation counts vary by database and over time; 2026 is partial. LDA c_v coherence is moderate, with k = 7 a close alternative. Dominant-topic counts exclude secondary topic probabilities; topic labels and thematic interpretations involve analytical judgment.

Generative AI Use Statement: GenAI supported language editing, review of methodological and coding steps, consistency checks, and manuscript revision. Final data-selection decisions, analytical choices, scientific interpretations, and responsibility for accuracy remain with the authors.

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Don't Get Sidetracked When Using AI in Schools: AI-Augmented Traditional Classroom Practices

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Abstract

Generative artificial intelligence is entering schools faster than stable classroom practices are being established around it. A recurring risk is that students use a language model as a rapid answer generator and bypass the reasoning that physics instruction is intended to develop. This study examines a guided alternative in secondary-school physics. The classroom work involved 63 students in Grades 9–12 and combined teacher-selected learning materials, Gemini Notebook (formerly NotebookLM), and customized Gemini Gems. The implementation covered systematic revision, acquisition of new knowledge, physics problem solving, video-based measurement, laboratory preparation, and retrieval practice. One Gem was configured as a Socratic tutor that withheld final solutions and guided students through short diagnostic questions; a second Gem asked questions, evaluated responses, and directed students back to the relevant source material. Pre- and post-test results were compared with textbook/workbook-supported learning. The retained statistical output contains 92 paired observations for the AI-supported condition and 40 for the workbook condition, accumulated across the classroom activities. Both conditions improved significantly, while the method-by-time interaction was not significant, $F(1,152) = 0.41$, $p = .523$, $\eta^2 = .0027$. Subgroup results indicated the largest relative benefit of guided AI among lower- and middle-performing learners, whereas the strongest students showed little or no advantage over textbook-based study. On the basis of these findings and classroom observations, we propose a Feynman-inspired explain-challenge-refine cycle as a further development of the Socratic design. The results support differentiated, source-grounded, teacher-directed AI use rather than unrestricted answer generation.

Keywords: generative AI; physics education; Socratic tutoring; self-explanation; Feynman-inspired learning; RAG; differentiated instruction

Introduction

Large language models (LLMs) offer new possibilities for feedback, tutoring, and individualized support, but the same systems can also make it easy to obtain a polished answer without carrying out the reasoning behind it. Reviews of generative AI in education therefore emphasize both its instructional potential and the need for critical evaluation, fact checking, and human oversight (Kasneci et al., 2023; Lo, 2023). Shoufan (2023) likewise showed that students with limited prior knowledge can sometimes use ChatGPT to answer assessment questions successfully, although performance varies by task and generated answers cannot be accepted uncritically. In school physics this creates a practical problem: a student may reach an answer more quickly while learning less from the route taken to reach it.

The present study began from this classroom problem. Its purpose was to examine whether AI can be integrated into ordinary physics lessons in a way that supports students with different levels of prior preparation without transferring the central intellectual work to the model. The design therefore combined three constraints: the learning environment was grounded in teacher-selected sources; the interaction style was predefined; and students remained responsible for interpreting the physical situation, selecting principles, checking representations, and completing the reasoning. This distinction matters in physics because a correct numerical result is not sufficient evidence of understanding. Students must connect verbal descriptions, models, diagrams, graphs, equations, and physical plausibility.

Two learning principles are particularly relevant to this design. Socratic dialogue develops reasoning through questions rather than direct exposition; recent work in physics education has shown how conversational AI can be used as a Socratic partner when the dialogue is deliberately structured (Suárez, 2025). Self-explanation research provides a second foundation: learners develop more transferable understanding when they explain examples and principles to themselves instead of processing them superficially (Chi et al., 1989). Learning by explaining is also a central generative-learning strategy (Fiorella & Mayer, 2015). These ideas motivate the Feynman-inspired extension proposed later in the paper. We use the term as a practical label for a simple explain-and-refine routine, not as a claim that a standardized 'Feynman method' was tested in the present study.

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Four questions guided the analysis:
RQ1: Does guided AI-supported learning produce measurable within-session gains in secondary physics?
RQ2: Do those gains differ from textbook/workbook-supported learning at the aggregate level?
RQ3: Does the relative benefit of guided AI differ across prior-performance groups?
RQ4: What design principles can be derived from the observed achievement patterns and classroom interactions for subsequent AI-supported physics instruction?

Methodology

Participants and classroom setting

The study involved 63 secondary-school students in Grades 9–12 and was conducted in ordinary physics lessons. The activities were intentionally heterogeneous because the original aim was to test how guided AI could complement established classroom practice across several types of learning rather than in one isolated task. The topics included gravitation; torque and rigid-body equilibrium; momentum conservation; friction and drag; Ohm's law; the characteristics of an electrical source; electrostatics; and direct-current circuits. The associated activities included new knowledge acquisition, systematic revision, problem solving, video measurement, and laboratory preparation.

Students worked either with textbook/workbook materials or with an AI-supported environment. Both conditions began with a short teacher-led introduction, after which students worked largely independently. Except for the video-measurement activity, learning episodes were assessed with a pre-test and a post-test completed without external assistance. The retained statistical output contains 92 paired observations in the AI-supported condition and 40 in the workbook condition. These are observation counts accumulated across the implemented activities, not numbers of unique students; the unique participant count was 63.

Classroom scenarios and instructional purpose

The original classroom work used AI in several distinct roles. Restoring these scenarios is important because the study was not designed as a simple comparison of one chatbot with one textbook. The same pedagogical rule was applied throughout: AI could organize material, prompt recall, or support a line of reasoning, but students were expected to interpret and verify the result, while the teacher defined the sources, constraints, and learning objective.

Table 1. Classroom scenarios, implementation, and instructional purpose

Scenario	Implementation	Instructional purpose
Systematic revision	Gemini Notebook with teacher-selected sources; mind maps, quizzes, presentations, and flashcards.	Organize and retrieve prior knowledge; used in end-of-course and modern-physics revision.
New knowledge	Textbook/workbook or source-grounded notebook after the same short teacher introduction.	Support independent concept acquisition in topics such as gravitation, torque, equilibrium, Ohm's law, and electrostatics.
Problem solving	Socratic Gem; short diagnostic questions; no complete solution or final numerical answer.	Keep representation, principle selection, algebra, and checking with the student.
Video measurement	Comparison of conventional video-analysis work with AI-supported interpretation.	Examine speed, graph interpretation, and the need to detect plausible but incorrect representations.
Laboratory preparation	Source-grounded review with study aids before an electrical-source measurement.	Link conceptual preparation to measurement planning, execution, and interpretation.
Retrieval practice	Question-answer Gem; short sequence of questions, response feedback, and source cues.	Provide targeted feedback and return students to assigned material when knowledge gaps appear.

AI environment and pedagogical constraints

The AI environment was chosen both for source control and for compatibility with the school's existing Google-based workflow. NotebookLM was introduced in 2023 as a notebook grounded in user-provided documents (Martin & Johnson, 2023) and was renamed Gemini Notebook in July 2026 (Google, 2026). In this study, teacher-selected curricular material provided the source base. This source-grounded design is related to retrieval-augmented generation (RAG), in which model output is informed by retrieved external information (Lewis et al.,

2020). Source grounding does not guarantee correctness, but it narrows the information context and makes it easier for students and teachers to verify a response against the assigned material.

Customized Gemini Gems were used to define how the model should interact with students. The first Gem acted as a Socratic physics tutor. It was instructed to diagnose the student's reasoning, ask rather than tell, decompose problem solving into manageable stages, and withhold both the complete solution and the final numerical answer. In a typical sequence the student first represented the situation, identified known and unknown quantities, selected the relevant physical principle, carried out the algebra, and then checked the result. The responses were kept short so that the exchange remained a dialogue rather than turning into extended exposition.

The second Gem supported revision and retrieval practice. It asked a short set of questions based on the assigned material, evaluated each response, suggested what was missing, and pointed the student back to the relevant source location. The two Gems therefore served complementary purposes: one scaffolded problem solving, while the other scaffolded recall and revision. In neither case was the model intended to replace the student's reasoning.

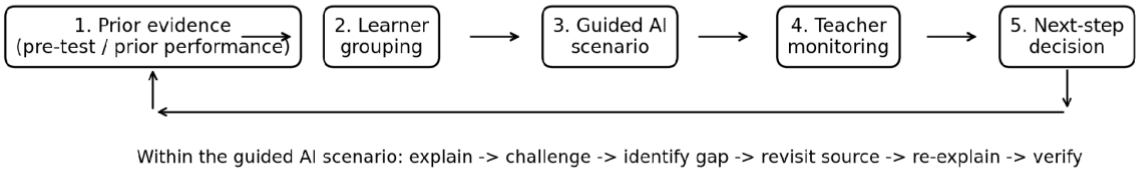


Figure 1. Data-informed guided-AI cycle with the proposed Feynman-inspired explain–challenge–refine loop.

Assessment and statistical analysis

Normality was examined before selecting within-condition tests. Difference scores in the AI-supported condition were treated as approximately normally distributed and analyzed with a paired-samples t test. Difference scores in the workbook condition were non-normal and analyzed with a Wilcoxon signed-rank test. Baseline comparison used a Mann-Whitney U test because normality was not satisfied in both pre-test distributions. The original analysis also included a two-factor repeated-measures test of the method-by-time interaction. Because observations were accumulated across several authentic classroom activities, the results are interpreted conservatively, with particular attention to effect direction, subgroup patterns, and the limits of the design.

Results

Overall learning gains and method comparison

Both learning conditions improved from pre- to post-test. In the AI-supported condition, the mean score increased from 50.8 (SD = 15.7) to 74.3 (SD = 20.6), $t(91) = 11.6$, $p < .001$. In the workbook condition, the median increased from 50.5 to 65.0; the Wilcoxon signed-rank test was also significant, $Z = 4.9$, $p < .001$, with a reported effect size of $r = .80$. Thus, substantial learning occurred in both conditions.

The method-by-time interaction was not significant, $F = 0.41$, $p = .523$, with a very small reported effect size (eta-squared = .0027). The aggregate analysis therefore does not establish a general advantage of AI-supported learning over textbook/workbook learning. This result shifts attention from the question of whether AI is better overall to the more useful question of which learners and which classroom tasks benefit from additional dialogue and scaffolding.

Table 2. Summary of the principal statistical findings

Analysis	Pre / Before	Post / After	Test	Result
AI-supported (n = 92)	M = 50.8; SD = 15.7	M = 74.3; SD = 20.6	Paired t test	$t(91) = 11.6$; $p < .001$
Workbook (n = 40)	Mdn = 50.5	Mdn = 65.0	Wilcoxon signed-rank	$Z = 4.9$; $p < .001$; $r = .80$
Method × time interaction	—	—	Repeated-measures analysis	$F = 0.41$; $p = .523$; $\eta^2 = .0027$

Performance-level differences and differentiated support

Students were grouped by prior academic performance and the relative change under AI-supported and textbook/workbook learning was examined. The largest AI-associated differences in the source analysis occurred in the lower- and middle-performing groups, at approximately 24-27 percentage points. The difference decreased markedly above 70% prior performance, and the 90-100% group showed a small advantage for textbook-based learning. Because the available manuscript does not document a prespecified, powered subgroup design, these findings should be treated as an exploratory pattern rather than as an independent confirmatory result. Pedagogically, however, the pattern is important: learners who have not yet developed stable problem-solving and self-regulation routines may have more to gain from short prompts, decomposition, and immediate feedback.

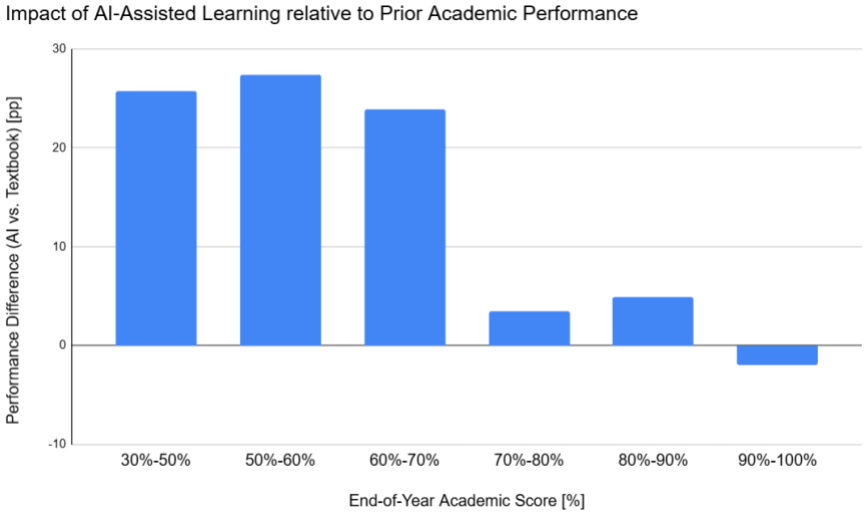


Figure 2. Relative performance difference (AI-supported learning minus textbook/workbook learning) by prior academic-performance group, as reported in the study material.

Classroom observations across learning scenarios

Classroom observation provided a second source of evidence about how the design functioned. Students who had already become accustomed to asking generative AI for direct answers were often surprised, and sometimes frustrated, when the Socratic Gem responded with questions instead of a solution. Students without this established habit more readily accepted the intended role of the system: to help them derive the answer themselves. This difference was repeatedly visible in the lessons and directly reflected the study's starting concern that unrestricted AI use can normalize the outsourcing of reasoning.

The learning scenarios also showed why speed cannot be treated as a substitute for correctness or understanding. In the video-measurement activity on friction and drag, students using conventional analysis software produced the expected representations, whereas AI-supported students could reach an interpretation more quickly but sometimes received unsuitable graph-like or infographic-style output. Students with stronger graph-reading experience were able to identify the problem; less prepared students were more likely to accept a plausible-looking representation. In laboratory preparation on the characteristics of an electrical source, source-grounded mind maps, flashcards, presentations, and quizzes offered useful ways to revisit the theory before measurement, but teacher oversight remained necessary to judge whether the generated representation was physically and pedagogically appropriate.

A representative conceptual example came from introductory mechanics. Students asked why, when a passenger jumps vertically inside a train moving at constant velocity, the train does not move out from underneath the passenger. Rather than stating Newton's first law and the reference-frame explanation, the Socratic design can begin by asking whether the passenger already has horizontal velocity before leaving the floor, what forces act horizontally during the jump, and how the motion would appear to an observer inside and outside the train. This type of dialogue illustrates the intended use of the system: the model structures the student's reasoning without taking over the explanation.

The original classroom notes also recorded a small descriptive advantage for AI-supported systematic revision (about four percentage points in one revision activity). Because the retained manuscript does not provide a corresponding inferential test for that individual activity, this observation is not treated as a separate confirmatory result. It is included here only to show how the broad classroom implementation generated scenario-level observations that were later examined together in the aggregate analysis.

Discussion

From AI access to teacher-orchestrated, data-informed support

The results do not support the simple conclusion that generative AI is superior to conventional material. Both conditions improved, and the overall method-by-time interaction was negligible. A more useful interpretation is that the value of AI depends on how the interaction is designed and on the learner's prior level of independence. The subgroup pattern is consistent with this view: lower- and middle-performing learners may benefit from additional prompts, decomposition, and immediate feedback, while high-performing students may already have efficient strategies for working with concise, information-dense material. The instructional objective is therefore not to maximize AI use, but to match the level of support to the learner and the task.

This suggests a teacher-guided differentiation cycle. Evidence from a pre-test or previous performance can indicate where additional scaffolding is likely to be useful. The teacher can then select an appropriate mode of support, observe the quality of the student's reasoning and the model's responses, and decide whether the next step should involve further questioning, a return to source material, independent problem solving, or conventional instruction. AI-supported and non-AI resources are therefore complementary rather than mutually exclusive. Figure 1 summarizes this sequence from prior evidence through guided interaction to the next instructional decision.

Feynman-inspired self-explanation as the next design layer

The Socratic Gem already prevented direct answer delivery, but the design can be strengthened by making self-explanation an explicit requirement. In the proposed Feynman-inspired cycle, the learner first explains the concept, model, or solution idea in simple language. The system then challenges one specific part of the explanation, asks for justification, or identifies a contradiction. The learner locates the knowledge gap, returns to a teacher-selected source, and produces a revised explanation. The cycle ends with verification through a short question, a transfer task, or a check of whether the result is physically reasonable.

For physics problem solving, this extension can be expressed as six steps: explain the initial model; challenge one element of the explanation; identify the gap; revisit the source; re-explain the idea or solution; and verify it in a new or slightly modified situation. The model's role is limited to prompting, checking, and scaffolding the next step. The student still performs the explanation and the reasoning. This preserves the central principle of the original classroom design while making the learning process more explicit.

The Feynman-inspired component is a proposed development of the tested Socratic design, not an additional empirical result of the present dataset. A follow-up study could compare (a) textbook/workbook learning, (b) Socratic AI tutoring, and (c) Socratic AI tutoring combined with structured self-explanation. Delayed retention, transfer, explanation quality, misconception repair, and student-AI dialogue should be examined alongside immediate post-test scores. Such a design would test whether the explain-challenge-refine cycle adds measurable value beyond guided questioning alone.

Limitations

Several limitations constrain interpretation. The study was conducted in authentic classroom settings across multiple grades, topics, and activity types rather than as one tightly controlled experiment. The retained statistical output contains more paired observations than unique students, so observation-level results must not be interpreted as independent student counts. Motivation, independence, and critical AI use were prominent classroom observations but were not measured with a standardized validated scale in the material available for this paper. The subgroup pattern requires replication with larger samples and prespecified comparisons. Finally, the Feynman-inspired self-explanation cycle has not yet been independently tested in this dataset and is presented as a next research step.

Conclusions

The study shows that guided generative AI can be integrated into ordinary secondary physics lessons without turning the model into a substitute for student reasoning. Students improved substantially under both AI-supported and textbook/workbook learning, while the overall comparison did not establish a general advantage for AI. The more informative pattern was differentiated: the largest relative benefits of guided AI appeared among lower- and middle-performing learners, whereas stronger students gained little additional benefit. The classroom implementation also demonstrated that the same design principle can be applied across revision, new knowledge acquisition, problem solving, video measurement, laboratory preparation, and retrieval practice.

The practical implication is to control the interaction, not merely provide access to the technology. Educational AI is most useful when it keeps reasoning visible, returns students to trusted sources, withholds answers when the reasoning itself is the learning target, and offers only as much scaffolding as the learner needs. The proposed Feynman-inspired explain-challenge-refine cycle extends the tested Socratic approach in that direction. Future work should evaluate the combined framework with controlled comparisons, delayed assessment, transfer tasks, and systematic analysis of student-AI dialogue.

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Evidence-Based Decision-Making as Governance: Lessons from a Two-Stage AI Pilot in Distance Higher Education

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Abstract

Distance higher education institutions face a structural support gap: without semester rhythms and with predominantly asynchronous learning, scalable and time-independent student support is difficult to provide (Rotar, 2022). AI-based systems are widely discussed as a solution, yet most implementations lack systematic evaluation protocols and institutional governance frameworks (Batool et al., 2025). At the same time, the EU AI Act imposes binding obligations on deployers, including risk management, human oversight and auditable documentation. This paper reports a two-stage AI pilot at a German distance university and derives three transferable process principles for institutions deploying AI in teaching and student support. Stage one involved a Retrieval-Augmented Generation chatbot; a content analysis of 74 question-answer pairs found approximately 63 % of responses unsatisfactory, and a targeted optimisation raised accuracy in the assessment category from 45 to 70 % without reaching the institutionally defined threshold of 80 percent. The institution decided not to move the system into regular operation. Stage two introduced an AI professor as a digital twin of a real academic, formally appointed by the university senate. An exploratory survey (n = 32) indicated high general openness toward AI-supported teaching formats and identified governance clarity as an acceptance factor. The paper argues that institutional capability is demonstrated less by adoption speed than by the ability to translate empirical evidence into structured decisions, including decisions against deployment.

Keywords: AI governance, distance higher education, digital twin, RAG chatbot, evidence-based decision-making

Introduction

Distance education institutions operate under a specific structural condition. Their students are often employed, study asynchronously and organise learning around fragmented time budgets. The flexibility that makes this model attractive also removes the temporal scaffolding that campus-based institutions provide: there is no lecture after which a question naturally arises, and no corridor in which it is answered. Support needs emerge in the evening, at weekends and in the days before an assessment deadline, while institutional support operates within office hours. Research on retention in online and distance settings has long identified delayed feedback and weak orientation as risk factors for disengagement (Hone & El Said, 2016; Tinto, 1975), and frameworks for embedding support into the online learning cycle explicitly address this timing mismatch (Rotar, 2022).

The support gap is therefore not only quantitative but temporal and organisational. Students may need orientation when preparing an assessment after work, when encountering a technical obstacle outside service hours, or when deciding how to proceed in a self-paced module without a cohort schedule. In such situations, the promise of AI lies not primarily in innovation as such but in providing a channel that can respond when institutional staff are unavailable and when asynchronous learning creates immediate and unpredictable support needs.

AI-based assistants appear to close this gap. They are continuously available, scale without proportional staffing, and require no appointment. This apparent fit explains the speed with which higher education institutions have adopted them. What has not kept pace is the governance around them. Reviews of AI governance find that organisational mechanisms like who decides, based on what evidence and against which criteria decisions are made remain underdeveloped relative to the technical deployment itself (Batool et al., 2025). While other research concentrates on tool selection, integration and cost, while systematic quality assessment and documented decision-making processes concerning system deployment remain rare.

This gap is no longer merely a matter of good practice. Regulation (EU) 2024/1689, the EU AI Act, obliges deployers of AI systems to implement appropriate technical and organisational measures, to monitor operation, to ensure human oversight and to document deployment (European Parliament & Council of the European Union, 2024). Higher education institutions are thus expected to make decisions about the use and non-use of AI systems in a traceable, documented, and risk-aware manner. How this expectation translates into institutional practice is rarely described empirically.

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In this context, governance operates across connected levels. While macro-level regulation establishes the normative framework, institutions must translate this into organisational structures, responsibility assignments, and operational decisions. At the operational level, governance becomes apparent in specific decisions: which quality thresholds apply, how evaluation is conducted and when a system is adjusted, restricted or withdrawn. The transition from policy text to institutional practice is neither automatic nor uniform: policies are interpreted, reworked and selectively enacted as they move through an institution (Tsao, 2025).

Evidence-based management treats decisions as grounded in systematically collected findings, irrespective of whether those findings support the preferred course of action (Qian & Bowman, 2026). This implies thresholds defined in advance, evaluation planned in a traceable way, and discontinuation acknowledged as a legitimate outcome.

The literature shows a marked asymmetry in this respect. Systematic reviews of AI and chatbot use in higher education report predominantly on successful implementations and their benefits (Wollny et al., 2021; Zawacki-Richter et al., 2019), while cases in which a system was systematically evaluated and then not continued remain largely absent. Yet these cases are especially informative because they reveal how criteria, evidence and institutional decisions interact. The case reported here is offered as one such account.

This paper addresses the concept of a two-stage pilot at AKAD University of Applied Sciences, a German distance university. Stage one examined a Retrieval-Augmented Generation (RAG) chatbot (Lewis et al., 2020) as a generic support tool in the learning management system; stage two examined an AI professor as a personalised, institutionally legitimised teaching format. The two stages differed deliberately in purpose, risk profile and governance logic: the chatbot was assessed against a predefined operational quality threshold, whereas the AI professor was explored primarily in terms of acceptance, legitimacy and governance preconditions. Rather than assessing the technical performance of the systems alone, the paper reconstructs the decision processes around them and asks what other institutions can take from the case. The contribution is deliberately framed as a process model: three principles that are independent of the specific systems, the specific jurisdiction and the specific institution.

Companion papers examine the participation-theoretical dimensions of the same case (Markgraf et al., in press-b), its institutional decision process within the German regulatory context (Markgraf & Römer, in press), and the institutional learning process across three related projects (Markgraf et al., in press-a). The present paper differs by comparing the governance logic of the two pilot stages and deriving process principles intended to remain applicable across institutional and jurisdictional contexts.

Methodology

This study is designed as a single-case account of a two-stage AI pilot at AKAD University of Applied Sciences, a private distance university in Germany offering distance-learning study programmes without fixed semester structures. The stage structure is central to the design. Stage one focused on a RAG chatbot intended to provide scalable, time-independent support during self-study; stage two focused on an AI professor intended to test a more personalised and pedagogically attributed form of AI-supported teaching. The analysis takes AI governance as an organisational question: macro-level regulation such as the EU AI Act establishes the normative frame, while institutions translate this frame into committee decisions, quality assurance processes, responsibility assignments and operational criteria. The paper therefore examines how evidence was generated and used for deployment decisions rather than treating the systems primarily as technical artefacts.

The first system was a Retrieval-Augmented Generation chatbot integrated into the learning management system in December 2025 and piloted in two bachelor's programmes. The system was configured to answer questions about course materials on the basis of internal institutional documents. Students were informed before launch that the chatbot could not provide study-administration information and that such matters should be directed to student services.

Chatbot use was analysed for March 2026. In that month, 281 users asked 886 questions across 442 conversations. Of these, 558 questions were suitable for content analysis; 426 concerned general administrative matters. The category system was developed inductively, and a category-stratified random sample of 74 question-answer pairs was assessed for factual correctness, appropriate length and complexity, and correctness of referrals. Coding was carried out by one member of the project team in consultation with student services. No independent second coding and no blinding were applied.

Before evaluation began, the project team defined a threshold of 80 % correct answers as a condition for regular operation. This threshold was an institutional determination rather than a published norm. Because information about examinations, deadlines and responsibilities can directly affect students' progression, an error rate above one

fifth was judged not defensible. Setting the threshold in advance was treated as a governance act because it prevented retrospective calibration of the criterion to the result.

Research ethics were addressed before launch. Students were informed about the chatbot's function, its scope limits and the use of interaction data. Chat histories were anonymised, used exclusively for service improvement and deleted automatically after 30 days. No personal data were stored, and the analysis procedure did not permit attribution of individual queries to persons.

The second system was an AI professor, introduced as a digital twin of Prof. Valters Kaže from RISEBA University, Riga. The term digital twin is used here not for a full replication of academic work, but for an AI-based representation of selected features of academic presence, including subject knowledge and communication style as well as visual representation. Teaching materials and research formed the knowledge base; style, terminology and interaction patterns were adjusted iteratively; avatar and synthetic voice were generated during video calls. The real professor was appointed visiting professor for six months by the university senate, with an inaugural lecture on 21 November 2025. The appointment applies to the person, whereas the digital twin operates as a derived and institutionally attributed teaching format. The pilot was evaluated through an anonymous project-specific survey (n = 32). Closed items were adapted from selected parts of established instruments such as the User Experience Questionnaire (Schrepp et al., 2017), the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and supplemented with open questions concerning perceived risks and concerns.

Results

The distribution of chatbot questions diverged from the system's intended function. Although the chatbot had been configured exclusively for course-material questions and this scope had been communicated to students, around three quarters of the evaluable questions concerned administrative matters. Within the 426 administrative questions, 42 % concerned assessment matters, followed by study organisation (20 %), technical access (13 %), academic writing (10 %), documents (9 %), and contact and seminar queries (3 % each). Usage was widespread but limited: Eighty-one per cent of users asked fewer than four questions, with 44 per cent asking exactly one.

Quality assessment of the 74 sampled question-answer pairs found approximately 63 % of answers unsatisfactory because of factual errors, excessive complexity or incorrect referral information. A recurring problem was the use of a generic placeholder email address instead of the correct contact. In response, the most frequent category, assessment, was optimised by re-scoping the knowledge base, adding curated student-services information, segmenting a central administrative document and moving processing to an agentic framework with a constrained output format.

The optimisation was not limited to the replacement of individual documents. The knowledge base was restructured so that the retrieval process could locate relevant passages in smaller, topically coherent units rather than in a single large file. This distinction is important for RAG systems because retrieval quality depends not only on whether information is present, but also on whether it can be identified and combined appropriately at query time. The move to an agentic framework was intended to make query interpretation, source selection and output control more explicit and auditable than in a simple chatbot pipeline.

Accuracy in the assessment category improved from 45 to 70 % across 26 questions, but the predefined threshold of 80 % was not reached. The disaggregated result shows the limited reach of the intervention: eight answers improved, 13 remained unchanged, three deteriorated, and in two cases no matching information was present even after restructuring. On this basis, the institution decided not to move the chatbot into regular operation.

The AI professor evaluation was exploratory and focused on institutional acceptance and governance preconditions. Respondents reported a moderately high level of prior AI experience (M = 3.44 of 5), which provides relevant context for interpreting the acceptance findings. General openness toward AI-supported teaching formats was high (M = 4.48 of 5). Clear governance guidelines on responsibility, transparency and limits of use were perceived as acceptance-enhancing (M = 3.90), whereas intention to use the AI professor as a self-standing teaching format was markedly lower (M = 2.20). Among respondents expressing reservations, legal aspects and teaching quality were most frequently named, followed by technical reliability, ethical considerations, data protection and effects on professional roles. Because respondents were predominantly staff rather than students, these findings describe institutional rather than student acceptance.

From findings to transferable principles

Three transferable process principles emerged across both pilots. Firstly, measurable quality thresholds should be defined prior to deployment, as it is likely that adjustments will need to be made once the system is up and running. Secondly, governance structures should be considered a prerequisite for deployment: consent, responsibility,

transparency and institutional legitimation must be established prior to operation. Thirdly, discontinuation should be recognised as a legitimate, evidence-based outcome. The chatbot case shows that the scope of remediation itself is decision-relevant: if only part of the shortfall can be addressed, continuation cannot be justified by optimisation efforts alone.

The first principle transfers most directly across institutional and jurisdictional contexts. A threshold defined after deployment is vulnerable to pressure from sunk costs, user expectations and organisational momentum. In the chatbot pilot, the 80 % criterion made the decision situation explicit: the institution could either lower the criterion, narrow the scope of use or discontinue the system. Because the threshold had been documented in advance, lowering it would have been recognisable as a revision of the criterion rather than as evidence that the system had become acceptable.

A further implication concerns scope. The chatbot was evaluated against a demand it had not been designed to meet, because students redirected an unserved institutional need into the continuously available channel. Communicated scope therefore proved to be a weak constraint on actual behaviour. Institutions should derive quality thresholds not only from intended system function, but also from anticipated user demand, and should treat early interaction logs as instruments for demand sensing rather than only as performance metrics.

The second principle is procedural rather than tied to a specific legal instrument. In the AI professor pilot, consent, attribution of responsibility and labelling of AI-generated statements were settled before launch. The appointment by the university senate under regional higher education law is one possible way of conferring legitimacy on a novel teaching role. Other higher education systems may use different instruments. What transfers is the requirement that some formal act of legitimation precede deployment and remain identifiable afterwards.

The third principle is the most demanding because it depends on institutional culture as much as on procedure. If discontinuation is framed as failure, evaluation is likely to become a formality designed to justify continuation. If discontinuation is accepted as a legitimate evidence-based outcome, evaluation can be designed to produce decision-relevant knowledge. Documenting and communicating a decision against deployment is therefore not merely an administrative step; it is part of responsible AI governance.

Conclusions

This single-case study suggests that institutional capability in AI integration can be assessed not only through adoption speed but also through the capacity to define criteria in advance, evaluate systems systematically and act on the resulting evidence. In the chatbot pilot, the predefined quality standard supported a decision against regular deployment when the threshold was not met. In the exploratory AI Professor pilot, there was a high level of openness towards AI-supported teaching formats ($M = 4.48$), and clearly defined governance arrangements were perceived as acceptance-enhancing ($M = 3.90$). The intention to use the AI Professor as a standalone teaching format remained low ($M = 2.20$). Prior to operation, consent, responsibility and transparency had been established; however, the exploratory single-group design does not permit any inference about their effect on acceptance.

The study is limited by its single-case design, its institution-specific legal and organisational context, the one-month chatbot data window, the single-coder quality assessment, the small optimisation sample and the staff-oriented survey on the AI professor. The findings are therefore indicative rather than statistically generalisable. Their contribution lies in the ordering of governance decisions: criteria before deployment, legitimation before operation and evidence before continuation.

The case also points to three open questions for future research and institutional practice. First, learning effectiveness remains unresolved: acceptance of an AI-supported teaching format does not demonstrate its effect on learning outcomes. Second, scalability requires further examination, since governance arrangements that are feasible in a pilot may become more demanding when applied across programmes, subjects or institutions. Third, quality measurement itself needs further development. The chatbot case shows that answer correctness, referral accuracy and appropriate complexity are all decision-relevant dimensions, but also that the credibility of such an evaluation rests on transparent procedures for weighting them.

Acknowledgements

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Educational Research at the Intersection of EEG and Cognitive Load: A Bibliometric Review Using the PRISMA Protocol and BERTopic

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Abstract

Electroencephalography (EEG) is increasingly being used in educational research due to its potential to objectively and in real time measure cognitive load during learning processes (Li et al., 2026). However, a systematic overview of the growing body of literature in this field has not yet been adequately established. This study presents a comprehensive bibliometric analysis of publications covering EEG and cognitive load concepts, along with topic modeling conducted using the BERTopic machine learning method.

A total of 1,276 raw records spanning the years 1988–2026, compiled from the Web of Science, Scopus, and ERIC databases in accordance with the PRISMA protocol, were reduced to 1,245 unique publications following the deduplication process. The texts were lemmatized using spaCy, vectorized using the sentence-transformers model, and 30 topics were identified using the BERTopic model, which is built on UMAP + HDBSCAN clustering.

The distribution of studies by year reveals three distinct phases. In the early phase, covering the period from 1988 to 2014, EEG-based research was niche and sporadic; during the expansion phase, spanning 2015–2020, a marked concentration in the field of clinical neuropsychology was observed. The years 2021–2025 can be characterized as a boom phase in which research on digital learning—coinciding with post-COVID-19 remote education processes—gained momentum; data from the first six months of 2026 has also been included in the scope of the study.

When the 30 BERTopic topics were grouped thematically, the three largest clusters were T0 — Cognitive Load & Neurophysiological Measurement (n = 69), T1 — EEG-based Cognitive Load in Education (n = 59), and T2 — Mild Cognitive Impairment & Neuropsychology (n = 53). In terms of country distribution, the largest number of studies were produced by the United States (n = 430), China (n = 230), and the United Kingdom (n = 200); Germany ranked fifth with 103 publications, while Turkey ranked 17th with 28.

The review concluded that no distinct body of research has emerged on topics such as professional development, career choice, identification of interests, and cognitive aptitudes; it was determined that this situation points to a significant research gap in these areas. Consequently, this study provides a strong scientific rationale for original research to be conducted in these fields

Keywords: Electroencephalography, EEG, cognitive load, mental load, BERTopic

Introduction

Cognitive load refers to the extent of change in the brain's cognitive resources that occurs during the performance of a task or activity (Causse et al., 2017; Zhu et al., 2021). This change arises as a combination of the depth of information processing, the characteristics of the task or activity, and the individual's level of expertise (Van Merriënboer & Sweller, 2005). The degree of interaction among these three components is directly proportional to the mental effort expended during the task (Antonenko & Niederhauser, 2010; Zhu et al., 2021). Cognitive load is measured using individual measures, task-based (secondary) measures, and physiological measures (Wetzel et al., 2020; Makransky et al., 2019). Individual measures are used to assess cognitive load using graded rubrics and scales (Schmeck et al., 2015). Secondary measures are used to assess cognitive load for the primary task based on accuracy and response time during the given task or performed action. Physiological measures characterize cognitive load by measuring various physiological factors such as heart rate variability, eye movement, and brain activity. While individual and secondary measures do not provide clear and accurate measurements because they disrupt the flow of work and tasks during data collection, physiological measures allow for the continuous collection of clearer data because they take measurements without interfering while the individual is performing actions in the flow of work and tasks (Hogervorst et al., 2014; Zhu et al., 2021). This demonstrates that physiological measurements can produce more objective data than individual and secondary measurements when identifying cognitive load and its factors.

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This multidimensional and dynamic nature of cognitive load makes it important to measure it using objective indicators. Indeed, measuring cognitive load using physiological measurement data—such as brain signals—has become a significant area of research in the fields of human behavior and psychology (Sinha et al., 2014). Electroencephalography (EEG), one of the brain imaging techniques widely used for this purpose, relies on recording potential changes arising from the electrical activity of neurons at the scalp surface. The separation of the obtained signals into delta, theta, alpha, beta, and gamma frequency bands and their analysis using machine learning methods enables the determination of cognitive load during a task (Antonenko & Niederhauser, 2010). Because EEG has high temporal resolution, it is a highly suitable technique for objectively measuring both instantaneous and average cognitive load (Castro-Meneses et al., 2020). Studies examining the educational impact of EEG on cognitive load have utilized it to measure mental effort during multimedia learning, reading, navigation tasks, mathematics, problem-solving skills, and e-learning (Khan et al., 2025; Wang et al., 2024). In this context, the effects of learning activity design on cognitive load include the characteristics of instructional materials (Liu et al., 2021), learner characteristics (Pi et al., 2021), learning environment characteristics (Wang et al., 2020), the presence of an instructor, and the presence of external interventions (Nigbur et al., 2011; Wang et al., 2024). A review of the literature reveals that there is no bibliometric analysis specifically addressing the relationship between EEG spectral power and cognitive load (Wang et al., 2024). Therefore, our study aims to address the following research questions:

- What is the annual publication trend for EEG-based cognitive load studies from 1988 to 2026?
- Which main topic clusters stand out in the thematic structure derived using the BERTopic (transformer-based topic modeling) method?
- How does the semantic cluster structure in EEG-based cognitive load research reflect the interdisciplinary boundary between educational technology and clinical neurology?
- Which countries are the most productive in this literature?

Methodology

This study follows a bibliometric survey design. Bibliometric screening is a descriptive literature analysis approach that aims to systematically examine scientific publications in a specific subject area through quantitative indicators (number of publications, annual distribution, journal, author, country, citations, and keyword co-occurrence) and to map their thematic structure (Donthu et al., 2021). BERTopic modeling, on the other hand, is a natural language processing method that extracts the thematic structure of the literature by analyzing the abstract texts in the study index files (BibTeX/NBIB)—generated through database search queries during the systematic review process—using Transformer-based sentence embedding, dimension reduction, and density-based clustering steps (Grootendorst, 2022). In this study, BERTopic was applied using the PRISMA 2020 (Page et al., 2021) workflow with the search query "("EEG" OR 'electroencephalography' OR "electroencephalogram") AND("cognitive load" OR "mental workload" OR "cognitive demand")" using the PRISMA 2020 (Page et al., 2021) workflow, a total of 1,276 records were retrieved from WoS (n=1,217), Scopus (n=21), and ERIC (n=38) for the period 1988–2026. Thirty-one duplicate records were excluded based on DOI (n=2) and Title+Year (n=29) matches; after deduplication, 1. Of these, 17 records lacking an Abstract field were excluded from the BERTopic stage; the final topic modeling dataset was determined to consist of 1,245 records. For bibliometrics, annual publication trends, journal distribution, author analysis, and keyword co-occurrence analysis were performed using Python (pandas, matplotlib, plotly). The PRISMA 2020 flowchart for this study is presented in Figure 1.

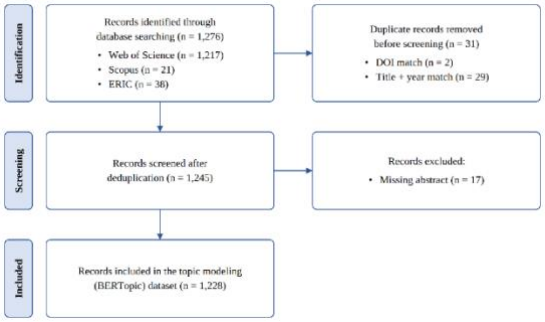


Figure 1. The study's PRISMA 2020 protocol.

Results

The semantic coherence of the 30 topics generated by the BERTopic model was evaluated using the gensim CoherenceModel class on a reference corpus of 1,245 documents, based on four metrics: for the top 10 representative words per topic, the average c_v = 0.5044 (median = 0.5185; SS = 0.1143), c_npmi = 0.0237 (median = 0.0452; SS = 0.0725), c_uci = −0.8568, and u_mass = −2.3889; The fact that the c_v value is above the 0.50 medium-to-high threshold accepted in the literature (Röder et al., 2015) and that c_npmi is positive indicates that the topic words generated by the model occur together in the corpus at a rate above the random level and that the model output is semantically consistent.

Distribution of Studies by Year

The distribution of studies by year reveals three distinct phases. In the early phase, covering the period from 1988 to 2014, EEG-based research was niche and sporadic; during the expansion phase, spanning 2015–2020, a marked concentration in the field of clinical neuropsychology was observed. The years 2021–2025 can be characterized as a boom phase in which research on digital learning—coinciding with post-COVID-19 remote education processes—gained momentum; data from the first six months of 2026 has also been included in the scope of the study.

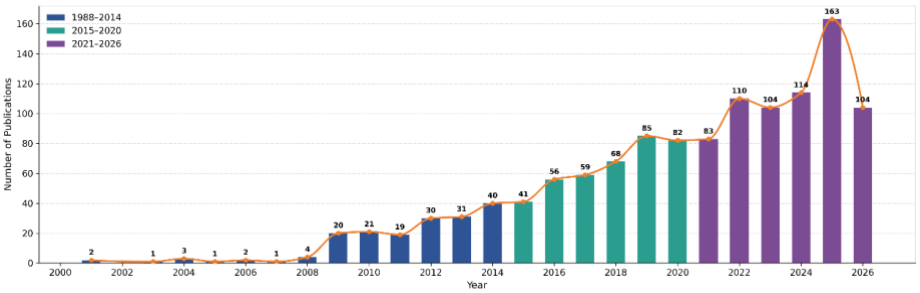


Figure 2. Distribution of studies by year.

Topic Distribution

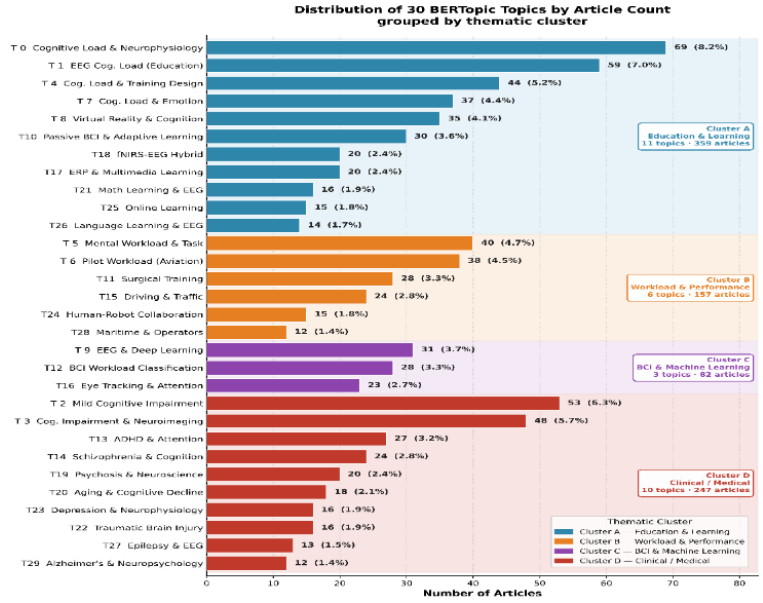


Figure 3. 30 topic models generated using the BERTopic modeling approach.

Figure 3 shows that the literature clusters around two main foci. The largest topic, T0 (Cognitive Load & Neurophysiological Measurement, n = 69), covers experimental studies using EEG as a physiological measure of cognitive load, while T1 (EEG-based Cognitive Load in Education, n = 59) applies these measurements directly to learning contexts. In the clinical domain, T2 (Mild Cognitive Impairment & Neuropsychology, n = 53) forms the third-largest topic, centred on early diagnosis. T4 (Cognitive Load & Behavioural Training, n = 44) and T8 (Virtual Reality & Cognitive Processing, n = 35) further indicate that EEG-based cognitive load research is expanding into technology-enhanced and simulation-based training environments, whereas T13 (ADHD & Neuropsychological Development, n = 27) represents a smaller but distinct clinical–developmental subfield.

Sets of Related Topics

The Ward-linked dendrogram presented in Figure 5 is structured in a way that demonstrates how the literature branches into two main branches: the left branch groups together clinical research focused on pathology, psychiatry, and neurology, while the right branch groups together applied research focused on education, performance, cognitive load, and technology.

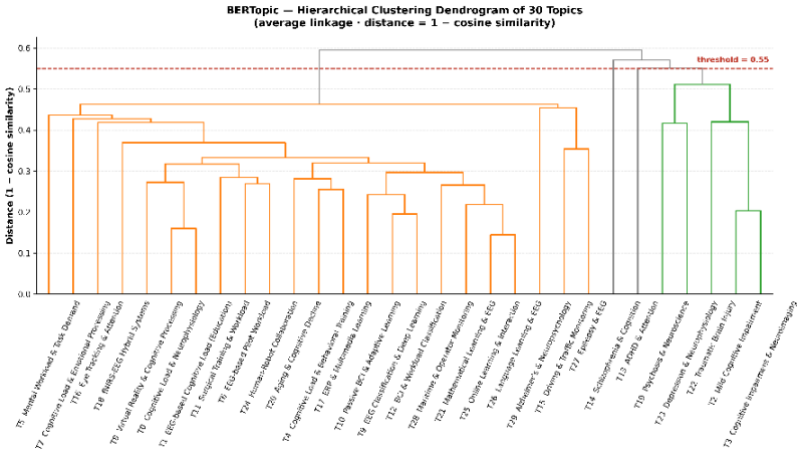


Figure 5. Hierarchical clustering dendrogram of BERTopic topics (Ward linkage).

Semantic Similarity Relationships

The semantic similarity matrix presented in Figure 4 highlights the strong conceptual overlap between T0 (Cognitive Load & Neurophysiological Measurement) and T1 (EEG in Education), while the dark blue regions above the ≥0.40 threshold highlight the intersection points where interdisciplinary knowledge transfer is

concentrated—particularly the clusters where virtual reality, motor learning, and eye-tracking technologies converge.

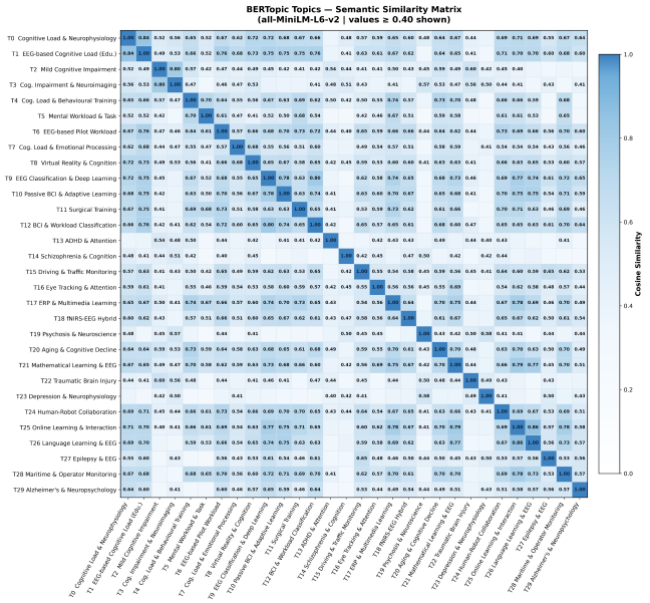


Figure 4. Semantic similarity matrix of BERTopic topics (Cosine similarity; n = 30 topics; Values ≥0.40 displayed).

Distribution of Studies by Country

According to Figure 6, the largest number of studies were conducted by the United States (430), China (230), and the United Kingdom (200). Germany ranks fifth with 103 studies, while Turkey ranks 17th with 28 studies.

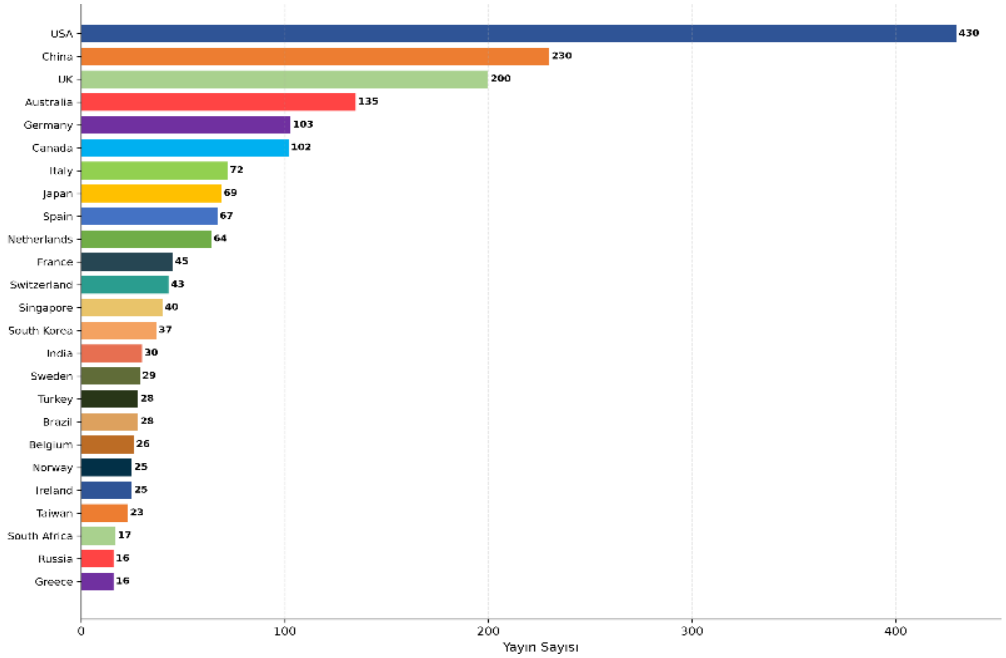


Figure 6. Distribution of studies by country.

Conclusions

When the research findings are evaluated as a whole, it is evident that the publication curve can be divided into three distinct phases: In the first phase, spanning 1988–2014, EEG-based cognitive load studies followed a sporadic trajectory; during the 2015–2020 period, a significant expansion in the literature was observed with the increase in studies focused on clinical neuropsychology; and from 2021 to 2025, a rapid acceleration in publication output was observed as post-COVID-19 remote education processes were reflected in the research agenda (see

Figure 1). The BERTopic modeling generated 30 topic clusters, with the largest clusters being T0 (Cognitive Load & Neurophysiological Measurement, n = 69), T1 (Cognitive Load with EEG – Education, n = 59), and T2 (Mild Cognitive Impairment & Neuropsychology, n = 53) (see Figure 2). While the semantic similarity matrix indicates a strong conceptual overlap between T0 and T1 (see Figure 3), the Ward linkage dendrogram revealed that the literature is divided into two main epistemic branches: clinical (pathology, psychiatry, neurology) and applied (education, performance, technology) (see Figure 4). When evaluated by country, the countries with the highest publication output are, in order, the United States (n = 430), China (n = 230), and the United Kingdom (n = 200), while Turkey ranks 17th with 28 publications. The results of the BERTopic-supported bibliometric analysis revealed that an independent set of topics centered on professional development, career choice, identification of areas of interest, and cognitive aptitude has not yet emerged. This finding highlights a significant gap, indicating a need for original and systematic research in these areas.

AI Use Statement: Grammarly and DeepL were used for translation and language editing, and Claude (Anthropic) was used to create the figures. All outputs were reviewed and edited by the authors, who take full responsibility for the content.

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Between Reflection and Routine: Human–AI Collaboration and Critical AI Competence in Distance Learning Teams

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Abstract

Generative AI is used for team-based decision-making in higher education, yet frequency of use does not provide insight into how teams evaluate and integrate AI outputs. This paper examines AI trust, self-assessed critical AI competence and collective AI use during a business simulation game in a distance learning programme. An exploratory longitudinal pre-post design with weekly surveys was used, with team processes and shared leadership captured as contextual variables. Descriptive findings from a small pilot cohort indicate a gap between the reported critical discussion of AI outputs within teams and their collective use for decision preparation. Among four longitudinally matched participants, trust trajectories varied, while post-measurement competence scores did not show a uniform relationship with trust. Perceived usefulness, trust and integration into joint decisions therefore emerge as analytically distinguishable dimensions. These preliminary observations motivate hypotheses about human-AI collaboration for examination in larger cohorts.

Keywords: human-AI collaboration, critical AI competence, business simulation games, distance learning, team processes

Introduction

Generative AI tools have become a routine part of academic work. Students use them for research, text production and increasingly for preparing decisions in group settings. High usage frequency, however, permits no inference about the ability to evaluate AI-generated content critically and to employ it productively (Laupichler et al., 2022). Reviews of AI competence in higher education consistently indicate that critical evaluation is rarely fostered systematically, although it is regarded as a core component of AI literacy (Ng et al., 2021).

This gap becomes more visible in team settings. When AI moves from being a personal tool to a participant in a shared decision process, questions of authority and accountability arise: who decides whether an AI recommendation is adopted, and who bears responsibility when a team-level decision based on it fails? Seeber et al. (2020) frame these tensions through the notion of machines as teammates, proposing that AI in collaborative work should be studied as a relational and evolving process rather than as a tool with fixed properties. Empirical work applying this lens to educational team settings remains scarce.

Business simulation games (BSGs) offer a setting in which this process becomes observable. Teams make sequential, interdependent decisions under time pressure, and the consequences of each decision become visible in the following period. Faisal et al. (2022) show in their systematic review that BSGs support knowledge acquisition as well as cognitive and interactive skills. Whether these established mechanisms extend to the comparatively recent competence of critical AI evaluation has received little attention.

This paper reports first descriptive findings from an ongoing pilot study. The guiding question is: what patterns emerge in AI trust, self-assessed critical AI competence and collective AI use during a BSG, and what do the group-level observations and matched individual trajectories suggest for conceptualising human-AI collaboration at team level?

Methodology

Setting

The simulation is a competitive management game used as a compulsory module in distance learning bachelor's and master's programmes. Teams of three to five students assume executive responsibility for a fictitious company and make decisions across several simulated business periods covering marketing, sales, research and development, purchasing, production, human resources and financial planning. Each period's outcome forms the starting position for the next, producing an iterative decision and interpretation cycle.

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Teams were free to use AI tools when preparing decisions. No obligation to use AI and no instruction to reflect on AI outputs were given. A conceptual introduction to the study design is provided in Markgraf and Römer (in press-a).

Design and instruments

The study follows a longitudinal pre-post design with weekly surveys and is conducted as an exploratory process analysis in an authentic teaching setting. The instrument consists of adapted items of validated scales and theory-led operationalisations. AI trust was measured following Jian et al. (2000), perceived usefulness with items adapted from the performance-expectancy scale of UTAUT2 (Venkatesh et al., 2012), collective AI use in teams following Seeber et al. (2020), and critical AI competence in line with the AI literacy model of Ng et al. (2021). Team processes (Fischer, 2020; Kauffeld & Frieling, 2001), transactive memory (Lewis, 2003) and shared leadership (Carson et al., 2007) were captured as contextual variables. All AI-related items used a five-point Likert scale.

The full multidimensional AI literacy construct was not operationalised. What was captured is a subset focused on critical evaluation, which includes assessing the reliability of AI outputs, knowing suitable and unsuitable areas of application, questioning AI outputs, and recognising errors or bias. Collective AI use was measured, for example, through the item "our team uses AI tools jointly to prepare decisions"; critical reflection through "AI results are critically discussed in our team before we adopt them".

Sample and limitations

The POST individual-scale means reported in Table 1 are based on n = 6 complete responses; the corresponding PRE means are based on n = 10. The team-level post-measurement items include one additional respondent who answered these items without completing the full survey. Four participants could be matched longitudinally across the relevant measurement points using an anonymised personal code. Accordingly, the group-level PRE and POST means are based on partially differing samples, whereas statements about individual trajectories refer only to the four matched participants.

The study uses no control group, and the sample size does not permit inferential analysis. Differences between the PRE and POST group means therefore describe cross-sectional patterns in partially differing samples, not within-person change or effects of the simulation. Individual trajectories are reported only for the four longitudinally matched participants. All constructs rest on self-assessment. The simulation continues to run; the values reported here are descriptive baseline findings. A didactic reading of the same pilot data, focusing on instructional design implications, is reported elsewhere (Markgraf & Römer, in press-b).

Results

Table 1. Descriptive overview of the reported AI- and team-related variables

Variable	Role in the analysis	PRE M	POST M
Critical discussion of AI outputs	Collective reflection	–	4.43
Joint AI use for decision preparation	Collective AI practice	–	3.71
AI trust	Individual perception	3.13	3.08
Critical AI competence	Individual competence	3.98	3.79
Perceived usefulness of AI	Individual perception	3.52	4.08
Shared leadership	Contextual team variable	3.73	4.45
Team processes	Contextual team variable	3.88	4.32

Note. All variables were measured on five-point Likert scales. PRE and POST values represent group means based on partially differing samples; they should not be interpreted as individual change scores.

Reported reflection exceeds reported collective use. At POST, agreement was higher for the item on critically discussing AI results within the team (M = 4.43) than for the item on jointly using AI tools to prepare decisions (M = 3.71). Participants thus rated collective scrutiny of AI output more positively than its systematic integration into joint decision-making.

Trust and competence show no uniform relationship in this pilot. At group level, AI trust is similar at PRE (M = 3.13) and POST (M = 3.08), while critical AI competence is reported lower at POST (M = 3.79) than at PRE (M = 3.98). Among the four matched participants, trust trajectories diverge: two show increases (Δ +0.17 and Δ +0.67) and two show decreases (Δ −0.50 and Δ −0.83). At POST, the participant with the highest self-assessed critical AI

competence (M = 5.00) shows the steepest decline in trust (PRE M = 3.50; POST M = 2.67; Δ −0.83). The participant with the lowest post-measurement competence value (M = 3.50) reports low trust at both measurement points (Δ −0.50). These cases illustrate heterogeneous trust trajectories but do not establish an association between competence and trust.

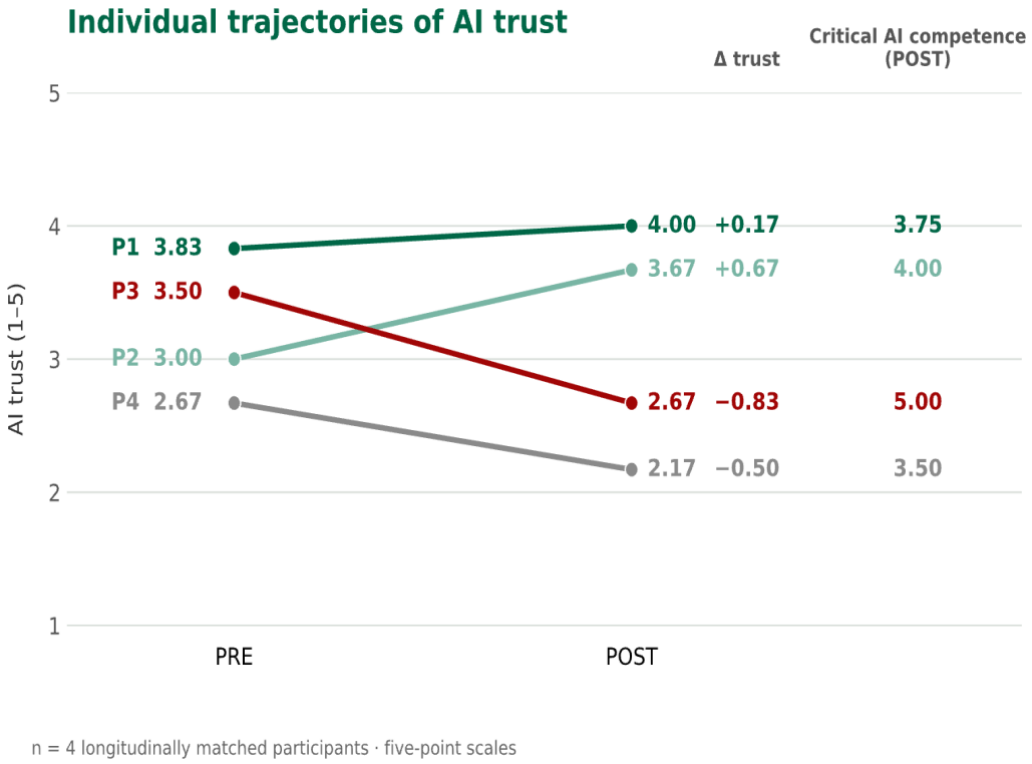


Figure 1. Individual pre–post trajectories of AI trust among the four longitudinally matched participants.

Usefulness differs from trust. The POST group reports higher perceived usefulness of AI (M = 4.08) than the PRE group (M = 3.52), while group-level trust is similar across the two measurement points (M = 3.13 vs. M = 3.08). Perceived usefulness and trust thus do not appear to move together.

Team variables. Shared leadership is higher at post (M = 4.45) than at pre (M = 3.73), as are team processes (post M = 4.32; pre M = 3.88). Higher post values also occur among participants who reported no active AI use throughout the weekly surveys. These data do not permit any conclusion about a relationship between AI use and the team variables. Team processes and shared leadership are examined as focal constructs in the related GeNeMe contribution (Markgraf et al., in press); in the present analysis, they serve only as contextual variables for interpreting human-AI collaboration at team level.

Discussion

The observed gap between reported reflection and collective use may extend existing AI literacy research. Although critical evaluation is often described as insufficiently developed in higher education (Ng et al., 2021), participants in the present pilot reported high agreement with critical discussion of AI outputs, but lower agreement with its systematic collective use for decision preparation. The findings therefore do not indicate uniformly weak reflection; rather, they suggest that reported reflection does not automatically translate into shared usage routines. For conceptualising human-AI collaboration, individual competence, collective reflection and collective practice should consequently be treated as related but distinct constructs.

The relationship between competence and trust warrants particular caution in interpretation. One reading is calibration: greater competence produces more differentiated, situation-dependent judgement rather than greater confidence. An equally plausible reading is task specificity. More competent users may have encountered the limits of generative AI in the quantitative decision problems the simulation requires. Whether the pattern generalises to other learning contexts remains open.

Similarly open is whether the higher POST values in the team variables and the high level of reported AI reflection are related, or whether both are shaped by a third factor such as prior team experience or selective participation at post.

Across the four matched participants, trust trajectories varied: one participant showed stable moderate trust with consistent use, one reported sustained non-use alongside strong team process values, one combined high post-measurement competence with a marked decline in trust, and one showed increasing trust over time. These case-level patterns demonstrate heterogeneity within the pilot sample but do not establish distinct developmental types. They provide provisional hypotheses that can be examined in larger cohorts.

Self-report is a further constraint. Reporting that one reflects critically on AI outputs is susceptible to social desirability, which may itself partly account for the observed discrepancy between reflection and use. Behavioural data such as prompt logs or analysis of team communication could address this in subsequent studies.

Conclusions

This pilot study shows how a business simulation game can be used to observe human-AI collaboration as a team-level process. Its analytical value lies in combining an authentic, sequential decision environment with separate measures of individual perceptions, self-assessed competence, collective reflection and collective AI practice. AI use was optional and the consequences of team decisions became visible across simulation periods. The setting therefore allows perceived usefulness, trust, critical evaluation and collective integration to be recorded separately and at repeated measurement points, which is a precondition for examining how they pattern together in larger samples.

Three preliminary observations emerge. First, agreement was higher for reported critical discussion of AI outputs than for reported collective AI use for decision preparation. Second, trust trajectories differ across the four matched participants and show no uniform relationship with post-measurement critical AI competence. Third, group-level perceived usefulness is higher at POST, whereas group-level trust is similar across PRE and POST; these comparisons are descriptive because the underlying samples partially differ. Taken together, the findings support analysing perceived usefulness, trust, critical competence, collective reflection and integration as distinct dimensions rather than relying on a single aggregate measure of human-AI collaboration.

The simulation continues, so more data will be collected. This will allow these observations to be examined with larger samples. Future work should establish whether the trajectory patterns identified here replicate, whether team composition moderates them, and how collective AI practice can be measured beyond self-report.

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No More Excuses: Mandating Online Learning Competencies in All Teacher Preparation Programs

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Abstract

The COVID-19 pandemic exposed a critical systemic vulnerability in education - a widespread lack of teacher readiness for online instruction, which resulted in improvised 'emergency remote teaching' rather than high-quality online learning. In this article, we argue that such unreadiness is part of a long-standing pattern in which educational disruptions caused by pandemics, natural disasters, and civil unrest have necessitated transitions to remote learning. Despite decades of federal guidance advocating for a teaching force skilled in distance delivery, many teacher preparation programs have historically treated remote instruction as a temporary crisis response rather than a core professional competency. To break this cycle of reactive improvisation, the authors propose a comprehensive roadmap for the mandatory integration of online and blended learning competencies into teacher preparation programs. This agenda outlines six essential actions: (1) developing validated, research-based standards; (2) creating reliable metrics and assessment instruments; (3) ensuring sufficient specialized coursework; (4) requiring teacher candidates to experience online learning as students; (5) mandating supervised field experiences in online settings; and (6) establishing enforceable preparation requirements through accrediting bodies and state agencies. By transitioning from theoretical endorsement to rigorous, evidence-based integration, teacher preparation programs can ensure that all future educators are prepared for modern instructional realities and inevitable disruptions.

Keywords: Teacher Preparation, Online Learning, Blended Learning, Emergency Remote Teaching, Pre-service Teachers, Educational Standards, Accreditation

Introduction

The COVID-19 pandemic revealed a fundamental weakness in teacher preparation. As schools rapidly transitioned to distance delivery in 2020, the reality was that most teachers were not adequately prepared to teach in remote environments. The result was not the implementation of carefully designed online learning, but rather what Hodges et al. (2020) characterized as emergency remote teaching. As has been repeatedly argued, emergency remote teaching should not be confused with intentionally designed online instruction because it represents a temporary response to crisis conditions rather than a systematic educational model (Barbour & Hodges, 2024a; 2025). While the pandemic highlighted these deficiencies, the challenge itself was not new. Researchers, policymakers, and government agencies had warned for decades that teachers needed preparation for online and distance instruction. Nevertheless, teacher education programs largely failed to institutionalize such preparation (Barbour & Hodges, 2024b). As a consequence, education systems entered the pandemic with a teaching force that was inadequately prepared to maintain high-quality instruction during school closures.

This paper argues that online teaching must be recognized as a core professional competency rather than a specialized skill reserved for a small subset of educators. Drawing on historical evidence, policy documents, and scholarship on teacher preparation, it outlines a comprehensive agenda for ensuring that all future teachers are prepared to design, facilitate, and support learning across modalities (Barbour & Hodges, 2026).

Historical Lessons and Persistent Unpreparedness

The use of distance education during periods of educational disruption has a long history. During the 1918 Spanish flu pandemic, school systems utilized available technologies or extended closures; for instance, California leveraged telephone technology for homebound instruction (McCracken, 2020), while a small Canadian town repeatedly altered academic calendars (Bishop Sterling, 2020). Subsequent public health crises, including the 1937 polio outbreak in Chicago that relied on radio broadcasts and the 1948 polio epidemic in New Zealand that deployed mail delivery and radio broadcasts via the Correspondence School, further demonstrate this historical pattern (German, 2020; Woods, 2022). More recently, jurisdictions across Asia deployed digital resources to maintain learning during the 2003 SARS outbreak and the 2009 H1N1 pandemic (Alpert, 2011; Barbour et al., 2011; Latchem & Jung, 2009).

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School disruptions have never been limited to pandemics. interruptions stemming from natural catastrophes, severe weather conditions, and social instability have regularly disrupted traditional schooling. Natural disasters, such as the 2011 Christchurch seismic events, forced institutions to rapidly blend face-to-face and distance modalities (Baytiyeh, 2018; Hua et al., 2017; Mackey et al., 2012). Extreme winter weather, severe flooding, seasonal wildfires, and civil discord continue to force short-term and extended closures across various regions (Buckner, 2025; Hawkins, 2026; Ignudo, 2023). Barbour and Hodges (2025) characterize this pattern as a form of historical amnesia, arguing that educational systems repeatedly fail to institutionalize lessons learned from previous crises.

Furthermore, federal agencies in the United States issued policy guidance for decades urging educational institutions to prepare for remote delivery. The U.S. Department of Education's (2017) Office of Educational Technology progressively shifted its focus from supplemental classroom technology in 1996 to explicitly directing institutions to "develop a teaching force skilled in online and blended instruction" (p. 88). The widespread failures associated with emergency remote teaching during COVID-19 were therefore not unexpected. They occurred despite decades of warnings from scholars and government agencies regarding the need for continuity-of-learning planning and teacher readiness. The evidence suggests that the challenge was not a lack of warning but a lack of action.

The Pre-Pandemic State of Teacher Preparation

Prior to 2020, preparation for online teaching remained uncommon in teacher education programs in the United States. Kennedy and Archambault (2012) found that only 1.3% of teacher preparation programs in the United States provided online field experiences. Five years later, Archambault et al. (2016) reported that figure had increased only to 4.1%. More recently, Woo et al. (2025) documented that just 14% of participating institutions offered such opportunities. These modest improvements illustrate the limited extent to which teacher education programs have responded to longstanding calls for reform.

The problem extends beyond field experiences. Research consistently demonstrated that coursework, practical experiences, and professional development focused on online teaching were unevenly distributed or often absent altogether (Barbour & Hodges, 2024c). Consequently, many teachers entered the pandemic without essential competencies required for digital instruction and learner support. This lack of preparation is particularly problematic because online teaching requires knowledge and skills that extend beyond those acquired for traditional classroom instruction. Although pedagogy remains relevant across learning environments, online teaching demands specific competencies related to instructional design, communication, learner engagement, technology integration, and digital assessment (Hodges et al, 2020). These competencies cannot reasonably be expected to develop through experience alone.

A Framework for Systematic Reform

In response to these challenges, Hodges et al. (2022) proposed a framework designed to ensure that all teacher candidates acquire the competencies necessary for online teaching. This framework has subsequently been refined and extended across multiple publications. This vision organizes needed reforms into a comprehensive three-part solution.

Part 1: Research, Validated Standards, and Assessment Metrics

A primary obstacle facing teacher preparation is the absence of empirically validated frameworks tailored to K-12 online learning. Many existing standards documents reflect commercial interests or professional consensus rather than rigorous empirical research (Molnar et al., 2021). While early initiatives like the US-based Virtual High School project utilized external evaluations, expert panels, and iterative data collection to establish reliable standards (Zucker & Kozma, 2003), widely adopted national benchmarks have often lacked rigorous psychometric validation (Adelstein & Barbour, 2018). Establishing research-backed standards is essential for institutional evaluation, because "a validated set of standards would provide accrediting bodies a guide to effective online teaching practices that could be used to hold teacher education programs accountable" (Hodges et al., 2022, p. 206).

Alongside research-based standards, the field requires validated measurement tools to evaluate pre-service candidates' growth in knowledge, skills, and attitudes. Theoretical progress has been hindered by a scarcity of psychometrically sound instruments, leading researchers to rely on custom, unvalidated surveys (Archambault, 2011; Molnar et al., 2021). Validated tools such as the Educational Success Prediction Instrument (Roblyer et al., 2008) and the K-12 Blended Teaching Readiness instrument (Graham et al., 2019) demonstrate the feasibility of structured assessment. Sustained federal research funding is necessary to incentivize the creation and refinement of robust evaluation tools across online teaching contexts (Mandt et al., 2020).

Part 2: Programmatic Integration of Online Pedagogy

Teacher education programs must deliver specialized instruction through program-wide and program-deep integration, ensuring candidates develop generic, content-specific, and modality-specific technological competencies (Schmidt-Crawford et al., 2020; Wang & Chen, 2006). Effective preparation balances integrated methods coursework with dedicated educational technology instruction, addressing specialized skill sets such as asynchronous facilitation, digital course design, and virtual student engagement (Barbour & Hodges, 2024c).

Furthermore, candidates must experience online learning firsthand as students prior to entering professional practice. Direct engagement in digital learning environments cultivates empathy for learners and builds instructional self-efficacy (Trust & Whalen, 2020). This experiential approach is grounded in the recognized principle that "teachers teach the way they were taught" (Davis & Rose, 2007, p. 7). Experiencing online coursework allows candidates to navigate interface navigation, communication workflows, and digital learning barriers from the student perspective (Zucker & Kozma, 2003).

Finally, programs must embed supervised clinical field experiences within K-12 online settings. Clinical practice provides essential hands-on learning, as "field experiences are the learning environments in which pre-service and in-service teachers are placed to get the hands-on experience they need to succeed in the education system" (Kennedy & Archambault, 2013, p. 5). Partnerships between higher education institutions and virtual schools, such as the long-standing collaboration between the University of Central Florida and Florida Virtual School, demonstrate workable models for clinical placements (Hynes et al., 2013).

Part 3: Regulatory Mandates and Accreditation Requirements

Systemic transformation requires regulatory action from state licensing agencies and national accrediting bodies. Decades of voluntary guidelines have failed to produce widespread adoption. Although accrediting organizations such as the Council for the Accreditation of Educator Preparation (CAEP) emphasize general technology integration, explicit requirements for online teaching competencies remain absent (CAEP, 2022).

In heavily regulated teacher preparation environments, unmandated competencies are frequently excluded due to strict program credit limits and competing curricular priorities (Graziano & Bryans-Bongey, 2018). Without formal requirements, teacher education programs lack the institutional mandate and curricular space required to incorporate distance pedagogy (Hodges et al., 2022). Accrediting bodies and state agencies must require all teacher preparation programs to demonstrate candidate proficiency in delivering instruction across online modalities.

Conclusion

The evidence accumulated over the past several decades leads to a clear conclusion: online teaching is no longer a specialized competency that can be reserved for a minority of educators. Historical experience demonstrates that educational disruption is a recurring reality rather than an exceptional event. Whether caused by pandemics, natural disasters, health concerns, severe weather, or geopolitical instability, interruptions to traditional schooling will continue to require teachers who can effectively deliver instruction across multiple modalities.

The central question confronting teacher education is therefore no longer whether online teaching preparation is necessary. Instead, the question is why teacher preparation systems have been so slow to institutionalize competencies that scholars, policymakers, and practitioners have identified as essential for decades. Moving forward, meaningful reform will require coordinated efforts among researchers, teacher education programs, accrediting organizations, and state agencies. Only through systematic implementation of research-based standards, validated assessments, meaningful coursework, online learning experiences, field placements, and accreditation requirements can the profession ensure that future teachers are prepared for the instructional realities of contemporary education.

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Access, Visibility, and the Right to Participate: Designing an Exploratory Visibility and Accessibility Analysis of Student Participation Structures in German Private and Distance Higher Education.

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Abstract

Student participation is widely regarded as constitutive of democratic higher education development, yet participation rates are declining and private higher education institutions (HEIs) remain largely absent from German participation research. Since the legal framework grants private HEIs considerable scope to design participation structures themselves, students must first be able to find and understand information about their opportunities for involvement before they can make use of them. This applies in particular to distance and hybrid study formats, in which such information reaches students almost exclusively through digital channels. The present work-in-progress paper outlines the design of an exploratory visibility and accessibility analysis conducted within the BMFTR-funded research project *StudiMi*. Using a non-user-based web content analysis, a stratified sample of 24 private HEIs is examined with regard to the presence, findability, and comprehensibility of defined participation-related information targets. The paper outlines the conceptual framing, the sampling strategy, and the coding scheme, and formulates expectations for the ongoing data collection.

Keywords: student participation, distance education, visibility and accessibility, students as partners, private higher education institution (HEI)

Introduction

Student participation is regarded as a driver of institutional innovation (Schrader, 2023) and as constitutive of democratic university development, with positive effects on academic success, identification with the institution, and quality assurance (Lizzio & Wilson, 2009; Bovill et al., 2011). Although the legal frameworks for student participation and representation in Germany have been formally strengthened over recent decades, actual participation rates are declining (Biehl, 2024). While the causes and consequences of this development are continually examined in German higher education research, private HEIs remain markedly underrepresented in it, even though they now account for more than a quarter of the German higher education landscape (Hachmeister, 2025). Given their high heterogeneity in ownership, governance, and study models and given the generally different legal provisions on student co-determination (Ditzel & Bergt, 2013), private HEIs warrant a distinct place in participation research.

Against this backdrop, the research project *StudiMi* (Student Participation at Private Higher Education Institutions), funded by the German Federal Ministry of Research, Technology and Space (BMFTR), addresses the lack of systematic knowledge about the legal foundations and institutional structures of student participation at private HEIs. A first analysis, of the 16 German state higher education acts, suggests, that these acts largely regulate whether private HEIs are required to provide for student participation, while the specific design is left to accreditation requirements and institutional statutes (Fischer et al., 2026a). It can therefore be assumed that participation structures will differ considerably between institutions.

In that case, students cannot rely on a common standard but have to inform themselves about the opportunities available at their own institution. The present contribution therefore examines a lack of transparency as one potentially central barrier to participation. It asks to what extent participation-related information is publicly available, findable, and comprehensible on the websites of private HEIs in Germany, and how this differs between distance or hybrid and campus-based institutions.

In this paper, visibility refers to whether participation-related information is present and can be found, while accessibility refers to whether it can be reached without prior enrolment and understood by its addressees. Accessibility is thus understood in an informational sense and does not refer to barrier-free web design (e.g., WCAG), which lies outside the scope of this study.

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Theoretical Framework

Information as a precondition for participation

The paper draws on an understanding of participation, that views students as active co-designers of institutional development and combines the concepts of *student engagement* (Trowler, 2010) as well as *students as partners* (Healey et al., 2016; Fischer et al., 2026b). Together, these approaches concieve participation as an interplay of access, actual opportunities for influence, and institutional anchoring. The present study focuses on access and on the condition that students can only take part in structures they know about.

As already described by Arnstein (1969), informing citizens of their rights and options is an important first step towards legitimate participation, while cautioning that a one-way flow of information alone does not constitute participation. Information is therefore a necessary but not a sufficient condition. Research on student participation accordingly identifies insufficient information about participation opportunities and intransparent communication, alongside a lack of time and economic pressure, as barriers to participation (Biehl, 2024; Ackermann et al., 2021). Where information is missing, hard to find, or incomprehensible, formally granted rights remain out of reach before institutional or motivational barriers even come into play. Some student representatives even report that some committees remain vacant, because students do not know they exist (Biehl, 2024). In this sense, a lack of transparency can be understood as a first-order barrier to participation.

This applies in particular to German private HEIs. If by design, student participation is laid down in individual statutes, election regulations, or organizational by-laws rather than in generally known legislation (Fischer et al., 2026a), the publication of these documents becomes a prerequisite for students to know their rights at all.

Digital access paradox

Private HEIs, and distance HEIs in particular, contribute considerably to widening access to higher education. According to Frank et al. (2020), they make up 48 percent of all part-time students and 41 percent of all distance students in Germany. These students typically have limited time and rarely, sometimes never, visit a campus. The informal channels, through which campus students learn about opportunities for involvement, such as notice boards, conversations with fellow students, or visible student representatives, are largely absent. Information about governing bodies, elections, representatives, and complaint procedures reaches them almost exclusively through digital channels, such as the HEI's public website, student portals, learning management systems, or via mailings.

The digital information architecture of the institution thus becomes the decisive gateway to participation. We refer to this tension as a digital access paradox: the very formats, that widen access to higher education may structurally weaken access to participation within it, through their dependence on digital information channels. Biehl (2024) similarly points out that, given increasing digitalization and students' weakening attachment to the university as a place, the outward visibility of student representation becomes relevant for students' willingness to participate. Whether this paradox materializes, is an empirical question that the present analysis aims to open up.

Methodology

Research design and sample

The study is designed as an exploratory, non-user-based content analysis (cf. White & Marsh, 2006; Blennerhassett et al., 2025), that follows approaches of web content analysis, that apply established content analysis procedures to the web (McMillan, 2000), and extend them to its hypertextual and dynamic characteristics (Herring, 2010). Rather than surveying students, it systematically records the information that institutions provide, simulating the perspective of a student searching for opportunities to participate, with the unit of analysis being each individual HEI.

The population referenced for this analysis comprises the 110 state-recognised private HEIs in Germany, not including church-run institutions (Hachmeister, 2025). The sampling frame is compiled from the HEI-Compass of the German Rectors' Conference (HRK, n.d.). From this frame, a sample of N = 24 institutions is drawn and stratified by study format, according to the predominant mode of delivery: 12 distance or hybrid institutions, whose programmes are delivered predominantly online or in blended formats, and 12 predominantly campus-based institutions as a comparison group. Within both groups, institutional type and size are balanced as far as the population allows. Distance and hybrid institutions are thus deliberately oversampled, since the digital access paradox is expected to be most pronounced there. To avoid insider bias, the authors' own institution is not included.

Coding scheme and procedure

Six information targets are examined for each institution and coded along three dimensions (Table 1). Presence records whether information is available at all, and whether it is publicly accessible or only referenced as being located behind an enrolment barrier. Findability is operationalized through click depth from the homepage and retrievability via the internal search function. Comprehensibility is rated on the basis of the Hamburg comprehensibility concept (Langer et al., 2019), using a simplified three-point scale. In the reporting of results, each information target will be mapped against the barriers recorded, so that barrier patterns can be compared across targets and strata.

Table 1. Coding scheme: information targets, coding dimensions, and recorded barriers.

Code	Information target	Examples of relevant content
T1	Governing bodies and academic self-governance	Senate, faculty councils, student seats in bodies
T2	Student representation	Student council or equivalent body, representatives
T3	Elections and participation procedures	Election dates, candidacy, terms of office
T4	Relevant regulations	Statutes, election regulations, rules of procedure
T5	Contact persons	Named contacts or functional addresses for participation matters
T6	Feedback and complaint channels	Evaluation, complaint procedures, ombudsperson
Dimension	**Coding values**	**Barrier recorded**
Presence	0 = absent, 1 = referenced as internal only, 2 = publicly available	Absence; enrolment barrier
Findability	Click depth from homepage; found via internal search (yes/no)	More than five clicks; search failure
Comprehensibility	1 = low, 2 = medium, 3 = high	Low comprehensibility

Especially in distance and hybrid formats, much participation-related information is likely to be provided via student portals and learning management systems that are accessible only after enrolment. Therefore the potential need of a second pass, in which such internal channels are examined at a small number of institutions, is very likely. Its design would depend on the findings of the prior analysis, and on field access. If the findings suggest the necessity of a second pass, the specifics will be determined at a later stage.

Expected Findings

As data collection is still ongoing, no empirical results can be reported at this stage. Based on the preceding regulatory analysis and the conceptual considerations above, three expectations guide the analysis.

E1: Heterogeneous visibility. In line with the assumption that private HEIs make very different use of their scope for self-regulation (Fischer et al., 2026a), a heterogeneous picture is expected, ranging from comprehensive and easily findable information to little or no publicly visible information.

E2: Enrolment barrier. Since the concrete design of participation is largely laid down in institutional regulations, relevant information, and regulations in particular, is expected to be located at least partly behind an enrolment barrier. It would then be neither accessible to prospective students choosing an institution nor traceable for external stakeholders.

E3: Format-specific patterns. Distance and hybrid institutions are expected to differ systematically from campus-based ones. The direction of this difference is open: well-developed digital infrastructures could improve public visibility, but could also shift participation-related information into internal portals.

Conclusions and Limitations

This paper has presented the design of an exploratory analysis, of the visibility and accessibility of participation-related information at private HEIs in Germany. Conceptually, it frames a lack of transparency as a first-order barrier to student participation, and highlights the digital access paradox of distance and hybrid formats. Methodologically, it provides a replicable coding scheme for assessing the gap between formally granted participation rights and their actual findability from a student perspective.

Several limitations must be noted. The analysis captures only the supply side of information and cannot analyse the actual practical application, whether students actually search for, find, or use it. The simulated perspective does

not fully reflect real search behavior, comprehensibility ratings remain partly interpretive, websites are recorded only as a snapshot, and the sample allows exploratory comparison rather than statistical representativeness. Data collection is expected to be completed by the end of 2026. Its results will subsequently be linked to a survey of students and institutional stakeholders within *StudiMi*, so that the objective visibility of information can be compared with students' perceived knowledge of their participation opportunities.

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Collaborative Curriculum Revision for 21st-Century Competencies: Preparing Learners for Uncertain Futures Through Digital Education Policy

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Abstract

This study analyzes the collaborative revision of the São Paulo City Curriculum for Learning Technologies, first published in 2017 and updated in response to Brazil's 2022 National Common Core Complement for Computing. The central question is how formative collaborative governance can respond to technological and policy changes while preserving a curriculum's pedagogical identity and strengthening educators' professional learning. A qualitative, documentary, and interpretive approach was adopted. The corpus included the 2017 curriculum, the 2022 national computing guidelines, successive drafts, meeting records, working-group materials, and contributions from public consultation. The revision involved 36 participants representing the city's 13 Regional Education Directorates, Digital Education Guidance Teachers, and school leadership, as well as student consultation and pedagogical advisers who had participated in the original curriculum. The analysis identified three complementary findings. First, the national computing requirements could be incorporated through continuity with the curriculum's constructionist and Web Curriculum foundations rather than through pedagogical rupture. Second, the participatory architecture connected central policy, regional structures, school experience, academic knowledge, and student perspectives. Third, the iterative work of comparison, discussion, rewriting, and validation generated professional learning while the curriculum itself was being reconstructed. The study proposes the concept of formative collaborative governance to describe this simultaneity between curriculum development and professional learning. The case indicates that curriculum revision can function as institutional learning when technology is integrated with educational purposes, local experience, critical reflection, and shared authorship.

Keywords: curriculum revision; digital education; Web Curriculum; collaborative governance; professional learning

Introduction

The accelerated expansion of artificial intelligence, the circulation of information in digital environments, and changes in educational policy have intensified demands for curricula that address digital culture and twenty-first-century literacies. These demands include critical thinking, creativity, collaboration, problem solving, media awareness, and civic participation. Curriculum updating, however, cannot be reduced to adding content or complying with new regulations. Its central challenge is to respond to social and technological change without erasing the pedagogical identity that an education system has built through practice.

The São Paulo Municipal Department of Education (SME-SP) faced this challenge after Brazil approved the National Common Core Complement for Computing in 2022 (Brasil, 2022). The new national guidelines required education systems to make computing-related learning explicit throughout basic education. São Paulo therefore initiated the revision of its City Curriculum for Elementary Education: Learning Technologies, originally published in 2017 (São Paulo, 2017). The scale of the policy makes the process especially relevant: administrative figures used during the revision indicate that the municipal system serves more than one million students, including approximately 437,000 elementary students in more than 600 schools, with about 1,000 Digital Education Guidance Teachers working across the network.

The 2017 curriculum had already articulated programming, information and communication technologies, and digital literacy. It defined curriculum as plural, non-linear, action-oriented, and continuously reconstructed by teachers and students. Its principles included knowledge construction, digital culture, learner agency, autonomy, inventiveness, collaboration, reflective thinking, and civic participation (São Paulo, 2017). This orientation is consistent with constructionism, in which learners develop ideas by creating and sharing meaningful artifacts (Papert, 1980), and with Valente's (2005) learning spiral, in which description, execution, reflection, and debugging generate successive reconstructions of knowledge. Computational thinking further supports the formulation and solution of problems through concepts that extend beyond computer science (Wing, 2006).

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The curriculum also reflects the concept of Web Curriculum. Almeida and Silva (2011), Almeida and Valente (2014), and Almeida (2019) describe curriculum as emerging through the intentional integration of digital culture, everyday knowledge, and systematized knowledge in social practice. Its principles include connections among times, spaces, and contexts; multiple languages; authorship and co-authorship; intercultural dialogue; collaboration; learner agency; documentation; critical reflection; and the reciprocal transformation of people, technologies, and curriculum. Technology acquires educational meaning through pedagogical mediation rather than through its mere presence.

The revision therefore posed a problem of implementation as well as curriculum design. Curricula are not produced only by experts or implemented automatically through regulation. Educators interpret, appropriate, and recontextualize them in schools. The way a curriculum is revised can consequently influence how it is later understood and enacted. This study proposes formative collaborative governance as an analytical concept for a process in which collective curriculum construction and participants' professional learning occur simultaneously. It asks: How can formative collaborative governance update a curriculum in response to technological transformations and national policy requirements while preserving its pedagogical identity and strengthening the professional learning of the educators responsible for implementation? The study analyzes the revision process with emphasis on participation, learning, and the principles of Web Curriculum.

Methodology

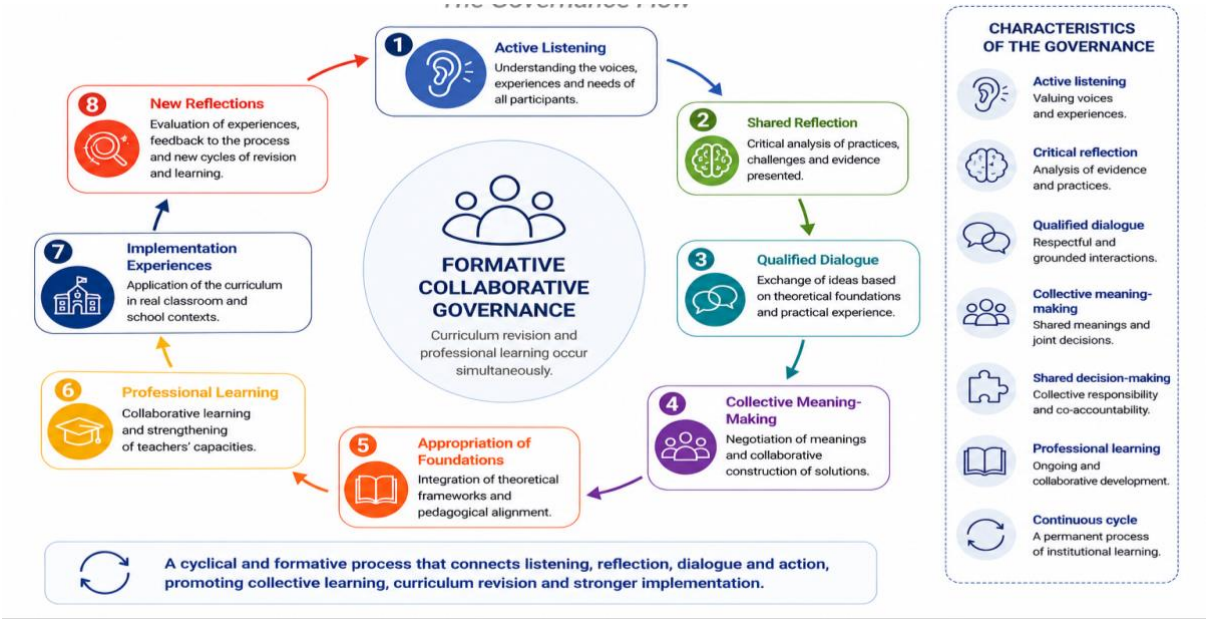
A qualitative, documentary, and analytic-interpretive design was used to examine both the curricular changes and the process through which they were produced. The corpus comprised the 2017 City Curriculum for Learning Technologies, the 2022 National Common Core Complement for Computing, successive curriculum drafts, official records of revision meetings, materials developed by the working groups, and contributions received through public consultation. Triangulation focused on three dimensions: changes in curricular content, characteristics of governance, and evidence of professional learning. The analysis sought interpretive convergence among the sources and did not attempt to establish causal relationships between participation in the revision and subsequent classroom practice.

SME-SP formed a working group of 36 participants. It included representatives of all 13 Regional Education Directorates, Digital Education Guidance Teachers who work directly with schools, and a school principal who contributed the perspective of school management and everyday implementation. Before the working group began, students were consulted through an online questionnaire about the digital-technology topics they considered relevant and how they preferred to learn them. This step connected the revision to students' interests and broadened the range of voices considered in the process.

The revision comprised six in-person meetings in 2025 and three in 2026, each lasting six hours. Participants worked in small groups to compare the objects of knowledge and learning and development objectives in the 2017 curriculum with the objects of knowledge and skills in the national computing complement. Groups rotated across sections of the document, produced syntheses, discussed disagreements, and participated in successive cycles of analysis and rewriting. These rotations enabled each participant to contribute beyond an initially assigned section and supported collective responsibility for the document as a whole.

Three pedagogical advisers who had participated in the 2017 curriculum supported the process: Maria Elizabeth Bianconcini de Almeida, Regina Célia Broti Gavassa, and Luci Ferraz de Mello. They contributed with perspectives on Web Curriculum and curriculum implementation, the institutional memory and pedagogical organization of the original curriculum, and the integration of the national computing guidelines with computational thinking and interdisciplinary approaches. Their contribution did not take the form of prescriptive lectures. Theoretical references were discussed in relation to almost nine years of experience accumulated in schools, and several working-group members also brought direct knowledge of the curriculum's original development or implementation.

After the 2025 meetings, the draft underwent technical review by SME-SP's curriculum division, critical reading by specialists and advisers, and consideration within the municipal education governance process. Public consultation in 2026 extended participation to Digital Education Guidance Teachers and teachers from different subject areas. The resulting contributions informed further revisions and formal review. Meeting records and produced materials were then coded according to the three analytical dimensions. Recurring references to learning, collaboration, reflection, dialogue, exchange of experiences, and collective construction were treated as evidence of the process's formative character, while recognizing that such evidence cannot by itself demonstrate later effects on school practice.



Source: This diagram was created using ChatGPT artificial intelligence, based on the content of the article presented here.

Results

The first finding was continuity with expansion. Incorporating the national computing guidelines did not require a rupture with the 2017 curriculum because programming, computational thinking, digital culture, and critical uses of technology were already present in the municipal framework. The revision made learning related to the national axes more explicit and strengthened project work, inquiry, maker education, authorship, collaboration, and the ethical, critical, creative, and responsible use of digital technologies. Constructionism and the learning spiral supported an understanding of programming and digital production as ways to represent ideas, test hypotheses, recognize errors, and reconstruct solutions rather than as technical training (Papert, 1980; Valente, 2005).

Continuity did not mean preserving the document unchanged. The working group reconsidered objectives in light of new national requirements, contemporary digital practices, and lessons learned during implementation. Participants who had worked with the curriculum over almost nine years contributed examples of difficulties, adaptations, and pedagogical possibilities observed in schools. The process converted implementation experience into curricular knowledge. The curriculum's identity was preserved through critical transformation with its practitioners and contexts, not through immobility.

The second finding concerned coherence between the curriculum's conception and the governance of its revision. The process connected central policy teams, regional structures, teachers, school leadership, specialists, institutional memory, student perspectives, and public consultation. This architecture brought together knowledge produced at different levels of the education system. It also reduced the distance between the prescribed curriculum and the enacted curriculum by allowing school-based experience to inform the text under revision.

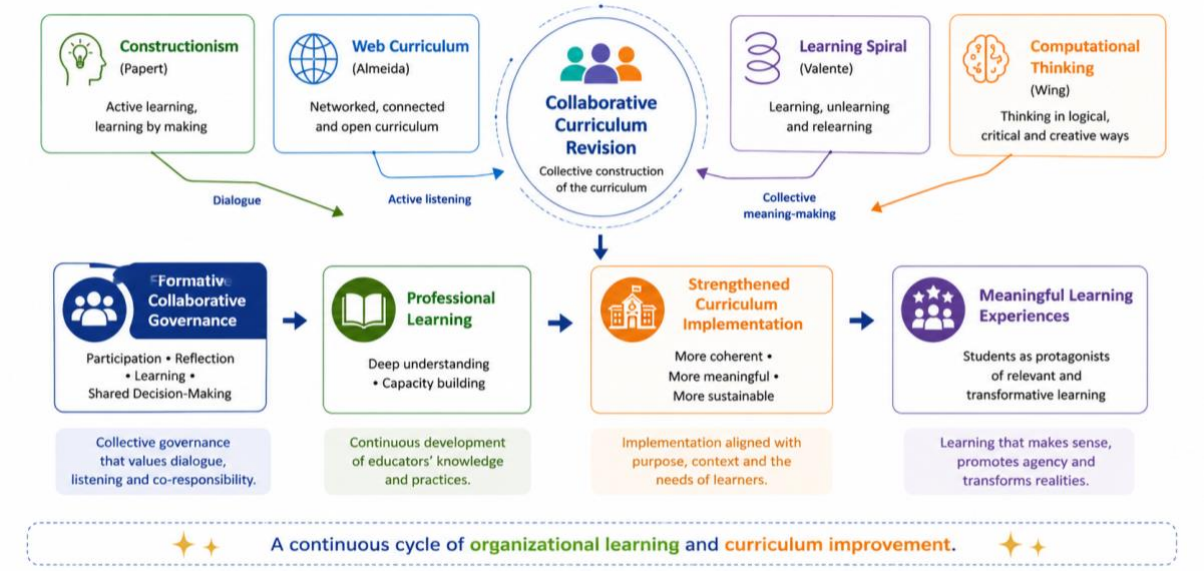
The process enacted principles of Web Curriculum rather than merely retaining them as content. Digital resources supported participation and documentation; dialogue connected school experience with central policy; rotating groups encouraged shared authorship; and successive drafts reconstructed the document through reflection. Collaboration, authorship, learner and educator agency, and critical mediation therefore characterized both the revised curriculum and the way in which it was produced. This coherence is particularly important for implementation because participants experienced the forms of learning and participation that the curriculum advocates for students.

The third finding was the double reconstruction generated by formative collaborative governance. While participants revised objectives and pedagogical guidance, they revisited experience, negotiated meanings, and reconstructed their understanding of curriculum, digital education, computational thinking, and pedagogical mediation. The process resembled the learning spiral at an organizational level: proposals were described, confronted with policy and practice, discussed, revised, and refined in recurring cycles. The meeting records and participants' final reflections repeatedly emphasized learning, collaboration, dialogue, exchange of experiences, and collective construction.

These records support the interpretation that professional learning occurred within the revision itself. The work did not postpone professional development until after the document had been completed. Instead, participants developed a shared language and deepened their understanding of the curriculum while making decisions about it. The presence of professionals connected to the 2017 development process strengthened institutional memory, while the inclusion of regional and school actors introduced situated knowledge about implementation. Student consultation and the later public consultation widened the process without eliminating the responsibility of the working group to synthesize and justify decisions.

Formative collaborative governance can thus be defined as a model of curriculum construction or revision in which actors from different levels of an education system participate in decision making while developing their own understanding of the curriculum through dialogue, active listening, theoretical engagement, and the collective reconstruction of meaning. Governance, in this formulation, is not limited to institutional coordination or representation. It creates conditions for organizational learning and for the development of capacities needed to interpret and implement the resulting policy.

The evidence also requires caution. Participation does not automatically produce consensus, equitable influence, or change in classroom practice. Meeting records and participant reflections indicate learning within the process, but longitudinal research is required to examine whether this learning changes regional training, school planning, teacher mediation, or student experience. The study therefore identifies plausible implementation conditions rather than claiming measured impact.



Source: This diagram was created using ChatGPT artificial intelligence, based on the content of the article presented here.

Conclusion

The São Paulo case indicates that updating a curriculum for digital culture requires more than adding competencies, devices, or contemporary terminology. It requires coherence between content and process, integration between national guidance and knowledge developed within the education system, and meaningful participation by the professionals who will interpret the curriculum in schools. From a Web Curriculum perspective, technologies contribute to learning when they are connected to educational purposes, participants' cultures, and critical, collaborative, authorial knowledge production and civic participation.

The main analytical contribution of the study is the concept of formative collaborative governance. Curriculum development and professional learning can occur as a single process when revision is organized through structured comparison, dialogue, shared authorship, iterative rewriting, and engagement with implementation experience. This simultaneity can strengthen appropriation of the curriculum's foundations and may improve the conditions for implementation, although subsequent research must examine its effects in regional training and school practice.

The experience also suggests a broader understanding of curriculum policy. Revision need not be treated only as an occasional response to new regulation. It can become a process through which an education system learns from implementation, preserves institutional memory, incorporates new voices, and critically renews its pedagogical commitments. By integrating constructionism, the learning spiral, Web Curriculum, computational thinking, and

national computing guidelines, the case shows that systems learn not only by implementing curricula, but also by revising them with the educators and students who give them meaning in practice.

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Curriculum Implementation for Uncertain Futures: Contributions of Web Curriculum to the Development of 21st-Century Literacies

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Abstract

Curriculum documents increasingly include digital competencies and twenty-first-century literacies, but their presence in policy does not ensure their development in classrooms. This study investigates how teachers transform curriculum proposals into meaningful learning experiences through pedagogical mediation. It reports a qualitative documentary case study of the STEM Expansions Project in the São Paulo Municipal School System. Three Grade 9 teachers from different subject areas, working in the same school and within the same professional development program, adapted a common STEM proposal to their classes. Evidence comprised their final implementation reports, presentations at the project's closing event, and semi-structured interviews. Analysis used indicators derived from Web Curriculum, including authorship, collaboration, contextualization, critical reflection, knowledge sharing, and active student participation. Despite common curricular guidance and access to similar technologies, the three implementations differed in student engagement, participation, authorship, and competency development. The strongest experiences combined authentic problems, sequenced inquiry, dialogic interaction, collaboration, formative assessment, and opportunities for students to create and revise solutions. Technology contributed when teachers connected it to clear educational purposes and intentionally mediated the learning process. The investigation also informed the Visible Learning Experience Design Matrix, known as DEAV in Portuguese, which makes relationships among curriculum goals, activity sequences, competency dimensions, participation, teacher interaction, assessment, technologies, and evidence of learning more explicit. The findings indicate that curriculum implementation is a process of interpretation and design through which curriculum becomes learning. Preparing students for uncertain futures therefore requires sustained professional learning that strengthens teachers' capacity to plan, enact, monitor, and improve contextualized and authorial learning experiences. The small number of cases and the documentary nature of much of the evidence limit causal claims and broad generalization. Even so, the comparative analysis offers transferable questions for curriculum implementation and identifies dimensions that can guide observation, teacher reflection, and future studies in other educational contexts.

Keywords: curriculum implementation; Web Curriculum; pedagogical mediation; STEM education; digital education; teacher professional learning

Introduction

Rapid technological and social change has led education systems to incorporate digital competencies and twenty-first-century literacies into their curricula. Critical thinking, creativity, collaboration, problem solving, media awareness, and responsible participation have become central to preparing students for futures that cannot be predicted with certainty. Yet the inclusion of these competencies in curriculum documents does not guarantee that learners will develop them. Curriculum establishes educational intentions, while learning depends on how those intentions are interpreted, adapted, and enacted in classrooms.

Between prescribed curriculum and students' lived experience lies teachers' pedagogical mediation. Decisions about context, questions, activities, participation, feedback, resources, and assessment determine whether curricular goals become meaningful opportunities to learn. Curriculum implementation is therefore not the final or mechanical stage of policy. It is a continuing process of interpretation and design in which teachers connect general orientations with students, local conditions, subject knowledge, and emerging classroom responses. Sacristán (2017) describes curriculum as a dynamic process shaped through successive interpretations, while Coburn (2001) shows how educators collectively make sense of policy and mediate its meaning in practice.

This challenge is particularly relevant to digital education. The São Paulo City Curriculum for Elementary Education: Learning Technologies integrates programming, information and communication technologies, and digital literacy with principles such as authorship, collaboration, autonomy, problem solving, and reflective thinking (São Paulo, 2017). Its didactic guidelines emphasize the active construction of knowledge and the

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integration of technologies with curricular purposes (São Paulo, 2018). Such an orientation moves beyond instrumental technology use and approaches the concept of Web Curriculum.

Web Curriculum refers to the integration of curriculum, digital media, technologies, and the cultures in which learning takes place. It becomes visible in authentic contexts characterized by interaction, authorship, reflection, theory-practice articulation, multiliteracies, sharing, collaboration, participation, and ubiquity (Almeida, 2019). Technologies are not an external supplement to the curriculum. They participate in the ways learners investigate questions, represent ideas, communicate, create, and reconstruct knowledge. Their educational value nevertheless depends on intentional mediation and on the meanings produced by participants.

The STEM Expansions Project offered an empirical context for examining this relationship. STEM education connects science, technology, engineering, and mathematics through inquiry and problems that require learners to mobilize knowledge from more than one field (Maslyk, 2016). In the project analyzed here, this approach expanded across curricular areas and culminated in the construction and programming of a robotic glove. The artifact was not treated as an end in itself. It organized a learning process in which students investigated questions, developed explanations, tested possibilities, and integrated conceptual knowledge with practical action.

The study asked: How do curriculum implementation processes enable teachers to transform curriculum proposals into meaningful learning experiences that develop the competencies students need to thrive in uncertain futures? Its purpose was to analyze three implementations of the same professional development and curricular proposal through indicators associated with Web Curriculum. The study also sought to identify the pedagogical decisions that distinguished the experiences and to develop an analytical framework that could support future research and professional reflection.

Theoretical Framework

Web Curriculum provides the central theoretical lens. Almeida (2019) defines it as both a theoretical construct and an interdisciplinary category of action emerging from the integration of curriculum, digital technologies, media, and multiple cultures. This integration requires more than placing devices within pre-existing lessons. It changes the relationships among knowledge, contexts, languages, participants, and forms of authorship. Almeida and Silva (2011) further emphasize that curriculum and digital culture are reconstructed through practices distributed across different spaces and times.

This perspective converges with dialogic education. Freire (2002) understands education as communication among subjects who jointly seek meaning rather than as the transmission of finished knowledge. Mercer (2003) similarly highlights the educational value of dialogic talk and purposeful questioning. In the STEM Expansions approach, teachers prepared sequences of provocative questions, used students' responses to guide subsequent interventions, and created cycles in which reflection generated new questions and actions. Dialogue thus served both learning and formative assessment.

Competency development also requires integration. Zabala and Arnau (2010) argue that competent action combines conceptual or factual knowledge, practical procedures, and attitudes in response to contextualized problems. A sequence designed for competencies must create opportunities to mobilize these dimensions together, observe evidence during the process, and revisit learning through decontextualization and recontextualization. This view clarifies why an engaging digital product alone cannot demonstrate learning. Teachers need evidence of how students understand concepts, apply procedures, justify choices, collaborate, and regulate their work.

The combined framework positions pedagogical mediation as the link among curriculum, context, technologies, and evidence of learning. It also reframes teacher agency. Teachers do not simply deliver a prepared project; they select emphases, redesign tasks, organize participation, respond to emerging needs, and decide when and how technologies will support inquiry. These decisions help explain why a shared proposal can generate different learning experiences.

Methodology

A qualitative documentary case study was conducted to understand how teachers appropriated a curriculum proposal and translated it into classroom experience. The investigation represents an initial empirical case within a broader research agenda on curriculum implementation in authentic educational contexts. It analyzes the STEM Expansions Project as an implementation setting rather than evaluating the project as a standardized intervention.

The project, developed by Testo Educational Consulting, supported teachers from different subject areas in designing inquiry-based experiences mediated by digital technologies and aligned with the São Paulo City Curriculum for Learning Technologies. Its professional development model combined conceptual study, synchronous and asynchronous collaborative work, contextual adaptation, classroom experimentation, and

pedagogical support. Teachers studied the STEM approach, planned versions appropriate to their classes, implemented them in service, and documented the process.

The study examined three Grade 9 teachers from different subject areas in the same municipal school. All participated in the same professional development program and implemented the common challenge of constructing and programming a robotic glove, while connecting the work to their respective curricular areas. This shared setting enabled comparison without assuming that identical training, resources, and general guidance would produce identical enactments.

The primary evidence consisted of the teachers' final implementation reports, which documented lesson planning, adaptations, mediation strategies, student participation, evidence of learning, and teacher reflection. Presentations delivered at the project's closing event and semi-structured interviews complemented the reports by clarifying decisions and perceptions that were not always explicit in writing. The researcher analyzed the materials retrospectively and did not implement the classroom activities.

The analysis used indicators derived from Web Curriculum: contextualization, authorship and co-authorship, collaboration, dialogic interaction, critical reflection, theory-practice articulation, knowledge sharing, multiple languages, and active student participation. It also considered how each sequence integrated the dimensions of competencies, formative assessment, teachers' forms of interaction, digital technologies, and evidence of learning. The cases were compared to identify recurring principles and differences in pedagogical mediation. As a small, context-specific study based largely on teacher-produced evidence, it supports analytical interpretation rather than causal or statistical generalization.

Source: This diagram was created using ChatGPT artificial intelligence, based on the content of the article presented here.

Results

The first finding was that a common curriculum proposal did not determine a common learning experience. Although the teachers worked in the same school, joined the same professional development process, and had access to similar technological resources, their implementations differed in the intensity of student engagement, participation, authorship, collaboration, and demonstrated competency development. The differences were associated with how teachers interpreted the proposal, connected it to their subject areas, organized the sequence, and responded to students during implementation.

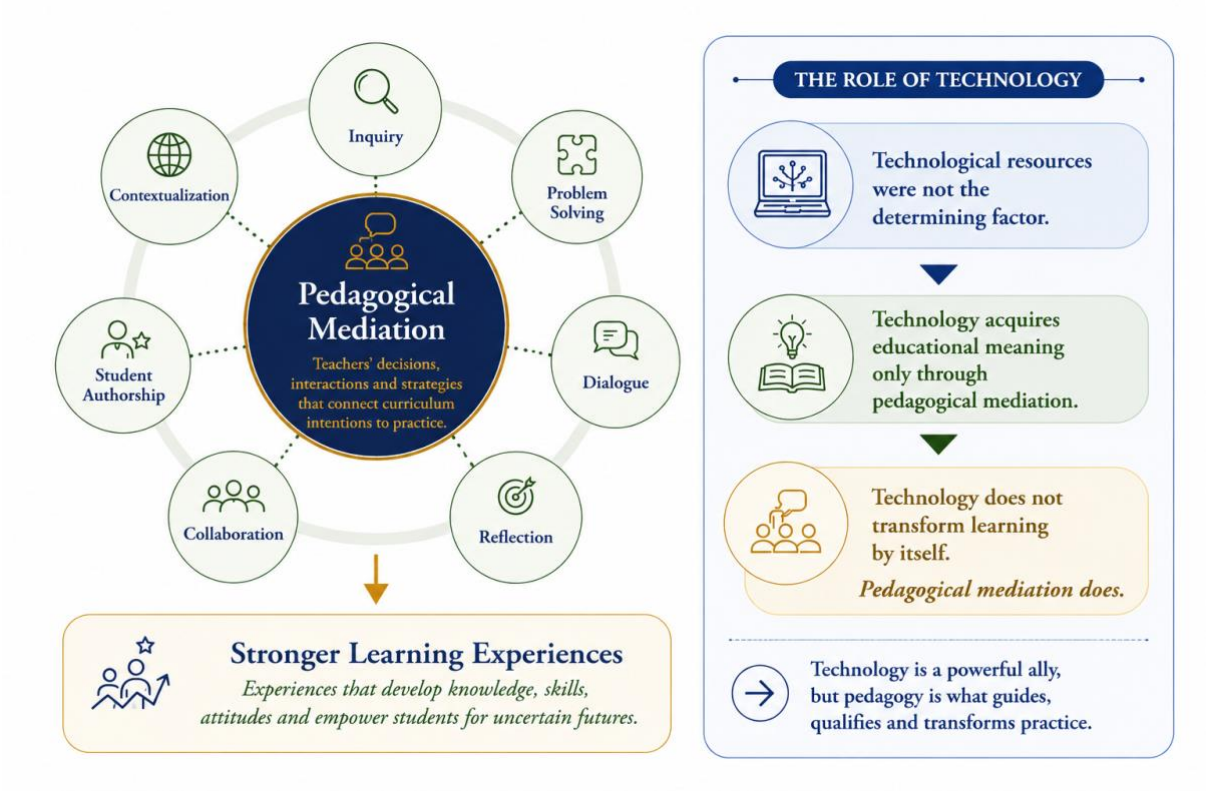
The three cases converged around the production of the robotic glove and around objectives related to programming, information and communication technologies, and digital literacy. They also integrated mathematics, natural sciences, arts, and other knowledge mobilized by the challenge. The strongest implementations, however, treated the artifact as part of an inquiry rather than as a task to reproduce. Students investigated authentic or plausible problems, proposed explanations, tested mechanisms and code, discussed errors, revised decisions, and communicated what they had learned. Digital production became a means of thinking and representing knowledge.

The second finding concerned dialogue and the changing role of the teacher. The reports described sequences of provocative and reflective questions prepared in relation to learning objectives and competencies. Teachers alternated explanation with observation, orientation, and dialogic intervention. Students' responses informed the next questions and actions, generating a spiral of reflection and reconstruction. In the more participatory experiences, teachers moved away from the position of principal knowledge holder and acted as designers, evaluators, and instigators of inquiry. This shift strengthened student agency while also making teacher agency more visible.

The third finding was that technology was necessary to some activities but did not explain the differences among cases. Similar resources supported contrasting levels of participation and learning because technologies acquired meaning through the tasks, questions, interactions, and feedback in which they were embedded. The evidence therefore supports a central interpretation: technology does not transform learning by itself; pedagogical mediation does. This conclusion does not minimize infrastructure or access. It distinguishes access from educational appropriation and reinforces the need to align technological choices with formative intentions.

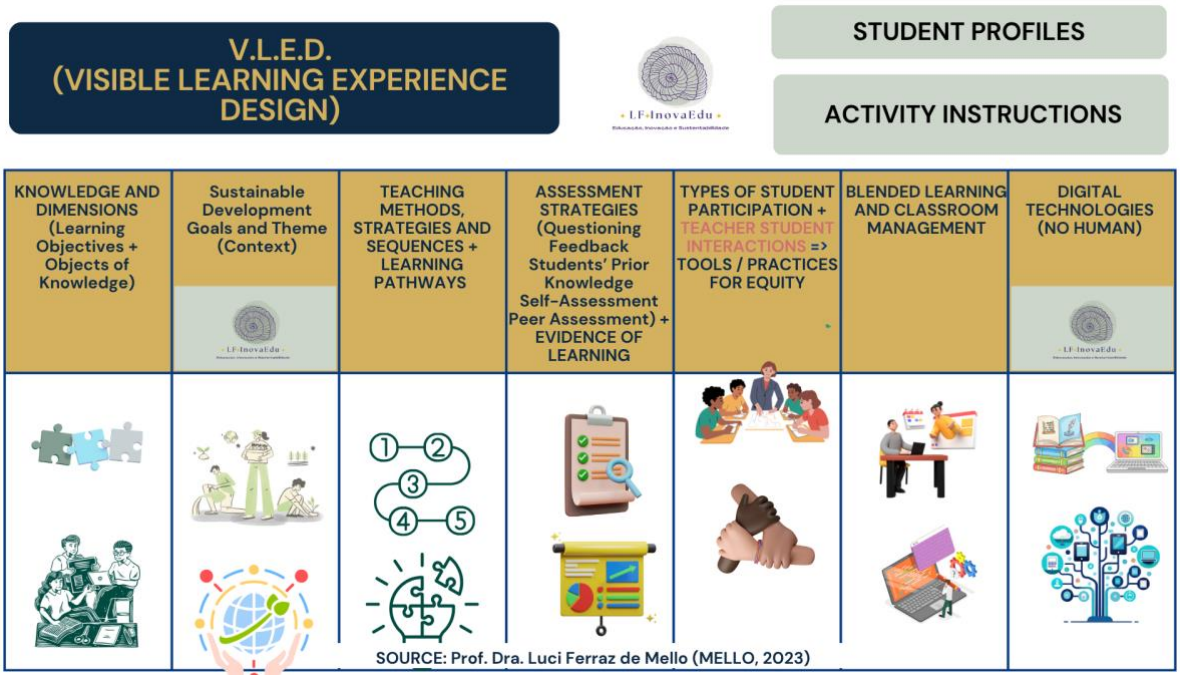
The Web Curriculum indicators helped identify this alignment. Authorship appeared when students developed and justified solutions rather than merely following instructions. Collaboration involved the interdependence of ideas and actions, not only division of labor. Contextualization connected disciplinary concepts to problems that students could investigate and discuss. Critical reflection became visible through questioning, error analysis, revision, and explanation. Knowledge sharing occurred through dialogue and presentations, while multiple languages combined

oral, written, visual, computational, and material representations. These elements were mutually reinforcing rather than isolated features.



Source: This diagram was created using ChatGPT artificial intelligence, based on the content of the article presented here.

A further outcome of the investigation was the development of the Visible Learning Experience Design Matrix, or VLED Matrix, known as DEAV in Portuguese. The matrix emerged as a way to make pedagogical decisions that often remain implicit more visible for planning, monitoring, and reflection. Its purpose is not to standardize teaching or replace professional judgment. It organizes relationships among learner profiles, objectives, skills and knowledge, activity sequences, competency dimensions, assessment strategies, expected forms of participation, teacher interaction, learning environments, digital technologies, and notes produced during or after implementation (Mello, 2022).



Source: adapted from Mello (2023)

Subsequent incorporation of the VLED Matrix (into the guidance for full-time municipal schools in Ceará extended this contribution beyond the original cases. The document positions digital technologies after the definition of formative intentions, competencies, activities, participation, interaction, and assessment. It also includes space for teachers to record what occurred during implementation, enabling comparison between planned and enacted experience. School leaders can use the resulting visibility to identify gaps, professional learning needs, and resource requirements, while education systems can curate practices without detaching them from their contexts (Ceará, 2023, pp. 76-82).

This later application reinforces the matrix's role as an implementation support rather than the main object of the present study. The empirical contribution remains the comparison of teachers' enactments through Web Curriculum. The matrix translates insights from that comparison into a framework for future inquiry and professional learning. Its value depends on reflective use: making decisions visible should support questioning and improvement, not convert complex learning into a checklist.

The findings also point to the importance of sustained professional development. Short introductions to technologies or methods are insufficient when implementation requires teachers to coordinate curriculum, context, participation, assessment, and classroom interaction. The STEM Expansions model combined conceptual foundations, collaborative planning, immediate experimentation, documentation, and pedagogical support. These elements created opportunities for teachers to learn from enactment and revise their understanding of both the curriculum and their role.

Conclusion

Preparing students for uncertain futures depends less on predicting particular technologies than on developing their capacity to investigate, create, collaborate, evaluate information, solve problems, and participate responsibly. Curriculum documents can establish these intentions, but teachers make them educationally consequential through implementation. The three cases demonstrate that a shared proposal and similar resources may produce different experiences because pedagogical mediation shapes the relationships among curriculum, students, knowledge, and technology.

Web Curriculum offers a productive framework for analyzing these relationships. Its principles became visible when technologies supported contextualized inquiry, dialogue, authorship, collaboration, critical reflection, and knowledge sharing. The most significant transformation was not the presence of a digital device or robotic artifact, but the organization of experiences in which students could propose, test, explain, revise, and collectively construct meaning.

The VLED/DEAV Matrix represents a practical and research-oriented outcome of the study. By making planning and implementation decisions visible, it can support teachers in designing coherent sequences, monitoring

evidence, and reflecting on the effects of their choices. Its later adoption in Ceará's curriculum guidance illustrates its potential use in broader public education contexts, provided that it remains flexible and responsive to local realities.

The study's small sample and documentary basis limit claims about student outcomes and broader transfer. Future research should apply the analytical indicators and matrix in different educational settings, incorporate direct classroom observation and student perspectives, and examine how professional learning changes implementation over time. Even with these limitations, the study supports a clear implication: curricula do not transform education merely when they are published. They contribute to transformation when teachers appropriate them and convert their intentions into meaningful learning experiences through informed pedagogical mediation.

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Managing Formative Feedback in Asynchronous Project-Based Learning: A Competency-Oriented Approach

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Abstract

Asynchronous participation in blended (HyFlex) learning environments presents significant challenges for formative feedback. In project-based STEM courses, in-person active learning traditionally benefits from continuous interaction and feedback from an on-the-spot instructor. Asynchronous participation presents a mismatch between the timing of student learning needs and instructor availability for feedback. Mechanisms for asynchronous feedback can also be cumbersome to implement and sustain, further highlighting the already-limited capacity of instructors' workloads. The combination of challenges introduces a feedback lag, reducing the quality of student reflection and opportunities for iterative improvement.

This study applies a design-based, practice-informed approach, examining course design and implementation within blended and partially HyFlex project-based courses in engineering design and manufacturing. Course artifacts—including formative learning activities, project structures, and scoring rubrics—are analyzed alongside instructor observations, drawing on iterative teaching practice and reflective analysis. Principles from self-regulated learning and competency-based education provide lenses for interpreting observed challenges and informing proposed course design refinements.

Consistent with prior scholarship, asynchronous participation limited the feasibility of continuous instructor feedback and reduced visibility into student learning processes. Findings further suggest that the central challenge is not the absence of formative learning activities and resources, but uneven student engagement with those resources when instructor feedback is not continuously available. Structured formative ecosystems in the CAD, CNC machining, and manufacturing automation courses supported success for most students and reduced reliance on consistent instructor intervention. However, observations also revealed gaps in iterative feedback and reflection opportunities and in the explicit support of self-regulated learning processes, particularly for students less prepared to independently engage with formative activities. These gaps contributed to delayed recognition of misconceptions and uneven engagement prior to project completion.

Drawing on these observations and related scholarship, competency-based approaches offer a complementary framework by emphasizing demonstrated mastery as the primary basis for graded evaluation, while supporting iterative feedback, reflection, and revision throughout the learning process. Strategies such as competency gateways, structured checkpoints, and selective peer and instructor intervention are therefore proposed as refinements to redistribute responsibility for formative monitoring toward learners while preserving rigorous evaluation of project-based competencies. This literature-informed approach provides a transferable model for aligning formative learning, feedback, and competency demonstration in asynchronous project-based environments while supporting more sustainable use of limited instructor feedback capacity.

Keywords: asynchronous, formative feedback, HyFlex, blended

Introduction

Best practices in project-based STEM learning environments rely on iterative learning informed by formative feedback (Ash & Clayton, 2009; Kolb, 1984). Traditionally, much of that feedback occurs through instructor presence (National Society for Experiential Education., 1998), allowing frequent informal instructor feedback throughout iterative learning cycles. Blended and partially HyFlex environments complicate this model, introducing asynchronous participation, which sets up a mismatch between the timing of student learning activities and the instructor availability for observation and feedback.

The feedback lag for asynchronous students is further exacerbated by practical instructor workload limitations. Even within the in-person classroom, individualized attention and interaction from the instructor cannot be with all students simultaneously. Student readiness for self-directed learning (SDL) activities further challenges student engagement with feedback opportunities. These realistic logistical limitations hinder the instructor feedback necessary for students to make fully-informed observations and reflections toward learning and improvement.

This paper examines formative feedback challenges in blended and partially HyFlex engineering and manufacturing courses. Drawing on the literature of self-regulated learning and competency-based education, it

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identifies design gaps and proposes practical refinements to better support learner autonomy while making sustainable use of instructor feedback capacity.

Literature Review

Formative Feedback in Project-Based Learning

In a comprehensive 2006 review of the literature, Nicol & Macfarlane-Dick concluded that "There is considerable research evidence to show that effective feedback leads to learning gains." Best practices in experiential or applied learning expect formative feedback to support iterative reflection practice (Ash & Clayton, 2009; Kolb, 1984). Student learning comes not only from students' own self-assessment, but from instructor, mentor, and/or peer feedback, automated quiz feedback (Black & Wiliam, 1998; Morris et al., 2021; Sadler, 1998).

The Role of Self-Regulated Learning (SRL)

The study of self-regulated learning draws from a rich study in the educational psychology arena, founded by Zimmerman (2002), who simplified several skills associated with self-regulated learning into a cycle of three phases: (1) Forethought (involving task planning and self-motivational beliefs), (2) performance (involving self-control and self-observation), and (3) self-reflection. Today, these phases have been reworded as planning, monitoring, and reflection (Structural Learning, 2026), the terms applied in this work.

Informing Principles from Competency-Based Education (CBE)

Levine & Patrick (2019) summarize seven foundational principles of competency-based education, including learner agency, differentiated support, meaningful assessment, mastery-based progression, flexible pathways, and transparent competency expectations. While these principles span institutional and programmatic design, the present study focuses on course-level practices most relevant to formative feedback and self-regulated learning:

1. Students learn actively using different pathways and varied pacing.
2. Assessment is a meaningful, positive, and empowering learning experience for students that yields timely, relevant, and actionable evidence.
3. Students meet explicit competency expectations, with multiple opportunities to demonstrate competency.
4. Readiness checkpoints often guide students in learning prior to full application demonstration.

Beckway (2026) defines formative checkpoints as "quick, ungraded checks that happen during the learning process." The course design builds in multiple checkpoints. Students who demonstrate proficiency at that point move on, but those who are not ready receive feedback and work through repeated or scaffolded activity. Lee & Chiu (2022), applying competency-based assessment in medical education, affirm the central role of feedback in guiding the learner's development. They suggest several practical suggestions for delivering effective feedback, including student self-assessment prior to instructor feedback, specific instructor feedback with examples, a follow-up to confirm student understanding of the feedback, and action plans.

Methodology

This study employs a practice-based, interpretive analysis of three problem-based, project-based courses offering flexible, partially asynchronous support (HyFlex) for working interns and other student needs. Drawing on iterative teaching practice and instructor reflective self-analysis, existing course feedback structures are compared to principles from self-regulated learning and competency-based education to propose course design refinements.

Context and Scope

Three problem-based engineering technology courses were analyzed: Computer-Aided Design (CAD) Modeling, Automated Manufacturing, and Computer Numerical Control (CNC) Machining. Courses typically enroll 18–22 students, with equipment sessions divided into two smaller groups. HyFlex modalities have been integrated into these courses for three years, building on earlier flipped-classroom instructional techniques (J. Morse & Dandu, 2017; J. L. Morse, 2024).

Data Sources

The study draws on the course design structures implemented and documented in the course syllabi and the learning management system, as well as on iterative instructor observations and reflections.

Results

Existing Formative Ecosystems Support Student Success

Table 1 summarizes key support structures already established in the blended and HyFlex courses. The requirement for in-person participation for lab components for two of the three courses ensures weekly interaction with the instructor for the application portion of the course objectives. Each course has self-directed learning resources with various levels and types of feedback.

Examination of the existing course structures confirms strong availability of student learning resources linked directly to learning objectives. However, students differed in how they engaged with the available resources and guidance. While most students were successful and many students thrived in this flexible environment, some students experienced gaps in learning, such as skipped preparation, delayed help-seeking, and late recognition of misconceptions. Further, the possibility of fully asynchronous participation in the CAD modeling course allowed some students to have greater lag-time between performance and review by the instructor, resulting at times in late recognition of misconceptions and false starts.

Applying the Lens of Self-Regulated Learning

Examining student performance through the lens of self-regulated learning, we observed the following:

- **Planning** – Were students preparing appropriately? Finding: Students were mixed on preparation. Many students engaged thoroughly with the learning activities and resources, but it is common for students to overlook instruction details. Occasional students skipped formative activities entirely, jumping to projects under the assumption that they already knew what was needed.
- **Monitoring** – Were students recognizing errors? Finding: The functional nature of the problem-based labwork and built-in simulation routines tend to bring functional and quality errors to light. For example, CNC graphical simulation demonstrates coding that produces unexpected cut geometry before we get to the lab session at the equipment. Automated Manufacturing lab exercises give students the opportunity to test their PLC programs and wiring on real equipment to test and observe results. However, there are finer details of professional techniques and standards that may be overlooked despite apparent functional success of a project. For example, a student overlooking instruction on expected subroutine formatting or toolpath strategy could approach a CNC program differently and produce part geometry that appears appropriate but does not demonstrate competency with the learning objectives. This sometimes happened with students who were working program simulations outside of the lab, not checking progress with the instructor, or possibly depending on AI-generated results and guidance pursued without connection to the course instructions. Another gap in monitoring occurs occasionally when study guides and worksheets do not provide adequate self-check or instructor checks to catch errors or omissions.
- **Reflection** – Were students learning from formative experiences? Finding: Formative experiences helped students recognize major problem-based objectives, with some detail gaps and delays, depending on the timeliness of the feedback logistics. Formative experiences for some of the foundational learning (such as basic concepts and terminology) assigned outside of lab, usually achieved through multi-take self-check quizzes, worked well for many students. Overall, students learn well when they engage with the resources.
- **Strategic Resource Use** – Were students using available resources? Finding: Most, but not all students made use of resources provided as part of expected learning assignments.

Overall, findings indicate that successful student navigation of the formative ecosystem depends heavily on student engagement with built-in course assignments or logistics that lead students through expected learning cycles. Skipped assignments or limited feedback could result in gaps in quality of competency achievement.

Applying Competency-Based Learning Principles

Competency-Based Education principles depend on course design and support that allow students to engage in repeated practice and attempts to demonstrate competency. Because it assumes not all students may require the same number of learning activity iterations or the same pace, the design must support asynchronous learning, at least in part. Table 2 suggests strategies from competency-based education practices that align well with supporting self-regulated learning and the more regular formative feedback and reflection cycles necessary to ensure student engagement. Many of these practices are already designed into the courses, but additional structure, such as planning checklists, explicit learning-objective checklists, readiness checklists, and defined competency gateways should better assist the self-regulated learner.

Table 1. Existing student learning support ecosystems

Computer-Aided Design (CAD) Modeling Course	Automated Manufacturing Course	Computer Numerical Control (CNC) Machining Course
Fully HyFlex • Textbook Tutorial Exercises (self-paced). • "Work with me" Videos (or live in class). • Review work with professor in-person, or by appointment via videoconference. • Detailed project scoring rubrics focus on learning objectives.	*Partially HyFlex, with weekly in-person labs* • Required in-lab projects, self-paced with handout instructions. Instructor provides live assistance as needed. • Asynchronous practice worksheets. • Subscription online learning modules with multi-take quizzes.	*Partially HyFlex, with flexible in-person labs* • Practice programs and worksheets. • Videos with worksheets and self-check quizzes. • Design/Program projects drive application and competency demonstration. • Simulation program helps students recognize and troubleshoot major errors • Resources include example programs and documents, forms, professional technical resources, and subscription online learning modules with multi-take quizzes.

In addition to closing learning gaps, structured expectations set standards for student attention and prioritize instructor time for students who have already demonstrated self-directed engagement and readiness for additional feedback.

Figure 1 summarizes the proposed competency-oriented feedback workflow, positioning checkpoints as opportunities for reflection and feedback before competency demonstration.

Table 2. Competency-Based Education (CBE) support strategies aligned to better support self-regulated learning

Self-Regulated Learning Need	Competency-Based Support Strategies	Course Design Applications
Planning	Competency expectations (SLOs); readiness (milestone) checklists	*Provide a course journey map and/or project milestone planning form.* *Provide a project gateway checklist.*
Monitoring	Self-checklists and rubrics, self-check quizzes, instructor check-ins or milestones, possible peer review	*Provide self-check list, rubric, or other method to help students evaluate their success.* *Provide more self-check quizzes to help students recognize omissions in their preparation for project work.*
Reflection	Revision cycles and repeated demonstrations	*Check-in gateways can require a student reflection prior to instructor feedback.* *Require reflection memo with resubmitted projects.*
Strategic Resource Use	Gateway requirements tied to required preparation activities *(i.e. Instructor will not check until . . . or will not obtain equipment access until . . .)*	*Instructor will not evaluate the project for competency if the student has not demonstrated attention to important gateway requirements. (Ensure attention to instructions, prevent false starts. Ensure safe equipment use. Protect sustainability of instructor feedback time.)*

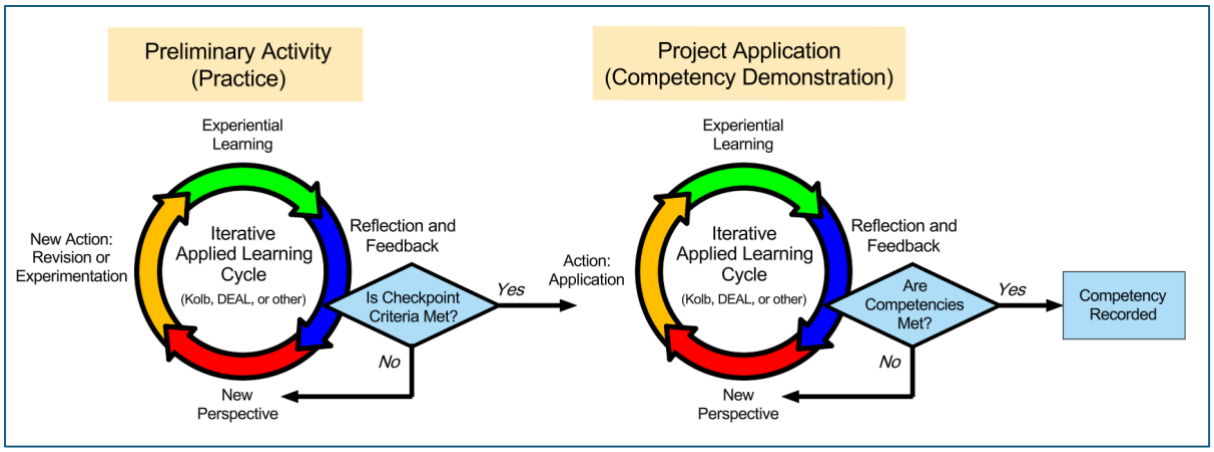


Figure 1. Competency-based learning workflow with checkpoint feedback. The iterative learning cycles suggest application using Kolb (1984) or the DEAL reflective learning cycle by Ash & Clayton (2009), but other cycles may be applied.

Limitations and Opportunities

The purpose of this study was not to measure an intervention but to analyze challenges in asynchronous or HyFlex learning and to draw on existing SRL and CBE scholarship to suggest opportunities for improvement. A next step is to test these refinements.

Conclusions

An analysis of these problem-based courses finds that, despite adequate asynchronous instructional activities and resources, uneven student engagement leads to gaps in competency achievement. Effective self-regulated learning depends upon timely feedback for planning, monitoring, and reflection; however, temporal and logistical mismatches between learner point-of-need and instructor availability often hinder such feedback. Drawing on principles from competency-based education and self-regulated learning, this study proposes a course design framework intended to better align formative feedback with learner needs while making sustainable use of instructor time. Competency-based structures such as gateways, checkpoints, mastery demonstrations, and targeted intervention points provide promising mechanisms for organizing formative feedback, supporting reflective learning, and making more sustainable use of limited instructor feedback capacity in asynchronous project-based learning environments.

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Beyond AI Literacy: Developing Responsible AI Competence in Pre-service Teachers

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Abstract

Artificial intelligence (AI) now shapes lesson design, assessment, learner support and educational decision-making. Teacher education has responded by emphasising AI literacy, yet the ability to operate AI tools is not enough to navigate the pedagogical, ethical and social implications of AI-enabled teaching. This conceptual paper argues for a shift from AI literacy to Responsible AI Competence (RAIC) in pre-service teacher education. Synthesising literature on AI literacy, responsible AI, digital competence, educational ethics and inclusive pedagogy, it proposes a framework of six interconnected domains: AI knowledge and critical understanding; pedagogical integration of AI; ethical reasoning and professional responsibility; inclusive and equitable AI practices; data privacy and algorithmic awareness; and reflective professional agency and lifelong learning. Together, these domains require future teachers not only to use AI effectively but also to evaluate its outputs critically, mitigate bias, safeguard learner data, promote inclusion and exercise informed professional judgement. The paper outlines implications for curricula, competency standards and professional learning, together with an agenda for empirical validation, and positions responsible AI competence as a core professional capability for trustworthy, human-centred education.

Keywords: Responsible AI competence, pre-service teachers, artificial intelligence, teacher education, AI literacy, educational ethics, inclusive education.

Introduction

Artificial intelligence (AI) has moved from the margins of educational technology to the centre of instructional practice. Generative tools help teachers draft lesson plans, design assessments, differentiate materials and give feedback, while adaptive platforms and analytics dashboards increasingly inform decisions about pacing, grouping and intervention. AI has become an infrastructural layer that mediates how teachers plan, teach, assess and reflect, in well-resourced urban schools and small rural classrooms alike.

Teacher education has responded by prioritising AI literacy. Following Long and Magerko (2020), AI literacy is the set of competencies that enable people to evaluate AI critically, collaborate with it and use it as a tool; Ng et al. (2021) distil it into four dimensions: knowing and understanding AI, using and applying AI, evaluating and creating AI, and AI ethics. These conceptions inform policy frameworks such as DigCompEdu (Redecker, 2017) and UNESCO's AI competency frameworks (Miao & Cukurova, 2024; Miao et al., 2024), and have given teachers a working vocabulary and baseline fluency. Yet AI literacy remains oriented mainly towards the operational: knowing what AI is, how it works and how to use it.

Operational fluency does not settle the harder questions teachers now face. Should an AI-generated rubric be trusted without verification? Does a tutoring recommendation disadvantage learners from a particular linguistic or socio-economic background? How do third-party vendors use learner data? When should professional judgement override an AI suggestion? These are questions of ethics, accountability, inclusion and judgement rather than technique. Jobin et al. (2019), analysing 84 AI ethics guidelines, found global convergence on principles such as transparency, fairness, non-maleficence, responsibility and privacy, alongside substantial divergence in how they are interpreted and applied, a divergence that classroom teachers are left to navigate largely unaided.

Existing scholarship has theorised AI literacy, educator readiness and digital competence, and UNESCO's framework embeds ethics and a human-centred mindset (Miao & Cukurova, 2024). Few studies, however, synthesise AI literacy, responsible AI, professional ethics and inclusive pedagogy into a single conceptualisation designed for pre-service teacher education. What is missing is not another inventory of technical skills but an architecture that treats ethical reasoning, inclusive practice, data stewardship and reflective agency as equal partners to technical knowledge. This conceptual paper therefore (a) argues that AI literacy is necessary but insufficient for teacher preparedness; (b) identifies the dimensions a broader construct must include; (c) proposes a six-domain Responsible AI Competence (RAIC) framework; and (d) discusses its implications for curricula, standards and policy.

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Conceptual Foundations

AI literacy and digital competence

Long and Magerko (2020) synthesised the literature into five themes (what AI is, what it can do, how it works, how it should be used and how people perceive it) spanning seventeen competencies; Ng et al. (2021) offered the more compact four-dimensional model above. Both make AI comprehensible to non-specialists, including teachers without computer science training. Their shared limitation is that ethics, or how AI *should* be used, is one strand among several rather than the principle organising professional practice. Digital competence frameworks such as DigCompEdu (Redecker, 2017) locate technical proficiency within instructional design, assessment and learner empowerment, and treat teacher agency as the capacity to make values-based decisions about when, why and how to use a technology.

Responsible and human-centred AI

Responsible AI originates largely outside education. Jobin et al. (2019) found convergence on transparency, justice and fairness, non-maleficence, responsibility and privacy, and the OECD (2019/2024) AI Principles commit adherents to AI that respects human rights, fairness, transparency, robustness and accountability across its lifecycle. The European Commission's High-Level Expert Group (2019) framed 'Trustworthy AI' around respect for human autonomy, prevention of harm, fairness and explicability, and Floridi and Cowls (2019) unified such principles as beneficence, non-maleficence, autonomy, justice and explicability. Read together, these are not a single technical safeguard but interdependent commitments enacted by every actor in an AI system's lifecycle, including the teachers who deploy AI with living, developing learners. A human-centred conception draws on care ethics, social justice pedagogy and learner autonomy: teachers must ask whether a recommendation might disadvantage a learner because of language, disability, gender or socio-economic circumstance, and retain the obligation to exercise oversight and override it. Human-centred AI is therefore less a property of software than a professional disposition.

Inclusive pedagogy

Universal Design for Learning (UDL; CAST, 2018) organises inclusive design around engagement, representation, and action and expression, aiming to remove barriers in advance rather than retrofit accommodations. In AI-enabled classrooms this raises questions of algorithmic bias, accessibility and equitable access to assistive technologies: systems trained on non-representative data may disadvantage linguistic minorities, learners with disabilities and those in under-resourced settings. Inclusive AI practice is thus a core professional capability, not a concern confined to special-education specialists.

Synthesis

These strands form a layered progression. AI literacy supplies operational knowledge; digital competence situates it in professional practice; teacher professional competence embeds it in contextual judgement and agency; and educational ethics and inclusive pedagogy supply the normative commitments (fairness, transparency, accountability and equity) that govern how judgement is exercised. Responsible AI Competence emerges where they converge: the capability to move from operating AI tools to exercising informed, ethical and inclusive judgement about when, whether and how they should shape teaching and learning. Responsible AI use must therefore be treated as a constitutive element of professional competence, on a par with content and pedagogical knowledge, because AI-mediated decisions now intersect with learners' opportunities, wellbeing and rights.

Why AI Literacy Alone Is Insufficient

Operational skill versus professional judgement

Literacy frameworks, including Ng et al. (2021), acknowledge an ethical dimension but emphasise functional proficiency: operating, prompting, interpreting and troubleshooting AI. Teaching, however, is a normative practice in which every decision, such as using an AI-generated lesson plan, an automated grade or a personalised pathway, affects learners' opportunities, dignity and development. Professional judgement cannot be reduced to a checklist; it requires weighing competing goods, anticipating downstream effects and remaining accountable under imperfect information. A teacher who is technically literate but lacks such judgement may defer uncritically to algorithmic suggestions, mistaking tool fluency for pedagogical reasoning. The difference is one of kind: literacy asks whether the teacher can operate the tool; responsible competence asks whether, and on what terms, it should be used here.

Ethical challenges of generative AI

Large language models produce hallucinations, that is, plausible but fabricated content that can mislead teachers and learners (Cotton et al., 2023). Deepfakes threaten the authenticity of educational media, generative tools can reproduce societal biases embedded in training data, and copyright questions are opaque to end users. Cotton et al. (2023) show that the ease of generating essays and solutions unsettles assumptions about authorship, requiring new assessment practices rather than prohibition or neglect. None of these challenges can be resolved by operational literacy alone; each demands ethical reasoning of the kind articulated by Floridi and Cowls (2019).

Privacy and data governance

AI-enabled tools depend on continuous collection of learner data. Consent is rarely straightforward where learners are minors and power asymmetries between institutions, vendors and families are pronounced, and learning analytics can generate behavioural and cognitive profiles that enable surveillance beyond the original pedagogical purpose. Teachers are often the first line of accountability, yet AI literacy curricula seldom equip them to interrogate data governance, question default privacy settings or advocate for learners. Responsible competence requires evaluating a tool's data practices against proportionality, transparency and learner welfare.

Equity and inclusion

AI systems are not neutral arbiters of merit; they encode the assumptions and blind spots of the data and design choices behind them. Tools optimised for majority populations may disadvantage learners who speak non-dominant languages, have disabilities or attend under-resourced schools, and unequal access to devices and connectivity can widen rather than narrow achievement gaps. Addressing this requires working knowledge of inclusive design, such as UDL (CAST, 2018), and the disposition to interrogate a tool's fairness before adopting it.

Human agency

Teachers remain decision-makers, not mere operators of AI. Priestley et al. (2015) conceptualise teacher agency as an ecological achievement shaped by individual capacities, professional and cultural resources and the structural conditions of work. Responsible AI use is therefore not only individual competence but also a matter of how teachers are supported and positioned to exercise judgement within systems that increasingly mediate their work. Where literacy frameworks risk treating teachers as end users to be trained, a responsible competence perspective insists that teachers retain interpretive authority, can override, adapt or reject AI suggestions, and are protected by institutional structures that do not erode this agency.

The Responsible AI Competence (RAIC) Framework

Approach

The framework emerged from conceptual synthesis rather than empirical derivation. Literature from five bodies of scholarship was analysed: AI literacy (Ng et al., 2021), responsible AI (Floridi & Cowls, 2019), international teacher competency frameworks (Miao & Cukurova, 2024; Redecker, 2017), educational ethics and inclusive education (CAST, 2018). The analysis had three moves. Recurring constructs (critical evaluation, bias awareness, data protection, inclusive design, reflective practice) were grouped by conceptual proximity; purely technical constructs were distinguished from professional, ethical and relational ones; and the groupings were organised into six domains broad enough for diverse contexts yet specific enough to guide curriculum design and assessment. Figure 1 presents the framework and Table 1 summarises the domains with illustrative learning outcomes.

The six domains

Domain 1, AI knowledge and critical understanding, concerns what AI is, how it works and where it fails: enough to explain why systems hallucinate, why outputs vary with prompts and why confident answers are not necessarily accurate (Cotton et al., 2023), together with the habit of treating output as a provisional draft to be verified.

Domain 2, pedagogical integration of AI, concerns purposeful use of AI in planning, assessment, differentiation and feedback, aligned with learning outcomes rather than tool availability, and alert to where AI narrows pedagogical possibilities or displaces productive struggle and creativity.

Domain 3, ethical reasoning and professional responsibility, draws on Floridi and Cowls (2019) to identify bias, uphold fairness, be transparent with learners and parents, safeguard academic honesty and accept accountability, positioning teachers as ethical gatekeepers rather than passive conduits of technology.

Domain 4, inclusive and equitable AI practices, applies UDL (CAST, 2018), assistive AI and sensitivity to linguistic and cultural diversity, with a proactive orientation to mitigating inequities, including those linked to the digital divide.

Domain 5, data privacy and algorithmic awareness, covers how learner data are collected, stored and used, the capacity to question defaults and seek meaningful consent, and the disposition to seek explicability before accepting algorithmic outputs as a basis for decisions about learners.

Domain 6, reflective professional agency and lifelong learning, extends Priestley et al.'s (2015) ecological agency to a fast-changing context. Because tools and risks evolve, responsible competence must be sustained through ongoing reflection, professional dialogue and a secure professional identity, so that teachers lead rather than follow AI-driven change.

Interaction among the domains

The domains are interconnected rather than hierarchical or sequential. Critical understanding (Domain 1) informs ethical reasoning (Domain 3) by helping teachers recognise unreliable output; ethical reasoning shapes pedagogical integration (Domain 2), keeping instructional uses accountable and fair; inclusion (Domain 4) and data governance (Domain 5) act as cross-cutting safeguards on integration; and reflective agency (Domain 6) is the integrative domain through which teachers recalibrate the other five as tools, evidence and contexts change.



Figure 1. The Responsible AI Competence (RAIC) framework: six interconnected, non-hierarchical domains.

Table 1. Domains of the RAIC framework with illustrative learning outcomes for pre-service teachers.

Domain	Core focus	Illustrative learning outcome
1. AI Knowledge and Critical Understanding	How AI works and fails; verifying outputs	Identifies and explains unreliable or fabricated output in sample AI-generated materials
2. Pedagogical Integration of AI	Purposeful use of AI in planning, assessment and feedback	Justifies when and how to use AI in a lesson against stated learning objectives
3. Ethical Reasoning and Professional Responsibility	Applying ethical principles to AI-supported decisions	Analyses an AI-related dilemma and justifies a course of action using recognised principles
4. Inclusive and Equitable AI Practices	UDL, assistive AI, bias and the digital divide	Evaluates whether a tool disadvantages learners by language, culture or disability
5. Data Privacy and Algorithmic Awareness	Learner data, consent and explicability	Identifies privacy risks in an AI tool and proposes safeguards
6. Reflective Professional Agency and Lifelong Learning	Ongoing reflection, agency and professional identity	Reflects on and adapts own AI practice as tools and evidence change

Implications

Teacher education curricula

Curricula built on AI literacy alone will leave graduates under-prepared for the ethical and relational demands of AI-enabled classrooms. The framework supports embedding the six domains across subject-specific pedagogy courses, practicum and reflective seminars rather than confining them to a single technology module, mirroring its claim that the domains are interdependent. Examples include case-based ethical reasoning in professional studies, UDL and assistive AI in inclusive education courses, and structured reflection on AI use throughout practicum and early induction (Table 1).

Standards, policy and international alignment

National teacher education standards have only begun to incorporate AI, often mirroring the operational orientation of AI literacy. RAIC offers councils and accreditation bodies a template for writing responsible AI competence, rather than tool proficiency, into the criteria by which programmes and pre-service teachers are evaluated. It resonates with UNESCO's AI Competency Framework for Teachers (Miao & Cukurova, 2024), which organises competence around human-centred values, ethics, technical foundations, pedagogy and professional learning; with the OECD (2019/2024) emphasis on fairness and accountability; and with DigCompEdu (Redecker, 2017), which embeds digital competence within professional competence. To our reading, each of these addresses elements of responsible AI use, but none spans all six domains specifically for pre-service teacher preparation. RAIC extends this trajectory by foregrounding responsibility as the organising construct.

Stakeholders

Teacher educators can model ethical and inclusive AI practice explicitly in methods courses, supervision and assessment, and curriculum developers can use the domains to audit where AI content is narrowly technical and where ethical, inclusive and data-related content is missing. Policy makers are encouraged to move beyond exhortations to adopt AI literacy towards requirements on bias, privacy, inclusion and accountability. Institutions should align their own AI-use policies, data governance and vendor partnerships with the practices expected of pre-service teachers, professional development providers should move beyond tool workshops to sustained reflective learning, and accreditation agencies can shift from checklists of tool competence towards evidence of ethical, inclusive and reflective AI practice. Throughout, AI should be positioned as a partner whose suggestions require ongoing scrutiny rather than as an efficiency tool, so that future teachers can model responsible use for their own learners.

Future Research

As a conceptual contribution, RAIC requires empirical testing. Priorities include developing and psychometrically validating a Responsible AI Competence Scale to test whether the six domains are empirically distinguishable, load onto a coherent higher-order construct and relate to existing measures of AI literacy and digital competence; mixed-methods studies combining surveys, classroom observation and interviews to show how competence is enacted beyond self-report; cross-country validation across contexts with differing AI infrastructure and regulatory maturity; longitudinal studies following pre-service teachers into early careers to examine whether competence is sustained or eroded by systemic constraints; and intervention studies testing strategies such as ethical reasoning modules or inclusive design activities.

Conclusions

This paper has argued that AI literacy, though a necessary foundation, does not suffice to prepare pre-service teachers for AI-enabled education. Operational skill is not professional judgement; generative AI raises distinctive ethical challenges; learner data demand active governance; algorithmic systems carry equity risks; and teachers must remain agents rather than operators. The RAIC framework integrates these arguments into six interconnected domains and reframes the central question for teacher education: not only how to make pre-service teachers proficient users of AI, but how to cultivate professionals capable of ethical, inclusive and reflective judgement in AI-mediated environments. Preparing teachers for an AI-enabled future is ultimately about empowering them to exercise informed professional judgement, uphold ethical and inclusive values, and lead human-centred learning in partnership with AI.

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Human-Centred AI Competencies for Future Teachers: Preparing Educators for Responsible and Resilient Digital Futures

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Abstract

Artificial intelligence (AI) is reshaping teaching, learning, assessment and educational decision-making. It offers new possibilities for personalisation and accessibility, but also raises concerns about ethics, algorithmic bias, data privacy, academic integrity and human agency. These developments call for teacher preparation that goes beyond AI literacy. This conceptual paper proposes a Human-Centred AI Competency Framework (HAICF) for pre-service teacher education, developed through an integrative review of scholarship on AI literacy, digital competence, responsible AI, inclusive pedagogy and teacher professional identity. The framework comprises six interrelated domains: AI literacy and critical understanding; pedagogical integration of AI; ethical and responsible AI practice; inclusive and equitable AI-supported teaching; data-informed professional judgement; and lifelong professional learning and adaptability. It positions AI as a collaborative partner that supports, rather than replaces, teachers' expertise, empathy, creativity and ethical responsibility. The framework offers a foundation for redesigning curricula, assessment, professional development and institutional policy for an AI-enabled educational future.

Keywords: Artificial Intelligence; Teacher Education; Human-Centred AI; AI Competencies; Responsible AI; AI Literacy; Future Teachers

Introduction

Classrooms once organised around a single relationship between teacher and learner are now being reconfigured by a third participant: the algorithm. Adaptive platforms recommend individualised pathways, generative tools draft lesson materials and provide instant feedback, and predictive analytics flag students at risk before a teacher has noticed a pattern. UNESCO has cautioned that the relationship is becoming triadic, involving teacher, AI and student (Miao & Cukurova, 2024). Generative AI has diffused into everyday teaching practice within months, outpacing the professional preparation, regulatory clarity and pedagogical consensus needed to guide its use (Bobula, 2024).

The opportunities are genuine. AI can personalise instruction at a scale no teacher could achieve unaided, generate multiple representations of content for diverse learners, and automate routine tasks, freeing time for the relational and creative dimensions of teaching (Zawacki-Richter et al., 2019). Yet the risks are neither marginal nor easily reversible. Generative tools can produce plausible but false information and raise questions of academic integrity and authorship (Bobula, 2024); predictive systems can amplify inequities along lines of gender, disability, language or ethnicity, often unnoticed by the teachers who rely on them (Baker & Hawn, 2022); data-intensive platforms raise concerns of privacy, consent and surveillance, particularly for minors (Holmes et al., 2021); and uncritical delegation of decisions to automated systems threatens the professional judgement and empathy that define good teaching (Shneiderman, 2020; Priestley et al., 2015).

These are professional and ethical problems, not merely technical ones. Existing digital competence frameworks were designed for discrete, rule-based software and are not fully adequate for generative, probabilistic systems whose outputs cannot always be anticipated (Redecker, 2017). International bodies have responded: UNESCO issued AI competency frameworks for teachers and students in 2024, grounded in human agency and accountability (Miao & Cukurova, 2024), building on its Recommendation on the Ethics of Artificial Intelligence (UNESCO, 2021), while the OECD (2023) has documented how algorithmic bias enters educational systems. Even so, a conceptual gap remains in teacher preparation. AI literacy is often treated as a technical competence, and ethics, inclusion and professional judgement as parallel strands rather than one integrated whole centred on the teacher (Ng et al., 2021; Almatrafi et al., 2024). This paper addresses that gap by (a) clarifying what existing frameworks leave unaddressed, (b) grounding an integrative framework in educational and human-computer interaction theory, and (c) offering teacher educators, curriculum designers and policy makers a coherent foundation for redesigning pre-service preparation.

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Methodology

The paper adopts a conceptual research design based on narrative synthesis and integrative literature review. Rather than testing a hypothesis against data, it draws together disparate bodies of theory and evidence to construct an internally coherent framework. Development proceeded in three stages. First, literature was selected purposively across five themes central to the problem: AI literacy, digital competence, responsible AI, inclusive AI and professional identity. Sources were mainly peer-reviewed journals in AI in education, teacher education and educational technology, supplemented by policy documents from UNESCO, the OECD and the European Commission, with emphasis on 2019 onwards and the inclusion of foundational works where conceptually indispensable. Second, each theme was compared for purpose, theoretical grounding, strengths and limitations, with attention to competencies that were underspecified when frameworks were considered individually. Third, insights were mapped onto explicit theoretical foundations and iteratively organised into six competency domains, testing each domain for coherence and distinctiveness. No empirical data are presented, and no claims are made about the framework's measured effectiveness.

Human-Centred AI and the Existing Landscape

Human-centred AI in education

Human-centred AI (HCAI) seeks high levels of both automation and human control, rejecting the assumption that greater autonomy in a system requires less human oversight (Shneiderman, 2020). Applied to education, it shifts the central question from how much of a teacher's work can be automated to how AI can strengthen the distinctly human capacities teaching requires: contextual judgement, relational trust, moral reasoning and creative responsiveness (Shneiderman, 2020; Holmes et al., 2021). Human-AI collaboration is therefore a stance toward professional practice. AI can extend a teacher's reach by drafting materials, surfacing patterns in assessment data or offering differentiated practice, while judgements about what is pedagogically appropriate, ethically sound and contextually meaningful remain with the teacher.

This differs from a technology-centred approach, which treats new tools as inherently beneficial, measures success by efficiency or adoption, and casts teachers as implementers of systems designed elsewhere. A human-centred approach treats teachers as co-designers and critical evaluators, requires transparency and explainability before adoption, and judges success by whether AI use strengthens equitable, ethical and pedagogically sound outcomes for learners (Holmes et al., 2021; Miao & Cukurova, 2024). The distinction motivates the framework below: preparing future teachers not merely to use AI tools but to interrogate, contextualise and, where necessary, resist or redirect them.

Existing frameworks and the gap

Five bodies of scholarship frame the problem (Table 1). The AI literacy literature offers developmental progressions from understanding to critical evaluation and creation (Long & Magerko, 2020; Ng et al., 2021), but a systematic review notes a persistent lack of domain-specific application and of instruments tailored to professional contexts such as teaching (Almatrafi et al., 2024). Digital competence frameworks such as DigCompEdu (Redecker, 2017) and TPACK (Mishra & Koehler, 2006) remain foundational, and TPACK's insistence that technology cannot be separated from pedagogy and content applies equally to AI, yet both predate generative systems with probabilistic outputs and opaque logic. Responsible AI work articulates ethical principles and documents concrete harms (Holmes et al., 2021; Baker & Hawn, 2022), but is typically pitched at the level of system design or policy, offering teachers less guidance on, for example, when to override an algorithmic suggestion. Inclusive design through Universal Design for Learning (UDL) (CAST, 2024) holds that AI can reduce barriers, yet this sits in tension with documented bias against learners with disabilities and minority groups, and accessibility and fairness are rarely treated as one competence. Finally, work on teacher agency, reflective practice and self-efficacy (Priestley et al., 2015; Schön, 1983; Bandura, 1997) has developed largely independently of AI-specific frameworks.

The gap is therefore one of fragmentation rather than absence: every dimension needed for responsible AI integration has been theorised somewhere, but none of the frameworks integrates technical, pedagogical, ethical, inclusive and professional-identity competencies into a single teacher-facing model. Programmes drawing on only one strand risk graduates who are AI literate but ethically underprepared, inclusive in intent but unable to evaluate an AI-generated lesson plan, or confident in judgement but lacking any framework for exercising it over algorithmic recommendations.

Table 1. Existing strands of scholarship and their limitations for teacher preparation.

Strand (key sources)	Contribution	Limitation for pre-service teacher education
AI literacy (Long & Magerko, 2020; Ng et al., 2021; Almatrafi et al., 2024)	Clear developmental progression from understanding to critical evaluation and creation	Built mainly for general or student populations; little on pedagogical decisions or professional judgement
Digital competence: DigCompEdu, TPACK (Redecker, 2017; Mishra & Koehler, 2006)	Comprehensive and widely adopted; links technology with pedagogy and content	Predate generative AI; silent on bias, opacity and hallucination
Responsible AI (Holmes et al., 2021; Miao & Cukurova, 2024; UNESCO, 2021)	Systematic ethical principles; policy authority; documented harms	Pitched at system and policy level; limited classroom-level operationalisation
Inclusive design (CAST, 2024; Baker & Hawn, 2022)	Strong UDL evidence base; evidence on algorithmic bias	Accessibility and algorithmic fairness treated as separate literatures
Professional identity and agency (Priestley et al., 2015; Schön, 1983; Bandura, 1997)	Accounts of agency, reflection and self-efficacy	Rarely engages AI-specific challenges such as automation bias

The Human-Centred AI Competency Framework (HAICF)

The HAICF is the principal contribution of this paper. It comprises six interrelated domains, each defined through knowledge, skills and dispositions, and places the teacher, rather than the technology, at its centre (Figure 1). The future teacher retains pedagogical expertise, empathy, creativity and ethical responsibility as irreducible professional qualities; the six domains surround the teacher as contiguous segments, signalling a connected whole rather than isolated modules; and an outer band of ethical foundations (human agency, transparency, fairness, accountability and privacy) bounds and conditions every domain, reflecting Holmes et al. (2021) and UNESCO (2021).



Figure 1. The Human-Centred AI Competency Framework (HAICF): conceptual model.

The framework is not derived from a single theory. Each domain draws on a complementary tradition, summarised in Table 2 together with core competencies and illustrative teacher practices. Human-centred AI (Shneiderman, 2020) provides the overarching philosophy: critical evaluation of AI, rather than passive acceptance of its outputs, is a precondition for safe classroom use. Socio-technical systems theory, which holds that a technology's effects depend as much on its organisational and pedagogical context as on its design, underpins the pedagogical domain. Responsible innovation and the ethics of care, together with UDL, ground the ethical and inclusive domains, while reflective practice and self-efficacy ground judgement and adaptability.

Table 2. HAICF domains: theoretical grounding, core competencies and illustrative practice.

Domain	Theoretical grounding	Core competencies (knowledge, skills, dispositions)	Illustrative teacher practice
D1. AI literacy and critical understanding	Human-centred AI (Shneiderman, 2020); AI literacy (Ng et al., 2021)	How generative models produce outputs and hallucinate; prompt literacy and verification against reliable sources; scepticism balanced with openness	Cross-checks an AI summary against the original source; teaches students to spot hallucinations
D2. Pedagogical integration of AI	Socio-technical systems theory; TPACK (Mishra & Koehler, 2006)	Instructional design and assessment principles; designing AI-supported differentiated pathways; treating AI as one resource among many	Edits AI-drafted reading passages before use; sets tasks that ask students to critique AI output
D3. Ethical and responsible AI practice	Responsible innovation; ethics of care (Holmes et al., 2021; UNESCO, 2021)	Privacy for minors, copyright and integrity policy; classroom AI-use policies and spotting likely sources of bias; accountability for AI-assisted decisions	Writes an age-appropriate AI-use policy; discloses AI use in materials; declines tools whose logic cannot be explained
D4. Inclusive and equitable AI-supported teaching	UDL (CAST, 2024); algorithmic bias research (Baker & Hawn, 2022)	UDL principles and known bias patterns; adapting materials to multiple means of representation, auditing tools for disparate impact; equity-mindedness	Uses text-to-speech while verifying accuracy; reviews AI grading for subgroup disparities; co-designs accommodations with learners
D5. Data-informed professional judgement	Reflective practice (Schön, 1983); teacher agency (Priestley et al., 2015)	Data literacy (correlation, sample bias, limits of prediction); triangulating AI analytics with observation; confidence to override recommendations	Checks an at-risk flag against classroom evidence before intervening; documents reasons for accepting or rejecting AI advice
D6. Lifelong professional learning and adaptability	Self-efficacy (Bandura, 1997); ecological agency (Priestley et al., 2015)	Awareness of rapid change; self-directed learning and communities of practice; resilience and openness to revising practice	Joins professional learning communities; revises personal AI-use policies; mentors colleagues

The domains are interdependent. D1 provides the critical foundation on which D2 (sound pedagogical use) and D5 (guarding against automation bias) depend; D3 constrains which pedagogical uses are acceptable and works with D4, since fairness is a component of ethics; D4 draws on D3's ethical grounding and D5's analytic judgement to detect bias in practice; D5 applies D1's critical stance to data and reinforces D3's accountability; and D6 sustains and renews all five as AI systems, policies and classrooms change. This is why no single domain, such as technical AI literacy, can be treated as sufficient on its own.

Discussion and Implications

The HAICF differs from existing models in three respects. First, DigCompEdu, TPACK and AI literacy models each address a single dimension of teacher competence, whereas the HAICF integrates six dimensions in an architecture where each is theorised as dependent on the others, directly addressing the fragmentation identified above. Second, it moves beyond the system- and policy-level orientation of much responsible AI literature by expressing ethical and inclusive principles as classroom-level teacher behaviours. This is consistent with, but extends, UNESCO's AI competency framework for teachers (Miao & Cukurova, 2024) by translating comparable values into a structure suited to pre-service curriculum design. Third, placing the teacher at the centre commits the framework to treating professional judgement and adaptive resilience as core competencies rather than afterthoughts, since AI's educational value ultimately depends on the strength and confidence of the professionals who mediate its use (Priestley et al., 2015; Bandura, 1997).

For pre-service programmes, the framework suggests embedding the six domains across existing coursework rather than isolating AI in one technology module: methods courses suit D2, practicum seminars suit D5's data-informed judgement under real classroom conditions, and D3 and D4 should be threaded through subject-specific

methods. Faculty development is an equally important lever, because teacher educators need the same competencies to model them, and limited confidence and training in AI-specific pedagogy have been reported (Bobula, 2024). For assessment, programmes might favour portfolio evidence, such as documented reasoning for accepting or rejecting an AI recommendation (D5) or a designed lesson showing inclusive AI integration (D4), over knowledge tests alone, while domain-specific micro-credentials could let practising teachers update individual competencies as tools evolve. Accreditation bodies could use the domains to complement digital competence standards such as DigCompEdu with explicit ethical, inclusive and judgement-related criteria, and institutions can align their AI-use policies with these competency expectations, adapting international guidance (OECD, 2023; Miao & Cukurova, 2024; UNESCO, 2021) to national and institutional contexts.

Limitations and Future Research

As a conceptual contribution, the HAICF is a foundation for, not a substitute for, empirical inquiry. Four directions follow. Validation studies should test whether the six domains hold together as distinct but correlated constructs among pre-service and practising teachers, supported by valid instruments, particularly for the dispositional and judgement-related competencies in D5 and D6 (see Ng et al., 2021; Almatrafi et al., 2024). Assessment research should compare portfolio, performance and self-report measures under authentic classroom conditions. Cross-country studies should examine whether the structure travels across systems with differing regulation and teacher education traditions. Finally, intervention and longitudinal studies are needed to establish whether HAICF-aligned preparation produces durable improvements in teachers' practice, professional confidence and, ultimately, student learning.

Conclusions

AI has moved from the periphery to the centre of educational practice faster than teacher preparation systems have been able to respond. Responding adequately requires more than adding AI literacy to existing curricula; it requires an integrative, theoretically grounded account of what it means to be a human-centred, AI-competent teacher. The HAICF brings together six interdependent domains in a single architecture that keeps the teacher, rather than the technology, at its centre. A teacher who is technically AI literate but ethically unprepared, or inclusive in intent but unable to exercise sound judgement over algorithmic recommendations, falls short of the standard it describes. As AI systems continue to evolve, the qualities that resist easy automation, namely empathy, contextual judgement, ethical responsibility and creative pedagogical reasoning, will only grow in importance. Preparing future teachers to lead, rather than simply adapt to, an AI-enabled future is a central obligation of contemporary teacher education.

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Beyond Programming: Ethical AI Literacy and Student Resilience in Indonesia's Deep Learning-Centric Curriculum Reform

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Abstract

Education systems must prepare students to learn, exercise judgment, and act responsibly amid technological and social uncertainty. Indonesia's Ministerial Regulation No. 13 of 2025 embeds deep learning as a curriculum approach and introduces Coding and Artificial Intelligence as a gradually implemented elective subject. This article examines how those provisions relate to responsible AI literacy and learner resilience. We conduct a qualitative document analysis of the regulation and its curriculum annexes, using UNESCO's AI Competency Framework for Students and the OECD Learning Compass 2030 as interpretive lenses; selected peer-reviewed studies provide contextual evidence. We compare policy provisions with eight analytic dimensions: meaningful learning, knowledge application, self-regulation, adaptive problem solving, agency, ethical judgment, citizenship, and inclusion. The regulation explicitly emphasizes mindful, meaningful, and joyful learning; understanding, application, and reflection; and graduate attributes that include citizenship, critical reasoning, collaboration, and independence. These provisions show conceptual compatibility with the international frameworks, while the elective status of the AI subject raises an equity and implementation question: how can all learners acquire foundational critical and ethical AI literacy? We propose a three-layer model of understanding AI, working with AI, and engaging ethically with AI across subjects. This is an interpretive proposal, not evidence that the proposed practices have been implemented or improved student outcomes. A universal cross-curricular foundation, coupled with deeper elective study, could align AI education with human agency, contextual problem solving, and collective responsibility.

Keywords: responsible AI literacy; learner resilience; deep learning; curriculum reform; student agency; Indonesia

1. Introduction

The growing presence of artificial intelligence (AI) in learning makes a narrow emphasis on coding insufficient. Students may use systems that generate plausible yet inaccurate answers, rely on opaque data practices, or reproduce unfair patterns. They therefore need to understand how AI works at an appropriate level, test its outputs against evidence, and decide when use is warranted. Reviews of educational AI identify privacy, bias, accountability, academic integrity, and unequal access as connected challenges (Ma et al., 2025; Zhu et al., 2025). AI literacy is consequently both a technical and a civic educational concern (Biagini, 2025).

Indonesia offers a timely setting for examining this concern. Ministerial Regulation No. 13 of 2025 amends the 2024 curriculum regulation, incorporates a deep learning approach in the curriculum's foundational framework, and provides for gradual introduction of the elective subject Coding and Artificial Intelligence from the 2025–2026 academic year (Ministry of Primary and Secondary Education [MoPSE], 2025, arts. 3 and 32A). In its first annex, deep learning denotes a pedagogical approach that values mindful, meaningful, and joyful learning through intellectual, ethical, aesthetic, and physical development. It should not be confused with deep learning as a machine-learning technique. The curriculum's stated learning experiences are understanding, applying, and reflecting (MoPSE, 2025, Annex I, § F).

These provisions invite a policy question. The elective subject may offer concentrated technical learning to students who take it, whereas everyday exposure to AI-generated information can occur across the curriculum. This article asks: (1) Which features of the 2025 curriculum amendment support responsible AI literacy and learner resilience? (2) Where do the policy text and global competency frameworks align or leave implementation questions? (3) What curriculum design might make responsible AI literacy available beyond the elective subject? We define learner resilience here as a proposed educational capacity to persist, revise judgments, seek support, and act responsibly when technological or social conditions change. This working definition is conceptual; it is not an outcome measured in Indonesian students.

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The contribution is a bounded reading of an actual regulatory text, followed by a practical curriculum proposal. It does not claim that schools already teach AI ethics consistently, that AI literacy causes resilience, or that conceptual alignment proves implementation. Those distinctions matter because research on teacher preparedness and curriculum enactment reports substantial practical constraints in an Indonesian primary-school case study (Sudirman & Pandang, 2025).

2. Literature and analytical framework

2.1 Responsible AI literacy and ethical judgment

UNESCO's AI Competency Framework for Students identifies four dimensions—human-centred mindset, ethics of AI, AI techniques and applications, and AI system design—at understand, apply, and create levels (UNESCO, 2024). Its structure treats learners as people who can question and shape AI, not merely use tools. The OECD Learning Compass 2030 likewise foregrounds student agency and co-agency, knowledge, skills, attitudes, values, and transformative competencies that include taking responsibility and reconciling tensions (Organisation for Economic Co-operation and Development [OECD], 2019). These are external analytic lenses, not legal requirements imposed on Indonesian schools.

Empirical and synthesis research strengthens the case for an ethics component. Ma et al. (2025), reviewing 68 publications on K–12 AI ethics education, report uneven attention to responsible AI principles and limitations in assessing ethical outcomes. Kajiwara and Kawabata (2024) find that an ethics-oriented chatbot curriculum can support understanding of large language models and their ethical use, while warning that younger participants may adopt chatbot responses too readily in decisions. A project-based secondary course studied by Kong et al. (2024) shows how AI literacy can be developed through structured activities. Taken together, these studies support teaching verification, appropriate reliance, and consequences of AI use; they do not establish that one curriculum design will work unchanged in Indonesia.

2.2 Resilience, uncertainty, and educational agency

Academic resilience research suggests a relationship worth investigating, but its scope should be kept clear. A cross-sectional study of 415 undergraduate nursing students in China found positive correlations between AI literacy and academic resilience, with self-efficacy and AI anxiety examined as mediating variables (Chen et al., 2026). Its design and population do not establish a causal effect in Indonesian schoolchildren. Zhao (2025) likewise links AI literacy and resilience with engagement and motivation in AI-based learning settings; the findings provide a rationale for inquiry rather than direct confirmation of the present model.

Educational agency also has social dimensions. In an open-schooling study across three countries, Okada et al. (2025) describe AI competence emerging as learners address community problems in social learning environments. Work on co-creative higher education suggests that uncertainty can be framed and supported through collective experimentation and dialogue (Kennedy et al., 2025). These different settings motivate a conception of resilience that includes help-seeking, deliberation, and locally useful action as well as individual persistence. Their transfer to Indonesian primary and secondary schools remains a hypothesis.

3. Method

This study uses qualitative curriculum policy analysis. The primary policy corpus is the supplied official text of Ministerial Regulation No. 13 of 2025, including its amended curriculum framework and relevant curriculum-structure provisions in the annexes. We read articles 3 and 32A, Annex I on the deep learning approach, and the provisions describing the elective subject. The UNESCO (2024) and OECD (2019) frameworks serve as comparison documents. The peer-reviewed publications cited above and below provide a contextual literature base; they are not treated as data on implementation of the 2025 regulation. We did not analyze separate Indonesian graduate-competency standards, process standards, or standalone AI subject guidelines because those documents were not in the supplied corpus.

Analysis proceeded in three steps. First, we extracted explicit policy statements about learning principles, learning experiences, graduate dimensions, and the status of Coding and Artificial Intelligence. Second, we compared those statements with eight predetermined categories derived from the research question and global frameworks: meaningful learning, application and transfer, self-regulation, adaptive problem solving, agency, ethical judgment, citizenship, and inclusion. Third, we recorded whether each category was explicit in the regulatory language, an interpretive connection, or an unresolved question. This is a transparent interpretive reading of selected texts, not a systematic literature review, a statistical content analysis, or an evaluation of schools. No interviews, observations, or claims of intercoder reliability are reported.

The analysis has three limits. Regulatory wording describes intended curriculum, not enacted classroom practice. International frameworks are normative comparators and cannot independently validate Indonesian outcomes. Finally, the corpus does not establish how many schools will offer the elective or which students will enroll. We therefore use "alignment" for conceptual correspondence and reserve "effectiveness" for future empirical testing.

4. Findings from the policy text

4.1 A holistic account of deep learning

Article 3 places the deep learning approach in the curriculum's foundational framework. Annex I describes mindful, meaningful, and joyful learning, integrated with intellectual, ethical, aesthetic, and physical development (MoPSE, 2025). Mindful learning positions students as active and self-regulating learners who understand learning goals and develop strategies. Meaningful learning requires contextual use of knowledge and engagement with real issues at personal, local, national, and global levels. Joyful learning refers to a positive, safe, motivating environment. The specified learning experiences—understand, apply, reflect—provide an especially clear route from conceptual knowledge to considered action.

The annex also identifies eight dimensions of the graduate profile: faith and devotion, citizenship, critical reasoning, creativity, collaboration, independence, health, and communication (MoPSE, 2025, Annex I, § F). Several dimensions provide plausible curricular entry points for responsible AI literacy. Critical reasoning can support checking an AI answer; citizenship can support discussion of bias and public impact; independence can support responsible decisions about when to use a tool. These examples are interpretive applications of the dimensions, rather than phrases explicitly naming AI in the deep learning section.

4.2 The elective subject and a universal learning question

Article 32A calls Coding and Artificial Intelligence an elective subject introduced gradually in basic and secondary education beginning in the 2025–2026 academic year (MoPSE, 2025). The elective arrangement creates a design question because critical evaluation of AI outputs can also matter in language, science, social studies, and civic learning. The regulation establishes the subject's status and phase-in; it does not, by itself, show unequal enrollment or prove that other subjects omit AI-related learning.

A contextual Indonesian study reports that primary teachers face capacity and professional-development challenges when implementing deep learning pedagogy (Sudirman & Pandang, 2025). A separate critical discourse analysis raises questions about how Merdeka Curriculum ambitions intersect with local conditions and inequality (Putri, 2026). Those studies do not measure implementation of the elective under this regulation. They do, however, justify examining teacher support, access, and local adaptation before expecting any universal AI literacy provision to succeed.

4.3 Comparison with international frameworks

Table 1 distinguishes text-based correspondences from proposed extensions. It avoids treating similarity of wording as evidence of equivalent competency levels or classroom outcomes.

Table 1. Policy provisions and analytical comparison

Dimension	Indonesian regulation	Interpretive comparison or gap
Self-regulation	Mindful learning; learners set goals and strategies (Annex I, § F).	Related to agency and reflection in the OECD framework; AI-specific verification is an extension.
Application and context	Meaningful learning; understand, apply, reflect; local to global issues.	Compatible with UNESCO's progressive competency design, but the two progressions are not identical.
Social responsibility	Citizenship, collaboration, critical reasoning, and communication in the graduate profile.	Supports comparison with OECD co-agency and UNESCO human-centred and ethical dimensions.
AI opportunity	Coding and Artificial Intelligence introduced gradually as an elective (art. 32A).	Depth of study is possible; universal AI-related learning across subjects remains a proposal.
Inclusion and accountability	Holistic learning and attention to the learner's context and needs.	AI-specific audit practices, access measures, and accountability indicators require local design.

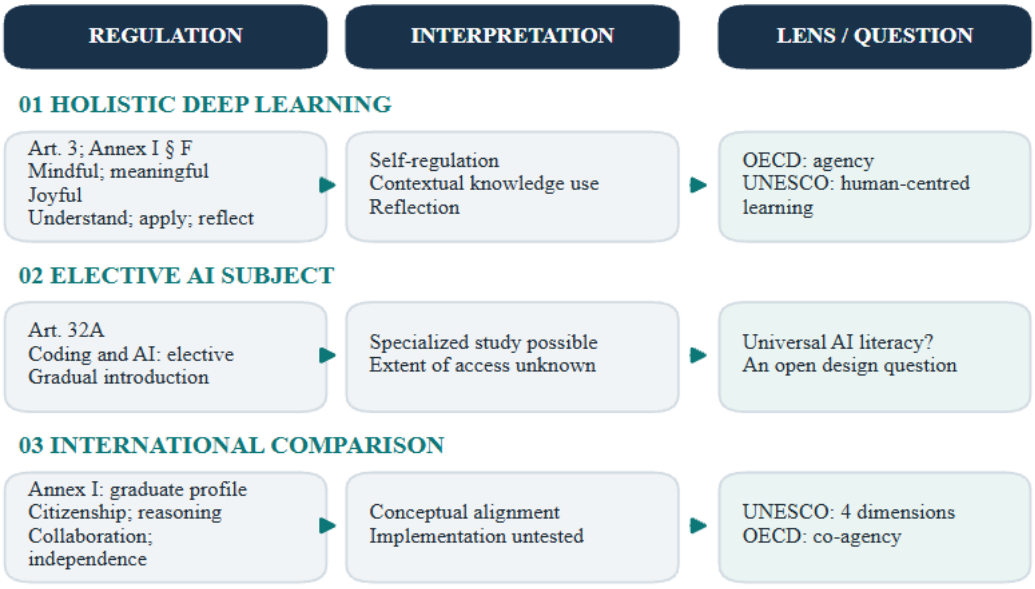


Figure 1. Policy findings and interpretive comparison

Note. Author synthesis of MoPSE (2025, arts. 3 and 32A; Annex I, § F), UNESCO (2024), and OECD (2019). The middle column is an interpretation; conceptual alignment does not establish classroom implementation.

5. Discussion

5.1 A three-layer curriculum model

The policy analysis supports a proposed three-layer design. Layer 1, understanding AI, introduces age-appropriate concepts: what kinds of tasks AI systems perform, why outputs can be mistaken, the role of data, and when a human source is preferable. Layer 2, working with AI, gives guided opportunities to formulate questions, compare an AI response with independent sources, document tool use, and revise one's own reasoning. Layer 3, engaging ethically with AI, asks learners to judge privacy, consent, bias, attribution, environmental or social trade-offs where relevant, and the effect of their choices on others. Across all three layers, teachers should make room for refusal or non-use when a system is inappropriate. The layers are a curriculum proposal synthesized from the policy text and international frameworks; they are neither named stages in the regulation nor a tested intervention. This synthesis draws on the regulatory learning sequence and the human-centred, ethical, and agency dimensions of the comparison frameworks (MoPSE, 2025; UNESCO, 2024; OECD, 2019).

The first and third layers could be taught within ordinary subjects, including where coding resources are limited. For example, a class might compare an AI-generated account of a local environmental problem with municipal information and community testimony, identify missing perspectives, and justify whether AI output belongs in a public-facing response. The activity would require source evaluation, reflection, and discussion; programming could deepen the work but is not a prerequisite. This example illustrates a possible task and is not a report of classroom practice.

Table 2 translates the model into observable tasks without claiming that one assessment can measure resilience as a whole.

Table 2. Proposed learning tasks and evidence

Layer	Example student task	Possible assessment evidence
Understanding AI	Explain why a generated answer may contain unsupported claims.	Identifies a limitation and states a checkable question.
Working with AI	Compare a response with two suitable independent sources and revise the response.	Shows source choice, corrections, and a record of AI use.
Engaging ethically with AI	Discuss a local use case involving privacy or unequal effects and justify a course of action.	Explains affected groups, a trade-off, and responsibility for the decision.

5.2 What resilience would require

The model links resilience to critical technological discernment: students should tolerate uncertainty long enough to check a claim, change a conclusion when evidence changes, and choose appropriate support. This conception extends individual persistence to collective agency. UNESCO's human-centred and ethics dimensions justify questioning AI's role in decisions (UNESCO, 2024); the OECD framework supports shared action and taking responsibility (OECD, 2019). Yet the relationship between any proposed classroom task and measurable resilience is untested here.

A responsible school-level implementation would align tasks with students' developmental stage, language, available connectivity, and teachers' preparation. Offline examples and teacher-led analysis can introduce errors, privacy, and bias before students have direct access to AI tools. More advanced elective work can then address coding and system design. Research on undergraduate curricula in Indonesia also suggests that responsible AI themes need visible learning outcomes and assessment rather than a general statement of intent, although that study concerns higher education and cannot be directly generalized to schools (Irwansyah et al., 2026).

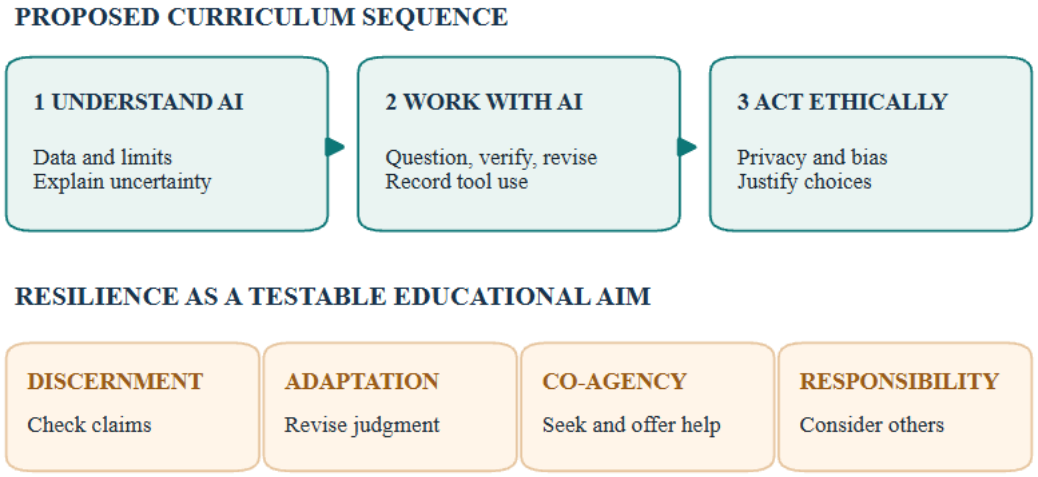


Figure 2. Three-layer curriculum model and proposed resilience capacities

Note. Author proposal informed by MoPSE (2025), UNESCO (2024), OECD (2019), Ma et al. (2025), Chen et al. (2026), and Mokgwathi (2026). These capacities are proposed outcomes, not outcomes measured by this study.

Evidence from a mixed-methods study of 341 South African distance-learning undergraduates places conditional trust, verification, self-regulation, and responsibility at the center of ethical and epistemic AI literacy (Mokgwathi, 2026). Its population differs from the Indonesian school context, but the study helps specify what future assessment might observe: whether students justify trust in outputs, retain responsibility for their work, and revise claims when verification fails.

5.3 Implications for policy and research

A practical policy next step is to specify a small set of transferable AI-related learning outcomes for all students while allowing the elective to provide greater technical depth. Outcomes could include checking evidence, explaining uncertainty, protecting personal data, documenting assistance, and considering who might be harmed by an output. Teachers would need exemplar tasks and assessment rubrics, time to adapt materials to local settings, and guidance on appropriate use of student data. None of these proposed steps should be presented as already required in the regulatory clauses examined.

Future studies could compare curriculum plans, teacher practices, and student work across schools with and without the elective. They should sample differing infrastructure contexts, attend to student voice, and assess whether learners can recognize unsupported outputs and explain ethical trade-offs in authentic tasks. Pre/post designs or longitudinal observation would offer stronger evidence of change than policy-language comparison alone. Researchers should examine the possibility that access to devices, language resources, and teacher training moderates both participation and outcomes.

6. Conclusion

Indonesia's 2025 curriculum amendment embeds a deep learning approach that emphasizes self-regulation, contextual application, reflection, and social dimensions of learning, while gradually introducing Coding and Artificial Intelligence as an elective subject. These features are conceptually compatible with UNESCO's student AI competencies and the OECD's account of agency and responsibility. The main unresolved curriculum issue is how to give every student a foundation for responsible AI engagement while maintaining space for specialized elective study. The proposed sequence—understanding AI, working with AI, and engaging ethically with AI—offers a design hypothesis for doing so. Its feasibility, equity, and effect on learner resilience require classroom evidence.

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From Prohibition to Traceability: New Forms of Assessment in the Face of Generative Artificial Intelligence Use at the University

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Abstract

The irruption of generative artificial intelligence (GenAI) in higher education has strained traditional assessment models centered on the written product. This article, derived from a doctoral thesis on the pedagogical appropriation of digital technologies, analyzes how university teachers reconfigure their assessment practices in response to students' use of GenAI. A qualitative study was conducted, grounded in the interpretive paradigm and in van Manen's hermeneutic-phenomenological method, based on in-depth interviews with 29 professors from the Mathematics Education program at Universidad Francisco de Paula Santander (Colombia). The results reveal pedagogical, research-oriented, verification, and teaching-efficiency uses of GenAI; ethical dilemmas related to authorship, superficial learning, and knowledge validation; and an assessment shift moving from prohibition and detection toward oral defense and traceability of the learning process. The study concludes that assessment in the age of GenAI demands new forms of evidence, prompt logs, drafts, oral defenses, and critical analysis of generated outputs, articulated with a formative rather than punitive institutional governance that subordinates technology to teachers' pedagogical judgment.

Keywords: generative artificial intelligence, learning assessment, higher education, traceability, technological appropriation.

Introduction

Generative artificial intelligence has become interwoven with teachers' processes of technological appropriation, as it presents information, communicates content, graphs, calculates, and manages academic activities. Its presence in university teaching forces a reconsideration of authorship, assessment, critical thinking, pedagogical mediation, and institutional forms of regulation, given the risks associated with plagiarism, dependence, cognitive superficiality, and the erosion of students' own reasoning. When any student can obtain, within seconds, a coherent, well-written, and apparently academic text, the central question is no longer whether the submitted information is correct, but whether the person submitting it understands it, validates it, and can defend it critically.

The first institutional responses to GenAI were organized around prohibition and automated detection. However, both strategies prove insufficient because these tools are already part of everyday practices of studying, writing, and producing information (Chan, 2023). Instead, international bodies have proposed frameworks oriented toward human oversight, transparency, and accountability for learning: UNESCO argues that teachers must know how to select, validate, and integrate AI tools within pedagogical strategies rather than use them automatically (Miao & Holmes, 2023); the Spanish Data Protection Agency (AEPD, 2021) requires governance, traceability, and control by design; and the International Committee of Medical Journal Editors (ICMJE, 2026) establishes that AI cannot be listed as an author and that human beings remain responsible for the accuracy and integrity of what they present.

Published research situates this problem at the intersection of assessment design and academic integrity. In a rapid review of 19 articles, Karadağ (2023) identified opportunities for assistance, grading, feedback, assessment improvement and time savings, alongside concerns about integrity, reliability and adaptability. More recently, Aydemir (2026) proposed a conceptual framework organized around processuality, dialogicity, situatedness and reflexivity. Together, these contributions support examining the evidence teachers use to judge learning when a polished final product may have been generated with AI.

This article is derived from a doctoral thesis on the pedagogical appropriation of digital technologies by university teachers, understood not as access to devices but as the process through which subjects incorporate, resignify, and endow technologies with pedagogical meaning in contexts marked by structural inequalities (Reygadas, 2008; Benítez & Guzzo, 2022). Within this framework, the aim of this study is to analyze how teachers in the Mathematics Education program at Universidad Francisco de Paula Santander (UFPS), a public institution located on the Colombian–Venezuelan border, reconfigure their assessment practices in response to students' use of GenAI, and which strategies emerge to shift the logic of prohibition toward assessment based on oral defense and traceability of the learning process.

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The study offers a situated interpretation of teacher educators' accounts, focusing on the meanings and pedagogical decisions associated with assessment. It does not experimentally test the effectiveness of oral defense or process documentation. Traceability is therefore presented as an interpretive and pedagogical proposition whose effects on learning require further empirical evaluation.

Methodology

The research was framed within the qualitative approach, grounded in the interpretive-constructivist paradigm, which seeks to inquire into the meanings people attribute to a social phenomenon while considering their historical and cultural contexts (Creswell, 2013). The study adopted van Manen's (2003) hermeneutic-phenomenological method, which understands the lifeworld as it is experienced pre-reflectively, developed in five moments: turning to the phenomenon and clarifying assumptions; gathering lived experience; thematic reflection through holistic, selective, and detailed readings (Ayala, 2008); interpretation through phenomenological existentials; and phenomenological writing and rewriting.

The research setting was the Mathematics Education program at UFPS, in Cúcuta (Norte de Santander, Colombia), where future mathematics teachers are trained in a border region marked by human mobility and digital inequalities. The informants were 29 university teachers, identified with alphanumeric codes ED01 to ED29 to protect their identity, selected according to criteria of program membership, diversity of professional trajectories, and willingness to narrate their experience. Data were collected through in-depth interviews in which participants were asked to recount concrete scenes from their practice: what happened, what they felt, what decisions they made, and what meaning the experience held for them. Thematic analysis organized the interpretation into hermeneutic-phenomenological cores, among them the pedagogical appropriation of artificial intelligence, from which the results presented here are drawn. Informed consent, confidentiality, and interpretive member-checking of the findings were guaranteed.

Results

Pedagogical and research uses of generative AI

The interviewed teachers define GenAI as a tool that answers, writes, suggests, organizes, corrects, plans, compares, explains, or solves. Their appropriation does not begin with expert knowledge of machine learning models, but with the usefulness they recognize within their pedagogical, research, and assessment practices. In pedagogical use, teachers employ GenAI to plan classes, design questions, generate workshops, prepare slides, correct writing, and support initial feedback. Teacher ED04, for instance, guided her students to first write their own essay and then use the tool only to correct wording, without changing the argument. In mathematics, validation is emphasized: teacher ED19 insists that one must first carry out the procedure manually in order to know whether what the AI shows is right or wrong, so that the tool operates as a point of contrast rather than a substitute for reasoning.

In research use, teacher ED27 employs GenAI so that students explore topics, titles, objectives, and methodological routes, comparing responses across different platforms and articulating this work with searches in academic databases, so that they grasp the variability of outputs and learn to contrast sources. A verification use also emerges, comparing responses, analyzing information quality, and reviewing errors, together with a teaching-efficiency use, since a task that could take four hours can be significantly reduced with AI support (ED29), freeing time for student support and feedback. Table 1 summarizes these findings.

Table 1. Uses of generative AI identified in the teachers' accounts.

Type of use	Informants	Identified practices
Pedagogical use	ED01–ED04, ED10, ED11, ED14, ED19, ED21, ED22, ED24, ED26, ED28, ED29	Lesson planning, question design, workshops, slides, writing correction, formative assessment, and guidance for responsible use.
Research use	ED06, ED08, ED09, ED15, ED18, ED25, ED27	Exploration of topics, titles, objectives, and methodological proposals; cross-platform comparison; statistical support and preliminary review of information.
Verification use	ED06, ED10, ED19, ED23, ED27	Comparison of responses, analysis of information quality, error review, and contrast with academic sources.
Teaching-efficiency use	ED01, ED11, ED22, ED24, ED29	Time savings in planning, generation of materials, and preparation of visual resources.

Source: authors' elaboration based on the in-depth interviews.

Ethical dilemmas: authorship, superficiality, and knowledge validation

The dilemmas produced by GenAI cluster around three cores. The first is authorship: teachers become concerned when the student simply copies what the artificial intelligence produces, pastes it, and submits it (ED10), or presents AI-generated work as their own without proper references (ED06). An academic text cannot be considered fully authorial if the person presenting it neither understands the content nor can defend the argument; authorship ceases to be a matter of ownership of the text and becomes tied to intellectual responsibility for what is claimed and submitted as evidence of learning.

The second dilemma concerns superficial learning and cognitive dependence. When students receive a quick, coherent, and apparently well-crafted answer without engaging in a real process of reading, analysis, and argumentation, the processes of searching, selecting, interpreting, and writing are impoverished; even teachers themselves may cease to be critical if the use becomes routine (ED11). The third dilemma is knowledge validation: these tools can produce coherent outputs that are not necessarily true, with serious errors in references, authors, and content (ED06), and the central risk lies in believing what the artificial intelligence says (ED23) without contrasting it against sources. The ethical question thus becomes epistemological: what counts as valid knowledge, how it is verified, and who assumes responsibility for what is submitted.

From prohibition to oral defense and traceability

GenAI compels a rethinking of university assessment. As ED09 puts it, it is no longer just about assessing information, but the analysis and interpretation the student makes of it. Prohibiting AI or attempting to detect it is insufficient because these tools are already part of study and writing practices; the challenge is to redesign assessment so that students must demonstrate understanding, explain their process, justify their decisions, and critically defend the product they submit. Some teachers respond through oral defenses: ED21 maintains that assignments must be argued and defended, and ED23 allows the use of AI assistants but gives the oral defense decisive weight in grading. The oral defense operates as a pedagogical and ethical strategy: it verifies whether students attain the intended competencies, whether they can explain how they arrived at their answers, and whether they retain responsibility for the work.

From this emerges traceability as a central strategy: making visible the process through which students construct their answers. This entails declaring AI use, preserving evidence of the process, showing drafts or versions, explaining the prompts employed, verifying sources, and orally defending the product. Tasks centered exclusively on final written products become vulnerable, whereas those demanding process, dialogue, contextualization, application, and defense prove more pertinent. Assessment in the face of GenAI therefore requires new forms of evidence: prompt logs, comparison of responses across platforms, error analysis of generated outputs, and written reflection on the process. This does not preclude differentiated decisions: ED25 proposes restricting the use of tools in certain assessments, except when their use is practical and justified, indicating that there is no single pedagogical answer but rather a repertoire of decisions according to the assessment purpose.

Teacher profiles and institutional governance

The accounts reveal three teacher profiles regarding GenAI: a cautious use, centered on the risks of plagiarism, loss of authorship, and dependence; a practical use, which values time savings in producing materials on condition of reviewing and contextualizing what is generated; and an integrated use, in which teachers not only use AI but teach students to interrogate, verify, and contrast it. This heterogeneity calls for institutional governance that is not conflated with prohibition: regulating AI means creating conditions for responsible exploration, defining which uses are formative, which require explicit declaration, how AI use should be cited, and which criteria should be incorporated into assessment (Chan, 2023; AEPD, 2021). Informants call for updating the regulations and the rules on learning assessment and for regulating the use of artificial intelligences (ED29), within an ecosystem where AI holds a place articulated with platforms, curricula, and academic integrity policies (ED08). Responsible governance should integrate four dimensions: teacher and student training, guidelines for academic use, assessment criteria including oral defense and traceability, and technical, pedagogical, and ethical support mechanisms.

Discussion

The assessment strategies described by participants can be interpreted through Aydemir's (2026) principles of processuality, dialogicity, situatedness and reflexivity. Drafts and documented decisions make the development of work visible; oral defense opens that work to questioning; contextualized tasks connect responses to specific educational situations; and critical review invites students to explain revisions and uncertainties. This correspondence is conceptual. The interviews do not establish that these strategies improve achievement or reliably

distinguish independent understanding from AI-supported performance. Instead, they describe how teachers understand the evidence needed to support judgments about learning.

The distinction between useful assistance and demonstrated learning is particularly important in mathematics teacher education. Bodur and Kobak Demir (2025) studied ChatGPT-supported lesson planning with 17 prospective mathematics teachers using a one-group pretest–posttest design. Changes in measured teaching-related competencies, anxiety and self-efficacy were not statistically significant. These findings establish neither effectiveness nor an absence of benefit, given the small sample and lack of a comparison group. They also encourage caution when interpreting the convenience reported in the present interviews as evidence of improved professional competence. Support with planning and time savings must be distinguished from students' ability to justify mathematical and pedagogical decisions.

Research on AI-supported argumentation offers a related perspective. In a two-cycle design study with nine prospective science teachers, Yıldız Feyzioğlu and Aymak (2026) found improvements in argument quality, including refutations and arguments with multiple components, although participants perceived feedback personalization as limited. These findings suggest a possible role for AI in supporting argument development rather than simply supplying finished answers. However, the different disciplinary context and small purposive sample limit their transfer to mathematics teacher education. In the present study, oral defense can therefore be understood as an opportunity to examine reasons, consider objections and discuss revisions. Its effectiveness remains a question for future research.

Related qualitative research also draws attention to institutional conditions. Tümen Akyıldız (2025) interviewed ten teachers of English as a foreign language in private secondary schools in Türkiye about privacy, academic integrity, excessive dependence, inadequate policies and insufficient professional development. Although this setting differs from a Colombian public university, the shared concerns suggest that individual willingness to use AI is not enough to address the institutional conditions surrounding its use. Kılınç's (2024) Comprehensive AI Assessment Framework offers guidance for aligning ethical expectations and AI use with educational levels and assessment purposes. It should, however, be treated as a proposed framework rather than evidence that a particular policy improves learning.

For the context examined here, these comparisons suggest an approach to governance based on the requirements of each task: clarify what assistance is allowed, ask students to explain substantial AI contributions, and examine their reasons for accepting, revising or rejecting generated material. A prompt log alone cannot establish understanding; its educational value lies in explaining and examining the decisions it records. The proposed approach combines process evidence with dialogue and contextualized performance. Because this study relies on teachers' accounts, future research should examine student work and observed assessment interactions to determine whether these practices provide credible and equitable evidence of learning.

Conclusions

The research evidences an ongoing shift in university assessment culture: from prohibition and detection toward oral defense and traceability. When information can be generated by a tool, academic value moves to the process: reading, validating, discussing, and turning information into one's own argument. Oral defenses, brief vivas, prompt analysis, comparison across sources, and critical review of generated outputs constitute new forms of learning evidence that make it possible to assess understanding and intellectual responsibility, not only final products.

This shift is not homogeneous: it depends on teachers' appropriation profiles, cautious, practical, and integrated, and on institutional conditions that still privilege individual responses over articulated policies. AI-mediated assessment must therefore be understood as part of teachers' professional education, especially in initial teacher education programs, whose graduates will assess students who use AI on a daily basis. Teaching how to defend, verify, cite, contrast, and explain emerges as a core teaching competency, articulated with critical AI literacy, prompt engineering, and critical thinking (Miao & Holmes, 2023). The pedagogical appropriation of GenAI will ultimately depend on the capacity to turn it into a formative mediation: the dilemma lies not in the tool, but in the pedagogical judgment that organizes its use.

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Building Institutional Readiness for AI-Enabled Teacher Education: A Framework for Sustainable Digital Transformation

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Abstract

The diffusion of artificial intelligence (AI) is transforming how future teachers are prepared, yet scholarly attention has focused on individual educators' AI competencies rather than on the institutional conditions that make AI integration sustainable, ethical and effective. This conceptual paper proposes the Institutional Readiness for AI-Enabled Teacher Education (IR-AITE) framework, developed through an integrative review of AI in education, digital transformation, organisational readiness, educational leadership and responsible AI governance. The framework comprises eight interdependent domains: leadership and strategic planning; policy and governance; digital infrastructure; faculty competence and professional development; curriculum innovation; ethical, legal and data governance; research and partnerships; and quality assurance. Readiness is theorised as an emergent, systems-level property rather than an aggregate of individual competencies. The paper positions IR-AITE against existing readiness and maturity models and makes it actionable through a domain-indicator table, maturity levels and a phased roadmap. It offers a theoretically grounded basis for institutional self-assessment and future empirical validation.

Keywords: artificial intelligence, teacher education, institutional readiness, digital transformation, responsible AI, AI governance

Introduction

Artificial intelligence is no longer a peripheral innovation in higher education; it is a structural force reshaping how institutions teach, assess, govern and prepare professionals (Zawacki-Richter et al., 2019; Holmes et al., 2023). In teacher education, AI is both subject matter and infrastructure: intelligent tutoring systems, learning analytics and generative AI tools are embedded in what pre-service teachers study and in the environments where they learn to teach (Ng et al., 2021; Miao & Cukurova, 2024).

Scholarship has responded largely by examining individual teachers' AI competencies, literacy and technology acceptance (Ayanwale et al., 2022; Bond et al., 2024). This emphasis is understandable, but competence without institutional capacity produces fragmented and short-lived innovation: pockets of enthusiastic use surrounded by institutional indifference (Selwyn, 2022; Bearman et al., 2023). Even highly AI-literate faculty cannot alone establish data governance, secure infrastructure or build quality assurance for AI-enabled teaching.

This paper therefore argues that teacher competence, while necessary, is not sufficient: institutions themselves must become AI-ready. Existing readiness constructs from change management (Weiner, 2009; Kotter, 1996), technology adoption (Rogers, 2003) and digital maturity (Hanelt et al., 2021; Vial, 2019) offer partial insight but were not designed for the ethical and pedagogical demands AI places on teacher preparation. The paper (a) reviews the relevant literature and identifies the gap left by competence-centred approaches, (b) proposes the IR-AITE framework, which treats readiness as a systems-level institutional property, and (c) renders it actionable through indicators, maturity levels and an implementation roadmap.

Conceptual Foundations and Research Gap

From technology adoption to digital transformation

Digital transformation is frequently conflated with technology adoption. Adoption concerns acquiring specific tools; transformation denotes a deeper reconfiguration of strategy, culture, governance and processes (Matt et al., 2015; Vial, 2019). An institution may buy AI plagiarism detectors or chatbot tutors without altering its governance, pedagogy or decision-making culture, and such adoption does not constitute transformation. For teacher education, genuine transformation spans governance (algorithmic accountability, data stewardship; Azevedo & Mallinson, 2025), curriculum (AI literacy integrated with pedagogical content knowledge; Mishra & Koehler, 2006), assessment (Perkins, 2023; Kofinas, 2025), research, and quality assurance (EDUCAUSE, 2024). Evidence

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suggests that gains from digital transformation depend more on leadership and strategic coherence than on technology expenditure (Ramadania et al., 2024).

Existing readiness traditions and their limits

Organisational readiness for change emphasises shared commitment and efficacy (Weiner, 2009); technology readiness and diffusion theory address adoption preconditions (Rogers, 2003); digital maturity models trace progression along a continuum (Hanelt et al., 2021; Vial, 2019). Each captures a partial picture (Table 1). Change models say little about technical or ethical demands; technology and maturity models tend to treat technology as ethically neutral (Jobin et al., 2019; Floridi & Cowls, 2019); and individual competence frameworks assume institutional enabling conditions exist. None addresses the triple function of teacher education institutions: they are simultaneously users of AI, teachers about AI and, through their graduates, transmitters of AI-related professional norms to schools.

Table 1. Comparison of existing frameworks with IR-AITE

Framework	Main limitation for AI-enabled teacher education	Missing institutional components
Organisational readiness for change (Weiner, 2009)	Generic; not technology-specific	AI ethics, governance, infrastructure
Technology readiness / diffusion (Rogers, 2003)	Treats technology as ethically neutral	Pedagogical redesign, ethics
Digital maturity models (Hanelt et al., 2021; Vial, 2019)	Broad; not education-specific	Teacher education pedagogy, AI governance
DigCompEdu (Redecker, 2017)	Individual-level, not institutional	Institutional systems, governance, infrastructure
UNESCO AI Competency Framework for Teachers (Miao & Cukurova, 2024)	Assumes enabling conditions exist	Institutional readiness preconditions
IR-AITE (this paper)	Conceptual; awaits empirical validation	Integrates eight interdependent domains

Thematic evidence across institutional domains

The literature converges on several themes, each with an unresolved tension. On leadership, transformational leadership stresses a single institutional vision (Bass, 1985) while distributed leadership stresses decentralised ownership (Spillane, 2006); neither resolves the fact that accountability for algorithmic decisions typically remains centralised, which motivates separating leadership from governance. Institutional AI policies vary widely in scope and enforceability and are often reactive (Azevedo & Mallinson, 2025; UNESCO, 2021; European Commission, 2022). Infrastructure is necessary but insufficient, since it enables AI use without generating governance or pedagogical capacity (EDUCAUSE, 2024; Selwyn, 2022). Faculty readiness is the best-researched theme, yet training does not automatically yield confidence or sustained practice without institutional support (Ayanwale et al., 2022; Ertmer & Ottenbreit-Leftwich, 2010). Curriculum and assessment must be redesigned structurally rather than incrementally, and responses differ across contexts (Holmes et al., 2023; Kofinas, 2025; Yusuf et al., 2024). Ethics guidelines converge on principles but not on institutional operationalisation (Jobin et al., 2019; Nguyen et al., 2023), and learning analytics research documents persistent concern about consent and surveillance (Slade & Prinsloo, 2013; Ifenthaler & Schumacher, 2016). Research partnerships build critical capacity but risk commercially shaped agendas (Williamson & Eynon, 2020), and quality assurance evidence lags behind the pace of adoption (Bond et al., 2024).

Research gap

Zawacki-Richter et al. (2019) found that research focused disproportionately on student profiling and prediction, with little attention to educators and institutions; Bond et al. (2024) found that ethics, governance and institutional evaluation remain the least developed strands five years later. Published readiness instruments overwhelmingly target individual teachers, and we could not identify validated institutional readiness instruments specific to AI-enabled teacher education in the reviewed literature. Individual competence and institutional capacity are not substitutable, and the absence of a systems-level framework leaves institutions assembling ad hoc responses from policy documents, vendor advice and isolated development initiatives.

Methodological Approach

The paper adopts a conceptual design using an integrative literature review and narrative synthesis. Sources were selected for relevance to institution-level constructs, recency (mainly 2019–2026, alongside seminal organisational theory) and authority, including UNESCO, OECD, European Commission, World Economic Forum and EDUCAUSE sources and peer-reviewed systematic reviews, across five areas: AI in education, digital transformation, organisational readiness, educational leadership and responsible AI governance. Synthesis proceeded in four stages: thematic coding into eight themes; comparative evaluation of existing frameworks (Table 1); theoretical mapping; and integrative construction of the IR-AITE domains. No empirical validation is claimed; the framework is a basis for future testing.

The IR-AITE Framework

Definition and theoretical grounding

Institutional readiness for AI-enabled teacher education is defined as the dynamic organisational capacity of a teacher education institution to strategically, ethically, technologically and pedagogically integrate AI through coordinated leadership, governance, infrastructure, human capability, curriculum, research and continuous quality improvement, such that AI adoption strengthens rather than compromises equitable and high-quality teacher preparation. The definition frames readiness as dynamic rather than a threshold crossed once (Teece, 2007; Senge, 1990), takes the institution as the unit of analysis, and ties readiness to an equity and quality outcome in line with human-centred AI (Shneiderman, 2020; UNESCO, 2021).

Several theories jointly ground the domains. Socio-technical systems theory (Trist, 1981) implies that infrastructure, human capacity and leadership must be developed jointly, not sequentially. Dynamic capabilities theory (Teece, 2007) links strategic leadership to quality assurance, which supplies the institution's sensing function. Institutional theory (DiMaggio & Powell, 1983) explains why governance and ethics are sources of legitimacy as well as risk management, while diffusion theory (Rogers, 2003) explains why top-down mandates and peer diffusion must operate together. Learning organisation theory (Senge, 1990) positions monitoring as a feedback loop rather than a terminal audit, and human-centred AI (Shneiderman, 2020) and responsible innovation (Jobin et al., 2019) permeate the ethical domain.

The eight domains

IR-AITE comprises eight interconnected domains (Figure 1, Table 2). Leadership vision shapes governance priorities; governance enables or constrains infrastructure; infrastructure supports faculty capacity; faculty capacity enables curriculum innovation; curriculum innovation raises ethical questions that require governance responses; research and partnerships generate evidence for quality assurance; and quality assurance feeds back into leadership strategy. This circular structure distinguishes IR-AITE from linear, checklist-based models. Leadership (Domain 1) and governance (Domain 2) are kept distinct because vision requires decentralisation to take root pedagogically, whereas accountability requires centralisation to remain auditable. The framework rests on a supporting layer of organisational culture, a responsible-AI orientation and a continuous improvement ethos.



Figure 1. The IR-AITE framework: Institutional Readiness for AI-Enabled Teacher Education.

Table 2. IR-AITE domains, focus and indicative evidence of readiness

Domain	Core focus	Indicative institutional indicators
1. Leadership and strategic planning	Vision, direction	Documented AI strategy aligned with mission; designated AI leadership; multi-year resourcing
2. Policy and governance	Accountability, decision structures	Adopted AI-use policies; defined authority for AI procurement; risk procedures
3. Digital infrastructure	Technical foundation	Reliable AI-capable computing; interoperable data systems; cybersecurity; technical support
4. Faculty competence and CPD	Human capacity	Structured development pathways; learning communities; recognition of AI competence
5. Curriculum innovation	Pedagogical redesign	AI literacy embedded across courses; redesigned authentic assessment; periodic review
6. Ethical, legal and data governance	Trust and compliance	Data-protection protocols; bias audits; human oversight of AI-assisted decisions
7. Research and partnerships	Innovation ecosystem	Active AI-in-education research; governed industry partnerships; internal innovation funding
8. Quality assurance	Continuous improvement	KPIs for AI integration; periodic maturity audits; peer benchmarking; closed improvement cycles

Five cross-cutting principles characterise institutions able to sustain readiness: interdependence over isolation (strength in one domain cannot compensate for weakness in another); human agency and oversight; equity as a precondition rather than an afterthought; evidence-informed iteration, given the immature evidence base (Bond et al., 2024); and distributed ownership within centralised accountability.

Operationalising IR-AITE

Maturity levels

Following digital maturity conventions (Hanelt et al., 2021; Vial, 2019), Table 3 differentiates four maturity levels, giving institutions a diagnostic reference point rather than a binary ready/not-ready judgement. Institutions are unlikely to sit at the same level across all domains, and uneven profiles are themselves diagnostic, indicating where interdependencies are most likely to create implementation friction.

Table 3. Indicative institutional maturity levels

Level	Leadership and governance	Infrastructure and faculty capacity	Curriculum, ethics and QA
1. Initial	No AI strategy; ad hoc decisions	Unreliable infrastructure; isolated enthusiasts	No curriculum integration; no ethics review
2. Emerging	Draft policy under discussion	Basic infrastructure; occasional training	Pilot courses; informal ethical awareness
3. Established	Approved AI strategy and policy	Reliable infrastructure; structured CPD pathways	Embedded curriculum strands; formal ethics review
4. Advanced	Strategy integrated into planning; distributed leadership active	Interoperable, scalable systems; institution-wide competence	Continuous curriculum review; proactive bias auditing; benchmarked QA

Implementation roadmap

Implementation proceeds through six phases: (1) institutional diagnosis, applying the domain indicators and consulting stakeholders to produce a readiness profile; (2) strategic planning, yielding an approved AI strategy and resource plan; (3) capacity development in faculty competence and infrastructure; (4) pilot implementation of AI-enabled courses and governance trials; (5) institution-wide scaling with formalised policy; and (6) evaluation and improvement through KPI monitoring and periodic audits. Phase 6 feeds back into Phase 1, so that readiness remains a continuing learning loop (Senge, 1990).

Discussion and Implications

IR-AITE integrates dimensions that prior frameworks treated separately and extends dynamic capabilities theory into an education-specific application in which quality assurance is the principal sensing function. Its originality lies not in the novelty of individual components, each of which draws on established literatures, but in their

systemic integration and calibration to teacher education's ethical and pedagogical stakes. Unlike general digital transformation models that treat technology adoption as the starting point (Matt et al., 2015; Vial, 2019), IR-AITE treats institutional capacity as the precondition for adoption.

For institutions and leaders, the framework offers a baseline self-assessment and shows that AI transformation cannot be delegated to IT departments. For faculty, it clarifies that professional development translates into practice only within a supportive institutional system. For accreditation bodies, ministries and funders, it suggests candidate institutional indicators and a more balanced investment portfolio spanning governance and quality assurance as well as infrastructure and training. Curriculum reform in particular cannot be reduced to adding an AI module: pre-service teachers cannot be expected to model responsible AI use that their own institutions do not practise.

IR-AITE is designed to complement international guidance. UNESCO's policy guidance and teacher competency framework (UNESCO, 2021; Miao & Cukurova, 2024) and the European Commission's (2022) ethical guidelines provide principles and individual competency levels but presuppose institutional enabling conditions. The OECD's (2021) analysis operates at system level. IR-AITE supplies a meso-level, implementation-oriented layer between them.

Several challenges temper the framework's actionability. Under-resourced institutions may find simultaneous investment across eight domains unrealistic. Governance and ethics indicators are qualitative and context-dependent, complicating benchmarking. Distributed pedagogical leadership and centralised accountability may generate genuine internal conflict. Generative AI evolves faster than governance cycles, so quality assurance must be continuous rather than periodic. Finally, the immature evidence base (Bond et al., 2024) means that indicators will require revision. Future research should therefore validate the framework across contexts, develop a psychometrically sound institutional readiness scale extending individual-level instruments (Ayanwale et al., 2022), conduct case studies of the leadership–governance tension, and undertake cross-national and longitudinal studies (Yusuf et al., 2024).

Conclusions

Sustainable, ethical and effective integration of AI into teacher education depends on institutional readiness, a systems-level capacity that extends beyond individual competence. The IR-AITE framework reconceptualises readiness as a dynamic, mutually reinforcing system of eight domains, shifting responsibility for responsible AI integration from individual educators to the institutions that structure their work, without diminishing the importance of teacher competence. As institutions navigate an increasingly AI-mediated landscape, readiness rather than technology adoption alone should be the foundation of responsible, sustainable and pedagogically sound AI-enabled teacher education.

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Advanced Business Analytics – Modelling Company as Intelligent Business Network Information System to Predict and Synthesize Business Future and Present Behavior

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Abstract

Organizations increasingly operate through heterogeneous enterprise platforms, distributed expertise, dynamic learning resources, and artificial-intelligence models that evolve at different speeds. Conventional business intelligence remains largely retrospective and fragmented, while contemporary organizations require predictive intelligence, knowledge-driven reasoning, coordinated action, and continuous learning. This paper modernizes the author's Business Random Access Intelligent Network and Constantly Changed Self-Learning Organization System (CCSL-OS) as an AI-native, human-governed Intelligent Business Network Information System. Its purpose is to explain how Advanced Business Analytics, Generative AI, Agentic AI, foundation models, knowledge graphs, and predictive analytics can be integrated without transferring organizational authority to an unconstrained model. A conceptual design-science method was applied in four stages: extraction of architectural requirements from two author-developed presentations; functional decomposition; mapping to established technical, analytical, and educational constructs; and analytical evaluation through requirement traceability, internal-consistency checks, and a scenario walkthrough. The resulting reference architecture preserves six interconnected subsystems: RING (Rollout Interconnection Network Gainer), CFL (Crossover Fast Links), PIIWS (Pick and Involve Intelligent Workflow System), MMR (Man to Media Relationship), KCSIS (Knowledge & Certification Secured Insurance System), and SLTC (Self-Learning Task Cell). N.E.U.R.O.N. operates as a multidimensional process platform whose Matrix routes demands to addressable TASK Cells or temporary cell coalitions. Each cell combines a bounded objective, competency requirements, authorized data and tools, rules, quality criteria, validation tests, human approval, and an explicit feedback contract. Retrieval-augmented generation grounds model outputs in controlled organizational memory; event-driven integration and process mining reveal actual workflows; and learning analytics links workplace evidence to adaptive support and measurable capability development. KCSIS is implemented as a skills-and-knowledge graph that incorporates S.U.I.T., B.O.N.D., and R.U.N. functions for governed knowledge transfer, external learning networks, competency validation, and recognition. SLTC converts verified experience into reusable organizational knowledge, while RING reconnects learning and process outcomes to strategy, performance, risk, and forecasting. The analytical results indicate conceptual coherence between the original model and current AI capabilities, if prediction, synthesis, recommendation, and execution remain explicitly separated and governed through risk-tiered controls. Provenance, least privileged access, validation thresholds, monitoring, contestability, and meaningful human review are therefore architectural requirements, especially for consequential educational or employment decisions. The contribution is a unified, testable architecture linking business analytics, intelligent decision support, workplace learning, organizational intelligence, and responsible Agentic AI. Future research should evaluate it through simulation, organizational digital twins, bounded field pilots, and longitudinal studies.

Keywords: Advanced Business Analytics; Intelligent Business Network Information System; Business Random Access Intelligent Network; Agentic AI; Generative AI; Knowledge Graphs; Predictive Analytics; Organizational Learning; Learning Analytics; Responsible AI

1. Introduction

Business intelligence traditionally describes and explains organizational performance; an intelligent organization must additionally learn from events, anticipate plausible futures, coordinate action, and preserve accountable human control. The problem is not a lack of data or models. It is the fragmentation of operational systems, documents, skills, rules, educational content, and decision rights. Generative AI can connect these assets through natural-language interfaces, but an unconstrained language model is not an organizational control system. Its output may be ungrounded, nondeterministic, or inconsistent with policy. A viable architecture must therefore combine probabilistic AI with deterministic process controls, traceable knowledge, explicit authorization, and feedback from real outcomes.

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This study revisits the author's Business Random Access Intelligent Network and Constantly Changed Self-Learning Organization System (CCSL-OS). The source model defines six mutually connected subsystems: RING (Rollout Interconnection Network Gainer), CFL (Crossover Fast Links), PIIWS (Pick and Involve Intelligent Workflow System), MMR (Man to Media Relationship), KCSIS (Knowledge & Certification Secured Insurance System), and SLTC (Self-Learning Task Cell). It also introduces N.E.U.R.O.N. as a multidimensional open-architecture intelligent process platform. The original names are retained because they express a distinctive organizational ontology; their implementation is updated for current AI.

Here, random access does not mean random or uncontrolled decision making. It denotes context-dependent, non-hierarchical addressing of the most relevant knowledge, person, service, model, or TASK Cell. The approach is especially relevant to lifelong and workplace learning: competence must be identified now of need, learning must be linked to authentic work, and verified experience must return to institutional memory. Learning analytics provides the measurement and interpretation layer for learners and their contexts (Long & Siemens, 2011; Siemens, 2013), while process mining connects event data to the discovery and improvement of real processes (van der Aalst et al., 2012).

The study addresses three questions: RQ1: How can the six original subsystems be mapped to contemporary AI, data, process, and learning technologies without losing their conceptual identity? RQ2: What runtime logic allows N.E.U.R.O.N. and TASK Cells to predict, recommend, act, validate, and learn safely? RQ3: Which governance constraints and evaluation measures are necessary for responsible use in organizational learning and decision support? The paper contributes a reference architecture, traceability mapping, and testable design propositions rather than claims of field-proven effectiveness.

2. Conceptual Foundations

2.1 From organizational learning to grounded AI

Organizational learning requires more than storing documents. It involves detecting and correcting errors, revising governing assumptions, and converting individual experience into shared capability (Argyris & Schön, 1978; Nonaka, 1994). Contemporary AI adds three complementary mechanisms. First, transformer-based models provide a general interface for interpreting and generating language (Vaswani et al., 2017). Second, retrieval-augmented generation (RAG) combines parametric models with external, updateable memory and enables evidence-linked responses (Lewis et al., 2020). Third, agent patterns interleave reasoning with tool use (Yao et al., 2023) or coordinate specialized agents through structured conversation (Wu et al., 2023). These mechanisms make parts of the source vision technically feasible, but only when their authority and evidence are bound.

The proposed architecture therefore separates four functions that are often collapsed in AI demonstrations: prediction estimates future states; synthesis generates possible explanations, plans, or artifacts; decision recommends or selects an option according to policy; and execution changes an external system. Increasing autonomy across these functions requires increasing evidence, validation, and approval. This separation also supports education: an AI tutor may synthesize feedback, while certification or employment decisions require independent evidence and human accountability.

2.2 Responsible analytics and educational relevance

Human-centered guidance for generative AI in education emphasizes agency, inclusion, privacy, transparency, and capacity building (Miao & Holmes, 2023). NIST organizes AI risk work through Govern, Map, Measure, and Manage functions (Tabassi, 2023), while its generative-AI profile highlights confabulation, data privacy, harmful bias, information integrity, and human-AI configuration risks (Autio et al., 2024). The European AI Act further applies a risk-based approach and identifies certain educational, and employment uses as high-risk (European Parliament & Council of the European Union, 2024). Recent human-centered assessment research similarly argues that assessment should evidence genuine human learning rather than automatable output production (Aydemir, 2026). Consequently, KCSIS cannot merely infer competence from opaque interaction data. It must distinguish learning support from consequential assessment, document evidence, allow contestability, and minimize personal data.

3. Methodology

A conceptual design-science approach was used to reconstruct and modernize an existing design artifact, following the problem identification, design, demonstration, and evaluation logic described by Peffers et al. (2007). The evidence base comprised two author-developed presentations: AI Business Random Access Intelligent Organization (37 slides) and AI Neuron System (3 slides). The analysis proceeded in four stages. Stage 1 extracted

named components, relationships, management functions, process levels, and implementation phases. Stage 2 normalized duplicated terms and converted each component into implementation-neutral requirements. Stage 3 mapped requirements to current constructs using peer-reviewed and authoritative literature on organizational learning, learning analytics, process mining, RAG, language-model agents, and AI governance. Stage 4 evaluated the resulting artifact through requirement traceability, internal-consistency checks, and an illustrative scenario walkthrough.

The evaluation is analytical, not experimental. No learner, employee, or company performance dataset was used, and no causal effect is claimed. A mapping was accepted when a contemporary mechanism preserved the original component's purpose, defined observable inputs and outputs, and supported audit or validation. This conservative criterion prevents technological novelty from replacing the model's organizational logic. Future empirical evaluation is specified in Section 5.

4. Results: Modernized CCSL-OS Architecture

4.1 Six-subsystem capability model

Table 1. Mapping of the original subsystems to contemporary capabilities and learning functions.

Subsystem	Preserved purpose	2026 implementation	Educational / organizational-learning role
RING	Performance, strategy, risk, information, and cash-flow coordination	Event/data fabric; semantic metrics; observability; forecasting; scenario services	Connects learning outcomes and competency gaps to operational performance
CFL	Fast links across documents, hierarchy, databases, and reporting	APIs; event streaming; identity federation; document pipelines; metadata and lineage	Delivers governed, just-in-time access to learning and work resources
PIIWS	Pick and involve processes, rules, planning, assets, and workflows	BPM/workflow engine; process twin; rules; agent orchestrator; approval gates	Embeds instruction, practice, feedback, and assessment in authentic tasks
MMR	Human-to-media and external relationship interface	Multimodal assistants; portals; CRM; collaboration; accessibility layer	Provides inclusive dialogue, coaching, explanation, and stakeholder exchange
KCSIS	Acquire, verify, transfer, and reward knowledge and competence	Knowledge/skills graph; RAG; learning record store; evidence portfolio; micro-credentials	Maps current/required skills, personalizes learning, and validates competence
SLTC	Self-learning task execution, prediction, innovation, and quality	Bounded agentic TASK Cells; reflection memory; experimentation; quality evaluation	Turns verified task experience into reusable learning and improved practice

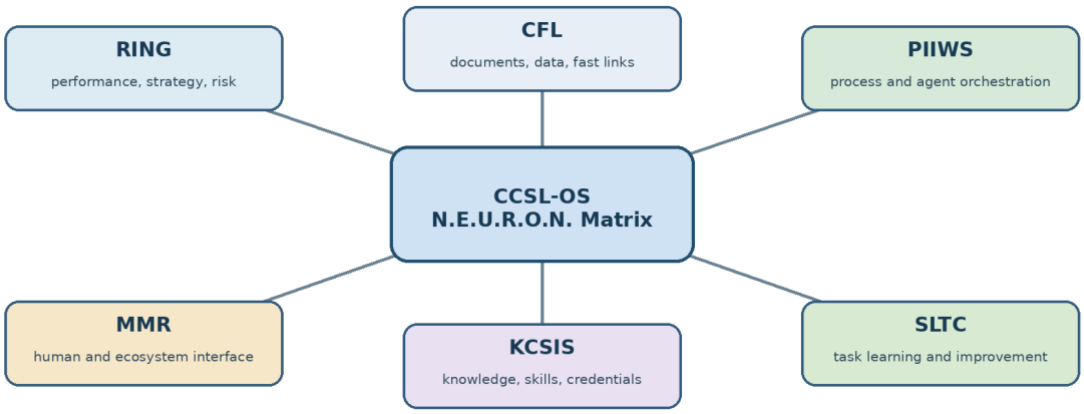


Figure 1. CCSL-OS capability architecture and the six connected subsystems.

As summarized in Table 1 and Figure 1, the six subsystems are not separate applications. They are logical responsibilities connected through shared identity, policy, ontologies, and event contracts. RING defines what must be observed and optimized; CFL makes authorized information movable; PIIWS coordinates work; MMR

mediates human interaction; KCSIS manages knowledge and competence; and SLTC performs bounded learning and improvement. This arrangement preserves the source model while avoiding a monolithic AI platform.

Their interaction creates three mutually reinforcing loops. The operational loop runs from RING observations through PIIWS coordination to SLTC execution and back to measured outcomes. The knowledge loop uses CFL to move controlled evidence into KCSIS, where skills, learning resources, procedures, and validation records are connected and made retrievable. The human-governance loop uses MMR to expose explanations, approvals, exceptions, and feedback to employees, educators, managers, and external partners. N.E.U.R.O.N. does not replace these loops; it routes work among them and preserve the context required to interpret each result. A change in one subsystem is therefore propagated as an event and evaluated for effects on process, knowledge, competence, and risk.

4.2 N.E.U.R.O.N. Matrix and TASK Cell runtime

N.E.U.R.O.N. is implemented as the runtime that converts a demand or detected event into a governed result. A TASK Cell is the smallest addressable unit of intelligent work. Its contract contains: objective and completion criteria; role/competency requirements; authorized data and tools; applicable rules; acceptable risk; model configuration; validation tests; human approver; and feedback fields. Cells may represent a business process, an adaptive learning intervention, a forecasting routine, a compliance check, or a human-led team supported by AI.

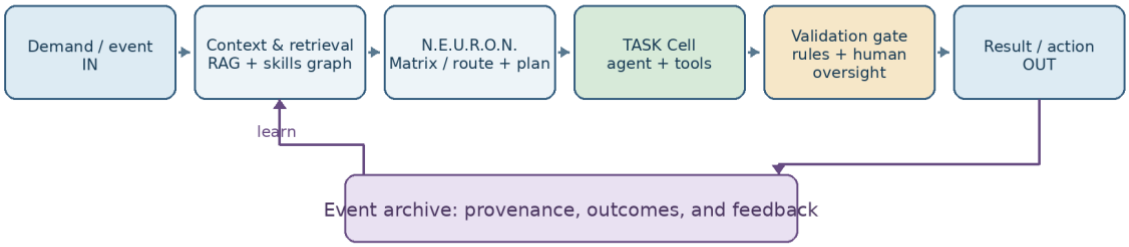


Figure 2. Governed N.E.U.R.O.N. execution and learning loop.

As shown in Figure 2, the runtime follows seven logical levels derived from the source presentations: (1) process goal; (2) subprocess decomposition; (3) TASK Cell selection; (4) active and passive modules and connections; (5) messages and state; (6) cell characteristics and evidence; and (7) rules, algorithms, and authorized actions. The N.E.U.R.O.N. Matrix ranks eligible cells rather than asking for one general-purpose model to solve every task. A conceptual selection rule is:

$$c^* = \arg\max_{c \in C} \{wgG(c,x) + wqQ(c,x) + wtT(c,x) + wkK(c,x) - wrR(c,x) - wcostCost(c,x)\}$$

where G is goal fit, Q expected quality, T timeliness, K competency/evidence fit, R risk, and Cost resource consumption for context x. The weights are policy parameters, not model preferences. Hard constraints—authorization, data classification, required certification, and mandatory human approval—are applied before ranking. The selected cell retrieves evidence, creates a plan, invokes permitted tools, validates outputs, and either returns a recommendation or executes an approved action. Every transition writes a structured event with provenance, enabling later conformance checking and learning.

The source N.E.U.R.O.N. modules can now be implemented as explicit services. The Connection Constructor resolves permitted dependencies among cells, people, models, and tools. The Process Event Archiver stores time-stamped events and provenance. Process Intelligence Learner uses process mining and outcome evaluation to identify recurring paths, deviations, bottlenecks, and candidate improvements. The Operations Control Mechanism enforces state transitions, while the Quality and Surveillance Module applies acceptance tests, drift monitoring, and escalation thresholds. Mathematical Algorithm and Matrix Constructors manage deterministic analytics and routing scores; the Time and Event Managers schedule deadlines, triggers, and temporal windows. The Automated Modelling Decision Maker is deliberately restricted to evidence-backed recommendation or pre-authorized low-risk action. Finally, the Intelligence Module supports prediction, optimization, and validation; the User In-Time Learning Module delivers contextual explanation and practice; and Other Cell Existing Awareness provides a registry of active cells, capabilities, status, and dependencies. This decomposition makes every original function observable, testable, and replaceable.

4.3 KCSIS as an AI-enabled lifelong-learning system

KCSIS operationalizes the educational core of architecture. The source subsystems S.U.I.T. (Strategic Unified Information Transfer), B.O.N.D. (Beyond Organization – Network Developer), and R.U.N. (Record and Utilize Network) become, respectively: a governed knowledge-transfer pipeline; an external learning ecosystem connecting universities, consultants, partners, and open resources; and a recognition layer linking validated competence to roles, progression, and rewards. A skills graph relates people, roles, tasks, concepts, evidence, learning objects, credentials, and organizational objectives. RAG retrieves only resources allowed for the learner's role and presents source-linked explanations. Learning analytics measures engagement, mastery evidence, transfer to task performance, and equity indicators without treating activity counts as competence.

An illustrative walkthrough begins when RING detects repeated quality deviations in a process. PIIWS decomposes the deviation into affected tasks and queries KCSIS for required competencies. CFL retrieves current procedures, event traces, and approved learning objects. The N.E.U.R.O.N. Matrix assigns a diagnostic SLTC and a human process owner. The cell generates hypotheses grounded in retrieved evidence, proposes microlearning activity and supervised practice, and records completion and performance evidence. KCSIS updates competence only after validation; PIIWS adjusts the workflow only after approval. RING then compares post-intervention quality and recurrence. The loop connects analytics, learning, action, and outcome without allowing the LLM to award a credential or change a critical process autonomously.

4.4 Design propositions and governance controls

Table 2. Design propositions and measurable evaluation indicators.

Proposition	Expected mechanism	Candidate indicators
P1 Grounded memory	RAG and provenance improve updateability and evidential traceability compared with model-only answers.	Citation precision/recall; unsupported-claim rate; evidence freshness
P2 Addressable cells	Task specialization and hard authorization constraints reduce coordination and autonomy risk.	Task success; policy violations; escalation rate; latency/cost
P3 Closed-loop learning	Linking learning evidence to process outcomes improves transfer and organizational memory.	Competency gain; time-to-proficiency; recurrence; knowledge reuse
P4 Human-governed autonomy	Risk-tiered validation and approval preserve agency and accountability.	Override quality; harmful-action rate; contestability; audit completeness

Table 2 formalizes four design propositions and their candidate indicators. Governance is cross-cutting. Each model and cell requires an owner, intended-use statement, data inventory, evaluation set, change log, monitoring thresholds, and retirement rule. High-impact educational or employment decisions require independent evidence and meaningful human review. Security follows least privilege: the model never inherits the user's full access, tool calls are schema-constrained, retrieved content is treated as untrusted input, and actions are isolated from reasoning. Quality gates check source support, numerical consistency, policy compliance, uncertainty, and adverse impact. The event archive records prompts or structured task inputs where lawful, retrieved evidence identifiers, model/version, tool calls, approvals, outputs, and observed outcomes. This converts explainability from a narrative afterthought into operational provenance.

4.5 Implementation and maturity path

Implementation should proceed incrementally because the value of the architecture depends on organizational readiness rather than model capability alone. Phase I establishes system guidance: strategic objectives, benchmark and KPI definitions, reference points, documentation standards, data ownership, identity, and a real-time measurement baseline. Phase II connects existing systems through CFL and introduces controlled organizational memory in KCSIS, including document lineage, a shared vocabulary, a skills graph, and access-aware retrieval. At this stage, AI is limited to search, summarization, explanation, and draft recommendations.

Phase III introduces PIIWS orchestration and selected SLTC pilots for bounded, reversible tasks. Each pilot must have a baseline, acceptance tests, a human owner, an explicit rollback path, and outcome measures. Phase IV scales proven cells into temporary coalitions, introduces scenario simulation and organizational digital-twin functions, and uses RING to monitor portfolio-level value and risk. Promotion between phases is evidence-based: a component advances only when it meets quality, security, educational-validity, and governance thresholds. This maturity path converts the source implementation matrix into a practical sequence and prevents premature automation of poorly understood processes.

5. Discussion

The principal contribution is the integration of organizational analytics and educational technology in one operating model. Existing learning systems often stop content delivery and completion, while business analytics often treat competence as an external variable. CCSL-OS links the two: operational signals generate learning needs; knowledge and credential evidence constrain task assignment; verified task outcomes update both process models and learning pathways. This supports ICETOL 2026 themes of learning analytics, adaptive pathways, lifelong learning, institutional resilience, and responsible AI.

The model also clarifies where current AI does and does not satisfy the earlier vision. LLMs, RAG, multimodal interfaces, process mining, and agent orchestration can implement connection constructors, event archivers, process intelligence learners, model constructors, and decision-support modules. However, automated modelling decision makers should not be interpreted as unrestricted autonomy. Prediction is conditional, retrieved sources can be wrong, agent interactions can amplify errors, and feedback loops can institutionalize bias. The architecture therefore makes validation, human authority, and reversibility first-class components rather than external safeguards.

Three limitations are material. First, the paper evaluates conceptual coherence, not organizational impact. Second, legacy subsystem boundaries may require revision after field deployment and stakeholder co-design. Third, the architecture does not prescribe a vendor or model; performance and risk will depend on implementation, domain, language, and data quality. A future evaluation program should progress from offline benchmarks to simulation and then bound field pilots. Recommended studies include ablation of RAG, skills-graph, and validation components; comparison of single-agent and multi-cell orchestration; process-conformance analysis before and after learning interventions; longitudinal measurement of time-to-competence and error recurrence; and participatory assessment of trust, workload, inclusion, and contestability. A digital twin can test policies and failure modes before any connection to production systems.

6. Conclusions

This paper has modernized the Business Random Access Intelligent Network, CCSL-OS, and N.E.U.R.O.N. concepts as contemporary, AI-enabled organizational learning architecture. The original RING, CFL, PIIWS, MMR, KCSIS, and SLTC names remain intact, but their implementation is reframed through event-driven data, process mining, RAG, skills graphs, learning analytics, agentic TASK Cells, and risk-tiered human governance. The resulting system does not equate intelligence with one large model. Intelligence emerges from the controlled interaction of people, evidence, processes, models, tools, and feedback. Its central educational contribution is a closed loop in which real work identifies learning needs, adaptive support builds capability, validated performance updates competence, and organizational outcomes guide further learning. The architecture is sufficiently specified for prototyping and falsifiable evaluation, while its effectiveness remains an empirical question for future studies.

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The conceptual model, terminology, source presentations, architectural interpretation, and final responsibility for the manuscript belong to the author. OpenAI ChatGPT/Codex was used to assist with literature discovery, drafting support, language editing, document structuring, and formatting. The author reviewed the claims, selected the sources, and remains fully responsible for accuracy, originality, interpretation, and the submitted version. No AI system is listed as an author.

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Generative AI in Leadership Development: A Systematic Literature Review of Applications, Evidence and Ethical Risks

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Abstract

Purpose – This paper synthesises the scholarly literature on artificial intelligence (AI) in leadership development. It establishes which AI applications are discussed, their empirical support, and examines how ethical risks condition their adoption.

Design/methodology/approach – A systematic literature review (SLR) following the PRISMA 2020 protocol was conducted in the Web of Science Core Collection for the period 2016 to 2026. The analysis identified 94 records, of which nine peer-reviewed English-language articles met the inclusion criteria

Findings – (1) The application landscape converges on personalised learning pathways, conversational coaching and immersive simulation. (2) AI literacy affects leadership outcomes only indirectly, through collaborative knowledge practices. (3) Leadership roles shift towards decision architecture and boundary spanning. (4) Bias, opacity and privacy risks are substantial and documented. (5) Conceptual work markedly outpaces empirical testing. Arranged as an evidence chain, the corpus documents technology adoption and, in part, the underlying mechanisms, but offers almost no evidence on competency acquisition, transfer or leadership outcomes.

Research limitations/implications – Nine studies retrieved from a single database using a deliberately narrow search string. The review is a structured map of an emerging field rather than pooled evidence.

Originality/value – To the best of our knowledge, this is the first SLR on AI and leadership development.

Keywords: Generative AI, leadership development, human resource development, workplace learning, algorithmic bias, systematic literature review

Introduction

The integration of artificial intelligence (AI) into organisational learning and development represents one of the most profound transformations organisations currently face (Sposato & Dittmar, 2026). Leadership development is directly affected as virtual leadership is of paramount importance, for instance when leading flexibly working employees (Tirrel et al., 2026). A field traditionally built on in-person coaching, mentoring and standardised training now encounters technologies that promise personalised learning pathways, scalable coaching formats, data-driven competency analyses and real-time feedback. At the same time, executives report that their organisations lack the leadership capacity required to navigate AI-driven transformation (Bevilacqua et al., 2025). Demand for leadership capability and the supply of it are moving in opposite directions, which makes leadership development a strategically central field for AI adoption (Sacavém et al., 2026; Santiago-Torner et al., 2026).

Despite a rapidly growing body of publications, the field remains fragmented. Existing reviews illustrate the breadth of activity rather than resolving it. Aziz et al. (2024) identify the complexity of human–AI interaction, implementation barriers and long-term risks as the dominant challenges. Bevilacqua et al. (2025) show that AI changes managerial demands and requires new, AI-specific competencies. Bhatt and Muduli (2022) conclude that AI makes learning and development faster, more precise and more scalable. A recurring theme across these reviews is AI-supported coaching: large language model-based coaching chatbots improve interaction quality and engagement in structured tasks such as goal setting, reflection and feedback (Terblanche, 2024), and AI-supported platforms may democratise leadership development by reaching managers at all hierarchical levels (Passmore et al., 2025). Nevertheless, the application of generative AI in leadership development remains under-researched, and robust empirical evidence of its effectiveness is lacking (Aboumoussa & Pfister, 2024), representing the gap. Therefore, the SLR is guided by two research questions:

RQ1: Which AI technologies and applications in leadership development are discussed in the scholarly literature, and what empirical evidence exists regarding their effectiveness?

RQ2: How do ethical risks, e.g. algorithmic bias, data privacy issues and transparency deficits, affect AI-supported leadership development?

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By bridging educational science and management science perspectives, the paper consolidates a fragmented literature into a synthesised framework and maps the open research questions.

Methodology

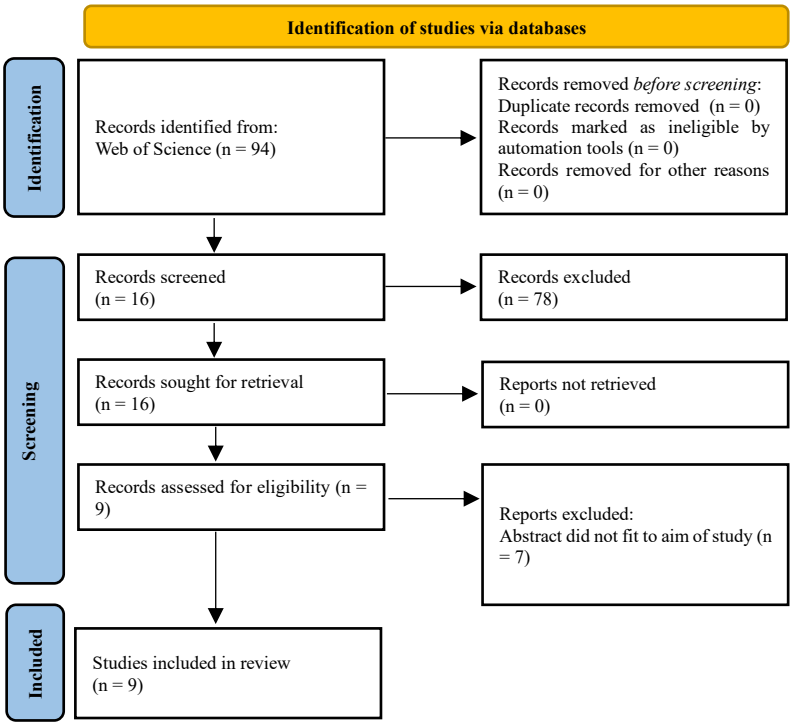


Figure 1. Data generation process. Source: Own depiction based on Page et al. (2021)

A systematic literature review (SLR) was conducted to condense the most relevant literature (Brereton et al., 2007). The PRISMA 2020 (Page et al., 2021) was applied as a review protocol, cf. figure 1. To assess papers of high quality only, the SLR solely includes papers that are based on implicit quality, i.e., peer-reviewed papers from ranked journals (Tranfield et al., 2003). In- and exclusion criteria were defined. First, only papers listed in Web of Science Core Collection were included due to the relevance of this database in management research. Second, a narrowed search string was defined to identify relevant articles for the SLR (Kauppi et al., 2018; Tirrel and Winnen, 2018). The following search string was used: "leadership development" AND ("artificial intelligence" OR AI) and the last decade was analysed. Third, only papers in English were included. Fourth, the timeframe was set to the last decade.

Results

Descriptive results

The nine relevant studies were identified and published in eight journals between 2023 and 2026. The absence of a full decade of literature is itself a finding: the intersection of AI and leadership development is not a maturing research stream but one that is evolving in the past three years.

Four studies are conceptual papers that propose a framework without testing it (Chen, 2025; Jenkins & Khanna, 2025; Shouman et al., 2026; Sposato & Dittmar, 2026). One is a systematic review of adjacent literature (Sacavém et al., 2026), one an interpretive literature review (Dittmar et al., 2025) and one a practice report (Flood, 2025). Only two studies generate and analyse original data: Asghar et al. (2025) and Newstead et al. (2023).

Geographical and cultural distribution of the corpus

Table 1 shows where the nine studies were conducted. Author affiliations span Europe, the Gulf region, Asia and Australasia; data collection does not. Only Ashar et al. (2025) generated data in more than one country. Newstead et al. (2023) analyse machine-generated text rather than human participants, and the leadership examples the system produced are dominated by figures from Western and Anglophone history.

Therefore, three consequences arise. First, no study in the corpus observes practising leaders in a European organisation; the only cross-cultural empirical evidence comes from students rather than from leaders in post. Second, cultural moderators are asserted more frequently than they are measured. Third, entire regions are absent as empirical contexts, among them Sub-Saharan Africa, Latin America and most European countries.

Table 1. The nine studies in the corpus: type, evidence base and geographical information

Author(s) (year)	Study type	Evidence base	Author affiliations	Context of data generation
Asghar et al. (2025)	Empirical, mixed methods	Survey, n = 458 students; 40 interviews; PLS-SEM and fsQCA	Finland, China, Türkiye	Bangladesh, China, Finland, Türkiye (higher education)
Chen (2025)	Conceptual	Theory synthesis; secondary corporate cases	China	None; cases from large US-headquartered corporations
Dittmar et al. (2025)	Interpretive literature review	65 articles retained; thematic analysis	Spain, United Arab Emirates	None; anonymised cases (healthcare, consulting, banking)
Flood (2025)	Practice report	Anecdotal implementation account; no design reported	Not stated (industry)	Two hospitals; country not stated
Jenkins and Khanna (2025)	Conceptual essay	No data generated; literature and professional experience	United States	None; US higher education and industry examples
Newstead et al. (2023)	Empirical, qualitative	50+ AI-generated narratives, 40,000+ words; manual analysis	Australia, New Zealand	Machine-generated corpus; Anglophone/Western content
Sacavém et al. (2026)	Systematic review	84 studies from 452 records (Scopus, Web of Science)	Portugal, Brazil	None of its own; included studies span Asia, Africa, the Gulf
Shouman et al. (2026)	Conceptual	Three theories combined; three secondary cases	Lebanon, Spain	None; global framing, MENA–Western comparison proposed
Sposato and Dittmar (2026)	Narrative literature review	Framework of four domains; three hypothetical scenarios	United Arab Emirates, Spain	None; scenarios explicitly fictitious

Themes

The synthesis evolved five themes, which will be discussed in the following sections.

Theme 1: A converging application landscape

Three application clusters recur across the corpus. The first and most frequently described is personalised learning pathways, in which systems analyse behavioural and performance data to construct individual development paths and adapt content as learners progress (Chen, 2025; Jenkins & Khanna, 2025). The second is conversational coaching, in which large language models support goal setting, reflection and feedback at scale, and workflow-embedded assistants act as continuously available mentors (Flood, 2025; Sposato & Dittmar, 2026). The third is immersive simulation, which allows leaders to rehearse crisis communication and comparable high-stakes situations in virtual environments without organisational consequence (Dittmar et al., 2025). They call for the same: scale without a loss of personalisation, and therefore access for managers who have never been included in formal development programmes (Flood, 2025).

Theme 2: Collaborative practice as the active ingredient

The strongest empirical finding in the corpus concerns the mechanism rather than the technology. Asghar et al. (2025) show that AI literacy has no significant direct effect on inclusive leadership ($\beta = 0.062$, $p = 0.122$). It strongly predicts collaborative knowledge practices ($\beta = 0.523, p < 0.001$), which in turn strongly predict inclusive leadership ($\beta = 0.738$, $p < 0.001$). The indirect effect is substantial and highly significant ($\beta = 0.386$, $p < 0.001$), and AI literacy together with collaborative knowledge practices explains 59.6 per cent of the variance in inclusive leadership. Dittmar et al. (2025) highlight that successful AI integration depends on an organisation's capacity to facilitate collective meaning-making rather than on technological sophistication.

Theme 3: Competency requirements and role shifts

Sacavém et al. (2026) describe three role shifts: from analysts to decision architects, from controllers to coordinators, and from individual experts to boundary spanners. AI and data literacy become baseline requirements, while strategic vision and emotional intelligence remain necessary but are no longer sufficient (Bevilacqua et al., 2025; Chen, 2025). As AI absorbs routine analysis, human-centred capabilities become more important. Jenkins and Khanna (2025) report a 32 per cent gap between AI and human performance in detecting emotional cues during leadership interactions, alongside a documented failure to grasp cross-cultural nuance. Furthermore, the literature describes which competencies leaders must have; it does not establish which competencies they acquire through AI-supported formats.

Theme 4: Ethics, bias and equity

Analysing more than 50 AI-generated leadership narratives (40,000+ words), Newstead et al. (2023) uncover that gender-neutral prompts produced only male-named leaders, and that named women were roughly twice as likely as men to be cast as bad leaders, with good leadership framed as strength and strategy for men but confidence and priorities for women. This pattern reproduces second-generation gender bias (Eagly & Karau, 2002) not as an artefact of use but as a property of the generated content itself. Algorithmic bias may lend the appearance of objectivity to discriminatory appraisal and promotion decisions (Sacavém et al., 2026; Shouman et al., 2026). Opacity undermines the ability to contest a decision, which leads both Sacavém et al. (2026) and Shouman et al. (2026) to argue for an explicit right to question and appeal AI-supported decisions. Continuous behavioural analysis raises privacy and surveillance questions that the corpus names but does not resolve (Sposato & Dittmar, 2026).

The decisive point is that these are not compliance matters to be settled after adoption. Perceived fairness conditions whether a system is used, resisted or constrained. Ethical legitimacy is an antecedent of adoption, not a downstream obligation.

Theme 5: The state of the evidence base

Research designs are predominantly cross-sectional and self-reported, so causal claims are not to be drawn; Asghar et al. (2025) name social desirability bias among their own limitations. No study in the corpus examines the transfer of learning into day-to-day leadership practice. Practice-oriented percentages lack design and sample size: Flood (2025) reports a 30 per cent rise in leader rounding with no method section, and Jenkins and Khanna's (2025) 30–45 per cent gains stem from secondary sources, not original data.

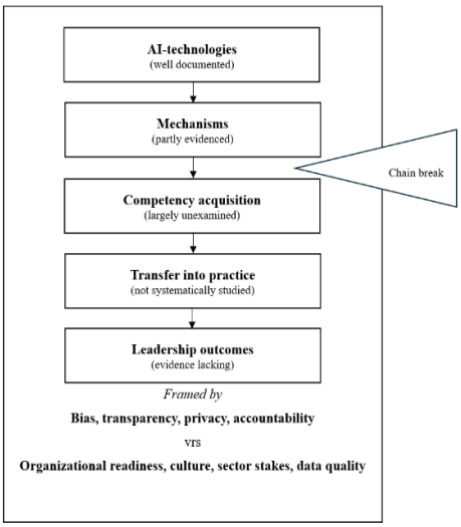


Figure 2. Conceptual framework. Source: Own depiction

A synthesised framework: the evidence chain

The findings are synthesised in the conceptual framework, cf. Figure 2. AI technologies enable mechanisms such as personalisation, feedback and collaboration. Those mechanisms must produce competency acquisition. Acquired competencies must transfer into daily practice. Transfer has to finally produce leadership outcomes. This chain is framed by a conditioning layer of accountability, bias, privacy and transparency, which shapes trust and legitimacy at every stage rather than at any single one.

Read against the corpus, the chain breaks after the second stage. Stage one is well documented by all nine contributions. Stage two is partly evidenced, but by two studies only, one of which samples students. Stages three, four and five are, respectively, largely unexamined, not systematically studied and without effectiveness evidence. The framework's value is therefore diagnostic.

Discussion

Research agenda

The SLR uncovers five research streams for further research. (1) The mediation reported by Asghar et al. (2025) is the corpus's strongest empirical result and most needs replication with practising leaders in organisational, not educational, settings. Cultural moderators should be measured in further research. (2) The corpus treats leaders as a single population despite markedly heterogeneous settings, from high-digital-maturity technology firms (Chen, 2025; Dittmar et al., 2025) to clinical nursing units (Flood, 2025). Comparative designs across team types, where task interdependence and error tolerance differ systematically, would be another avenue for further research. (3) Newstead et al. (2023) and Shouman et al. (2026) flag race, age, disability and generational identity as unexamined barriers; an intersectional design remains outstanding. Bias audits should also extend from generated narratives to the personalisation layer, where recommendation logic is entirely unexamined. (4) Academic leadership rests on collegial rather than hierarchical authority yet appears in the corpus only as a data source (Asghar et al., 2025), not as a development setting. Whether AI-supported formats transfer to scholarly rather than positional legitimacy remains open, despite evaluated academic interventions existing (Zulfqar et al., 2021). (5) Fairness, contestability and transparency are discussed narratively but rarely instrumented. If perceived fairness conditions are adopted (Theme 4), it should be modelled as an antecedent alongside outcome variables, not appended as a normative closing section.

Managerial implications

Four implications for organizational practice have been uncovered. The scope of decisions and the level of technological maturity should be assessed prior to implementation, while clearly delineating areas that primarily require human judgment. Decision rights require formalization; specifying when a system informs, recommends or may trigger action. Generated content warrants systematic auditing, including provider disclosure and bias screening, a measure Newstead et al. (2023) deem necessary rather than precautionary. Organizations should further establish psychological safety for experimentation alongside a substantive right to contest AI-supported decisions.

Limitations

Nine studies do not represent the entire literature on this topic. The SLR is based on a single database. Thus, studies indexed elsewhere, have not been included in the SLR. The search string was very narrow, so adjacent terminology such as coaching, executive education and talent development was not captured, i.e., those contributions are missing. As the corpus contains only two empirical papers, findings are often lacking evidence. The lack of evidence in a field of research that is only three years old is less significant than in a well-established field. The conclusions should therefore be reevaluated as soon as further empirical studies become available. Thus, this review offers a structured map of an emerging field, not pooled evidence.

Conclusions

Across nine studies, AI is reshaping how leaders are developed, through personalised learning pathways, conversational coaching and immersive simulation. The evidence, however, stops shortly after technology adoption. Which competencies leaders actually acquire, and whether the leaders apply those competencies in their behaviour at work, was not examined. AI literacy alone does not result in better leaders; its effect operates through collaborative knowledge practice. The field's pathway argument – from technology through mechanism and acquisition to transfer and outcome – currently has evidence for only the first two aspects. Ethical legitimacy conditions adoption rather than following it, making bias auditing and contestability design questions, not compliance ones. Thus, AI technology is not the bottleneck. Collaborative practice, shared interpretation and ethical legitimacy determine whether AI improves leadership development. There is now an open call to evaluate the established frameworks and propositions.

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Design and evaluation of a distance-mode blended online course in Medical Laboratory Science: Learner perceptions

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Abstract

This study aimed to explore learner perceptions of learning in a distance mode blended learning course, offered for Medical Laboratory Technologists (MLTs) in government hospitals in Sri Lanka, in studying Diagnostic Bacteriology as a part of the Bachelors degree in Medical Laboratory Sciences (BMLS) at the Open University of Sri Lanka (OUSL). The course employed a blended learning model having different delivery methods, with an online learning component through the Learning Management System (LMS) and some face-to-face components. The online leaning component was designed based on the framework of Universal Design for Learning (UDL), following its three core principles: multiple means of representations, multiple means of engagement and multiple means of expressions. Face to face component was mainly to conduct laboratory sessions for skills development, and also to conduct final examinations. Learner perceptions were gathered through quantitative and qualitative research methods, by administering a questionnaire with close and open-ended questions. Thirty-one (31) adult learners employed as MLTs in government hospitals across seven districts of Sri Lanka, participated in the course. Out of 31 adult learners, 24 learners responded to the questionnaire. Overall, learners reported positive perceptions on their blended learning experience. PowerPoint presentations and lecture recordings were widely used for independent learning and examination preparation. Online quizzes, guided practical videos, and virtual simulations were perceived as effective means of promoting active engagement with the course content and practical preparation. Although the mind map assessment was considered the most challenging, learners recognized its value for revision and knowledge integration. Key challenges included work-study balance and internet connectivity. Overall, the findings support the use of UDL-informed blended learning for working adults in distance education, while highlighting the need for additional guidance for higher-order activities such as concept mapping.

Keywords: Blended learning, Universal Design for Learning, Medical Laboratory Science, Diagnostic Bacteriology, Adult learners, Microbiology, Distance learning.

Introduction

Bachelor of Medical Laboratory Sciences (BMLS) is a four-year degree programme, offered by the Open University of Sri Lanka (OUSL) to provide an integrated education and training for those who are employed in the field of Medical Laboratory Sciences, to support their academic and professional development in response to the evolving demands in the filed (OUSL, 2026). Diagnostic Bacteriology is one of the subjects offered in the second year of the BMLS degree programme. This course was previously offered as a traditional distant learning course, with a supplementary online component with E-course materials and face to face (F2F) components, including Interactive Learning Sessions and Practical Classes. Since learners are working adults, who are employed in hospitals/clinical laboratories as Medical Laboratory Technologists (MLTs), regular attendance at face-to-face learning sessions was observed to be challenging for them due to their work commitments and limited availability. Therefore, with the aim of enhancing learner engagement, it was decided to implement a distance mode blended online learning approach, providing more flexibility to learn at their own pace and time, from the academic year 2024/2025.

This study aimed to explore learner perceptions of learning in a distance mode blended online course, specially designed for Medical Laboratory Technologists in government hospitals in Sri Lanka, in studying Diagnostic Bacteriology as a part of the BMLS degree at OUSL. The specific objectives of this study are to:

1. Design a distance mode blended online course based on the principles of UDL
2. Explore learner perceptions in learning in UDL based blended learning course

The first objective of the study is explained in the Methodology section and hence there is no Research question for that objective, as it describes the design process. For the second objective, the Research question is

- Research Question - What are learners' perceptions in learning in the distance mode blended online course, designed based on the principles of Universal Design for Learning (UDL)?

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Conceptual Framework

Conceptual framework of this study was based on the Universal Design for Learning (UDL). The intention of UDL is to design the online course in advance, based on the principle of inclusion of diverse populations. In light of that, UDL provides flexible ways for the learners to access, engage with, and demonstrate their learning, reducing unnecessary barriers for learning (Dell et al., 2015). According to Meyer, Rose, and Gordon (2014 & 2025), UDL framework guides designing of teaching and learning environment from the very outset, accommodating learner variability rather than requiring individualized adaptations.

There are three overarching principles that UDL guides inclusive learning environments: Multiple Means of Representation, Multiple Means of Engagement and Multiple Means of Expression (Dzaman et al., 2022; Dell et al., 2015; Meyer, Rose, and Gordon, 2014).

1. Multiple Means of Representation refers to providing multiple ways of presenting information, comprehending information and experiencing of information. (e.g., video, audio, graphics, symbols, tactile objects etc.)
2. Multiple Means of Engagement encompasses providing different ways to motivate and engage learners by fostering their interests, encouraging self-reflection on learning, promoting collaboration and accommodating various levels of challenge (e.g., class discussions, question answer sessions, problem solving and goal setting etc.)
3. Multiple Means of Expression focuses on providing different ways for learners to demonstrate what they have learned) (e.g., assignments, multimedia presentations, concept maps). (Dzaman et al., 2022).

These three principles informs the conceptual basis for the study, in selecting different kinds of resources, activities, instructional approaches and assessment methods, aligning with learning outcomes of the course. MOODLE the official Learning Management System (LMS) of the OUSL (Moodle resources and activities) provide technological affordances through which the UDL principles are integrated in designing the online learning experiences intended for this study.

Methodology

Designing the course

The first objective of the study was to design a distance mode blended online course based on the principles of UDL. Accordingly this section describes how the UDL principles were incorporated in designing the course.

In providing Multiple Means of Representation, the course content was presented through multiple instructional formats, including reading material, recorded lectures, PowerPoint presentations, and teacher produced guided practical videos through the LMS. In addition, a Glossary of technical terms was also added to support students understanding of the subject specific terminology and concepts, as English, the medium of instructions, is the second language of learners; A few Synchronous Interactive Learning Sessions (ILS) were conducted through video conferencing, to discuss the course content and address learners' questions and areas of uncertainty.

To involve learners through Multiple Means of Engagement, different types of activities were embedded in the LMS using self assessment quizzes with feedback, discussion forum activities for collaboration and interact, virtual microbiology simulations and short answer questions. Interactive 'Mentimeter' based activities were included in ILS to engage the learners during video conferencing sessions. In addition, hands on laboratory skills were provided through F2F laboratory sessions, and group-based activities were incorporated to promote collaborative learning during lab classes.

Moving away from the traditional approach of written continuous assessments previously used, learners were provided with a variety of continuous assessments that offered multiple ways to demonstrate their understanding, and thereby in supporting Multiple Means of Expression. In that, a mind map activity, online quiz test and a reflecting report on practical sessions were included as new continuous assessment activities. In addition, F2F component was utilised for laboratory based skills assessments and final examinations.

Research Methods

This section focuses on the second objective and addresses the resech question of the study - What are learners' perceptions in learning in the distance mode blended online course, designed based on the principles of Universal Design for Learning (UDL)?

In this context, a mixed-method approach was employed and learner perceptions were gathered through quantitative and qualitative research methods by administering a Google questionnaire with closed and open-ended questions. The questionnaire was administered among all 31 learners enrolled during the 2024/2025 academic year. Quantitative data were analyzed using descriptive statistics, while qualitative responses were analyzed using content analysis.

Results & Discussion

Demographic characteristics of learners

Thirty-one (31) adult learners employed as Medical Laboratory Technologists in government hospitals across seven districts of Sri Lanka, participated in the course. Out of 31 adult learners, 24 learners (4 males and 20 females) aged 28–42 years responded to the questionnaire. Majority of the learners (45.8%) were in the age group of 25 -29 years while one learner 1 (4.2%) was in the age group of 40–44 years. Half of the learners (n = 12, 50.0%) were registered at the Colombo OUSL main center, while others came from different parts of the country registering at six other OUSL regional centers (Anuradhapura (n=1), Badulla (n=1), Batticaloa (n=5), Kandy (n=2), Kurunegala (n=2) and Matara (n=1). They were attached to 16 different hospitals and Medical Research institutions across the country.

Perceptions of learning through course resources

According to learner perceptions, PowerPoint presentations (PPTs) were the most frequently used resource in their studies compared to other resources (Figure 1). Hundred percent of learners agreed (75% strongly agreed; 25% agreed) that PPTs have helped them understand the content clearly and easily. This means that the PPTs have served as a concise and accessible format of representation of course content. Access to those resources through LMS may have provided a convenient means of revisiting and reviewing the content, rather then going through the lengthy course materials and recordings, while balancing their studies with work and family commitments.

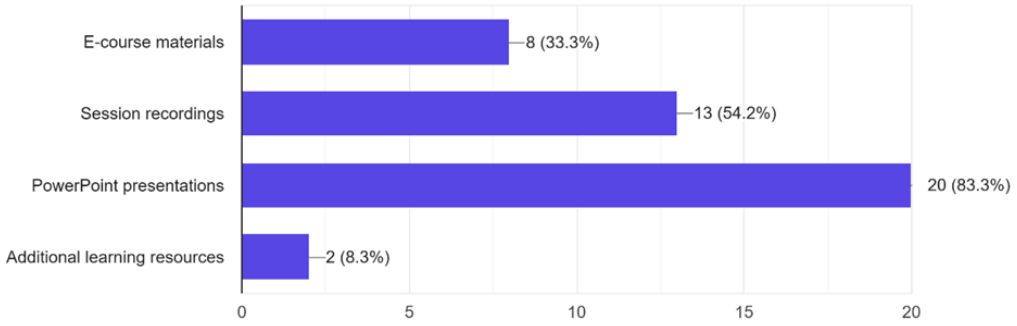


Figure 1 – Course resources most frequently used by learners

Perceptions of engagement with activities

Self assessment quizzes were reported as the most useful activities by 79% of learners. They also indicated that quizzes helped them identify areas requiring further attention, learn by searching for answers, recall and refresh their memory, and encouraged them to review the course materials. Discussions were mentioned as the second most useful activity (n = 6, 25.0%) in the course. These results suggest that this group of learners' value independent and self directed learning rather than learning collaboratively. This may be link with their busy work life, and have limited time to collaborator with others. However, further evidence is required to establish such relationships between learners work commitments and preference for independent learning.

Perceptions of course assessment methods

Of all the course assessments, mind map assessment was perceived as the most challenging by 67% of the learners, followed by the reflective report writing on laboratory experiments (12.5%) and the online quiz tests (8.3%). A smaller proportion of learners (n=2, 8.4%) identified histology sectioning during laboratory assessments was the most challenging component. Despite being perceived as most challenging assessment, mind map assessment activity was positively evaluated by the learners. Nearly 79% of them indicated it as a useful activity for revision and summarizing, while 63% of learners reported that it improved their memory and recall. Further, more than 92% of learners found the mind map activity as interesting or very interesting. Response to open-ended questions

further indicated that learners perceived the mind map assessment as beneficial for developing ICT skills, supporting examination preparation, enhancing creativity, and promoting active learning.

These results indicate that mind map assessment activity has provided learners opportunity to express their understanding in an innovative way by means of keywords, symbols and conceptual connections, while engaging actively in the learning process. Further the learners have perceived additional benefits in developing their ICT skills, enhancing their creativity, and strengthening their preparation for examinations. Hence the mind map assessment strategy has not only served as an assessment method, but it has also served as a pedagogical activity allowing learners to construct knowledge, rather than conventional text based forms of demonstrating understanding.

Perceptions of engagement with laboratory learning

All learners (100%) agreed that guided practical videos have helped them understand how to conduct the laboratory experiments and provided an opportunity to prepare for laboratory activities before attending to practical classes. Similarly virtual simulations activities provided in the LMS were also perceived as useful on laboratory learning. In addition, 100% of the learners agreed that the practical manual is clear and well structured. These findings indicate the usefulness of preparing learners in advance for laboratory activities, particularly within a distance learning context. In this regard, the multiple means of representation and engagement strategies integrated based on UDL principles have supported learners' preparedness and facilitated their participation in face-to-face laboratory activities.

Table 1 presents the thematic representation of responses received to the open-ended questions regarding learners' laboratory learning experiences. Accordingly, six main themes emerged from the learners' responses. The responses were subsequently consolidated and organized according to the identified themes, as presented in Table 1.

Table 1 – Thematic representation of responses regarding the laboratory learning experience

Theme	Count	%	Consolidated Responses
Hands-on experience	8	34.8	Practical sessions gave direct hands-on practice and "hand skills"
Knowledge consolidation and revision	7	30.4	Sessions provided opportunities to revisit previously taught lessons, linked topics together, and a more integrated understanding of subject content.
Specific technical skills	6	26.1	Thorough understanding on Gram staining, culture media preparation, aseptic technique, specimen handling, biochemical tests, bacterial identification, and observing organism growth and morphology
Accuracy, safety, and correct procedure	3	13	Improved better observation skills, enhance accuracy in performing practical tasks, develop awareness of laboratory safety practices and use of standard procedures
Confidence and day-to-day applicability	3	13	Greater confidence in preforming laboratory procedures, recognising the relevance of the knowledge and skills acquired to routine laboratory practices
Other (organisation, group work, new technologies)	3	13	Overall organisation of the learning experience, opportunities for group work and exposure to new technologies.

These results reflect learners' perceptions towards laboratory-based learning, emphasising the value of practical laboratory experiences and bridging theoretical knowledge with professional application.

As MLTs are required to perform laboratory investigations of direct medical importance, the laboratory learning experiences provided at the university are particularly valuable for developing essential practical skills, technical competence, accuracy, and adherence to appropriate laboratory procedures. Such experiences provide learners with opportunities to develop the skills required for safe and accurate practice in their future professional roles.

Overall, learners reported positive feedback on blended learning experience, describing the course as well organized and interesting. A great majority of learners (92%) agreed that they had sufficient computer skills, although some experienced difficulties during the mind map activity. Most learners (72%) found that the instructions are clear and felt the course was useful for their professional role as Medical Laboratory Technologists.

Challenges faced by the learners

Despite positive learning experiences reported by the learners, several challenges were also identified in response to the open-ended questions regarding their experience with the blended learning process. Table 2 present the thematic representation of the challenges faced by the learners. Accordingly six main themes were identified based on the learners' responses.

Table 2- Thematic representation of learners' responses regarding the challenges faced by learners

Theme	Responses	% (n)
Time and work-related challenges	"Time management with work life" "Balancing academic activities with my hospital duties…" "To manage with work load and e-learning" "Time management during working in the hospital lab" "Time" "Attending lectures online due to work commitments" "There is no time to participate in interactive learning sessions during the working hours actively" "Sometimes I could not attend to course work due to hospital workload"	32% (8)
Internet/connectivity issues	"Poor internet connection" "Network problem" "Signal issues" "Internet connection problem"; "Slow internet facilities"; "I faced difficulty maintaining consistent internet connectivity during some sessions"; "Loss of internet connection in my area"	28% (7)
Learning/participation difficulties	"Less opportunity for teamwork and real lab exposure" "Couldn't read the course material, only learn through PPTs" "Couldn't read the session, only learn using presentation and videos"	12% (3)
Family responsibilities	"Commitment with my 2-year-old baby"	4% (1)
Digital/IT skills	"I have poor IT knowledge"	4% (1)
No significant challenges	"No special challenges"; "Nothing"	12% (3)

Time, Internet connectivity, work and family related challenges were identified by a majority of learners. Although the UDL-based course design provided greater flexibility in accessing and engaging with learning activities, learners were required to organize and manage their time effectively to balance their academic responsibilities with work and other personal commitments. This indicates that the flexibility offered by the blended learning course did not necessarily eliminate the challenges associated with time management. Therefore, learners need to take greater responsibility for planning their learning. Such time-management difficulties are common challenges experienced by distance learners, particularly those who have employment and other competing responsibilities.

Internet connectivity was identified as a technology related challenge among learners. This can be associated with demographic and geographical factors such as learning from remote areas, where the Internet facilities are still not be at the same levels as those available in major cities. This highlight the importance of having stable and reliable Internet connectivity for successful, continuous participation in blended learning.

Learner suggestions to improve the course

When learners were asked for suggestions to improve the course, most learners suggested incorporating more quizzes with feedback, short questions, practical demonstration videos, and case-based learning activities to reinforce learning. They also recommended flexible assignment deadlines during busy clinical periods and alternative solutions for network stability. Overall, learners found the course well organized and satisfactory.

Conclusions

The blended online course, designed based on the principles of UDL, supported the learning needs of working MLTs in a distance-learning context. Different types of online resources and activities integrated in the course have enhanced learners' understanding and revision, while promoting greater engagement in learning. Findings also highlight the importance of hands-on skills development in blended learning, particularly for courses involving laboratory and practical components. Mind map assessments activity has been identified as the most challenging, but most interesting, engaging and pedagogically active assessment activity by the learners. Furthermore, some learners identified work-life balance and Internet interruptions during online activities as key challenges in their blended learning experience.

In an overall, this study provides insights in designing blended online courses, grounded in the three core principles of UDL to facilitate learning among working adults studying at a distance. The findings demonstrate the potential of a UDL-based approach to provide flexible, accessible, and engaging learning experiences while addressing the diverse needs and circumstances of distance learners.

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Improving Student Awareness and Achievement through Unplugged Coding and Parent Involvement: An Interdisciplinary Pedagogical Approach

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Abstract

This study investigates the impact of unplugged coding activities as an interdisciplinary teaching tool to improve student awareness and achievement and explores the role of parental involvement in enhancing these activities. Conducted in 3rd and 4th grade science classes, the study focuses on the interdisciplinary application of this method. Science courses were selected due to their relevance to interdisciplinary topics such as climate change and environmental issues, ensuring alignment with current curricula. A quasi-experimental design with a pretest/posttest control group was employed, involving 60 students and 30 their parents from a science and art center in the Aegean Region of Turkey. The data collection tools included an "Awareness Questionnaire" to assess students' awareness of climate change and an "Achievement Test" to evaluate their academic achievement. Participants were divided into three groups: an experimental group using unplugged coding activities without parental involvement, a second experimental group where activities were supported by parental involvement, and a control group engaged in a video-based educational activities. The results show unplugged coding activities improved students' climate change awareness and achievement compared to the video-based activities. Moreover, parental involvement significantly enhanced both awareness and academic achievement. These findings highlight parental involvement's critical role in innovative teaching. Furthermore, students in unplugged coding activities exhibited higher levels of awareness and achievement than the control group. This suggests unplugged coding, especially with parental support, can be effective across disciplines like science, mathematics, social sciences, and arts.

Keywords: Unplugged coding, interdisciplinary pedagogy, parental involvement, awareness, academic achievement.

Introduction

Among 21st century skills, computational thinking stands out as an important tool in developing individuals' ability to generate solutions to problems, think creatively, and analyze critically (Wing, 2006; Guggemos, Seufert, & Román-González, 2023). Unplugged coding, a method for developing this skill, is considered as an effective pedagogical approach in environments where access to digital tools is limited (Bell & Vahrenhold, 2018). Unplugged coding, which is based on physical activities, enables students to learn programming concepts such as sequencing, loops, conditional statements, and algorithms in a concrete way, while also supporting 21st century skills such as collaboration, problem solving, and critical thinking (Dağ, Şumuer, & Durdu, 2023; Threekunprapa & Yasri, 2020).

Interdisciplinary approach is an educational and research approach that aims to address complex problems in a more comprehensive way by bringing together the knowledge, methods and perspectives of more than one discipline (Tonbuloğlu & Tonbuloğlu, 2019). One of the areas that can be subject to interdisciplinary approaches is current and complex problems such as climate change. Climate change draws attention as a field where many different disciplines come together due to its nature. This issue, which can be associated with various disciplines such as science, mathematics, social sciences and arts, offers opportunities for students to develop both awareness and solution-oriented thinking skills. However, effective teaching of this complex structure requires innovative and interdisciplinary approaches (Markowitz et al., 2018; Tonbuloğlu & Tonbuloğlu, 2019). In this context, the unplugged-coding method for developing computational thinking skills is considered as an effective tool that can contribute to students' understanding of such interdisciplinary issues and to the process of making more careful decisions about these problems. While unplugged-coding activities enable the development of computational thinking skills without the need for digital devices, they also facilitate students' understanding of concepts in different disciplines (Bell & Vahrenhold, 2018; Dağ, Şumuer, & Durdu, 2023). This pedagogical approach supports students to have not only theoretical knowledge but also skills such as problem solving, critical thinking and awareness development in interdisciplinary subjects such as climate change and environmental education (Tonbuloğlu & Tonbuloğlu, 2019; Wing, 2006). However, it is possible for students' gains in this process to be more effective and permanent with the inclusion of parent in the process (Pınar & Yakışan, 2018). In addition to

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increasing students' motivation in the education process, parent involvement plays an important role as a supportive element in applying what they have learned in real life (Erbaş, 2023).

The aim of this study is to examine the impact of unplugged coding activities as an interdisciplinary teaching tool on improving students' awareness and achievement, while explores the critical role of parental involvement in enhancing the effectiveness of these activities. To achieve this, the following research problems are addressed:

1. Is there a significant difference in awareness scores among the unplugged coding group, the parent-supported unplugged-coding group, and the video-based activity group?
2. Is there a significant difference in achievement scores among the unplugged coding group, the parent-supported unplugged-coding group, and the video-based activity group?
3. Is there a significant difference between parents' pre-test and post-test awareness scores in the parent-supported unplugged-coding group?

Methodology

This study employed a quasi-experimental design with a pretest-posttest control group. A quasi-experimental design, similar to a true experimental design, aims to establish a cause-and-effect relationship between independent and dependent variables. However, in quasi-experimental designs, the groups involved are pre-existing rather than randomly assigned (Büyüköztürk et al., 2019).

Participants

The study included a total of 60 fourth-grade students attending a Science and Art Center in the Aegean Region of Turkey. These students were divided into three groups, each consisting of 20 participants. The first experimental group (EG1), which received unplugged coding-supported education, was composed of 20 students, including 11 males and 9 females. The second experimental group (EG2), which participated in unplugged coding activities supported by parental involvement, also consisted of 20 students, with 12 males and 8 females. Also, their parents in EG2 with 30 person is our participants for this study. Lastly, the control group (CG), which continued with the existing education program using video-based textbooks, comprised 20 students evenly distributed as 10 males and 10 females.

Data Collection Process

The data collection process in this study was carried out through a structured workshop program focusing on climate change and unplugged coding activities. The program lasted for nine weeks, during which pre-test and post-test assessments were conducted to evaluate participants' awareness and achievement related to the topics covered.

In the first week, the workshop plan was introduced to participants, and pre-tests, including the "Awareness Questionnaire" and the "Achievement Test," were administered. The second week focused on introducing unplugged coding and the concept of algorithms. In the third and fourth weeks, students worked on solving problems related to water and electricity conservation through coding activities centered on algorithms. During the fifth week, the concept of variables was introduced, allowing students to explore the variables found in nature. In the sixth week, students were taught conditional structures and applied this knowledge by classifying waste into different types. The seventh week involved learning about loops, with activities focused on calculating average temperature data and greenhouse gas emissions. In the eighth week, students were introduced to functions and worked on developing a project called the "Environmental Robot Activity." Finally, in the ninth week, post-tests were conducted to reassess participants' awareness and achievement using the same instruments as in the pre-test phase.

This structured process aimed to evaluate the impact of unplugged coding activities on students' awareness and achievement, as well as the effectiveness of integrating these activities into climate change topics.

Results

The results of the study were analyzed in line with the research questions, and presented accordingly.

Results of the First Research Question

The first research question aimed to determine whether there was a significant difference between the pre-test and post-test scores of the climate change awareness test for experimental and control group students (Table 1).

Table 1: Kruskal-Wallis test results on awareness scores

Tests	Group	n	Mean Rank	χ^2	p
Awareness Pre-test	EG1	20	29.75	.824	.670
	EG2	20	31.57		
	CG	20	26.72		
Awareness Post-test	EG1	20	29.06	19.811	.001*
	EG2	20	40.39		
	CG	20	16.64		

According to Table 1, the results regarding the first research question indicate that there was no significant difference in the pre-test awareness scores of climate change among the students in EG1 (unplugged coding activities), EG2 (parent-supported unplugged coding activities), and the CG (video-based activity) [$\chi^2 = .824$; $p = .670$; $p > 0.05$]. However, the post-test results revealed a significant difference in awareness scores among the groups [$\chi^2 = 19.811$; $p = .001$; $p < 0.05$]. These results suggest that while the groups had similar levels of awareness at the beginning, the interventions, particularly in the experimental groups, resulted in significant improvements in awareness.

Furthermore, the results of the Mann-Whitney U Test, presented in Table 2, were used to evaluate whether there was a statistically significant difference between the experimental and control groups in terms of awareness scores.

Table 2: Mann-Whitney U test results on post-awareness scores

Groups	n	Mean Rank	Sum of Ranks	U	*p*
EG1	20	16.19	291.50	120.50	.033*
EG2	20	24.02	528.50		
EG1	20	22.36	402.50	92.50	.027*
CG	20	14.64	263.50		
EG2	20	27.86	613.00	36.00	.001*
CG	20	11.50	207.00		

According to Table 2, significant differences were found in the total post-test climate change awareness scores. EG2, which participated in parent-supported unplugged coding education workshops, outperformed EG1 ($U = 120.00$; $p = 0.033$) and the CG ($U = 36.000$; $p = 0.001$). Similarly, EG1, which engaged in unplugged coding-based education, showed significantly higher scores than the CG ($U = 92.500$; $p = 0.027$). These results highlight the effectiveness of both interventions, particularly those with parental support, in enhancing climate change awareness.

Results of the Second Research Question

The second research question aimed to determine whether there was a significant difference between the pre-test and post-test scores of the climate change achievement scores for experimental and control group students (Table 3).

Table 3: Kruskal-Wallis test results on achievement scores

Tests	Group	n	Mean Rank	χ^2	p
Achievement Pre-test	EG1	20	40.75	.640	.320
	EG2	20	51.72		
	CG	20	30.57		
Achievement Post-test	EG1	20	54.06	22.81	.001*
	EG2	20	65.38		
	CG	20	31.64		

According to Table 3, the Kruskal-Wallis test showed no significant difference in the total pre-test scores of the climate change awareness scale among EG1, EG2, and the CG [$\chi^2 = 0.640$; $p = 0.320$; $p > 0.05$]. However, a significant difference was found in the total post-test scores [$\chi^2 = 22.81$; $p = 0.001$; $p < 0.05$], indicating that the interventions effectively enhanced climate change achievement scores in the experimental groups compared to the control group.

Furthermore, the results of the Mann-Whitney U Test, presented in Table 4, were used to evaluate whether there was a statistically significant difference between the experimental and control groups in terms of achievement scores.

Table 4: Mann-Whitney U test results on post-achievement scores

Groups	n	Mean Rank	Sum of Ranks	U	*p*
EG1	20	16.19	291.50	120.50	.033*
EG2	20	24.02	528.50		
EG1	20	22.36	402.50	92.50	.027*
CG	20	14.64	263.50		
EG2	20	27.86	613.00	36.00	.001*
CG	20	11.50	207.00		

Table 4 shows significant differences in post- achievement test scores. EG2, which received parent-supported unplugged coding education, outperformed EG1 (U = 130.500; p = 0.038) and the CG (U = 54.000; p = 0.001). EG1 also outperformed the CG (U = 98.500; p = 0.032), highlighting the effectiveness of both interventions, particularly those with parental support.

Results of the Third Research Question

The third research question aimed to examine whether parent-supported unplugged coding activities have a significant impact on parents' climate change awareness levels, with the results presented in Table 5.

Table 5: Paired Sample t-test awareness results of parents in EG2

Test	n	X	S	t	df	p
Pre-test on awareness	30	60.33	5.855	17.65	29	.001
Post-test on awareness	30	95.28	7.703			

The results of the Paired Samples t-test presented in Table 5 indicate a significant increase in the climate change awareness levels of parents who participated in parent-supported unplugged coding activities alongside their children. The pre-test mean score of parents' climate change awareness was (X=60.33), while the post-test mean score increased to (X=95.28), demonstrating a statistically significant improvement ($t(29) = 17.65, p<.05$). This finding suggests that the unplugged coding activities, which involved both students and their parents engaging in coding-related tasks at home, contributed to a substantial enhancement in parents' awareness of climate change. This finding indicates that these parent-supported activities not only enhanced students' environmental awareness but also significantly improved parents' understanding of interdisciplinary issues like climate change, fostering greater knowledge and sensitivity toward such global challenges.

Conclusions

Given the interdisciplinary pedagogical framework of this study, climate change was chosen as the central topic to explore the nature of unplugged coding activities in fostering awareness and understanding of global issues. After treatment based on Climate Change topics, the analysis of the post-test scores from the Awareness Questionnaire and the Achievement Test revealed significant differences among the groups. Both experimental groups, namely the group that participated in unplugged coding activities (EG1) and the group that engaged in parent-supported unplugged coding activities (EG2), showed higher total post-test scores compared to the control group that followed a video-based activities. Notably, the students in EG2 achieved significantly higher scores in both awareness and achievement tests compared to the other two groups. Similarly, students in EG1 performed better than those in the control group in both tests. The findings suggest that unplugged coding activities have a significant positive impact on students' awareness and academic achievement regarding interdisciplinary topics. Moreover, parent-supported unplugged coding activities further enhance these outcomes, demonstrating the critical role of parental involvement in maximizing the educational benefits of such pedagogical approaches.

The study supports the conclusion that unplugged coding activities enhance participation and motivation, especially among younger students (Dağ, Şumuer & Durdu, 2023). These activities also promote active participation, leading to more meaningful and positive attitudes toward learning (Nishida et al., 2008). Including parents in such educational interventions further strengthens these effects, as it encourages collaborative learning and fosters sustainable behavioral changes in both students and parents (Erbaş, 2023). Therefore, parent-supported

unplugged coding emerges as a highly effective approach for addressing complex and interdisciplinary subjects such as climate change. Morever, the findings suggest that parent-supported unplugged coding activities significantly enhance awareness of interdisciplinary topics. Activities conducted at home with parent involvement not only benefit students but also positively impact parents' awareness on the topic. These results highlight the potential of integrating parent-based activities into educational policies to support learning beyond the classroom and foster broader engagement in interdisciplinary subjects.

In conclusion, these outcomes emphasize the importance of parent involvement in the educational process and highlight the potential for out-of-school activities, such as parent-oriented projects, to enhance learning outcomes. This allows education systems to be developed in a more innovative and inclusive way. As a result, these findings offer valuable insights for educational policymakers, particularly regarding the design and implementation of strategies that support home-based collaborative learning activities. Encouraging interdisciplinary approaches with unplugged coding could lead to more holistic and impactful educational experiences for both students and their parent.

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Conceptualizing Collaboration with Generative AI Across Theoretical Traditions

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Abstract

Generative artificial intelligence (GenAI) is increasingly described as a collaborator, partner, or co-creator in educational research and practice. The terminology now appears in empirical studies, usage categories, and measures of human–AI activity, which gives the label analytical consequences. This conceptual study examines what happens when established theories of collaboration are applied to human–GenAI interaction. Three accounts are compared: Roschelle and Teasley's (1995) Joint Problem Space (JPS), Bedwell et al.'s (2012) multilevel conceptualization of collaboration, and Tomasello et al.'s (2005) account of shared intentionality. The analysis examines each account's stated requirements, its treatment of participants, and the implications of extending its terms to artificial systems. Source-defined requirements are distinguished from the inferences made in applying the theories to GenAI. The comparison shows that direct AI contribution and interactional richness do not, on their own, settle whether an activity qualifies as collaboration. Roschelle and Teasley's (1995) account directs attention to the construction and maintenance of a shared conception of a problem, but leaves open when a computational mediator becomes a participant. Bedwell et al.'s (2012) definition requires an account of GenAI as a social entity and evidence of a mutually agreed or defined shared goal. Applying Tomasello et al.'s (2005) account requires justification for admitting an artificial participant and for attributing shared commitments, mutual knowledge, and the relevant motivational structure. The study identifies theory-specific questions that researchers must address when claiming human–AI collaboration and distinguishes evidence of interactional processes from assumptions about the status of participants.

Keywords: human–AI collaboration; generative AI in education; Joint Problem Space; shared intentionality; construct validity

Introduction

Educational researchers use collaboration to describe different aspects of human–GenAI activity. Nguyen et al. (2024) examine patterns in AI-assisted doctoral writing, while Sidra and Mason (2026) develop measures of collaborative AI literacy and metacognition. The shared terminology does not mean that these studies examine the same construct. Writing with a system, responding to its feedback, and producing a document may count differently depending on how collaboration is defined. Türkmen Çiçek and Tüfekci Can (2026), for example, use human–AI collaboration in their account of vocational writing while describing AI as a mediating agent that provides feedback and scaffolded practice. This use illustrates why the role assigned to AI needs to be specified.

This study compares Roschelle and Teasley's (1995) Joint Problem Space, Bedwell et al.'s (2012) integrative definition, and Tomasello et al.'s (2005) shared intentionality. Each account specifies conditions for collaborative activity. Applying these conditions to GenAI raises questions about whether a system can occupy a role originally examined through human interaction. It also creates a risk of changing the construct by substituting a convenient indicator for a defining requirement. Bedwell et al. describe the related problems of construct contamination and construct deficiency. The concern here is whether a claim about human–GenAI collaboration preserves the requirements of the account on which it relies.

Cukurova (2026) addresses this problem within the collaborative-learning tradition and distinguishes collaboration from other forms of teaming. The present study compares accounts from different traditions. It asks what each requires of the interaction and its participants, and what further justification is needed when one proposed participant is a GenAI system. The accounts are considered separately because an observation that supports one interpretation of collaboration may be insufficient for another.

Methodology

The study uses comparative conceptual analysis of primary theoretical texts. Jaakkola (2020) argues that conceptual research should explain why particular theories were selected and how they inform the argument. Roschelle and Teasley (1995) were selected for their treatment of shared problem construction, Bedwell et al. (2012) for their multidisciplinary definition, and Tomasello et al. (2005) for their explanation of the intentions and

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motivation involved in collaborative activity. The comparison examines these differences without assuming that the authors intended their accounts to classify GenAI.

Each text was examined for its stated requirements, its treatment of participants, and the implications of applying it to GenAI. Page references document the basis for the interpretation. In Table 1, STATED marks a claim made in the source, and INFERENCE marks an implication drawn in this paper. This distinction matters where an author does not address artificial participation. Silence on that question cannot establish either permission to include GenAI or a rule excluding it.

The analysis distinguishes evidence about the interaction from assumptions about who can participate. An exchange may display the processes described by a theory while leaving the status of the artificial participant unresolved. Extending a construct to additional participants need not change its meaning, but researchers must explain why the proposed participants can satisfy its requirements. This paper examines those requirements in the theoretical texts. It does not classify recorded interactions or assess the capabilities of particular models.

The selection has limits. Dillenbourg (1999) directly discusses artificial agents and examines collaborative situations, interactions, learning mechanisms, and effects. His framework also considers symmetry, common goals, and negotiability (author manuscript, pp. 6–8, 12–13). It would require separate treatment because these criteria connect several levels of analysis. The present paper confines detailed comparison to the three selected accounts. Omitting Dillenbourg limits what it can conclude about the broader collaboration literature.

Theoretical comparison

The Joint Problem Space

Roschelle and Teasley (1995) describe collaboration as a continuing, coordinated effort to construct and maintain a shared conception of a problem (p. 70). They distinguish this activity from cooperation through the organization of the work. Dividing a task among participants does not, on its own, establish mutual engagement in problem solving. Although their working definition includes synchrony, they do not rule out asynchronous collaboration (p. 70). Synchrony should therefore not be treated as a universal requirement.

The Joint Problem Space consists of goals, descriptions of the current problem state, available actions, and relations among them (Roschelle & Teasley, 1995, pp. 70–71). Participants develop this space through their contributions and their responses to one another. They identify differences in understanding and repair them sufficiently for the work to continue. Mutual intelligibility does not require identical private representations (pp. 75–78). Evidence for this account can therefore be found in how participants organize their problem solving; it need not meet the stronger intentional requirements of Tomasello et al.

Applied to GenAI, this account would direct attention to changes in the understanding of the problem. Researchers could examine how a contribution changes the problem representation and whether later work incorporates that change. A correction matters when it affects what follows. These are proposed applications of Roschelle and Teasley's requirements. The amount of generated text or the fluency of a response would not establish on its own whether a Joint Problem Space was being constructed and maintained.

The question of participation remains. In the original study, the students collaborate, while the Envisioning Machine mediates their activity (Roschelle & Teasley, 1995, p. 95). The computer influences the work without being treated as one of the collaborators. GenAI complicates this distinction because its generated contributions enter the verbal exchange. Roschelle and Teasley do not specify when such a resource becomes a participant. Researchers who regard sustained contribution to problem construction as sufficient for participation need to explain that interpretation. The source leaves the question open.

An integrative definition of collaboration

Bedwell et al. (2012) define collaboration as an evolving process in which two or more social entities engage actively and reciprocally in joint activity toward at least one shared goal (p. 130). Their definition concerns how the activity unfolds. Contributions may be unequal, but producing something together does not establish that the process was collaborative. At least one goal must also be mutually agreed or mutually defined (p. 134). This requirement calls for more than an interaction organized around one party's instructions.

The difficulty concerns what counts as a social entity. Bedwell et al. (2012, p. 130) specify human individuals and collectives, including teams, departments, and organizations. A reading restricted to those categories would exclude GenAI. An open reading treats the passage as describing the source's human setting while leaving artificial participation undecided. That interpretation is an inference made in extending the account, not an explicit position

taken by the authors. The comparison considers both readings because the article does not directly address whether an artificial system could qualify.

Nass et al. (1994) show that people can respond socially to computers. These responses do not establish that a computer is a social entity in Bedwell et al.'s sense. Nor does a social response demonstrate that a goal has been mutually defined. Placani's (2024) discussion of anthropomorphism cautions against attributing human properties to AI through familiar descriptions. How users respond to a system and whether it meets a theoretical participant requirement are separate questions. Öksüz Gül (2025) found that students interpreted ChatGPT as a peer, group member, or teacher-like presence during course activities. These perceptions are relevant to how users experience AI-supported interaction, but they do not establish that the system meets Bedwell et al.'s participant requirement.

Even under an open reading of social entity, the shared-goal requirement needs explanation. A system may produce an answer consistent with a learner's objective. That consistency does not establish how the objective became mutually agreed or defined. A study using Bedwell et al. would need to state what counts as mutual definition between these participants and show evidence of it. The authors' distinction between coordination and collaboration helps explain the issue. Coordination can involve nonsocial resources and need not be reciprocal (p. 135). Organizing a workflow effectively is therefore insufficient to establish collaboration under their definition. Reciprocal adjustment provides further evidence, but the participant and goal requirements still have to be addressed.

Shared intentionality

Tomasello et al. (2005) develop their account of shared intentionality through an evolutionary and developmental comparison of humans and other species, particularly great apes (pp. 675–676). Their claim that the capacity is distinctively human belongs to this comparison. Artificial systems are not assessed as prospective participants. The claim therefore cannot, by itself, establish that GenAI is excluded. Applying the account to GenAI nevertheless requires an argument that the source does not supply.

A goal, in this account, is an internal representation that guides action (Tomasello et al., 2005, p. 676). Collaborative activity involves a shared goal or commitment, coordinated roles, and intentions that incorporate the other's participation (p. 680). Mutual knowledge or joint attention and motivation to share psychological states also matter (p. 681). An externally observed result that advances a human's objective is insufficient evidence for these relations.

The account can be examined conditionally by first allowing an artificial participant and then asking what evidence would establish shared intentionality. This is a proposal made in the present analysis. Contingent responses and repair may be relevant, but an interpretation would still need to explain how those observations support the attribution of intentions or commitments. Describing a response as agreement does not settle the question. First-person-plural language likewise cannot establish that the participants share intentions.

Applying Tomasello et al. thus requires justification for admitting the artificial participant and for attributing the intentional relations described in the theory. Neither the claim of human distinctiveness nor successful coordination settles both issues. The task is to explain how observations warrant the interpretation being made. This need not require direct access to private mental states, but it does require evidence suited to the claim. Changes in a shared problem representation may support Roschelle and Teasley's account while leaving shared intentionality unestablished.

Comparative findings

Goals illustrate an important difference among the accounts. A goal is one element of a Joint Problem Space. Bedwell et al. require a goal that is mutually agreed or defined, while Tomasello et al. place it within a relation of shared intentionality. A single measure of goal alignment would obscure these differences. Table 1 presents the requirements alongside the questions raised by their application to GenAI.

Table 1. Source requirements and their application to GenAI

Account	Requirements and source scope STATED	Questions about GenAI INFERENCE
Joint Problem Space Roschelle and Teasley (1995)	Continued construction and maintenance of a shared conception of the problem; mutual engagement and repair (pp. 70–71, 75–78). Computer as mediator (p. 95).	When does a system become a participant in constructing the Joint Problem Space? Evidence about the interaction must be accompanied by an explanation of that role.

Account	Requirements and source scope STATED	Questions about GenAI INFERENCE
Integrative definition Bedwell et al. (2012)	Social entities (p. 130); active reciprocal, interdependent activity and at least one mutually agreed or defined goal (p. 134).	Can GenAI count as a social entity under the interpretation adopted? What shows that a goal is mutually defined, beyond consistency with a human objective?
Shared intentionality Tomasello et al. (2005)	Shared goals or commitments, coordinated roles, mutual knowledge, and motivation to share psychological states (pp. 680–681).	What justifies including an artificial participant? What evidence supports the attribution of shared intentionality? The claim of human distinctiveness does not explicitly decide these questions.

The comparison identifies different grounds for caution when calling human–GenAI activity collaboration. Roschelle and Teasley leave the distinction between a computational mediator and a participant unresolved. Bedwell et al. require an interpretation of social entity and an explanation of mutual goal definition. Tomasello et al. require evidence for shared-intentional relations under a justified extension to artificial participants. These conclusions concern the selected texts. A source's silence about artificial participation cannot establish that an observed system lacks the relevant capacities.

These questions do not remove the need to examine the interaction. Accepting GenAI as a possible participant would leave each account's process requirements in place. Showing those processes would not necessarily establish that GenAI qualifies as a participant. Both judgments need to be explained. Where the sources leave their relationship uncertain, researchers face a theoretical decision that should be stated openly. Treating that uncertainty as automatic failure, or leaving the decision implicit in a coding scheme, would obscure the basis of the classification.

Discussion and implications

The distinction matters when educational studies measure human–GenAI activity. Nguyen et al. (2024) analyze writing sequences, whereas Sidra and Mason (2026) develop measures of the skills used to manage human–AI work. Sidra and Mason allow asymmetric collaboration without attributing intentions, self-awareness, or shared mental models to the AI (p. 5085). Evidence that a measure captures these skills supports that interpretation. It does not also establish shared intentionality or demonstrate a mutually defined goal. Studies using the same term may consequently be measuring different aspects of the activity.

Researchers should choose indicators that reflect the account they use. Under Roschelle and Teasley, changes in the problem representation and the handling of differences in understanding are relevant evidence. A study drawing on Bedwell et al. needs to examine reciprocal interdependence and explain its interpretation of social entity and shared goal. Work using Tomasello et al. must show how observed conduct supports claims about intentions and commitments. Readers should be able to distinguish what the study observed from what it assumed about the participants.

For teaching and assessment, the question is also what the learner did. An instructor may need to establish who introduced a criterion, how the learner examined it, and whether it affected later reasoning. The label collaboration does not provide this information. Descriptions such as AI-assisted revision or AI-supported problem framing can specify the activity under examination. A claim of collaboration can then be evaluated against the chosen account, alongside evidence of the learner's contribution and understanding.

Limitations

The three accounts do not cover the whole collaboration literature. The comparison omits Dillenbourg (1999), who directly addresses artificial agents. Contemporary AI-specific definitions may also justify participation differently; this study does not rank them. Applying the comparison to recorded interaction would require further decisions about what constitutes evidence for the processes and relations described in each account.

Conclusions

The justification for calling human–GenAI activity collaboration depends on the theory being used. Evidence of shared problem construction addresses different requirements from evidence of a mutually defined goal or shared intentionality. Researchers need to explain why an artificial system can occupy the proposed role and how the interaction meets the relevant requirements. The comparison leaves the classification of particular interactions open. It establishes the questions that an analysis must address before drawing that conclusion.

Statement on the use of generative AI

ChatGPT was used to help draft and shorten the manuscript, check sources, and revise wording. The author is responsible for verifying the references and approving the final analysis and text.

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Experiential Learning Through VR-Supported Earthquake and Emergency Evacuation: Implications for Open and Distance Learning

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Abstract

Disaster education requires more than theoretical knowledge: learners must also interpret hazardous situations, consider appropriate responses and recognise the need for preparedness. Since earthquakes and emergency evacuations cannot be recreated as authentic disasters for educational purposes, virtual reality (VR) may provide opportunities for experiential learning. This study examined how university students interpreted a VR-supported earthquake and evacuation scenario and considered its implications for open and distance learning. The study followed a mixed-methods, one-group pre-test–post-test design, with qualitative interpretation at its centre. Twenty-four third- and fourth-year undergraduate students (12 from Architecture and 12 from Education) completed open-ended questions before and after individually experiencing a VR scenario involving spatial hazards, safe behaviours and evacuation. Responses were examined through reflexive thematic analysis, and theme frequencies were reported descriptively. Six themes were identified: experiential learning, realism and empathy, disaster awareness and emergency evacuation literacy, perceived lasting learning, behavioural preparedness, and perceived educational effectiveness. Mentions of disaster awareness increased from 12/24 (50.0%) to 20/24 (83.3%), behavioural preparedness from 8/24 (33.3%) to 15/24 (62.5%), and perceived lasting learning from 4/24 (16.7%) to 14/24 (58.3%). Architecture students highlighted spatial realism, while Education students more often emphasised learning and teaching. Participants' immediate reflections became more experience-based and behaviour-oriented. These findings concern reported perceptions, not verified long-term retention or observed behavioural change. VR may complement disaster education and inform the design of interactive open and distance learning activities.

Keywords: virtual reality, earthquake simulation, emergency evacuation, experiential learning, disaster education, open and distance learning

Introduction

Reducing disaster-related losses depends not only on physical measures but also on individuals' awareness of risks, preparedness and ability to consider safe actions. Disaster risk reduction frameworks emphasise preparation before disasters and appropriate decisions during emergencies (United Nations Office for Disaster Risk Reduction [UNDRR], 2015). Although lectures, visual materials and drills can communicate important information, it is difficult to reproduce the uncertainty and spatial demands of an earthquake within conventional instruction. Accordingly, the educational challenge is to help learners connect what they know with how they might interpret and respond to a hazardous situation.

Experiential learning provides a relevant perspective on this challenge. Kolb (1984) conceptualised learning as a cycle involving concrete experience, reflective observation, abstract conceptualisation and active experimentation. From this perspective, encountering a situation, reflecting on it and relating it to prior knowledge can support meaning-making. In disaster education, the actual event cannot be intentionally provided as a learning experience. Simulated experiences may nevertheless give learners a context for examining risks and evaluating possible responses without exposure to the hazards of a real disaster.

VR offers three-dimensional, interactive environments through which learners may engage with scenarios that would otherwise be difficult or unsafe to experience. Research on VR in education has discussed its potential for immersion, interaction and active participation (Luo et al., 2021; Radianti et al., 2020). Within disaster-related education, reviews and applications have considered how simulated earthquakes, evacuation situations and other emergencies might support awareness and preparedness (Alshowair et al., 2024; Brown et al., 2023; Feng et al., 2018; Feng et al., 2020). Such work does not mean that a simulation duplicates the physical and psychological conditions of a disaster; rather, it suggests a possible complementary learning setting.

Open and distance learning can extend access to educational content, but experience-intensive topics present particular challenges when students and instructors are not in the same physical space. Reviews of augmented and

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virtual reality in remote higher education identify immersive technologies as potential resources for such contexts (Nesenbergs et al., 2021). Their educational contribution, however, depends on learning design and access to the technology. The present study did not test a distance learning course: it examined students' perceptions of an individual VR experience and considered possible implications for future integration into remote learning environments.

The study also considered disciplinary perspectives. Architecture students may attend to spatial organisation and environmental conditions, whereas Education students may focus on how an experience contributes to learning and instruction. The purpose was therefore to examine pre- and post-experience reflections on disaster awareness, emergency evacuation, perceived preparedness and technology-supported learning, and to compare the emphases of students from the two faculties.

This disciplinary comparison was intended to provide different perspectives on a shared experience rather than establish that one faculty gained more from VR. For Architecture students, recognising spatial hazards and considering the physical environment may be especially salient when interpreting an earthquake setting. For Education students, the process by which an unusual experience can become meaningful and memorable may draw attention to instructional possibilities. Examining both groups within one study therefore creates an opportunity to consider how the same technology-supported scenario is interpreted through different learning concerns. These expectations informed the rationale for comparison; the actual findings were developed from participants' responses.

Methodology

Research design and participants

The study adopted a mixed-methods approach with a single-group pre-test–post-test design. Its central evidence consisted of participants' written responses to open-ended questions; participant counts and percentages were used to describe how often particular themes appeared before and after the VR experience. The study thus emphasised interpretation of perceptions rather than a standardised measurement of knowledge or performance. No comparison or control group was included, and the VR experience was not designed as a complete instructional programme.

The study group comprised 24 volunteer undergraduate students from a state university, selected using convenience sampling: 12 students from Architecture and 12 from Education faculties. The participants were in their third or fourth year of study. Their identities were kept confidential during analysis, and code numbers were assigned to responses. Both faculty groups completed the same pre-experience, VR and post-experience sequence.

Data collection and VR experience

The researchers developed pre-test and post-test forms containing open-ended questions about earthquake awareness, emergency evacuation, VR-based experiential learning and the perceived contribution of technology-supported experiences. In the first stage, participants described their existing ideas about earthquakes, evacuation behaviours and the possible educational value of VR. This provided a record of their expectations and prior reflections before the scenario.

In the second stage, students individually experienced a VR-based earthquake and emergency evacuation scenario. The virtual environment allowed participants to notice spatial and environmental risks, consider safe behaviours and experience the evacuation process. Its purpose was not to deliver a structured lesson with explicitly taught outcomes, but to make an otherwise difficult-to-experience disaster situation available within a controlled virtual setting. In the third stage, participants completed the post-test questions, describing their impressions of the experience, preparedness-related considerations and views about VR-supported learning. The resulting pre- and post-experience responses were compared at the thematic level.

Data analysis and trustworthiness

Open-ended responses were analysed according to the reflexive thematic analysis approach associated with Braun and Clarke (2021). The original analysis proceeded through repeated reading and familiarisation with the responses, identification of meaning units, inductive coding, development and review of candidate subthemes and themes, comparison of pre- and post-experience patterns, and interpretation supported by participant quotations. The researchers also compared thematic emphases across the Architecture and Education faculty groups. Coding and theme development were intended to reflect recurring patterns of meaning in the data rather than predetermined response categories.

For descriptive presentation, the number and percentage of participants whose statements contributed to each theme were calculated. A response could contribute to several themes; accordingly, the percentages in the tables are not mutually exclusive and are not expected to total 100%. Frequency differences are presented in percentage points, not as statistical significance tests or causal effect estimates. To support credibility and the transparency of interpretation, the original study compared both sets of responses, considered differing perspectives and linked its thematic interpretations to participant statements (Lincoln & Guba, 1985).

The approach to research quality described in the original manuscript focused on the connection between the dataset, the researchers' interpretations and the developed themes. During coding, comments representing different experiences were considered alongside recurrent statements so that the analysis did not rely exclusively on favourable descriptions of VR. Illustrative quotations were then used to show how participants expressed the themes. This is important because a theme frequency alone cannot explain what participants meant by an experience: the numbers provide an overview of occurrence, while the quotations show how meanings shifted from anticipation to retrospective appraisal. The analysis remains interpretive, and the descriptive counts are not substitutes for independent behavioural or achievement measures.

Results

Six main themes emerged from the comparative analysis: experiential learning; realism and empathy; disaster awareness and emergency evacuation literacy; perceived lasting learning; behavioural preparedness; and the perceived educational effectiveness of VR. The original report also recorded a separate category concerning VR limitations. Table 1 gives the overall distribution. These figures indicate the frequency with which a theme was expressed in written responses, not how many participants objectively attained a skill.

The original theme structure included several related subthemes. Experiential learning covered learning through experience, the perceived need for experience and practical learning; realism and empathy included realism and immersion; and disaster awareness encompassed risk perception, becoming aware and recognising appropriate responses. Perceived lasting learning concerned memorability and expectations of retention. Behavioural preparedness included intentions to take precautions and awareness of safe actions, while the educational-value theme brought together perceived instructional contribution, technology integration and motivation. Presenting these subthemes clarifies why the categories include a variety of statements rather than a single fixed-response measure.

Table 1. Pre-test and post-test theme frequencies across all participants (n = 24).

Theme	Pre-test n (%)	Post-test n (%)	Change (pp)
Experiential learning	12 (50.0)	18 (75.0)	+25.0
Realism and empathy	12 (50.0)	16 (66.7)	+16.7
Disaster awareness	12 (50.0)	20 (83.3)	+33.3
Behavioural preparedness	8 (33.3)	15 (62.5)	+29.2
Perceived educational value of VR	19 (79.2)	22 (91.7)	+12.5
Perceived lasting learning	4 (16.7)	14 (58.3)	+41.6
VR limitations	0 (0.0)	2 (8.3)	+8.3

Experiential learning

Before VR, participants tended to discuss experiencing a disaster as a desired or potentially useful way of learning. One pre-test comment stated, "It would not be the same without experiencing it," while another suggested that a simulation that conveyed the moment might be effective. In the post-test, references were based on their encounter with the virtual scenario: "It almost feels as though you have experienced it" and "Things experienced are learned more quickly." The theme appeared in 12 responses (50.0%) before VR and 18 (75.0%) afterwards. The pattern shows a move from general expectations about experience to descriptions of a particular simulated event; it does not independently establish learning gains.

The distinction between expectation and description is notable here. Prior to the simulation, students were reasoning about what an experience might offer; afterwards, they could refer to sensations and impressions from a shared scenario. Thus the contribution of this theme lies primarily in how participants articulated the experience. Their comments are compatible with experiential learning as a way of constructing meaning, while leaving open the question of how well specific knowledge was subsequently recalled or applied.

Realism and empathy

Perceived realism featured in both phases. Following VR, students described the scenario as "quite realistic" and said that it "really gave the feeling of experiencing an earthquake". At the same time, not all reactions were affirmative: comments included "I could not feel it as a real earthquake" and "It does not fully reflect the real atmosphere". The occurrence of the realism-and-empathy theme increased from 12 (50.0%) to 16 (66.7%). These contrasting perceptions suggest that participants recognised immersion as a feature of VR while also noticing the limits of reproducing an actual earthquake. The available quotations primarily illustrate realism; they should not be taken as a separate demonstrated increase in empathy.

These contrasting remarks were retained because the original analysis did not portray virtual realism as uniform across all learners. The scenario could provide a convincing sense of being present for some participants and still fall short of the felt conditions of a real emergency for others. The category is therefore most appropriately treated as an account of perceived realism and the limits of simulation, rather than an objective evaluation of the technological fidelity of the VR system.

Disaster awareness and emergency evacuation literacy

Before the experience, awareness was typically described in general terms, for example, "It raises people's awareness" and "It helps us understand earthquakes better". Afterwards, participants' responses referred to more specific considerations: "I learned what should be done before an earthquake", "I realised the importance of securing belongings" and "I understood that I needed to be prepared". References to disaster awareness increased from 12 (50.0%) to 20 (83.3%). This difference supports the interpretation that risks and precautions became more explicit in students' reflections. It does not verify that appropriate evacuation decisions would be made during a real emergency.

The specificity of these comments is important for the emergency evacuation literacy focus of the study. Instead of speaking only about the value of awareness in general, some students connected the event to concrete preparations that should be considered before an earthquake. The data support a change in the content of their stated considerations. Since the questionnaire was completed immediately after the simulation, however, whether these considerations became sustained practices cannot be determined.

Perceived lasting learning

The largest percentage-point difference in Table 1 was observed for the theme originally labelled lasting learning: from 4 participants (16.7%) to 14 (58.3%). The post-test included comments translated as "I will never forget it for the rest of my life", "It is more memorable" and "Learning through experience is more effective". Before VR, similar claims tended to express expectations; after VR, students described the recently completed experience as memorable. Since there was no delayed assessment or retention measure, this is more precisely interpreted as perceived memorability or anticipated lasting learning rather than evidence of long-term retention.

Behavioural preparedness

References to behavioural preparedness increased from 8 (33.3%) to 15 (62.5%). Students mentioned securing items, considering an evacuation plan, taking precautions and being ready for an earthquake. One wrote, "I will make more careful plans", while another stated, "I learned that belongings should be secured". These statements indicate greater attention to possible protective actions and, in some cases, intentions to prepare. The study did not observe later preparation activities or actual responses to an emergency, so the result concerns reported preparedness-related thinking, not verified behavioural change.

Perceived educational effectiveness of VR

Before the experience, VR was frequently described hypothetically as a method that "could be effective" or "would be interesting". Afterwards, participants commented, "VR was very effective", "It made me experience a real environment" and "Being personally involved in the event makes learning easier". Mentions of the perceived educational value of VR increased from 19 (79.2%) to 22 (91.7%). The shift from hypothetical evaluations to reports grounded in the experience is central to the study. Two students also mentioned limitations of VR in the post-test, indicating that favourable views did not exclude critical appraisal.

Comparison between faculties

Both groups reported the themes of experience, realism, awareness and perceived learning. Their emphases nevertheless differed in the original qualitative interpretation. Architecture students more often referred to spatial realism, physical atmosphere, environmental risks and relationships between the built environment and the

experience; Education students more often considered learning processes, memorability, instructional methods and prospective behavioural responses. Table 2 retains the faculty-level counts reported in the original paper; given the small groups, these differences are descriptive and were not tested for statistical significance.

Table 2. Faculty-level counts of participants mentioning each theme (12 in each faculty).

Theme	Architecture pre → post	Education pre → post
Experiential learning	5 → 9	7 → 9
Realism and empathy	5 → 8	7 → 8
Disaster awareness	6 → 10	6 → 10
Behavioural preparedness	3 → 7	5 → 8
Perceived educational value of VR	9 → 11	10 → 11
Perceived lasting learning	2 → 6	2 → 8

The faculty-level distribution places this interpretation in context. In both groups, disaster awareness was mentioned by six students before VR and ten afterwards. Mentions of experiential learning reached nine students in each faculty after the experience. The perceived lasting-learning category was recorded for six Architecture students and eight Education students in the post-test, compared with two in each group before VR. One student in each group mentioned VR limitations after the scenario (none before). These numbers do not by themselves explain why participants chose particular expressions or demonstrate a difference in learning effectiveness; they complement the qualitative observation that the two disciplinary groups attended to different aspects of the same scenario.

Discussion

Taken together, the pre- and post-experience responses suggest that a VR-supported earthquake and evacuation scenario helped participants formulate more concrete reflections on risks and preparedness. Before the scenario, they principally considered what simulations might offer; afterwards, they described the atmosphere, recalled particular precautions and evaluated the educational experience they had just completed. This pattern is consistent with the emphasis on experience and meaning-making in Kolb's (1984) framework, although the study did not directly test a complete experiential learning cycle.

The original report related the VR scenario to Kolb's four stages. First, concrete experience can be represented by encountering spatial hazards and evacuation circumstances in the virtual environment. Second, reflective observation is suggested by post-experience appraisals of realism, risks and safety-related considerations. Third, abstract conceptualisation may involve relating such reflections to principles of pre-disaster preparation, spatial safety and evacuation. Fourth, active experimentation is best understood here as thinking about prospective responses or expressing intentions to take precautions. The last two stages describe a pedagogical interpretation of the findings rather than stages whose successful completion was separately measured. The participants' statements do not demonstrate actual protective behaviour after the study.

Table 3 draws on the four-part mapping already proposed in the Turkish manuscript. It separates what the participants encountered or described from possible uses in an open and distance learning design. In particular, suggested online discussions or additional simulation activities are pedagogical possibilities, not activities evaluated during this study.

Table 3. Interpretive mapping of VR-supported experience to Kolb's learning cycle

Experiential learning stage	Connection to the VR experience	Potential open/distance learning use
Concrete experience	Experiencing a simulated earthquake and evacuation; noticing spatial hazards	Offering an experiential scenario when a real disaster cannot be reproduced
Reflective observation	Discussing realism, risks, precautions and one's impressions after the scenario	Supporting online reflection and discussion about safety-related choices
Abstract conceptualisation	Connecting those impressions to preparedness and evacuation principles	Relating theoretical learning materials to a remembered scenario
Active experimentation	Expressing intentions and considering possible safe responses	Using further simulations or exercises for prospective application

The findings also illustrate the boundaries of immersive disaster scenarios. While many participants reported a sense of realism, others said that the virtual environment could not fully reproduce the physical or psychological conditions of an earthquake. VR should therefore be framed as a complement to, rather than a replacement for,

other disaster education approaches. Similarly, an immediate statement that the experience will be unforgettable is an expression of perceived memorability, not proof of retained knowledge months later. These distinctions are especially important when translating learner perceptions into claims about educational effectiveness.

For open and distance learning, the principal implication is a possible instructional sequence, not a tested course model. A VR scenario could provide an experiential component alongside online information about preparedness, a subsequent reflective discussion of risks and choices, and activities relating the experience to evacuation principles. This is an interpretation based on the study's thematic findings and on the experiential learning framework; the research did not evaluate a fully online implementation. Access to compatible hardware, opportunities for participation and instructional support would need to be considered before such an approach could be adopted. The different emphases of Architecture and Education students also suggest the value of adapting reflective prompts to disciplinary learning goals.

Several limitations constrain interpretation. The sample comprised 24 volunteers from two faculties and was selected by convenience; the design involved only one group and one short-term experience. Results came primarily from open-ended self-reports and their descriptive thematic frequencies. No standardised achievement measure, delayed memory test, observation of subsequent disaster preparation or real-event behavioural assessment was reported. Consequently, neither causal effects of VR nor lasting learning or actual behaviour change can be established. Further research could examine diverse learner groups, delayed assessments and observed preparedness behaviours, as well as the feasibility of combining VR with online learning activities.

Conclusions

The VR-supported earthquake and emergency evacuation experience was associated with more detailed, experience-based participant reflections on disaster risks, preparedness and the potential educational value of simulation. The six themes, the overall frequency patterns and the faculty-level contrasts suggest that learners may interpret the same virtual scenario through different disciplinary concerns. The main contribution of the study is to describe these perceptions and to identify directions for incorporating experiential activities into open and distance learning. Its findings should be read as evidence about immediate perceptions and intentions, not as demonstrated long-term retention or behavioural change.

Declaration of Generative AI Use

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) for language refinement, improvement of academic clarity, and restructuring of manuscript sections to enhance coherence and readability. The authors critically reviewed and revised all AI-assisted suggestions and take full responsibility for the content and conclusions presented in this manuscript.

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From Reporting Guideline to Reporting Quality Instrument: Developing RAISE-QI for Artificial Intelligence Research in Education

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Abstract

The rapid growth of artificial intelligence (AI) in education has intensified the need for transparent and comprehensive reporting of empirical research. Inconsistent reporting of AI systems, pedagogical design, human involvement, ethical considerations, and evaluation methods limits reproducibility, hinders evidence synthesis, and reduces confidence in research findings. The Reporting AI Studies in Education (RAISE) framework was developed to improve reporting quality through 30 reporting recommendations spanning ten domains. Although RAISE provides structured guidance for reporting AI in education research, no corresponding instrument currently exists to evaluate adherence to these recommendations. This paper presents the development of RAISE-QI (Reporting AI Studies in Education Quality Instrument), a methodological extension of the original RAISE framework designed to facilitate systematic assessment of reporting quality in AI in education research. The objective is to transform RAISE from a reporting guideline into a practical appraisal instrument that can support researchers, peer reviewers, journal editors, and evidence synthesis teams in evaluating the completeness and transparency of published studies. The instrument was developed by operationalising each of the 30 RAISE reporting recommendations into an observable assessment criterion, accompanied by standardised assessment questions and a proposed ordinal scoring framework to promote consistent application across reviewers. The operationalisation was guided by established principles underpinning reporting guidelines and quality appraisal instruments while maintaining fidelity to the conceptual intent of the original RAISE framework. The resulting instrument enables each reporting recommendation to be evaluated systematically rather than interpreted solely as narrative guidance. The principal outcome of this work is RAISE-QI, a reporting quality instrument specifically designed for AI in education research. By converting reporting recommendations into measurable appraisal criteria, the instrument provides a structured foundation for assessing reporting completeness, identifying common reporting deficiencies, and supporting future investigations of reporting quality, inter-rater reliability, and construct validity. It is concluded that reporting guidelines can serve a dual purpose as both author guidance and quality assessment instruments. Future research should evaluate the psychometric properties of RAISE-QI and examine its application across diverse AI in education studies. The development of RAISE-QI represents an important methodological contribution towards improving research transparency, reproducibility, and evidence quality within the rapidly evolving field of AI in education.

Keywords: Artificial intelligence in education, reporting guidelines, research quality, RAISE, methodological assessment

Introduction

The increasing adoption of artificial intelligence (AI) technologies in educational settings has transformed instructional design, assessment, and learner support. AI-driven systems such as intelligent tutoring systems, adaptive learning platforms, and generative AI tools are now widely integrated into educational research and practice (Allison, et al., 2025). However, the rapid pace of innovation has outstripped the development of corresponding reporting standards, resulting in substantial heterogeneity in how AI interventions are described, evaluated, and interpreted. Inconsistent reporting limits the ability of researchers to replicate studies, compare findings across contexts, and assess the validity and reliability of reported outcomes. Key aspects such as model specification, prompt design, human–AI interaction, and ethical safeguards are often underreported or ambiguously described. These limitations are particularly problematic in AI-in-education research, where both technical and pedagogical dimensions must be transparently articulated. Without sufficient methodological reporting, it becomes difficult for educators and policymakers to interpret findings, reproduce interventions, or determine how AI systems may be transferred into practical educational settings.

To address these challenges, the Reporting AI Studies in Education (RAISE) framework was developed as an initial structured reporting guideline specifically for AI in education research (Allison, 2026a). RAISE comprises a 30-item checklist organised across ten domain areas including Educational Justification and Theoretical

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Grounding, AI System Specification, AI Role and Interaction, Accessibility and Cultural Fit, Educational Setting and Participants, Human Involvement, Study Design and Evaluation, Ethics and Trustworthiness, Transparency and Reproducibility, and Limitations and Implications (Allison, 2026a). In addition, the framework includes an ethics and risk matrix and illustrative examples of reporting practice. These artefacts are available as supplementary material in the original RAISE article (Allison, 2026a), and available at the Open Science Framework (Allison, 2026b). The framework was designed to encourage authors to provide clearer and more comprehensive descriptions of AI-related educational studies.

The first version of RAISE has begun to be used as a reporting reference in published manuscripts and has been incorporated as a recommended submission guideline within the Journal of Educational Computing Research (JECR), indicating early-stage adoption and community relevance. Recent empirical applications indicate that the RAISE framework has already been operationalised across a diverse range of AI in education contexts. For instance, it has been used in contexts such as language learning (Khodabandeh, 2026), creative writing (Oruç, Aktaş, & Kurt, 2026), and programming education (Wang, Li, & Huang, 2026). In several studies, researchers have implemented RAISE as a structured reporting and risk assessment tool, often including full ethics and risk matrices as supplementary materials (e.g. Guan & Bahari (2026)) or in appendices (e.g. Gong, et al., (2026) and Fang, et al., (2026)). Other studies have embedded RAISE within methodological or ethical reporting sections, explicitly aligning their research design and risk mitigation strategies with the framework (Lee, et al., 2026; Oruç, Aktaş, & Kurt, 2026). Selective adoption is also evident, with some researchers applying and referring to specific checklist items, such as those relating to AI risks and unintended consequences, to address targeted pedagogical concerns (e.g. Hwang, et al., (2026)). Collectively, these examples indicate both the flexibility and practical applicability of RAISE across methodological approaches, while also demonstrating emerging recognition of the framework as a mechanism for enhancing transparency, ethical rigour, and reproducibility in AI-supported educational research. These applications span experimental, design-based, and evidence synthesis approaches, indicating that RAISE is being interpreted and adopted across heterogeneous methodological traditions rather than within a single research niche, yet still largely contained to one main publication outlet. Nevertheless, beyond direct empirical applications, RAISE has also been recognised in other high quality publication venues such as Computers and Education: Artificial Intelligence, where the Editors in Chief describe RAISE as offering a “highly comprehensive reporting checklist covering technical, pedagogical, and ethical aspects” (Hwang, Xie, Wah, & Gašević, 2026) for AI-in-education research, although the authors note it is potentially complex for routine use without further refinement. This therefore highlights the need for ongoing refinement and contextual adaptation.

The development of the RAISE framework is aligned with established practices in reporting guideline design, particularly those promoted by the EQUATOR Network, which emphasises transparency, completeness, and reproducibility in research reporting. In related domains, consensus-based reporting guideline extensions such as CONSORT-AI and SPIRIT-AI (Liu et al., 2020) have been developed to address the specific challenges posed by AI-driven interventions in clinical research, while frameworks such as TIDieR (Hoffmann et al., 2014) provide structured guidance for the reporting of complex interventions. RAISE extends this lineage into the domain of artificial intelligence in education, addressing a gap where existing guidelines do not fully capture the intersection of technical system specification, pedagogical design, human–AI interaction, and ethical risk. However, this emerging usage of RAISE also reveals variation in the extent and consistency with which reporting elements are implemented, particularly in relation to AI system specification, interaction design, and ethical risk articulation. Such variability is consistent with early-stage adoption of reporting frameworks.

Furthermore, a reporting framework alone does not provide a mechanism for evaluating whether published research has successfully achieved appropriate reporting standards. Reporting guidelines indicate what should be reported, whereas quality assessment instruments enable reviewers to evaluate whether reporting requirements have been adequately addressed. Although reporting quality instruments exist in fields such as healthcare and education research, equivalent tools specifically designed for AI in education remain limited.

This paper therefore introduces the RAISE Quality Instrument (RAISE-QI), a reporting quality instrument developed to operationalise the 30 checklist items within the RAISE framework. The objective of RAISE-QI is to provide a systematic and reproducible method for evaluating reporting completeness in AI in education research.

Methodology

Development Rationale

The development of RAISE-QI was motivated by the need to move beyond narrative reporting guidance towards a structured assessment approach. While RAISE provides researchers with recommendations for improving transparency, applying the framework does not necessarily allow reviewers or editors to determine the extent to which reporting requirements have been fulfilled. For example, a recommendation requiring authors to describe

the AI system may result in different interpretations among reviewers. One reviewer may consider a general statement such as "an AI chatbot was used" sufficient, whereas another reviewer may expect detailed information regarding the model version, provider, architecture, training data, or adaptive capabilities. Without explicit assessment criteria, evaluations of reporting quality may therefore vary considerably. RAISE-QI addresses this issue by converting each reporting recommendation into a measurable assessment criterion. This process aims to improve consistency by ensuring that reviewers evaluate comparable evidence across different studies.

Development of RAISE-QI

The development of RAISE-QI followed a structured methodological process based on the original RAISE framework. The process began with examination of all 30 RAISE checklist items. Each item was analysed to identify the essential reporting expectations and determine how these expectations could be translated into observable assessment criteria. For each reporting item, three components were developed:

- Original RAISE item recommendation: The original reporting requirement from the RAISE framework was retained to maintain conceptual alignment.
- Assessment question: Each checklist item was transformed into a structured question designed to guide reviewers in identifying relevant evidence within a published study.
- Ordinal scoring framework: Each assessment question was accompanied by a scoring system designed to evaluate the completeness of reporting.

The scoring framework uses three levels:

- Score 0: The required information is absent or described only in highly general terms.
- Score 1: The information is partially reported, but important details are missing.
- Score 2: The information is comprehensively reported, providing sufficient detail for interpretation and potential reproduction.

This ordinal approach recognises that reporting quality exists on a continuum rather than representing a simple binary outcome. Many studies may provide some relevant information while failing to achieve complete reporting. Capturing these intermediate levels provides richer information about reporting practices and enables more nuanced evaluation. For example, the original RAISE item recommendation relating to AI model specification requires authors to report details including the model name, version, provider, and whether the system is static, adaptive, or generative. Within RAISE QI, this recommendation becomes an assessment question:

"Is the AI model sufficiently specified for readers to understand the technology used?"

A score of zero would represent cases where the AI system cannot be identified beyond a generic description, such as referring only to an "AI chatbot" or "language model". A score of one would represent partial reporting where the model is identified but important technical details are missing. A score of two would represent comprehensive reporting where sufficient information is provided to understand the AI implementation. This transformation process was applied consistently across all 30 RAISE checklist items.

RAISE-QI

Table 1 illustrates a sample of some of the RAISE-QI scoring criteria. The full RAISE-QI scoring criteria is available to download on the Open Science Framework: https://doi.org/10.17605/OSF.IO/5CQEP (Allison, 2026c).

Table 1. RAISE-QI Sample Items

Item	Original RAISE Item	Assessment Question	Score = 0	Score = 1	Score = 2
3. AI Model	Specify the AI model used (name, version, provider, static/adaptive/generative).	Is the AI model sufficiently specified for readers to understand the technology used?	The AI model cannot be clearly identified or is described only in generic terms (e.g., "an AI chatbot" or "a language model"	The AI model is identified, but important technical details such as version, provider, or model type are missing.	The AI model is fully identifiable, including its name, version, provider, and type, enabling readers to understand and potentially reproduce the AI implementation.

4. AI Access	Indicate whether the system is proprietary or open-source, and any limitations on access.	Does the study report whether the AI system is proprietary or open source and describe any access limitations?	The study does not report whether the AI system is proprietary or open source and provides no meaningful information regarding system accessibility or access limitations.	The study identifies either the ownership status (proprietary or open source) or mentions access arrangements, but important information regarding availability, licensing, or access restrictions is incomplete or unclear.	The study clearly identifies whether the AI system is proprietary or open source and provides sufficient information about access arrangements, licensing, subscription requirements, API availability, or other restrictions that could influence implementation or replication.
5. System& Prompt Design	Detail the design process of the AI system and/or prompt engineering (manual, iterative, instructional logic), including representative examples.	Does the study explain how the AI system or prompts were designed and provide illustrative examples?	The study provides little or no description of how the AI system or prompts were designed, preventing readers from understanding how the AI implementation was developed	The study provides a general description of the AI system or prompt design but omits important details regarding the development process, design rationale, iterative refinement, or representative examples.	The study describes the development process of the AI system or prompts, including relevant design decisions such as prompt engineering, instructional logic, iterative refinement, or optimisation, and provides representative prompt examples or system specifications sufficient to understand the implementation.

Potential Applications

RAISE-QI has several potential applications across the research ecosystem. For researchers, the instrument can function as a pre-submission quality assurance tool. Authors may use RAISE-QI alongside the original RAISE framework to identify reporting weaknesses before submitting manuscripts for peer review. For peer reviewers, RAISE-QI provides a structured approach for evaluating methodological transparency. By offering explicit criteria, the instrument may reduce inconsistencies in reviewer judgements and encourage more systematic assessment of reporting quality. For journal editors, RAISE-QI may support editorial decision-making by providing a mechanism for assessing whether manuscripts meet appropriate reporting expectations. Incorporating reporting quality assessment into publication workflows could contribute towards improving transparency standards within AI in education research. The instrument may also provide value for systematic review and meta-analysis teams. When synthesising evidence across AI in education studies, researchers require reliable methods for assessing the completeness and quality of reported information. RAISE-QI could support reproducible evaluation of reporting practices across larger bodies of literature. Ultimately, improved reporting benefits the wider educational community. Educators require sufficient methodological detail to understand how AI systems were implemented and evaluated before considering adoption within practice. Transparent reporting therefore represents an important foundation for translating research findings into meaningful educational applications.

Future Validation

Although RAISE-QI represents an important methodological contribution, its development constitutes only the next stage of instrument development. Further research is required to establish its scientific robustness. A key area for investigation is reliability, particularly through mechanisms such as inter-rater reliability. Future studies should examine whether independent reviewers applying RAISE-QI to the same research articles produce consistent scores. Such evaluation will determine whether the assessment questions and scoring criteria provide sufficient clarity. Construct validity represents another important consideration. Future research should investigate whether RAISE-QI genuinely measures reporting quality and whether the criteria align with expert perceptions of high-quality reporting. Engagement with journal editors, reviewers, and experienced AI in education researchers may provide valuable perspectives on the validity of the instrument. Usability should also be evaluated, as while comprehensive assessment instruments provide value, they must remain practical for researchers and reviewers. Studies should examine whether users find RAISE-QI understandable, efficient, and appropriate for evaluating different forms of AI in education research. Future validation studies should apply RAISE-QI across varied

research methodologies, including qualitative, quantitative, mixed-methods, and experimental studies. Such evaluation will help determine whether the instrument is sufficiently flexible for the diverse methodological approaches used within AI in education research.

Conclusion

AI in education research continues to develop rapidly; however, inconsistent reporting practices remain a significant challenge for reproducibility, evidence synthesis, and confidence in published findings. The RAISE framework provides valuable guidance for improving transparency, but it was not designed as an instrument for systematically assessing reporting quality. RAISE-QI addresses this limitation by transforming the 30 recommendations within RAISE into measurable assessment criteria, structured evaluation questions, and an ordinal scoring framework. The resulting instrument provides researchers, reviewers, editors, and systematic review teams with a practical approach for evaluating reporting completeness. RAISE-QI is not intended to replace RAISE, nor is a low RAISE-QI score necessarily evidence that the underlying research itself is methodologically poor. Rather, it evaluates the extent to which information required by RAISE is reported sufficiently for readers to understand, interpret, and potentially reproduce the study. Further validation is required to establish the reliability, validity, and usability of RAISE-QI. Nevertheless, the instrument represents an important step towards strengthening methodological transparency and improving the quality of evidence within the rapidly evolving field of artificial intelligence in education research.

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Beyond Final Scores: Identifying Behavioural Decision-Making Profiles from Cybersecurity Simulation Log Data

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Abstract

Simulation-based learning provides opportunities for learners to practise complex decision-making in authentic contexts while generating rich behavioural data that extend beyond traditional performance measures. In cybersecurity education, although technical laboratories and capture-the-flag activities develop important practical skills, they do not always represent the organisational, ethical, financial and human pressures involved in cybersecurity management. Learning analytics has traditionally focused on performance outcomes, yet these measures often reveal little about the decision-making processes that underpin learner behaviour. To address this challenge, a browser-based cybersecurity management simulation was developed for Level 6 and Level 7 cybersecurity students. The simulation places learners in the role of a cybersecurity manager and presents 15 organisational incidents, each offering three possible responses with consequences for security, budget, reputation, staff morale and board happiness. Each playthrough generates a decision log that records the sequence of choices made, providing a detailed account of how learners respond to risk and balance competing priorities over time. This study examines how these decision logs can be used within learning analytics to identify decision-making strategies that cannot be understood from final scores alone, thereby providing a richer understanding of learners' decision-making processes within simulation-based cybersecurity education. Following data preparation and validation, 136 playthroughs were available for analysis, including 2,009 decision-level observations. Of these, 125 included all 15 scenarios, while 11 ended early because the simulated organisation became bankrupt. These early-ending runs were retained as meaningful gameplay outcomes. To move from this cleaned dataset to an analysis of learner strategies, a theory-informed coding framework classified the 45 available decision options across four behavioural dimensions: decision orientation, risk management approach, human-element governance, and transparency strategy. These codes were then linked to the decision logs, allowing each playthrough to be represented as a proportional behavioural profile. Because the number of recorded decisions differed between complete and early ending runs, proportions were used instead of raw counts. Final simulation scores were deliberately excluded from the clustering process to ensure that the resulting groups reflected patterns of decision-making rather than performance outcomes. Multiple clustering approaches, including k-means, agglomerative clustering, Gaussian mixture models, spectral clustering and DBSCAN were compared using silhouette scores, cluster-size distributions and interpretability. K-means with k = 4 was selected as the optimal solution. This solution produced four behavioural decision-making profiles: Adaptive Balancers, Detached Operators, Surveillance Regulators and Protective Controllers. These profiles differed in risk tolerance, security prioritisation, operational focus, staff governance, monitoring and transparency, and were associated with different final outcome patterns. By transforming raw decision logs into interpretable behavioural profiles, the analysis revealed broader decision-making strategies that final scores alone could not capture. In this way, the study contributes to learning analytics by transforming decision logs into interpretable evidence that can support structured reflection, personalised feedback, adaptive simulation design, and the continued development of simulation-based cybersecurity learning. More broadly, the findings demonstrate the value of behavioural profiling for understanding complex decision-making in educational simulations, and provide a foundation for future research into learner modelling within AI-supported and simulation-based learning environments.

Keywords: Simulation-based learning; Learning analytics; Cluster analysis; Decision-making; Cybersecurity education

Introduction

Cybersecurity education has increasingly recognised the importance of experiential learning. Practical activities such as technical laboratories, capture-the-flag competitions and simulated environments enable learners to develop applied skills in vulnerability identification, exploitation, system defence and incident response (Mouhssine et al., 2025). Such activities are particularly valuable because cybersecurity is an applied discipline in which theoretical knowledge must frequently be translated into practical action. However, professional cybersecurity practice extends beyond technical execution. Practitioners regularly operate in environments

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characterised by incomplete information, competing organisational priorities and uncertain consequences. Security decisions therefore require practitioners to balance technical risk against financial, operational, human and governance considerations. Consequently, effective cybersecurity decision-making requires judgement and an ability to evaluate trade-offs rather than simply identify a technically correct response (Stsiampkouskaya et al., 2025). This creates a challenge for cybersecurity education. Assessment approaches that focus primarily on whether learners achieve a final score or successfully complete a technical task may provide limited insight into how they arrived at that outcome. Two learners may achieve comparable results while employing substantially different decision-making strategies. Learning analytics offers an opportunity to address this limitation by analysing the behavioural traces generated during learning activities (Pardo et al., 2019). Rather than treating interaction data simply as evidence of completion, educational data can be examined to identify patterns in learner behaviour and inform feedback and pedagogical intervention (Banihashem et al., 2022; Maldonado-Mahauad et al., 2018). This paper therefore investigates whether cybersecurity simulation log data can be used to identify distinct behavioural decision-making profiles. The study addresses the following research question: "What behavioural decision-making profiles can be identified from learner interaction data generated during a cybersecurity decision-making simulation?"

Decision-making in cybersecurity education

Cybersecurity decisions are frequently characterised by uncertainty, competing objectives and potentially significant consequences (AL-Dosari & Fetais, 2023). Similarly, research on crisis management and incident response highlights the importance of rapid judgement, prioritisation and coordination when responding to uncertain situations (Alwi et al., 2025). These characteristics suggest that cybersecurity education should provide opportunities for learners to practise not only technical execution but also judgement and strategic reasoning. Simulation-based learning is particularly appropriate for this purpose because it can place learners within realistic scenarios while allowing the consequences of decisions to be observed in a controlled environment (Allison, 2025). Allison's later work highlighted how simulations can also make trade-offs explicit, enabling learners to reflect on why a decision produced a particular outcome (Allison, 2026). The challenge is determining how such decision-making can be systematically analysed. Recording the action selected by a learner provides useful behavioural data, but the action alone does not necessarily capture the underlying decision logic.

Learning analytics and behavioural profiling

Learning analytics has increasingly been used to analyse learner-generated data in order to understand engagement, progression and performance (Ning et al., 2025). Much of this work focuses on observable behaviours such as activity frequency, assessment performance or interaction patterns. However, simulation environments provide a different form of evidence because learners' actions can represent choices within a consequential decision space. Behavioural profiling can potentially provide educators with information about how learners approach complex problems. Rather than simply identifying whether a learner performed well, profiling can reveal tendencies such as risk avoidance, enforcement orientation, prioritisation of security or attempts to balance competing objectives. Such information may support personalised feedback and reflective learning (Banihashem et al., 2022; Ning et al., 2025). This study applies this principle to cybersecurity decision-making. The approach first converts simulation responses into behavioural characteristics and then uses clustering to identify recurring combinations of those characteristics.

Methodology

Simulation environment and data collection

The study used a cybersecurity decision-making simulation designed around organisational incidents. Each playthrough consists of 15 incidents. For every incident, learners select one of three possible responses (for the full incident details used for the simulation, please contact the authors). Each response produces consequences across five organisational metrics: security, budget, reputation, staff morale and board satisfaction. For example, in a ransomware recovery scenario, a participant selecting "Refuse Payment and Restore from Backups" is associated with quantified effects on security, reputation, budget, and morale, reflecting the game's internal simulation model of organisational trade-offs. These outcome values were not used as subjective interpretations but as pre-defined system parameters embedded within the simulation logic to standardise consequences across participants. The simulation therefore represents cybersecurity as a multi-objective decision problem rather than a sequence of isolated technical tasks. Following each decision, learners receive feedback describing the outcome and the corresponding changes to their organisational metrics. Learners can also review their previous decisions, enabling them to observe how their choices contributed to their overall performance (Figure 1).

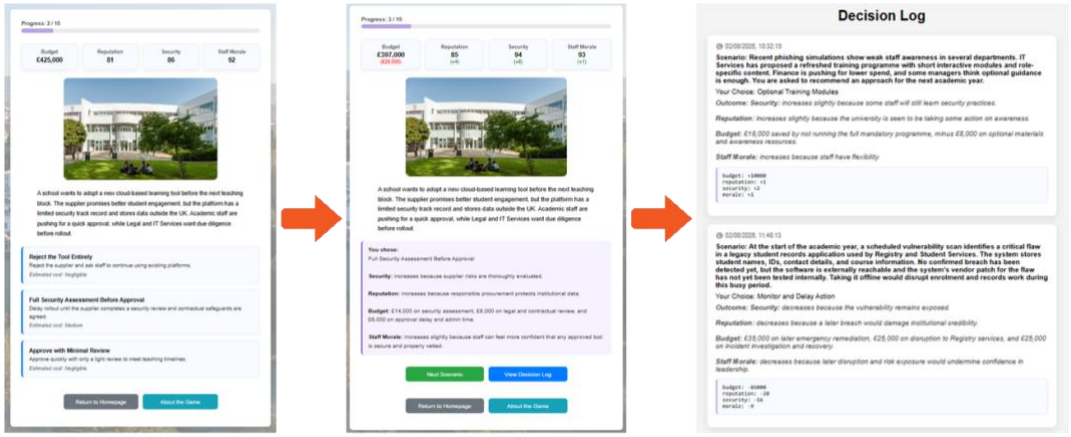


Figure 1. From Simulation Gameplay to Decision Logs

The system records each decision in a structured log containing information about the scenario, selected response, outcome and changes to the five metrics. Data were collected in both PDF and JSON formats. The PDF representation supported inspection of individual playthroughs, while JSON provided the structured data required for computational analysis. A total of 136 playthroughs were available, generating 2,009 individual decisions. Of these, 125 were complete playthroughs, while the remainder ended prematurely because the learner exhausted the available budget and the simulation terminated. These incomplete runs were retained because they still represented meaningful decision-making behaviour and therefore provided relevant evidence for behavioural profiling. Because the logs represent simulated rather than real-world decisions, the profiles should be interpreted as behavioural tendencies within the simulation context.

Behavioural coding framework

The 45 possible response options were coded using a theoretically informed behavioural framework consisting of four complementary dimensions: decision orientation, risk management, human elements and transparency. Decision orientation captured the principal organisational objective, including security, operational continuity, human well-being, financial efficiency, governance or explicit balancing. Next, risk management describes how the learner approached uncertainty and threats. Responses were categorised as preventative, containment-focused, investigative, reactive or risk-accepting, reflecting established distinctions within risk management (AL-Dosari & Fetais, 2023). Human elements captured the extent and nature of attention given to people affected by cybersecurity decisions such as supportive, neutral, enforcement-oriented or surveillance-focused, recognising that cybersecurity interventions can influence trust, employee behaviour, compliance and perceptions of organisational authority (AL-Dosari & Fetais, 2023). Finally, transparency captures how information is handled as part of the response. Decisions were categorised as open and transparent, selectively disclosed or concealed. Importantly, the dimensions were not treated as mutually exclusive representations of a decision. A response could possess multiple characteristics across the framework. This allowed the decision log to be represented as a multidimensional behavioural space rather than reducing each response to a single categorical label. To evaluate the reliability of the coding framework, two independent coders classified all 45 response options across the four behavioural dimensions, resulting in 180 individual coding decisions. The coders agreed on 154 classifications (85.6% agreement). Cohen's kappa was subsequently calculated to account for the possibility of agreement occurring by chance. The resulting overall mean kappa was $\kappa = 0.805$, indicating substantial to strong inter-rater reliability. Following this, the two coders discussed each item where there was disagreement and came to a consensus on the remaining items to code.

Clustering Procedure

Following coding, the proportion of responses associated with each behavioural characteristic was calculated for every playthrough. These proportions formed the behavioural feature set for subsequent clustering. This approach meant that profiles were derived from the decisions learners made throughout the simulation rather than from their final scores. See Figure 2 for the full analytical workflow which was used.

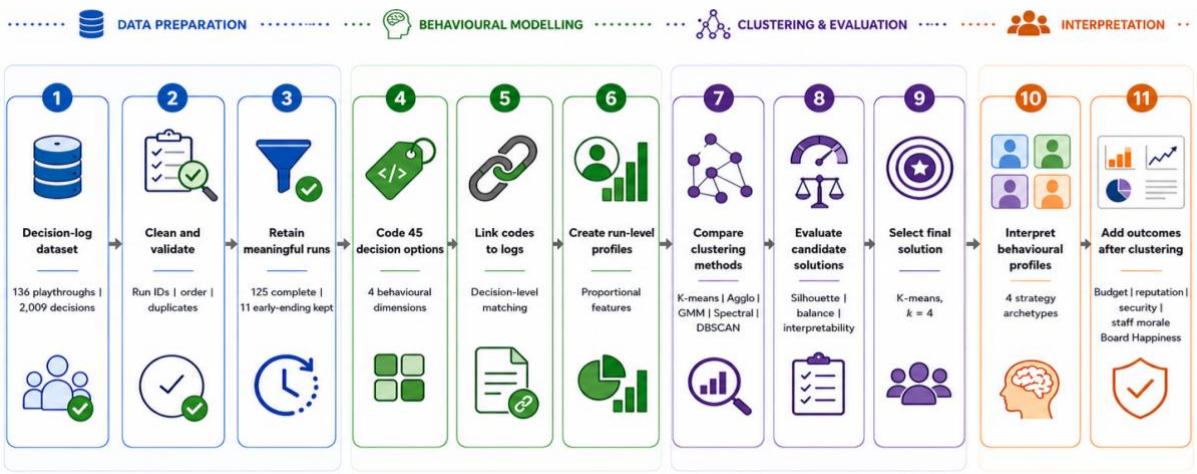


Figure 2. End to End Analytical Workflow

Several clustering configurations were compared in terms of the resulting behavioural patterns. This included Agglomerative, Gaussian Mixture Model, Spectral Clustering, DBSCAN, and K-Means. K-means produced the clearest candidate solutions. Although the k=3 solution achieved a higher silhouette score (0.241), indicating stronger numerical separation, it grouped 94 of the 136 playthroughs into a single balanced/selective cluster, potentially obscuring meaningful behavioural variation. The k=4 K-means solution produced a lower silhouette score (0.196) but separated this large group into more interpretable patterns, resulting in four clusters of 76, 10, 26 and 24 playthroughs and distinguishing adaptive trade-off management from a more monitoring-oriented regulatory style. Alternative methods provided useful validation of the broader structure. Agglomerative clustering identified a similar three-profile pattern but produced highly imbalanced clusters, while Gaussian mixture modelling favoured broader solutions with weak separation, including a k=3 silhouette score of only 0.090. Spectral clustering produced a comparable silhouette score (0.248) but again generated an imbalanced structure of 105, 9 and 22 playthroughs. DBSCAN, meanwhile, generally produced one dominant cluster with either noise or a very small additional cluster, suggesting the behavioural profiles are better understood as overlapping strategic tendencies than sharply separated natural groups. Consequently, K-means with k=4 was selected as the primary solution based on the combined evidence of statistical fit, better cluster balance and more interpretable behavioural profiles. Final simulation outcomes were subsequently associated with the clusters for interpretation and were not used as clustering features.

Results

The clustering analysis identified four distinct behavioural profiles: Adaptive Balancers, Protective Controllers, Surveillance Regulators and Detached Operators. See Table 1 for the full details of each profile.

Table 1. Behavioural Profile Key Features and Average Final Scores

Cluster and Profile	Key Features	Average Scores at End of Simulation			
		Budget	Reputation	Security	Staff Morale
Adaptive Balancers (55.9%)	High Explicit Balancing High Selective Disclosure Spread of Risk Management Strategies Spread of Focus on Human Element	£133,079	149	193	119
Detached Operators (7.4%)	Very High Operational Continuity Very High Risk Acceptance Neutral Focus on Human Element Very Low Preventative/Proactive Behaviour Low Open Transparency	£144,600	33	83	63
Surveillance Regulators (19.1%)	High Explicit Balancing High Investigative/Monitoring Very High Surveillance Orientated Spread of Focus on Transparency Low Supportive/Enabling of Human Element	£112,538	125	179	100

Protective Controllers (17.6%)	Very High Security/Risk Reduction High Preventative/Proactive Behaviour High Enforcement/Punitive of Human Element Very High Open Transparency Very Low Risk Acceptance	£52,250	153	199	107

The largest group was the Adaptive Balancers (76 students - 55.9%). These learners did not consistently prioritise a single organisational objective. Instead, their decisions demonstrated relatively balanced attention to security, organisational resources, staff and communication. This group achieved consistently strong outcomes across budget, reputation, security, and morale, without exhibiting the extreme trade-offs observed in other profiles, suggesting a robust and adaptable approach to decision-making under uncertainty. The Protective Controllers (24 students - 17.6%) displayed a stronger emphasis on security. Their decisions prioritised protective interventions and produced the highest security and reputation outcomes among the four groups. However, this strategy was associated with greater resource expenditure. The profile therefore illustrates a conventional security-oriented trade-off in which stronger protective action may require greater financial or operational cost. The Surveillance Regulators (26 students - 19.1%) relied more heavily on monitoring, control and enforcement-oriented responses. Although this approach maintained reasonable security outcomes, it was associated with lower staff morale and reputation. This profile highlights the potential organisational consequences of cybersecurity strategies that emphasise oversight and control. Finally, the Detached Operators (10 students - 7.4%) demonstrated greater willingness to accept risk and preserve organisational resources. They retained the largest proportion of their budget but recorded the lowest outcomes for security, reputation and staff morale. Their behaviour illustrates the consequences of prioritising operational or financial flexibility when this results in greater exposure to cybersecurity risks.

Discussion

The findings provide preliminary evidence that cybersecurity simulation logs can be used to identify meaningful behavioural decision-making profiles. This extends conventional learning analytics approaches by examining not simply what outcome a learner achieved, but the sequence and characteristics of decisions through which that outcome was produced (Jovanović et al., 2017; Maldonado-Mahauad et al., 2018). The identification of the Adaptive Balancer profile is particularly relevant to cybersecurity education as security professionals must frequently negotiate competing requirements such as organisational resources, employee welfare and stakeholder expectations. The existence of a large group displaying relatively balanced behaviour suggests that simulation environments may provide a useful means of observing learners' ability to navigate such competing priorities. The other profiles demonstrate the educational value of identifying trade-offs. A Protective Controller may appear highly successful if evaluated primarily through security metrics, yet their decisions may also impose substantial resource costs. Similarly, a Detached Operator may demonstrate effective resource management while producing undesirable security and reputational outcomes. These distinctions could form the basis for richer formative feedback. For educators, behavioural profiles could therefore provide a starting point for structured reflection. Rather than telling a learner simply that their final score was high or low, an educator could examine the decision pathway and discuss the assumptions underlying the learner's choices. For example, a learner who consistently selects enforcement-oriented responses could be encouraged to consider how alternative approaches might affect trust, staff morale and organisational reputation. The approach also has potential implications for learner modelling. Future implementations could use behavioural data to identify decision tendencies during a simulation and subsequently adapt scenarios or feedback to address learning needs (Banihashem et al., 2022; Emerson et al., 2020). However, such applications should be treated cautiously. A cluster should not be interpreted as a fixed psychological trait or definitive learner type. Rather, the profiles represent patterns of observed behaviour within a particular simulation context. Behaviour may change according to scenario, experience, knowledge and situational constraints.

Conclusions

The central contribution is the demonstration that simulation logs can provide evidence about the process of cybersecurity decision-making rather than only its final outcome. The findings suggest that behavioural profiling could support more meaningful learner reflection, formative feedback and future learner modelling. Further research should validate the profiles using larger and more diverse cohorts, examine whether profiles remain stable across different scenarios, and investigate whether providing profile-informed feedback produces measurable improvements in cybersecurity decision-making. Future work should also consider longitudinal data to determine whether learners' decision-making patterns change through education and experience.

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Designing Immersive Learning for Preservice Teachers to Teach Emerging Digital Technologies: The Adaptive Pedagogical Readiness Architecture (APRA)

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Abstract

The proliferation of emerging technologies in K-12 education increases the need for preservice teachers to be more familiar with artificial intelligence, computational thinking, and cybersecurity. Teachers and educators need opportunities to explain evolving concepts, respond to ethical and safety concerns, and adjust instruction as technologies and classroom conditions change. This conceptual paper introduces the Adaptive Pedagogical Readiness Architecture (APRA), a technology-agnostic instructional design architecture for designing immersive teacher preparation experiences. APRA connects five components: educational context, learning outcomes, instructional design engine, an immersive learning environment, and adaptive pedagogical readiness. Six design principles translate the architecture into practice by emphasizing authentic professional contexts, adaptive pedagogical decision-making, reflection and iteration, collaborative knowledge construction, evidence-informed design, and transfer to professional practice. An integrated cybersecurity and artificial intelligence scenario illustrates how the architecture can support pedagogical rehearsal across virtual reality, mixed reality, and screen-based simulations. APRA complements established instructional design and teacher knowledge models by providing design logic for developing and rehearsing professional judgment under changing technological conditions. The paper concludes with practical implications and priorities for empirical validation.

Keywords: adaptive pedagogical readiness, preservice teacher education, immersive learning, instructional design, artificial intelligence education, cybersecurity education.

Introduction

Cybersecurity, Artificial Intelligence (AI), computational thinking, and immersive technologies such as extended reality are increasingly shifting how we create information, protect data, communicate, and make instructional decisions. Preservice teachers, therefore, need conceptual technical knowledge; however, the tools often used during teacher training become outdated before they are integrated into professional practice. When technology is adopted, teachers are expected to judge the trustworthiness of digital outputs, explain uncertainty, recognize bias, and model responsible and secure behavior. Studies on AI literacy emphasize a shift in focus from operational skills alone to understanding, evaluation, ethical awareness, and communication (Long & Magerko, 2020; Ng et al., 2021).

Teacher preparation research indicates that access to technology does not directly lead to thoughtful classroom adoption. Effective preparation fosters connections among pedagogy, content, modeling, reflection, and authentic practice (Mishra & Koehler, 2006; Tondeur et al., 2012). Studies of professional digital competence also stress context-sensitive decisions involving ethics, safety, assessment, and learner participation (Fallon, 2020; Instefjord & Munthe, 2017). Consequently, these demands are especially difficult when the subject itself keeps changing.

Immersive learning environments such as virtual reality, mixed reality, and simulations can provide a productive and controlled practice setting. Immersive environments allow preservice teachers to experience realistic instructional problems, make decisions, receive feedback, and reattempt classroom scenarios without disrupting the real classroom. Research also suggests that immersion does not guarantee learning. Rather, learning depends on the value of the educational task, support, and feedback, as well as alignment with the intended learning outcome (Hamilton et al., 2021; Makransky & Petersen, 2021; Radianti et al., 2020). APRA seeks to address the design problem by treating immersion as a continuum for pedagogical rehearsal rather than the ultimate solution to instructional problems.

Conceptual Development Approach

The development of APRA stemmed from a conceptual integrative synthesis rather than from an empirical study or a systematic review. This approach is appropriate when addressing problems that no single research framework

https://doi.org/10.5281/zenodo.24340335

can explain in isolation or in its entirety (Jabareen, 2009; Jaakkola, 2020). This paper focuses on a central instructional design problem, that is, how preservice teachers can be prepared to make sound decisions when digital technologies, classroom conditions, and professional expectations are dynamic. The purpose of the synthesis was to examine how experiential learning, situated learning, reflective practice, cognitive apprenticeship, adaptive expertise, and evidence-informed instructional design can inform the preparation of teachers for changing digital domains. The framework is therefore a proposed architecture rather than a model.

Experiential learning contributes a cycle of action and reflection (Kolb, 1984), while situated learning places professional knowledge in meaningful contexts (Brown et al., 1989; Lave & Wenger, 1991). Reflective practice explains how professionals examine uncertain situations in which rules do not determine one correct response (Schön, 1983). Cognitive apprenticeship makes expert reasoning visible through modeling, coaching, scaffolding, articulation, and gradual independence (Collins et al., 1989). Adaptive expertise supplies the developmental aim: using knowledge flexibly when conditions change rather than reproducing one practiced procedure (Hatano & Inagaki, 1986). APRA organizes these ideas into a design logic for observable professional judgment.

The Adaptive Pedagogical Readiness Architecture (APRA)

APRA is an iterative instructional design architecture consisting of five interacting components that operate in a cyclical process rather than a rigid step-by-step sequence. The evidence from immersive pedagogical rehearsals informs the continuous refinement of context outcomes, design decisions, learning experiences, and readiness development. The five components include educational context, learning outcomes, instructional design engine, immersive learning environment, and adaptive pedagogical readiness.

Educational context defines the teacher education program, participants, digital domain, professional expectations, equity conditions, institutional constraints, and available delivery technologies. Learning outcomes specify professional capabilities that participants should demonstrate, such as recognizing a digital risk, explaining an AI limitation in age-appropriate language, selecting an ethically defensible response, or adapting instruction after learner feedback.

The instructional design engine converts outcomes into authentic tasks, scaffolds, pedagogical rehearsal, reflection, collaboration, feedback, and progressively complex cases. The immersive learning environment is the enacted space in which participants assume a professional role, interpret cues, interact with learners or colleagues, make decisions, and experience consequences. Immersion is functional rather than device-defined: the appropriate level is the one needed to make the professional problem believable and actionable without creating unnecessary cognitive or access burdens. Adaptive pedagogical readiness is the developing capacity to interpret unfamiliar teaching situations, justify actions, consider ethical and contextual consequences, use evidence, and revise practice. It should be inferred from performance across varied cases rather than from self-report alone.



Figure 1. The cyclical structure of Adaptive Pedagogical Readiness Architecture

Table 1. Components of the Adaptive Pedagogical Readiness Architecture.

Component	Design question	Illustrative evidence

Educational context	What conditions shape the preparation needed?	Learner needs, program constraints, policy, and access
Learning outcomes	What professional capability should be demonstrated?	Explanation, decision, adaptation, transfer
Instructional design engine	How will the capability be developed?	Rehearsal, scaffolding, reflection, feedback
Immersive learning environment	Where will professional action occur?	Scenario actions, interactions, consequences
Adaptive pedagogical readiness	What indicates flexible professional judgment?	Reasoning across varied cases and revised performance

Design Principles

Principle 1- Design authentic professional contexts

Scenarios should be designed to reflect plausible teaching decisions through meaningful goals, learner responses, policies, demands, and consequences rather than photorealism alone.

Principle 2 – Require adaptive pedagogical decision-making

Participants should be able to defend their options, compare them with other options, and explain their reasoning. Variation across cases should change learners' needs, available evidence, or technological behaviors to ensure that memorized answers will be insufficient.

Principle 3 – Build reflection and iteration into the experience

Reflection should occur immediately or close to the actions taken. This helps participants reconstruct what they noticed and assumed. Providing participants with the opportunity to reflect on their actions makes improvement observable.

Principle 4 – Support collaborative knowledge construction

Structured peer discussions reveal alternative interpretations when technical, ethical, or cultural considerations point towards different responses.

Principle 5 – Use evidence to align design and feedback

Designers should identify what performance would indicate readiness and capture decision paths, explanations, responses to feedback, and transfer.

Principle 6 – Design explicitly for transfer

Participants should apply their reasoning in another digital domain, group, or setting. This will show that they have learned a generalizable principle rather than a single scenario’s surface features.

Illustrative AI and Cybersecurity Scenario

Consider a virtual classroom with learners of the middle school age group. In this classroom, students prepare a shared presentation. One of the students pastes an AI-generated explanation into the workspace and assumes it is accurate because the system sounds confident. At the same time, another student receives a message containing a shortened link that appears to come from a classmate. The preservice teacher must decide which concern requires immediate attention, how to maintain learning momentum, how to explain uncertainty and risk without creating fear, and what type of evidence would show that students understood the response.

The participant receives a brief overview of learners, school policy, and lesson objectives. During the scenario, the participant can question students, pause sharing, inspect evidence, and select or compose an explanation. After the first attempt, feedback compares the response against relevant AI literacy, cybersecurity, and pedagogical principles. Participants then engage in a dialogue with peers to examine alternative reactions to the scenario. Next, participants complete a revised case in which the age group, institutional policy, or credible cues have changed. This aligns with the six design principles while practicing professional reasoning, which is made visible for onward feedback and assessment.

Implications and Research Agenda

APRA complements existing instructional design models rather than replacing them. ADDIE can be implemented to organize a broader development cycle, while technological pedagogical content knowledge (TPACK) can be useful in examining relationships among technology, pedagogy, and content (Mishra & Koehler, 2006). APRA provides design logic for rehearsing professional performance under changing conditions. It shifts the starting question from what an immersive tool can do to what professional capability should become observable, and evidence will demonstrate that capability.

In addition, APRA provides architectural support for a progression from a modelled case to coached decisions and to unfamiliar scenarios with reduced support. Instructional designers can use this framework as a guide in limiting instructionally weak experiences by aligning instruction with desired outcomes, decisions, feedback, and transfer. Because the framework defines immersion functionality, the same design logic can guide headset-based virtual reality, desktop simulations, synchronous virtual classrooms, or asynchronous branching cases. Therefore, programs can provide lower-bandwidth alternatives while preserving the central decision, reasoning, feedback, and reflection tasks.

APRA is a conceptual proposal, and it requires validation through empirical studies. Initial studies should examine content validity through review by teacher educators, instructional designers, and specialists in AI and cybersecurity education. Usability studies can investigate whether designers interpret the components consistently and can apply the elements within realistic constraints. Pilot research should compare APRA-aligned experiences with technology exposure or procedural training conditions and examine the quality of decisions, explanatory reasoning, ethical judgment, and transfer to unfamiliar cases. Research must equally consider cognitive load, accessibility, emotional comfort, and representational fairness.

Conclusion

Preparing preservice teachers for emerging technologies requires more than teaching current tools. Teachers also need opportunities to interpret uncertain situations, justify pedagogical decisions, and learn from evidence and feedback. Teachers should be able to revise practice and transfer their reasoning as technologies change. APRA organizes these needs through five components and six connected design principles. Its central contribution is to position immersive learning as a practice environment for developing adaptive professional judgment. The next phase suggests empirical work to test the architecture, refine its components, and establish the conditions under which it improves teacher preparation.

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Visualizing the Unseen: Virtual Reality as a Tool for Concretizing Abstract Biology Content and Lowering Cognitive Barriers, A Conceptual Framework

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Abstract

Introductory biology asks undergraduates to reason about processes they cannot see, such as cellular respiration and cell division, usually from static diagrams and spoken explanation. Immersive virtual reality (VR) can show these processes in three dimensions and in motion, yet controlled studies have found that immersion can also add cognitive demands that reduce learning. This conceptual paper asks how immersive VR can make invisible biological processes concrete without adding load that undermines learning. The method is an integrative literature review that connects cognitive load theory, the cognitive theory of multimedia learning, embodied cognition, and the Cognitive Affective Model of Immersive Learning with empirical studies of VR in science and biology education. The reviewed evidence indicates that immersion alone does not guarantee better learning; gains appeared when immersive lessons were segmented and followed by generative activities such as summarizing or teaching a peer. From this synthesis the paper proposes three testable design principles: guided navigation, scaffolded complexity (progressive sequencing with generative consolidation), and controlled interactivity. The framework is illustrated with modules on cellular respiration and mitosis. The paper also addresses cost, accessibility, and instructor readiness, and it closes with research propositions and a study design that separates the effect of instructional structure from the effect of the medium.

Keywords: virtual reality, cognitive load, undergraduate biology education, immersive learning, instructional design

Introduction

A first year biology student asked to explain how a cell turns glucose into usable energy has to describe three linked stages in two cellular compartments and a flow of electrons along a membrane that no teaching microscope can show. The usual tools are a textbook figure and lecture slides, perhaps with an animation; everything else has to be imagined. Many students do not manage it. In an analysis of 182 concept maps from introductory biology students, Bergan-Roller et al. (2020) found that knowledge of cellular respiration was simplified, with few, loosely connected schemas arranged in a linear way. Static diagrams compress time and space, so the learner must infer the motion between frozen snapshots and relate structures drawn at different scales, and cognitive load theory predicts that this integration consumes much of the limited capacity of working memory (Sweller et al., 1998). Introductory science courses are also points at which students leave science majors (Seymour & Hunter, 2019). Difficulty with abstract content is not the only reason, but it is one that instructional design can address.

Immersive virtual reality (VR) seems an obvious response, since a head mounted display can place a learner inside a mitochondrion or beside a dividing cell. The record is less straightforward. In several controlled studies, students learned less from immersive lessons than from simpler media, even though they enjoyed the immersive versions more (Makransky et al., 2019; Parong & Mayer, 2018), and many educational VR applications are built around what the technology can do rather than around an account of how people learn (Radianti et al., 2020).

This paper therefore asks a design question: how can immersive VR make invisible biological processes concrete without adding the kind of cognitive load that undermines learning? It does not propose new learning principles. Its contribution is to integrate established principles from cognitive load theory, multimedia learning, embodied cognition, and immersive learning research, and to translate them into a design framework for biological processes that are complex in both space and time. The framework is stated as a set of testable propositions.

Methodology

The paper is conceptual and reports no new data. It rests on an integrative literature review, a form of review that critiques and synthesizes literature from different traditions in order to produce a new perspective (Torraco, 2005); it does not aim for the exhaustive coverage of a systematic review. Literature was located through Google Scholar,

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ERIC, APA PsycInfo, and Scopus, using combinations of three concept groups: the technology (immersive virtual reality, head mounted display), the learning mechanism (cognitive load, multimedia learning, segmenting, generative learning, embodied learning, presence), and the content (biology education, biochemistry, cellular respiration, citric acid cycle, electron transport chain, mitosis, undergraduate). Empirical studies published between 2013 and 2025 were considered, together with foundational theory regardless of date.

Eligible work included theory on how learners process complex visual and spatial information, reviews and meta analyses of VR in education, and studies in which students learned science content through immersive or mobile VR with a measured learning outcome. Priority went to biology and biochemistry and to studies that compared instructional methods within VR. Findings were sorted by the mechanism they bear on, and a design principle was retained only when a theoretical rationale and at least one convergent empirical finding supported it. The selection reflects judgments about relevance, and the resulting principles are propositions to be tested.

Theoretical Background

Cognitive Load and Multimedia Learning

Cognitive load theory distinguishes a working memory that is sharply limited when handling new information from a long term memory that stores organized schemas (Sweller, 1988; Sweller et al., 1998). Intrinsic load arises from the number of interacting elements in the material; the citric acid cycle carries high intrinsic load because each reaction depends on the product of the one before it. Extraneous load arises from presentation, for example an interface that makes the learner work out how to move. Later work treats germane processing as the resources a learner devotes to intrinsic load rather than as a separate source (Sweller et al., 2019); either way, capacity consumed by extraneous load is unavailable for the content. Mayer's (2001) cognitive theory of multimedia learning adds that visual and verbal information travel through separate, limited channels and that meaningful learning requires selecting, organizing, and integrating information. From it come methods such as segmenting and signaling (Mayer & Moreno, 2003). VR is multimedia in an extreme form, and it also requires the learner to look around, move, and operate controllers, which is why the environment itself can become a source of extraneous load.

Embodiment and Immersive Learning

Johnson-Glenberg (2018) argues that learning is strengthened when a learner's physical action is congruent with the concept: reaching out to turn a molecule maps onto rotation in space, while pressing an arbitrary button does not. The Cognitive Affective Model of Immersive Learning (CAMIL) identifies presence and agency as the affordances of immersive VR and describes how they act on learning through interest, motivation, embodiment, and cognitive load, including the route by which immersion overloads learners (Makransky & Petersen, 2021).

The four perspectives divide the explanatory work. Cognitive load theory explains why capacity is the constraint; multimedia learning supplies tested methods for managing processing; embodied cognition explains when physical action helps; and CAMIL links the affordances of immersion to both affective and cognitive outcomes. None of them says how to build an immersive lesson on a multistage cellular process, and the framework proposed here works at their intersection.

Review Findings

Promise and Uneven Evidence

Reviews agree more readily about engagement than about learning. Di Natale et al. (2020) found in 18 studies that immersive VR can support knowledge and motivation, but they noted nonrandomized designs, small samples, and unvalidated measures. Luo et al. (2021) reported a medium effect across 149 studies, moderated by discipline, level of immersion, and instructional design, while a meta analysis restricted to immersive VR found a smaller effect, $g = 0.38$ across 48 studies (Coban et al., 2022). The estimates depend on what VR is compared with and on how it is designed.

When Immersion Reduces Learning

Parong and Mayer (2018) had college students study a biology lesson either in immersive VR or as a desktop slideshow; the VR group reported more motivation and interest, but the slideshow group scored significantly higher on the posttest. Makransky et al. (2019) added immersion to a science laboratory simulation used by 52 university students; presence rose, learning fell, and electroencephalography recorded higher cognitive load. These studies do not show that VR is ineffective. They support the organizing proposition of this paper: immersion

describes what a system presents to the senses, cognitive load describes what the learner must process, and the two are different things.

Segmentation and Generative Activity

In a second experiment, Parong and Mayer (2018) found that students who wrote a summary after each segment of a VR lesson outperformed those who experienced it continuously, with no loss of interest. Klingenberg et al. (2020) found that teaching a peer after learning the electron transport chain produced large gains in transfer for 89 undergraduate biochemistry students who had used immersive VR, but not for those who had used desktop VR. With 190 sixth and seventh grade students, Klingenberg et al. (2023) found that segmentation or summarizing improved transfer, though not factual knowledge. Outside VR, a meta analysis of 56 studies found that learner paced segments improved retention and transfer and reduced cognitive load, although they increased learning time (Rey et al., 2019). Segmenting and generative activity remain separate mechanisms: the first limits how much is processed at once, and the second prompts learners to organize and integrate what they have just processed (Fiorella & Mayer, 2015).

VR in Cellular and Molecular Biology

Braga et al. (2025) randomly assigned 95 undergraduate nutrition students to learn the citric acid cycle through immersive VR or a video; the VR group scored higher on a quiz, at the threshold of significance, and rated the experience as more engaging. Nasharuddin et al. (2021) reported pretest to posttest gains and favorable usability for InCell VR, a mobile application on mitosis and meiosis, and students in a molecular biology module reported better understanding and engagement with a simulation they had helped design (Reen et al., 2022). These studies show that cellular topics are workable in VR. They do not show which design features produce the gains.

Proposed Framework

The three principles below are not new: guided navigation draws on signaling, scaffolded complexity on segmenting and generative learning, and controlled interactivity on embodied design. What the framework adds is an account of how they must change when the learner is inside the representation. Because a learner in VR controls viewpoint and position, guidance has to organize movement rather than attention within a fixed frame, segmenting has to divide a space as well as a stream of information, and interaction becomes a bodily movement whose meaning is part of what is learned. Table 1 states each principle as a proposition and records the status of its evidence.

Table 1. Design principles stated as propositions, with proposed mechanisms and evidence status

Principle	Proposed cognitive load mechanism	Theoretical basis and evidence status
Guided navigation	Reduces extraneous load from wayfinding and visual search	Signaling (Mayer & Moreno, 2003). Indirect: not yet isolated in a VR study
Scaffolded complexity	Sequencing manages intrinsic load; generative consolidation directs freed capacity toward schema construction	Segmenting (Rey et al., 2019); generative learning (Fiorella & Mayer, 2015). Direct evidence for related methods in VR (Klingenberg et al., 2020; Klingenberg et al., 2023; Parong & Mayer, 2018)
Controlled interactivity	Reduces extraneous load from irrelevant or unclear actions while keeping meaningful agency	Embodied design (Johnson-Glenberg, 2018); CAMIL (Makransky & Petersen, 2021). Theoretical: not yet isolated in biology VR

Guided Navigation

Movement through the virtual space should follow the sequence of the biological process. In an open environment, students must decide where to go before they can attend to the content, and that decision contributes nothing to understanding. When the route mirrors the process, navigating and following the content become one act. Learners can still pause or look back; what disappears is the need to discover the route. Because no VR study has yet isolated navigation structure, this proposition rests on indirect evidence.

Scaffolded Complexity

This principle has two components that should be designed and tested separately. Progressive sequencing presents one stage at a time and adds complexity across segments, which manages intrinsic load (Klingenberg et al., 2023; Rey et al., 2019). Generative consolidation asks the learner to summarize, predict, explain, or teach a stage before advancing, which directs the capacity that sequencing frees toward schema construction (Klingenberg et al., 2020; Parong & Mayer, 2018).

Controlled Interactivity

Each action should pass two tests: relevance to the current stage, drawn from cognitive load theory, and congruence with the concept, drawn from embodied design (Johnson-Glenberg, 2018). Turning a mitochondrion to locate the matrix passes both; throwing decorative objects around the scene passes neither. Limiting actions in this way reduces the effort of working out what is allowed while keeping the meaningful agency that CAMIL links to learning (Makransky & Petersen, 2021).

Discussion

Applications to Cellular Respiration and Mitosis

In a respiration module (Figure 1), the learner moves from glycolysis in the cytosol to the citric acid cycle in the mitochondrial matrix and then to the electron transport chain in the inner mitochondrial membrane. At the citric acid cycle, labels appear as acetyl coenzyme A joins oxaloacetate, carbon dioxide leaves, and NADH and $FADH_2$ form; the only interaction is to turn the mitochondrion, and the stage ends with a prediction about where NADH delivers its electrons. For mitosis, the learner stands beside one cell as it passes through prophase, prometaphase, metaphase, anaphase, and telophase, with cytokinesis overlapping the end of telophase; the learner follows one pair of sister chromatids at anaphase and describes each change before moving on. Existing modules on the citric acid cycle (Braga et al., 2025), the electron transport chain (Klingenberg et al., 2020), and cell division (Nasharuddin et al., 2021) could be extended in this way.

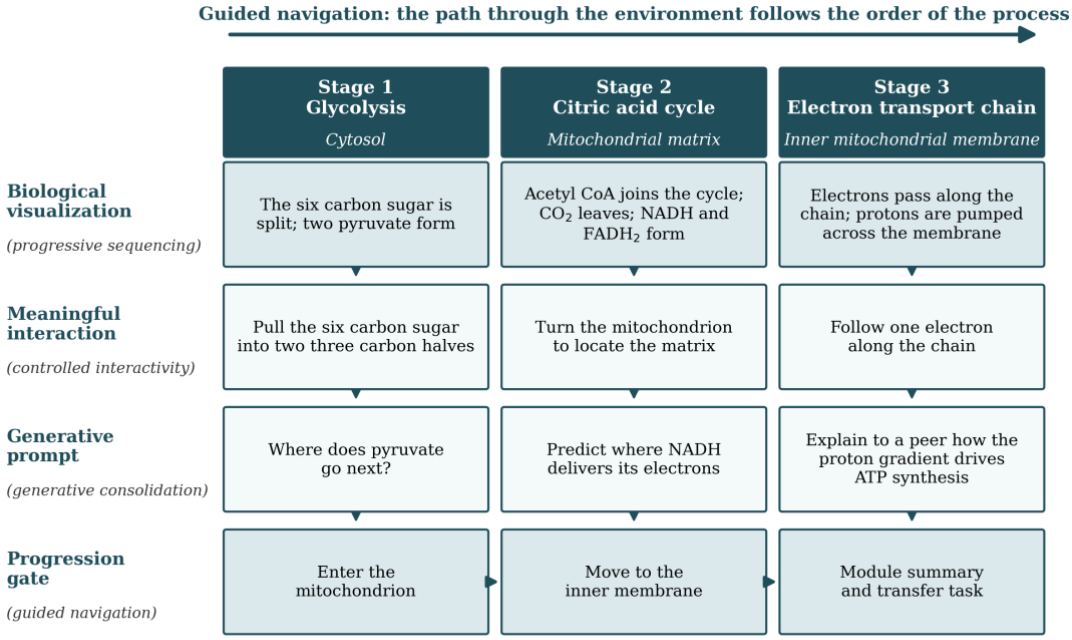


Figure 1. Proposed design framework applied to cellular respiration. Each stage passes through the same four steps; labels in parentheses show the principle each step puts into practice. Author's own design.

Implementation and Accessibility

Headsets remain a substantial cost for a whole class once storage, charging, software, and support are included, and students without their own devices depend on what their institution provides. Accessibility also depends on design. VR sickness varies with how users move and increases after sessions of 20 minutes or longer (Saredakis et al., 2020), so short staged segments and teleporting between fixed stations help. Modules should offer seated use, alternatives to fine controller movements, captions, and an equivalent desktop path (Dudley et al., 2023). Faculty also need time to design around the hardware; partnering with students, as Reen et al. (2022) did, is one way to anchor design in what learners actually find difficult.

Limitations and Research Propositions

This is a conceptual synthesis, not an empirical study, and some of the supporting studies involved school students or general science content. The framework yields four propositions for testing: guided navigation will lower extraneous load relative to open navigation without reducing presence (P1); sequencing with generative consolidation will improve transfer and delayed retention relative to continuous VR (P2); congruent interactions will improve transfer relative to arbitrary ones (P3); and the combined framework will improve learning efficiency relative to unstructured VR (P4). A first study could compare principled VR, unstructured VR, and conventional visualization, measuring cognitive load with a validated instrument (Leppink et al., 2013) or physiological indicators, and measuring transfer and delayed retention rather than engagement alone.

Conclusions

Immersive VR can show biological processes that students would otherwise have to imagine, but the evidence reviewed here indicates that immersion is not the same as learning; students can enjoy an immersive lesson more and learn less from it. This paper translates principles from cognitive load theory, multimedia learning, and embodied learning into concrete decisions about the route through a virtual space, the order and consolidation of stages, and the actions a learner may take. The design question thereby shifts from whether VR should be used to how an immersive environment can be structured so that its representational advantages do not become additional cognitive demands. Whether the resulting modules improve learning in undergraduate classrooms is an empirical question, and the four propositions are meant to make it answerable.

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Teachers' Technology Proficiency Self-Assessments

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Abstract

This study aimed to investigate teachers' technology proficiency self-assessments. The study was designed using a survey research model. The sample of the study consisted of 283 teachers working in public schools in Türkiye. Research data were collected using a personal information form and the "Technology Proficiency Self-Assessment for 21st Century Learning Scale". Descriptive statistics, independent groups t-test, one-way analysis of variance were used for analysis of the data. As a result of research, it was found that teachers' technology proficiency self-assessments were at a high level. Teachers' technology proficiency self-assessments demonstrated significant differences based on gender (in favor of female participants), occupational position (in favor of administrators), educational attainment (in favor of teachers who graduated from master's/doctoral degree programs), computer ownership (in favor of personal computer owners), attending digital security related courses (in favor of participants attending digital security related courses), and familiarity with concept of 21st century skills (in favor of participants familiar with concept of 21st century skills) but no significant difference was found based on professional work experience. Based on these results, it was recommended that technology focused in-service training programs be developed to enable teachers to safely integrate 21st century skills into their educational environments.

Keywords: Technology proficiency self-assessment, 21st century learning, survey research model, teacher

Introduction

Self-assessment is the process by which an individual examines their own knowledge, skills, performance, and level of development according to specific criteria to identify their strengths and areas for improvement. Teachers' technological proficiency is not limited to basic computer use or the ability to access digital tools (Eskici & Çayak, 2023). This proficiency includes the ability to use technology for pedagogical purposes, design digital content and learning environments, facilitate students' active participation in technology-supported learning processes, and integrate digital tools in a way that aligns with instructional goals.

When the relevant literature is examined, it is observed that studies on technology proficiency have been conducted with different sample groups, ranging from primary school students to pre-service teachers and in-service teachers. Technology proficiency has been evaluated alongside variables such as digital literacy, lifelong learning, academic achievement, student engagement, and 21st century skills in the studies. It has been observed that students and pre-service teachers generally possess moderate to high levels of 21st century skills, and the level of supporting these skills with information and communication technologies mostly remains more limited in related studies (Gülen, 2013; Önür, 2018). While studies reveal positive and significant relationships between 21st century skills and variables such as technology proficiency, digital literacy, lifelong learning tendency, and student engagement (Kozikoğlu & Altunova, 2018; Şahin, 2025; Yağlı & Öztürk, 2025; Yıldırım, 2021), they emphasize that technology self-efficacy is a significant predictor in developing these skills (Erten, 2020; Yu & Lwin, 2024). In addition, it has been determined that measurement instruments such as Technology Proficiency Self-Assessment for 21st Century Learning Scale (TPSA C-21S) are valid and reliable in identifying these proficiencies, and demographic variables are influential in some sub-dimensions (Christensen & Knezek, 2017; Woods et al., 2021). Furthermore, it has been stated that innovative approaches such as STEM, flipped learning, augmented reality, and connected learning significantly support the development of 21st century skills (Eken, 2023; Polat, 2024; Uzun, 2022). Overall, findings indicate that technology integration and contemporary instructional practices play an important role in developing 21st century skills.

The widespread adoption of digital technologies in education demonstrates that teachers' professional proficiencies are not limited solely to content knowledge and pedagogical knowledge but also encompass the proficiency to integrate technology into instructional processes in an appropriate, effective, and conscious manner. Teachers' technology proficiencies extend beyond the skill of using digital tools to include using these tools for pedagogical purposes, designing digital learning environments, and guiding students' technology-supported learning processes (Ertmer & Ottenbreit-Leftwich, 2010; Koehler & Mishra, 2005; Mishra & Koehler, 2006). Therefore, determining teachers' technology proficiency self-assessment levels is considered important for revealing the quality of technology integration in education (Christensen & Knezek, 2017; Fidan et al., 2020). In this direction, the present study was conducted to reveal the technology proficiency self-assessment levels of teachers working in public

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schools. The study also aimed to examine whether teachers' technology proficiency self-assessments differed significantly in terms of gender, occupational position, educational attainment, professional work experience, personal computer ownership, attending digital security related courses, and familiarity with concept of 21st century skills. The research questions of the study are presented below:

1. What are teachers' technology proficiency self-assessment levels?

2. Do teachers' technology proficiency self-assessments differ significantly according to the variables of gender, occupational position, educational attainment, professional work experience, personal computer ownership, attending digital security related courses, and familiarity with concept of 21st century skills?

Methodology

The study was conducted with survey research model, which is suitable for describing existing situations and examining differences among groups based on selected variables (Büyüköztürk et al., 2016). As the study aimed to investigate teachers' technology proficiency self-assessment levels and explore whether these levels differed across various demographic and professional characteristics, the survey design was deemed appropriate.

A convenience sampling method was used in the study. Convenience sampling is a sampling method based on collecting data from individuals who are accessible to the researcher and volunteer to participate in the study, taking into account conditions such as time, cost, accessibility, and ease of application (Büyüköztürk et al., 2016; Fraenkel et al., 2012). The sample of the study consisted of 283 teachers working in public schools in Türkiye. The participants comprised 176 females and 107 males. In terms of occupational position, 203 participants were teachers and 80 were administrators. Regarding educational attainment, 194 participants graduated from a two-year college or undergraduate program, and 89 graduated from a master's or doctoral program. In terms of professional work experience, 39 participants had 10 years or less, 111 participants had 11–20 years, 109 participants had 21–30 years, and 24 participants had 31 years or more of experience. Furthermore, 267 participants stated that they had a personal computer, while 16 stated that they did not. While 135 participants reported that they had attended digital security related courses, 148 reported that they had not. Finally, 249 participants stated that they were familiar with concept of 21st century skills, whereas 34 stated that they were not familiar with it.

Research data were collected using a personal information form and the Technology Proficiency Self-Assessment for 21st Century Learning Scale (TPSA C-21S) developed by Christensen and Knezek (2017) and adapted into Turkish by Fidan et al. (2020). The personal information form included questions regarding gender, occupational position, educational attainment, professional work experience, and personal computer ownership. Additionally, to determine participants' status regarding their digital competencies, items were included inquiring whether they had attended digital security related courses and whether they were familiar with concept of 21st century skills. TPSA C-21S, , is a five point likert type scale consisting of a total of 24 items. Participants indicate their level of agreement with the TPSA C-21S items by selecting one of five options ranging from 1 (strongly disagree) to 5 (strongly agree). Total scores obtainable from the scale range between 24 and 120. TPSA C-21S scores were calculated by dividing the total score by the number of items, and the score ranges were evaluated as follows:1.00-1.80 as "strongly disagree", 1.81-2.60 as "disagree", 2.61-3.40 as "undecided", 3.41-4.20 as "agree", and 4.21-5.00 as "strongly agree". The scale consists of four dimensions, including Email (Items 1–5), WWW (Items 6–10), Integrated Applications (Items 11–15), and Teaching with Technology (Items 16–24), and includes no reverse-scored items. As the TPSA C-21S score increases, the technology proficiency self-assessment level also increases. The Cronbach's alpha coefficient for the original scale was calculated as .89 (Fidan et al., 2020). The Cronbach's alpha coefficient of the scale for this study's sample was found to be .91.

The skewness values of TPSA C-21S scores ranged between -1.176 ile -0.239, and the kurtosis values ranged between -1.123 ile +1.315 across all subgroups. Since the skewness and kurtosis values fell within the range of -1.5 to +1.5, the data were considered to be normally distributed (Tabachnick & Fidell, 2013). Because these values were within acceptable limits of normal distribution, it was concluded that the use of parametric tests was appropriate in the study (Büyüköztürk, 2023). Descriptive statistics, independent groups t-test, and one way analysis of variance (ANOVA) were used for the analysis of the data.

Results

To answer the first research question, descriptive statistics of TPSA C-21S scores were calculated (Table 1).

Table 1. Descriptive statistics of TPSA C-21S scores

N	x̄.	S	Minimum	Maximum
283	4.35	0.55	2.25	5.00

Not. TPSA C-21S: Technology Proficiency Self-Assessment for 21st Century Learning Scale, N: number of participants, x̄: mean, S: standard deviation

Teachers' mean TPSA C-21S score was found to be 4.35 (Table 1). This value corresponds to the "strongly agree" level According to the scaling described in the methodology section. Accordingly, it can be interpreted that teachers' technology proficiency self-assessments was at a high level.

When the mean scores for the TPSA C-21S items were examined, it was observed that the item with the highest mean belonged to "I can find my university's or the Ministry of National Education's websites" (x̄=4.96). Based on this finding, it can be stated that information searching on the web and accessing relevant resources represent a strong area of proficiency for the participants. In the scale, the item with the lowest mean was found to be "I can save documents in formats so that others can read them across different word processing programs" (x̄=3.17). Accordingly, it can be interpreted that participants may need support in integrating technology into the instructional process and technically formatting digital content.

An independent groups t-test was first performed to analyze TPSA C-21S scores according to gender, occupational position, educational attainment, personal computer ownership, attending digital security related courses, and familiarity with concept of 21st century skills to address the second research question (Table 2).

Table 2. Results of the t-test for TPSA C-21S scores according to variables

Variables		N	x̄	S	t	df	p	Cohen d
Gender	Female	176	4.264	0.586	3.291	281	.001	.403
	Male	107	4.483	0.466				
Occupational position	Administrator	80	4.469	0.411	2.741	208	.007	.310
	Teacher	203	4.299	0.595				
Educational attainment	Associate/bachelor's degree programs	194	4.256	0.594	4.884	248	.000	.538
	Master's/doctoral programs	89	4.545	0.387				
Personal computer ownership	Yes	267	4.363	0.548	2.068	281	.040	.532
	No	16	4.070	0.598				
Attending digital security related courses	Yes	135	4.487	0.481	4.190	281	.000	.499
	No	148	4.219	0.585				
Familiarity with concept of 21st century skills	Yes	249	4.392	0.534	3.817	281	.000	.698
	No	34	4.015	0.588				

Not. TPSA C-21S: Technology Proficiency Self-Assessment for 21st Century Learning Scale, N: number of participants, x̄: mean, S: standard deviation, df: degree of freedom

It was observed that the male teachers' mean TPSA C-21S score (x̄=4.483) was significantly higher than the female teachers' mean TPSA C-21S score (x̄=4.264), t(267)=3.291, p<.0001, Cohen d=.403 (Table 2). A statistically significant difference was found in TPSA C-21S scores between the administrator group (x̄=4.469) and the teacher group (x̄=4.299) in favor of administrators, t(281)=2.741, p<.05, Cohen d=.310. It was determined that there was a statistically significant difference in the teachers' mean TPSA C-21S scores between the associate/bachelor's degree group (x̄=4.256) and the master's/doctoral degree group (x̄=4.545) in favor of the master's/doctoral degree group, t(281)=4.884, p<.0001, Cohen d=.538. The mean TPSA C-21S score of teachers who owned a personal computer (x̄=4.363) was significantly higher than those who did not (x̄=4.070), t(281)=2.068, p<.05, Cohen d=.532. It was observed that the mean TPSA C-21S score of teachers who had attended digital security related courses (x̄=4.487) was significantly higher than those who had not (x̄=4.219), t(270)=4.190, p<.0001, Cohen d=0.499. The mean TPSA C-21S score of teachers who were familiar with concept of 21st century skills (x̄=4.392) was found to be statistically significantly higher compared to those who were not familiar with concept of 21st century skills (x̄=4.015), t(270)=3.817, p<.0001, Cohen d=0.698.

An ANOVA for independent groups was secondly performed to analyze TPSA C-21S scores according to professional work experience to address the second research question (Table 3).

Table 3. Results of ANOVA for TPSA C-21S scores according to professional work experience

Professional work experience	N	x̄	S	F	df1	df2	p	η²
10 years or less	39	4.323	0.450	0.436	3	279	.728	0.005

11-20 years	111	4.377	0.521
21-30 years	109	4.309	0.627
31 years or more	24	4.418	0.508

Not. TPSA C-21S: Technology Proficiency Self-Assessment for 21st Century Learning Scale, N: number of participants, $\bar{x}$: mean, S: standard deviation, df: degree of freedom

As a result of the ANOVA, it was determined that the teachers' mean TPSA C-21S scores did not differ statistically significantly according to their professional work experience, $F(3,279)=0.436$, $p>.05$ (Table 3). Accordingly, it can be stated that teachers' technology proficiency self-assessment levels does not demonstrate a significant difference according to their professional work experiences.

Conclusions

It was determined that the teachers' mean TPSA C-21S score was high in this study. This result largely aligns with studies conducted outside the city where the present research was carried out and across different types of institutions. In a study conducted with 400 teachers in another city in Türkiye, Okur-Türk (2024) revealed that technology proficiency self-assessments were high. The consistency of these results can be interpreted as indicating that teachers in Türkiye generally perceive themselves as competent regarding technology proficiency for 21st century learning.

It was found that male teachers' TPSA C-21S scores were significantly higher than female teachers' TPSA C-21S scores in this study. In contrast, Kozikoğlu and Altunova (2018) and Erten (2020) determined that gender did not create a significant difference in TPSA C-21S scores. Based on these conflicting results, it can be interpreted that the relationship between gender and technology proficiency self-assessment may vary depending on sample characteristics, institutional support, or differences in individual technology access and usage habits. It was found that administrators' TPSA C-21S scores were significantly higher than teachers' TPSA C-21S scores. There is no study available in the literature with which this result can be directly compared. Administrators' use of technology for functions such as institutional planning, coordination, and supervision may be the reason they exhibit higher technology proficiency self-assessments. It was found that the TPSA C-21S scores of teachers who graduated from master's/doctoral degree programs were significantly higher than teachers who graduated from associate/bachelor's degree programs. There is no study available in the literature with which this result can be directly compared. The fact that graduate education fosters research skills, awareness of technological tools, and self-directed learning tendencies may be the reason for this result. It was found that the mean TPSA C-21S score of teachers who owned a personal computer was significantly higher than who did not own a personal computer. This result is similar to the results of Önür's (2018) and Şahin's (2025) studies. Based on this finding, it can be interpreted that having continuous and direct access to a personal computer facilitates more frequent digital practice, thereby positively reinforcing teachers' confidence and proficiency in integrating technology into 21st century learning environments. The mean TPSA C-21S score of teachers who had attended digital security related courses was found to be significantly higher. This result aligns with the findings of Erten (2020), who emphasized that competence in information and communication technologies is a decisive factor in acquiring 21st century skills. In this context, it can be interpreted that targeted training in digital data security not only enhances specific technical safeguards but also broadly fosters teachers' overall technology proficiency and readiness for 21st century educational environments. Teachers who were familiar with concept of 21st century skills had significantly higher TPSA C-21S scores compared to those who were familiar with concept of 21st century skills. Erten (2020) revealed that competence in the field of information and communication technologies is effective in acquiring 21st century skills, Kozikoğlu and Altunova (2018) demonstrated a positive relationship between pre-service teachers' self-efficacy perceptions regarding 21st century skills and their lifelong learning tendencies. The result obtained in the present study conceptually aligns with these studies, and it can be interpreted that it demonstrates that conceptual awareness is strongly associated with practical proficiencies. Knowing the name of a concept and assimilating its content may facilitate teachers allocating more space to this area in their educational agendas and increasing their motivation for self-development. Teachers' mean TPSA C-21S scores did not differ according to their professional work experience. This result is similar to the results of studies of Yılmaz (2015), Yılmaz et al. (2016), and Gökkaya-Babacan (2025). Accordingly, it can be interpreted that teachers' technology proficiency self-assessment levels may not be explained solely by the professional experience.

This study was limited to school administrators and teachers working in public schools. Future research could be conducted with larger samples selected from different provinces, regions, and school types to increase the generalizability of the results. Such studies may enable the comparison of results obtained in diverse sociocultural and institutional contexts. A quantitative research method was employed in this study. In future research, mixed methods designs could be utilized to provide qualitative depth to quantitative findings. The results of this study

are limited to data obtained from participants working in public schools; therefore, similar research could be carried out with teachers working in private educational institutions in the future.

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Teachers' Digital Data Security Awareness

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Abstract

This study aimed to investigate teachers' digital data security awareness. The study was conducted using a survey research model. The sample of the study consisted of 283 teachers working in public schools in Türkiye. Research data were collected using a personal information form and the "Digital Data Security Awareness Scale". Descriptive statistics, independent groups t-test, one way analysis of variance were used for analysis of the data. It was found that teachers' digital data security awareness was at a high level. It was found that teachers' digital data security awareness differed significantly according to gender (in favor of male participants), attending digital security related courses (in favor of participants attending digital security related courses), and familiarity with concept of 21st century skills (in favor of participants familiar with concept of 21st century skills), but there were no significant differences based on occupational position, educational attainment, professional work experience, and personal computer ownership. Based on these results, it was recommended that digital data security focused in-service training programs be developed to enable teachers to safely integrate technology into their educational environments.

Keywords: Digital data security awareness, survey research model, teacher

Introduction

Digital data security is a combination of technical, administrative, and behavioral measures intended to protect data generated, stored, processed, and shared in electronic environments against threats such as unauthorized access, change, damage, exposure, or destruction (Öztürk, 2022). Digital data security awareness is defined as the ability of individuals to recognize the risks they may encounter in digital environments, develop appropriate measures against these risks, and demonstrate secure digital behavior. Digital data security awareness in educational institutions is required to ensure the security of data, such as students' personal information, academic records, digital materials, online activity data, and communication records, to prevent violations of student privacy, to prevent the sharing of personal data with unauthorized individuals, and to prevent risks such as cyberbullying, identity theft, and institutional security weaknesses. Therefore, teachers' digital data security awareness is important not only in terms of individual technology use but also in terms of protecting student rights, school safety, and ethical responsibilities (Araycı & Özyurt, 2026).

A review of the relevant literature reveals that digital data security awareness has been addressed across different participant groups ranging from primary school students to pre-service teachers, and from teachers to academicians. Digital data security and cybersecurity awareness are evaluated as a multidimensional competency domain that is not limited to technical knowledge and skills alone, but is related to concepts such as digital literacy, digital citizenship, and technological pedagogical content knowledge in the studies. Relevant studies generally indicate that digital data security and cybersecurity awareness is an important competency domain for teachers, pre-service teachers, academicians, and students (Aksoğan & Atıcı, 2023; Singh, 2024; Yılmaz, 2015; Yılmaz et al., 2016). Research demonstrates that although the level of awareness is mostly high, various deficiencies persist in areas such as password security, phishing, online storage, social media use, and data privacy (Alqahtani, 2022; Bhatnagar & Pry, 2020; Leung et al., 2026; Raju et al., 2022; Ravichandran et al., 2025). In addition, variables such as gender, technology usage time, digital literacy, digital citizenship, Technological Pedagogical Content Knowledge (TPACK) competence, and ownership of technological devices have been identified to be related to the level of digital data security awareness (Gökkaya-Babacan, 2025; Göldağ, 2021; Hızmalı, 2022; İbekçi, 2025; Öztürk & Çakır, 2022). Results obtained from the studies reveal that digital security awareness is not limited to individual technology use but is a multidimensional construct that must be addressed alongside digital literacy, professional competence, and applied training processes (Göldağ, 2021; Leung et al., 2026).

The intensive use of digital technologies in educational environments has turned the issue of data security into an important area of responsibility for the teaching profession. Teachers are in constant interaction with students' personal information, academic records, digital materials, online learning platforms, and school management systems as part of their duties. This situation requires that teachers not only possess the ability to use technology, but also manage digital data in a secure, ethical, and conscious manner. Malicious software, data security breaches, social engineering threats, and various security risks emerging in digital environments demonstrate that digital data security awareness is a crucial competency domain for teachers (Canbek & Sağıroğlu, 2006, 2007a, 2007b;

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Tekerek, 2008; Yılmaz et al., 2016). In this context, examining teachers' digital data security awareness levels is considered essential to reveal the current state of ensuring data security in educational environments and to identify potential areas of need. Accordingly, this study was conducted to determine the digital data security awareness levels of teachers working in public schools. The study also aimed to investigate whether teachers' digital data security awareness levels differed significantly according to gender, occupational position, educational attainment, professional work experience, personal computer ownership, attending digital security related courses, and familiarity with concept of 21st century skills. The research questions are given below:

1. What are the teachers' digital data security awareness levels?
2. Do teachers' digital data security awareness levels differ significantly according to gender, occupational position, educational attainment, professional work experience, personal computer ownership, attending digital security related courses, and familiarity with concept of 21st century skills?

Methodology

The study was conducted using a survey research model, which is commonly used to describe existing conditions and examine the characteristics of a particular population (Büyüköztürk et al., 2016). Since the aim was to determine teachers' digital data security awareness levels and examine them in relation to various variables, the survey model was considered appropriate.

A convenience sampling method was used in the study. Convenience sampling is a sampling method based on collecting data from individuals who are accessible to the researcher and volunteer to participate in the study, taking into account conditions such as time, cost, accessibility, and ease of application (Büyüköztürk et al., 2016; Fraenkel et al., 2012). The sample of the study consisted of 283 teachers working in public schools in Türkiye. The participants comprised 176 females and 107 males. In terms of occupational position, 203 participants were teachers and 80 were administrators. Regarding educational attainment, 194 participants graduated from associate or bachelor's degree programs, and 89 graduated from master's or doctoral programs. In terms of professional work experience, 39 participants had 10 years or less experience, 111 participants had 11-20 years' experience, 109 participants had 21-30 years' experience, and 24 participants had 31 years or more experience. Furthermore, 267 participants stated that they had a personal computer, while 16 stated that they did not. While 135 participants reported that they had attended digital security related courses, 148 reported that they had not. Finally, 249 participants stated that they were familiar with concept of 21st century skills, whereas 34 stated that they were not familiar with it.

Research data were collected using a personal information form and the Digital Data Security Awareness Scale (DDSAS) developed by Yılmaz (2015). The personal information form included questions regarding gender, occupational position, educational attainment, professional work experience, and personal computer ownership. Additionally, to determine participants' status regarding their digital competencies, items were included inquiring whether they had attended digital security related courses and whether they were familiar with concept of 21st century skills. DDSAS is a five point likert type scale consisting of a total of 32 items. Participants indicate their level of agreement with the DDSAS items by selecting one of five options ranging from 1 (strongly disagree) to 5 (strongly agree). Total scores obtainable from the scale range between 32 and 160. DDSAS scores were calculated by dividing the total score by the number of items, and the score ranges were evaluated as follows:1.00-1.80 as "strongly disagree", 1.81-2.60 as "disagree", 2.61-3.40 as "undecided", 3.41-4.20 as "agree", and 4.21-5.00 as "strongly agree". The scale has a single factor structure and contains no reverse coded items. As the DDSAS score increases, digital data security awareness increases. The Cronbach's alpha coefficient for the original scale was calculated as .95 (Yılmaz, 2015). The Cronbach's alpha coefficient of the scale for this study' sample was found to be .94.

The skewness values of DDSAS scores ranged between -1.373 and -0.424 and the kurtosis values ranged between -0.583 and +1.175 across all subgroups. Since the skewness and kurtosis values fell within the range of -1.5 to +1.5, the data were considered to be normally distributed (Tabachnick & Fidell, 2013). Because these values were within acceptable limits of normal distribution, it was concluded that the use of parametric tests was appropriate in the study (Büyüköztürk, 2023). Descriptive statistics, independent groups t-test, and one way analysis of variance (ANOVA) were used for the analysis of the data.

Results

Descriptive statistics of DDSAS scores were calculated to answer the first research question (Tablo 1).

Table 1. Descriptive statistics of DDSAS scores

N	x̄.	S	Minimum	Maximum
283	4.57	0.45	2.91	5.00

Not. DDSAS: Digital Data Security Awareness Scale, N: number of participants, x̄: mean, S: standard deviation

Teachers' mean DDSAS score was found to be 4.57 (Table 1). According to the scaling described in the methodology section, this value corresponds to the "strongly agree" level. Accordingly, it can be interpreted that teachers' digital data security awareness was at a high level.

When the mean scores for the DDSAS items were examined, it was observed that the participants' awareness levels regarding digital data security were generally high. The item with the highest mean was determined to be "I know that login procedures performed with a onetime password sent to a mobile phone increase security" (x̄=4.86). Based on this result, it can be stated that participants are aware of the importance of basic security measures aimed at ensuring personal account security in digital environments. On the other hand, the item with the lowest mean was found to be "I have knowledge about firewall software" (x̄=3.59). Accordingly, it can be interpreted that participants' awareness levels are lower in subjects requiring more technical knowledge, such as firewall software.

An independent groups t-test was first performed to analyze DDSAS scores according to gender, occupational position, educational attainment, personal computer ownership, attending digital security related courses, and familiarity with concept of 21st century skills to address the second research question (Table 2).

Table 2. Results of the t-test for DDSAS scores according to variables

Variables		N	x̄	S	t	df	p	Cohen d
Gender	Female	176	4.499	0.483	3.676	267	.000	.422
	Male	107	4.686	0.368				
Occupational position	Administrator	80	4.593	0.422	0.537	281	.592	.071
	Teacher	203	4.560	0.464				
Educational attainment	Associate or bachelor's degree programs	194	4.539	0.471	1.677	281	.095	.215
	Master's or doctoral programs	89	4.636	0.403				
Personal computer ownership	Yes	267	4.576	0.448	1.043	281	.298	.269
	No	16	4.455	0.519				
Attending digital security related courses	Yes	135	4.686	0.367	4.306	270	.000	.506
	No	148	4.464	0.495				
Familiarity with concept of 21st century skills	Yes	249	4.600	0.444	3.128	281	.002	.572
	No	34	4.346	0.450				

Not. DDSAS: Digital Data Security Awareness Scale, N: number of participants, x̄: mean, S: standard deviation, df: degree of freedom

It was found that the male teachers' mean DDSAS score (x̄=4.686) was significantly higher than the female teachers' mean DDSAS score (x̄=4.499), t(267)=3.676, p<.0001, Cohen d=0.422 (Table 2). No statistically significant difference was found in DDSAS scores between administrator and teacher groups, t(281)=0.537, p>.05. It was determined that the difference between the teachers' mean DDSAS score with an associate or bachelor's degree programs and those with a master's or doctoral degree programs was not statistically significant, t(281)=1.677, p>.05. The mean DDSAS score of teachers who owned a personal computer and those who did not, demonstrated no statisticlly significant difference, t(281)=1.043, p>.05. It was observed that the mean DDSAS score of teachers who had attended digital security related courses (x̄=4.686) was significantly higher than those who had not (x̄=4.464), t(270)=4.306, p<.0001, Cohen d=0.506. The DDSAS score of teachers who were familiar with concept of 21st century skills (x̄=4.600) were found to be statistically significantly higher compared to those who were not familiar with concept of 21st century skills (x̄=4.346), t(281)=3.128, p<.05, Cohen d=0.572.

An ANOVA for independent groups was secondly performed to analyze DDSAS scores according to professional work experience to address the second research question (Table 3).

Table 3. Results of ANOVA for DDSAS scores according to professional work experience

Professional work experience	N	x̄	S	F	df1	df2	p	η²
10 years or less	39	4.459	0.474	2.261	3	279	.082	0.024
11-20 years	111	4.582	0.441					
21-30 years	109	4.555	0.477					
31 years or more	24	4.758	0.272					

Not. DDSAS: Digital Data Security Awareness Scale, N: number of participants, x̄: mean, S: standard deviation, df: degree of freedom

As a result of the ANOVA, it was determined that the teachers' mean DDSAS scores did not differ statistically significantly according to their professional work experience, $F(3,279)=2.261$, $p>.05$ (Table 3). Accordingly, it can be stated that teachers' digital data security awareness does not demonstrate a significant difference according to their professional work experiences.

Conclusions

It was determined that the teachers' mean DDSAS score was high. This result is consistent with the results of studies conducted with teachers by Yılmaz (2015) and Yılmaz et al. (2016). Similarly, Aksoğan and Atıcı (2023) and Gökkaya-Babacan (2025) characterized participants' digital data security awareness levels as high and adequate in their studies conducted with different samples. Accordingly, it can be inferred that teachers consider themselves sufficiently equipped to navigate digital risks and ensure data security.

In studies conducted by Yılmaz (2015), Yılmaz et al. (2016), Hızmalı (2022), Göldağ (2021), Aksoğan and Atıcı (2023), and Gökkaya-Babacan (2025), it was found that male teachers' digital data security awareness was significantly higher than female teachers' digital data security awareness. The result obtained in the present study is also consistent with results of these studies. Accordingly, obtaining similar results across studies conducted with different samples can be evaluated as an indication that gender may be one of the variables associated with digital data security awareness. Participants' mean DDSAS score did not demonstrate according to occupational position. According to this result, it can be interpreted that digital data security awareness is not a role based competence. The result that the teachers' mean DDSAS score did not demonstrate statistically significant difference according to educational attainment is similar to the results of studies by Yılmaz (2015) and Yılmaz et al. (2016). Based on this, it can be interpreted that digital data security awareness is not solely associated with educational attainment. Participants' mean DDSAS score did not demonstrate according to personal computer ownership. This result can be interpreted that digital data security awareness is related not only to device ownership, but also to knowledge and attitudes about using these devices safely. The mean DDSAS score of teachers who had attended digital security related courses was significantly higher. Yılmaz (2015) also anticipated in his study that teachers who had received training related to digital security could have higher levels of awareness, emphasizing that digital data security was not sufficiently included in projects implemented by the Ministry of National Education and that this deficiency should be addressed. When these results are evaluated together, it can be interpreted that in-service training programs have positive effects on teachers' digital security awareness. Teachers who were familiar with concept of 21st century skills had significantly higher DDSAS scores compared to those who were familiar with concept of 21st century skills. The result obtained in the present study can be interpreted that it demonstrates that conceptual awareness is strongly associated with practical proficiencies. Knowing the name of a concept and assimilating its content may facilitate teachers allocating more space to this area in their educational agendas and increasing their motivation for self-development. Teachers' mean DDSAS scores did not differ according to their professional work experience. This result is similar to the results in the studies of Yılmaz (2015), Yılmaz et al. (2016), and Gökkaya-Babacan (2025). Accordingly, it can be interpreted that teachers' digital data security awareness may not be explained solely by the professional experience.

This study was limited to school administrators and teachers working in public schools. Future research could be conducted with larger samples selected from different provinces, regions, and school types to increase the generalizability of the results. Such studies may enable the comparison of results obtained in diverse sociocultural and institutional contexts. A quantitative research method was employed in this study. In future research, mixed methods designs could be utilized to provide qualitative depth to quantitative findings. The results of this study are limited to data obtained from participants working in public schools; therefore, similar research could be carried out with teachers working in private educational institutions in the future.

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Designing an Immersive Virtual Reality-Based Extracurricular STEM Activity for Gifted Middle School Students: The Case of "Pain and Painkillers"

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Abstract

Gifted students need interdisciplinary extracurricular activities that challenge them beyond the standard curriculum. Immersive virtual reality (IVR) has increasingly been used in science education for gifted students in recent years. However, studies that transform IVR content based on authentic scientific research into pedagogically sound and directly implementable extracurricular activities for gifted students remain limited. This study designs an extracurricular STEM activity for gifted middle school students and evaluates it based on science and information technology (IT) teachers' views. The activity is built on the "Pain and Painkillers" IVR simulation, supported by the US National Science Foundation and the National Institutes of Health. The simulation focuses on how Protoxin-II and morphine inhibit pain signals through different mechanisms. The simulation was translated into Turkish with support from the 10k Science platform. Within the activity, the neuroscience content presented in the simulation was integrated with an engineering design task. In this task, students are expected to design a conceptual model of a novel analgesic molecule by drawing inspiration from nature through a biomimicry-based approach. The activity was structured according to the 5E instructional model—Engage, Explore, Explain, Elaborate, and Evaluate—and was designed to be implemented in two 90-minute sessions. The engineering design process was integrated into the Elaborate phase of the second session. The activity consists of four major components. The first component involves guided observation during the IVR experience. The second involves a rotation-based small-group implementation necessitated by the limited number of available IVR headsets. While one group participates in the IVR experience, the remaining students engage in a complementary learning task at a separate station. The third component is an open-ended engineering design task that specifies the scientific criteria and constraints that the molecule designed by the students is expected to satisfy. The fourth component is a structured discussion addressing opioid dependence and the ethical implications of developing pharmaceutical products from animal-derived venoms. The activity was evaluated by 11 experts (8 science and 3 IT teachers) with experience working with gifted students, using an Expert Evaluation Form comprising Likert-type items across six dimensions, open-ended questions on strengths and areas for improvement, and an overall suitability judgment. The activity was rated as highly appropriate overall (M = 4.63, SD = 0.28), with the highest ratings obtained for alignment with learning outcomes and effectiveness of IVR integration (both M = 4.88, SD = 0.23); the understandability of the scientific terminology for the target age group received the lowest mean score (M = 3.64, SD = 0.81). Overall, 81.8% of the experts judged the activity as "appropriate" and 18.2% as "appropriate with revisions," and none rated it as "not appropriate." The findings suggest that IVR is most valuable for gifted science education when integrated with appropriate pedagogical scaffolding, differentiation, and age-appropriate scientific content, rather than used as a stand-alone technological tool.

Keywords: gifted students, immersive virtual reality, STEM education, extracurricular activity design

Introduction

Gifted students benefit from enriched learning experiences that extend beyond the standard curriculum, focus on their interests and abilities, provide cognitive challenge, and create opportunities for creative production (Reis et al., 2021; Sternberg et al., 2022). Extracurricular enrichment programmes are among the approaches commonly used to foster the creativity and abilities of gifted students. Rather than consisting of fragmented activities that merely introduce students to new topics, extracurricular enrichment programmes are recommended to be systematically structured in ways that deepen students' knowledge and skills (Tan et al., 2020). In this regard, interdisciplinary STEM activities may provide appropriate enrichment opportunities for gifted students by integrating science knowledge with tasks that require problem solving, design, creativity, and the use of knowledge from different disciplines.

Immersive virtual reality (IVR) can enable students to examine scientific structures that are difficult to observe directly or are complex across different scales through interactive virtual environments (Matovu et al., 2023;

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Mokmin & Apandi, 2025). In science education, IVR has been used particularly to facilitate the visualisation of abstract concepts and to enrich learning experiences. However, it has been emphasised that the technological features of IVR alone do not guarantee effective learning and that pedagogical structuring is important (Matovu et al., 2023; Won et al., 2023). In recent years, studies examining the use of IVR in science education for gifted students have also begun to emerge. In studies focusing on activity development, IVR has been integrated with pedagogical approaches such as creative thinking, differentiation, and the 5E learning model. For example, Avcu and Yaman (2024) used IVR in a differentiated science activity based on inquiry and creative thinking within the context of sustainability for gifted students, whereas Ayverdi and Avcu (2025) structured a learning experience related to space science using the 5E learning model and IVR. Empirical studies have also examined IVR-supported science learning environments in relation to different variables. These have included scientific creativity, engagement in science lessons, and self-regulated learning (Avcu & Yaman, 2026), conceptual understanding (Ayverdi, 2026), and nature relatedness and attitudes towards the environment (Avcu & Yaman, 2025).

Although these studies indicate that IVR can be used for different pedagogical purposes in science education for gifted students, design examples in which IVR content based on authentic scientific research is transformed into directly implementable extracurricular STEM activities remain limited. In particular, transferring scientific knowledge acquired through IVR to an open-ended engineering design problem may enable students to move beyond merely experiencing the virtual environment and apply scientific knowledge in a new problem context. Accordingly, the present study aims to design an extracurricular STEM activity based on the "Pain and Painkillers" IVR simulation for gifted middle school students and to evaluate the suitability of the activity based on the views of teachers experienced in working with gifted students. In the activity, the IVR experience concerning pain transmission and the different mechanisms of action of morphine and Protoxin-II was integrated with the 5E learning model, a biomimicry-based engineering design task, and scientific and ethical discussions.

Purpose

The aim of this study was to design an extracurricular STEM activity for gifted middle school students and to evaluate the activity based on the views of teachers who work with gifted students.

Method

IVR Simulation and Instructional Design

The extracurricular STEM activity was designed based on the Pain and Painkillers IVR simulation developed by 10k Science. The scientific content of the simulation focuses on how Protoxin-II and morphine inhibit pain signaling through different mechanisms. The IVR simulation was localized by translating it into Turkish. The activity was structured in accordance with the 5E Learning Model and planned to be implemented in two sessions, each lasting 90 minutes. Neuroscience and engineering design constitute the core STEM components of the activity. As part of the engineering design task, students are expected to develop a conceptual design for a novel analgesic molecule using a biomimicry-based approach. This task was integrated into the Elaborate phase of the 5E model.

Core Components of the Activity

The activity consists of four core components: guided IVR observation; small-group rotation and station-based activities; an open-ended engineering design task incorporating scientific criteria and constraints; and a structured discussion addressing opioid dependence and the ethical dimensions associated with the use of animal-derived toxins. These components were integrated to ensure that the IVR experience did not remain merely an observation-based use of technology and that students could apply the scientific knowledge they acquired in problem-solving, design, and discussion processes.

Expert Evaluation

The designed activity was evaluated by 11 experts with experience working with gifted students. The expert group consisted of 8 science teachers and 3 information technology (IT) teachers. An Expert Evaluation Form was used in the evaluation process. The form consisted of three sections. The first section included Likert-type items across six dimensions designed to evaluate different aspects of the activity. The second section contained open-ended questions asking experts to identify the strengths of the activity and the aspects requiring improvement. In the third section, experts were asked to provide an overall judgment regarding the suitability of the activity.

Findings

Table 1 presents the descriptive statistics of expert opinions across the six dimensions of the Expert Evaluation Form.

Table 1. Descriptive statistics on expert opinions.

Dimension	*n*	*M*	*SD*
Content and Scientific Accuracy	11	4.21	0.43
Alignment with Learning Outcomes	11	4.88	0.23
Suitability for Gifted Students	11	4.79	0.27
Effectiveness of IVR Integration	11	4.88	0.23
Activity Flow, Duration, and Feasibility	11	4.24	0.68
Appropriateness of the Assessment Rubric	11	4.86	0.45
Overall	11	4.63	0.28

At the item level, Table 2 presents the Likert items that received the highest and lowest mean ratings from the experts.

Table 2. Highlighted Likert items in expert evaluations.

Highlighted Item	*n*	*M*	*SD*
Observation notebook questions and design constraints are open-ended and flexible in line with differentiation principles.	11	5.00	0.00
The integration of the IVR experience into the 5E instructional flow is coherent and meaningful.	11	5.00	0.00
The scientific terms used in the activity are understandable for the target age group.	11	3.64	0.81
Safety notes regarding screen time, break arrangements, and sensitive-topic management are sufficient and appropriate.	11	4.36	1.03

Descriptive findings based on expert opinions indicate that the activity received generally positive evaluations across the assessed dimensions. The highest mean scores were obtained for alignment with learning outcomes and the effectiveness of IVR integration (both M = 4.88). Suitability for gifted students (M = 4.79) and the appropriateness of the assessment rubric (M = 4.86) were also among the dimensions with relatively high mean scores. At the item level, the open-ended and flexible nature of the observation notebook questions and design constraints, together with the integration of the IVR experience into the 5E instructional flow, received the highest mean ratings (both M = 5.00). In contrast, the understandability of the scientific terminology for the target age group received the lowest mean score (M = 3.64).

The open-ended responses were analyzed and organized into themes and codes. Table 3 presents the themes, codes, and sample participant comments regarding the strengths of the activity, and Table 4 presents the themes, codes, and sample participant comments on the aspects of the activity that require improvement.

Table 3. Themes, codes, and sample participant comments regarding the strengths of the activity.

Theme	Code	Example Participant Comment
IVR-Supported Experiential Learning	Concretizing abstract concepts	"*The activity is quite strong because it gives students the opportunity to experience a topic that might otherwise be hard to concretize*." (Science Teacher 4)
	Increasing curiosity and engagement	"*The use of IVR in the activity is quite important, as it triggers students' curiosity while providing a realistic experience*." (IT Teacher 2)
Suitability for Gifted Students	Enrichment and differentiation	"*That the activity was structured taking into account gifted students' cognitive characteristics, learning pace, and higher-order cognitive needs is one of the study's important strengths*." (IT Teacher 3)
	Higher-order thinking and problem solving	"*It supports gifted students' higher-order thinking and problem-solving skills*." (Science Teacher 5)
Interdisciplinary STEM and Design	Interdisciplinary integration	"*The interdisciplinary approach (biology, engineering, medicine, and ethics) is capable of developing students' higher-order thinking skills.*" (Science Teacher 2)
	Transforming knowledge into an original design	"*The strength of the activity is that it is designed to enable students, starting from pain-transmission mechanisms, to construct an original analgesic*

		based on biomimicry — transforming theoretical knowledge into an innovative product." (Science Teacher 3)
Student-Centered Learning and Assessment	5E-based structured learning	"*The activity plan was prepared in a systematic and holistic structure in line with the 5E learning model.*" (Science Teacher 2)
	Process-oriented assessment	"Process-oriented assessment tools (observation notebook, rubric, etc.) show variety." (Science Teacher 5)

Table 4. Themes, codes, and sample participant comments on areas for improvement.

Theme	Code	Example Participant Comment
Conceptual Load and Age Appropriateness	Simplification of terminology	"*The depth of the scientific terminology should be reduced, and the concepts need to be made more concrete.*" (Science Teacher 3)
	Readiness and conceptual support	"*Because the topic is terminologically dense, students' readiness matters; repetitions to help students grasp the terms could be increased.*" (Science Teacher 4)
Duration and Activity Flow	Flexibility in duration	"*Because the design and ethical-discussion parts of the second session are quite extensive, duration could be planned more flexibly according to classroom dynamics.*" (Science Teacher 5)
	Revising presentation and evaluation time	"*Time planning is unrealistic: the 10 minutes allocated for the presentation stage is insufficient for the number of groups, and no time at all has been allocated for the evaluation stage.*" (IT Teacher 1)
Technical Feasibility and Safety	Access to IVR devices	"I *think the biggest problem that could arise during implementation is procuring the IVR headsets.*" (IT Teacher 2)
	Detailing the safety protocol	"*The safety precautions consist of a single sentence; screen-time limits, break arrangements, and the procedure to follow in case of discomfort are not defined.*" (IT Teacher 1)
Learning Support and Assessment	Increasing scaffolding for conceptual understanding	"More animations, simulations, and everyday-life analogies could *be used to support understanding of abstract concepts such as neurons and synaptic transmission.*" (Science Teacher 2)
	Individual contribution and peer assessment	"*An individual contribution form and/or structured peer assessment is therefore recommended.*" (IT Teacher 3)

In the experts' open-ended responses, views regarding the strengths of the activity were grouped under the themes of IVR-supported experiential learning, suitability for gifted students, interdisciplinary STEM and design, and student-centered learning and assessment. Among the points that emerged in these responses were the concretization of abstract concepts, increased curiosity and engagement, enrichment and differentiation, higher-order thinking and problem solving, interdisciplinary integration, the transformation of scientific knowledge into an original design, 5E-based structured learning, and process-oriented assessment. Views regarding aspects requiring improvement were grouped under the themes of conceptual load and age appropriateness, duration and activity flow, technical feasibility and safety, and learning support and assessment. Within these themes, simplifying terminology, considering students' readiness and providing conceptual support, allowing greater flexibility in duration, revising the time allocated for presentations and evaluation, ensuring access to IVR devices, detailing the safety protocol, increasing scaffolding for conceptual understanding, and incorporating individual contribution and peer assessment were among the main suggestions expressed by the experts.

Table 5 presents the experts' overall judgments regarding the general appropriateness of the activity.

Table 5. Expert judgments on the overall appropriateness of the activity.

Overall Judgment	*f*	%
Appropriate	9	81.8
Appropriate with revisions	2	18.2
Not appropriate	0	0
Total	11	100

As shown in Table 5, the majority of experts (81.8%) judged the activity as "appropriate," while 18.2% judged it as "appropriate with revisions"; none of the experts judged the activity as "not appropriate."

Conclusion and Discussion

Expert evaluations of the IVR-based extracurricular STEM activity developed in this study indicated that the activity was generally viewed positively in terms of alignment with learning outcomes, IVR integration, suitability for gifted students, and its assessment structure. In particular, the integration of the IVR experience into the 5E instructional process, together with the open-ended and flexible design tasks, emerged as notable strengths of the activity. At the same time, the age appropriateness of the scientific terminology, the need for conceptual support, and time planning were among the main areas that experts recommended for improvement. The fact that the great majority of experts judged the activity to be appropriate and the remaining experts considered it appropriate with revisions suggests that the design offers an implementable framework, while also indicating a need for some adjustments, particularly in relation to age-appropriate scientific language and the implementation process.

In the expert evaluations, the integration of IVR with the 5E model, its use with open-ended tasks, and its alignment with differentiation principles were among the aspects that stood out as strengths of the activity. This supports the view that, for gifted students, IVR should be used within a clear pedagogical structure rather than simply as a technological tool. Similarly, previous studies have reported positive outcomes in IVR-supported science learning environments in relation to nature relatedness and attitudes towards the environment (Avcu & Yaman, 2025), as well as engagement in science lessons, self-regulated learning, and scientific creativity (Avcu & Yaman, 2026). The study by Ayverdi and Avcu (2025), in which IVR was integrated with the 5E learning model, and the comparative findings reported by Ayverdi (2026) also point to the importance of how the technology is structured and the learning purposes for which it is used. Considered together with these studies, the present expert evaluations indicate the importance of combining IVR in gifted science education with pedagogical support, differentiation, and tasks that allow students to use scientific knowledge in inquiry and design processes.

Recommendations

– The advanced scientific terminology used in the activity should be simplified in accordance with the cognitive characteristics of the target age group and supported with analogies, visuals, animations, and concrete examples.

– The activity duration should be planned more flexibly, particularly to allocate sufficient time for the design, presentation, ethical discussion, and assessment stages.

– Technical and safety protocols for IVR implementation should be further detailed, including access to devices, rotational use, screen-time limits, break arrangements, and procedures for possible discomfort.

– Future studies should implement the activity with gifted students and empirically evaluate its effectiveness in terms of learning outcomes, engagement, scientific creativity, and students' experiences.

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Beyond Technology Acceptance: Exploring the Cognitive, Ethical, and Motivational Factors Shaping ChatGPT Engagement in Cybersecurity Education

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Abstract

The increasing integration of generative artificial intelligence tools such as ChatGPT into computing education raises important questions about their relationship with students' critical thinking and problem-solving skill development. This study explores associations between ChatGPT usage and students perceived development of higher-order thinking skills, including critical thinking and problem-solving, within a cybersecurity education context. This context is particularly relevant because computing and cybersecurity students regularly engage with tasks such as debugging or threat analysis, which require analytical reasoning, evaluation, and independent decision-making. As AI becomes increasingly embedded in these activities, understanding how students engage with such tools is important for determining their role within learning processes that traditionally depend on independent reasoning. Drawing on survey data from 84 students, we employ partial least squares structural equation modelling (PLS-SEM) to examine a multi-construct model incorporating usage behaviour, perceived usefulness, self-efficacy, ethical awareness, and perceived skill development. The study used a cross-sectional observational design based on students' self-reported perceptions and experiences. The model was used to explore both the relationship between ChatGPT usage and perceived skill development and the psychological and institutional factors associated with students' engagement with the tool. The structural model explained 70.9% of the variance in ChatGPT usage and 45.7% of the variance in perceived critical thinking and problem-solving skill development. ChatGPT usage demonstrated a significant positive association with perceived skill development ($\beta = 0.506$, $p < .001$). However, the factors associated with ChatGPT engagement revealed more complex patterns than conventional technology acceptance perspectives suggest. Perceived usefulness ($\beta = 0.267$, $p = .042$) and motivation for learning ($\beta = 0.220$, $p = .008$) were positively associated with ChatGPT usage, whereas self-efficacy ($\beta = -0.219$, $p = .043$) and ethical awareness ($\beta = -0.245$, $p = .004$) demonstrated significant negative associations. University support was positively associated with perceived skill development ($\beta = 0.261$, $p = .007$), suggesting that institutional guidance may contribute to how students perceive the educational value of AI-supported learning. This study contributes to educational technology research by providing an exploratory model that reveals both enabling and constraining factors associated with students' engagement with generative AI. Although ChatGPT usage was positively associated with perceived critical thinking and problem-solving skill development, higher levels of ethical awareness and self-efficacy were negatively associated with usage. These findings suggest that students' engagement with generative AI is more nuanced than simple technology acceptance models imply and reinforce the importance of pedagogical approaches that encourage critical and responsible AI use. Limitations related to the use of self-reported measures and a relatively small sample size are acknowledged, indicating the need for further research incorporating behavioural and performance-based assessments.

Keywords: Generative artificial intelligence; ChatGPT; cybersecurity education; higher-order thinking skills; technology acceptance

Introduction

Artificial Intelligence (AI) has become an integral part of modern technology, with a growing influence in education (Hussain & Anwar, 2024). Although the use of educational chatbots is widely discussed (Hussain & Anwar, 2024), their actual impact on students' learning and cognitive processes remains insufficiently understood (Tayan et al., 2024). This issue is particularly important in IT and cybersecurity education, where analytical reasoning and decision-making are required to respond to threats. This study examines the extent to which ChatGPT usage is associated with students' self-reported perceptions of development of critical thinking and problem-solving (CTPS) skills among IT students and explores factors that may influence students' engagement with the tool. Given the cross-sectional and self-reported nature of the data, the study focuses on associations between ChatGPT usage and perceived skill development rather than establishing causal effects. The findings provide evidence of statistical associations between ChatGPT usage and students' perceived higher-order cognitive skill development in IT education.

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Literature Review

Overall, this research considers nine independent constructs, which are outlined below:

- ChatGPT Usage (CU). CU refers to how frequently and purposefully students integrate ChatGPT into learning and problem-solving activities. ChatGPT may support engagement, understanding, and independent learning when used critically and as a cognitive aid (Hmoud et al., 2024; Zizar, 2023). However, excessive or uncritical use may reduce independent reasoning and longer-term learning (Valova et al., 2024).
- Critical Thinking and Problem-Solving Skills Development (CTPSSD). Critical thinking and problem-solving are central to computing and cybersecurity education, requiring analysis, evaluation, and decision-making under uncertainty (Ohm et al., 2024). ChatGPT may support these skills when students verify outputs, reflect on responses, and maintain independent reasoning (Hmoud et al., 2024; Rahman & Watanobe, 2023; Tayan et al., 2024). In computing, these skills include debugging, evaluating solutions, and analysing vulnerabilities.
- Perceived Usefulness (PU). PU refers to students' perceptions of ChatGPT's value for learning and problem-solving (Kiryakova & Angelova, 2023). Perceived benefits include time savings, assistance with complex tasks, personalised learning, and improved efficiency (Kiryakova & Angelova, 2023; Malinka et al., 2023; Valova et al., 2024). However, reliability and overreliance remain concerns (Hmoud et al., 2024).
- Motivation for Learning (ML). ML influences how students engage with ChatGPT during learning. Intrinsically motivated students may use the tool to deepen understanding, while extrinsically motivated learners may rely on it to obtain quick solutions (Hmoud et al., 2024).
- Ethical Awareness (EA). Ethical concerns surrounding ChatGPT include academic integrity, privacy, fairness, and dual-use risks (Farhi et al., 2023; Gupta et al., 2023; Ohm et al., 2024; Vaccino-Salvadore, 2023). Students may submit or modify AI-generated work in ways that undermine academic integrity (Hmoud et al., 2024; Malinka et al., 2023).
- Perceived Self-Efficacy (PSE). PSE refers to students' confidence in managing learning tasks and using technology effectively (Hussain & Anwar, 2024). Although higher self-efficacy may support technology use, perceived ability does not necessarily correspond to actual performance (Yang et al., 2025).
- University Support (US). US can influence responsible AI integration (Tayan et al., 2024). However, the literature consistently suggests that effective integration requires training, ethical guidance (Kiryakova & Angelova, 2023), and assessment design that encourages deeper engagement, independent learning, and analytical reasoning (Ohm et al., 2024; Zizar, 2023).
- Learner Expectations (LE). LE reflects students' expectations regarding ChatGPT, including independent learning, examination preparation, and personalised responses, alongside concerns about reliability and accuracy (Hmoud et al., 2024; Malinka et al., 2023; Tayan et al., 2024).
- Perceived Learning Performance (PLP). PLP reflects how students perceive the impact of ChatGPT on their learning efficiency and academic outcomes through accessible and tailored responses (Rahman & Watanobe, 2023). Previous research suggests that ChatGPT can support academic performance and engagement (Hussain & Anwar, 2024).

Research Gap and Research Hypotheses

This study therefore examines several interrelated psychological and institutional factors associated with ChatGPT usage and perceived CTPS skill development. The proposed relationships are presented in Figure 1.

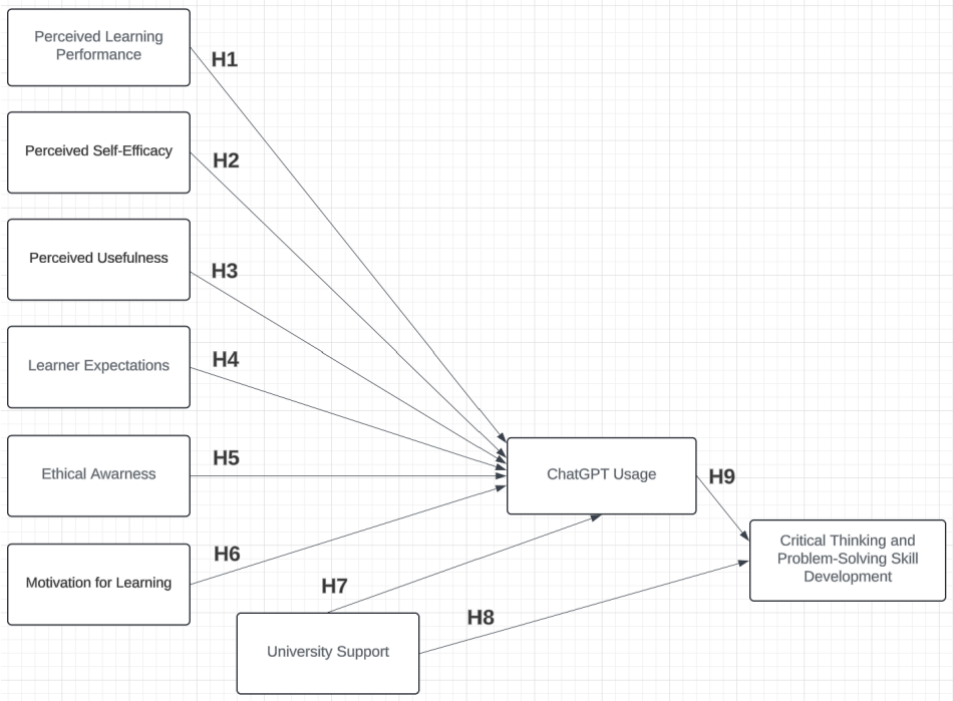


Figure 1. Proposed Research Model and Hypotheses.

To provide conceptual clarity and align the study with established practices in computing education research, this work is guided by the following research questions: RQ1: To what extent is ChatGPT usage associated with students' self-reported perceptions of development of critical thinking and problem-solving skills in IT and cybersecurity education? RQ2: Which psychological and institutional factors significantly influence students' engagement with ChatGPT in an educational context?

Methodology

To address the exploratory nature of the study and the relatively small sample size, Partial Least Squares Structural Equation Modelling (PLS-SEM) was adopted as it does not rely on strong assumptions of normality or large samples (Dash & Paul, 2021). A cross-sectional observational design was employed, with self-reported data collected during a short period in March 2025. A quantitative method was employed using an online survey created in Microsoft Forms. A 38-item questionnaire was measured on a 5-point Likert scale ranging from "Strongly disagree" to "Strongly agree" with items linked to the constructs shown in Figure 1. Sample items for ChatGPT use include "I often use ChatGPT for solving technical problems and generating code individually and in projects" or "I often use ChatGPT for learning by asking questions, explaining difficult concepts, or clarifying ideas". Meanwhile, some sample items for CTPSSD include: "Using ChatGPT helps develop critical analysis skills, including verifying the accuracy of and questioning responses" or "Using ChatGPT improves the ability to solve problems independently". For the full survey items, please contact the author(s). The final sample consisted of 84 students, which meets minimum requirements for exploratory PLS-SEM analysis, although it constrains statistical power and model stability. Ethical standards were maintained throughout the study. Participation was voluntary, informed consent was obtained at the beginning of the survey, and no personal data were collected beyond what was required for the study.

Results

Measurement Model Assessment

The outer model evaluated construct reliability and validity by examining the relationship between indicators and their latent constructs. Convergent validity showed that most indicators met the recommended loading threshold of 0.70 (Ernawati et al., 2022; Henseler et al., 2015). One indicator (CTPS5) initially showed a weak loading and was removed during model refinement, which improved internal consistency reliability. The removal of CTPS5 was based on low indicator loading; however, such data-driven refinement may affect content validity. This highlights the need for further validation of the measurement instrument in future studies. Construct reliability and

convergent validity metrics are reported in Table 1, with Cronbach's alpha and AVE meeting recommended thresholds.

Table 1. Model Constructs and Validity.

Construct	Cronbach's alpha	AVE	Loading range
PLP	0.862	0.643	0.741–0.850
PSE	0.811	0.638	0.771–0.813
PU	0.885	0.744	0.831–0.896
LE	0.804	0.629	0.763–0.822
EA	0.756	0.575	0.709–0.816
ML	0.925	0.817	0.843–0.946
US	0.748	0.617	0.693–0.908
CU	0.877	0.676	0.693–0.893
CTPSSD	0.838	0.679	0.674–0.882

However, the SRMR value of 0.115 exceeded the commonly used 0.08 threshold, suggesting that the model does not achieve a strong level of approximate fit. This result is reported as an important limitation of the model rather than as grounds for rejecting the exploratory PLS-SEM analysis outright. This likely reflects the combined effects of model complexity, sample size constraints, and potential construct overlap, and should therefore be interpreted with caution, but is not uncommon in complex exploratory models (Pavlov et al., 2020). Discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). Overall, most construct pairings satisfied the relevant criteria, indicating satisfactory discriminant validity across the majority of the measurement model. However, several HTMT values exceeded conventional thresholds, indicating potential empirical overlap between some constructs, particularly CTPSSD, LE, PSE, PLP, and PU. Similar concerns emerged from the Fornell–Larcker assessment. Nevertheless, the full measurement model was retained without modification because the constructs are theoretically and conceptually distinct within the proposed framework. Specifically, LE captures the anticipations students hold before engaging with AI-assisted learning tools, whereas PLP reflects their evaluations of actual outcomes following the learning experience. Similarly, PU and PSE represent distinct psychological processes relating to technology adoption and skill development. Thus, although some empirical overlap is evident, the constructs were retained in accordance with their established theoretical distinctions and their respective roles within the conceptual model.

Structural Model Assessment

The model explained 70.9% of the variance in ChatGPT usage ($R^2 = 0.709$) and 45.7% in CTPS skill development ($R^2 = 0.457$). Effect size analysis also confirmed that ChatGPT usage had the strongest influence on CTPS skill development (see Table 2). It is important to note that this relationship reflects perceived development and should not be interpreted as direct evidence of actual cognitive skill improvement. Furthermore, regarding potential multicollinearity, most VIF values were below 5, although LE exceeded this threshold (5.385). Hypothesized relationships were tested using a bootstrapping procedure with 5,000 resamples and a two-tailed significance level of 0.05. A hypothesis was supported when the path coefficient was significant ($p < 0.05$). As shown in Table 2, six out of nine hypotheses were supported. ChatGPT usage showed the strongest positive association with students' self-reported perceptions of development of critical thinking and problem-solving skills. University support also demonstrated a significant association with perceived CTPSSD. Among the predictors of ChatGPT usage, perceived usefulness and motivation for learning showed significant positive effects, while ethical awareness and perceived self-efficacy showed significant negative effects.

Table 2. Hypothesis Testing Results from PLS-SEM Analysis including Path Coefficients and Effect sizes

Hypothesis	Path	Path Coefficient β	T-statistics	f^2 Value	p-value	Result
H1	PLP → CU	0.242	1.571	0.049 (small)	0.116	Rejected
H2	PSE → CU	-0.219	2.020	0.037 (small)	0.043	Supported
H3	PU → CU	0.267	2.039	0.052 (small)	0.042	Supported

H4	LE → CU	0.236	1.724	0.035 (small)	0.085	Rejected
H5	EA → CU	-0.245	2.864	0.130 (small)	0.004	Supported
H6	ML → CU	0.220	2.637	0.106 (small)	0.008	Supported
H7	US → CU	0.102	1.231	0.025 (small)	0.218	Rejected
H8	US → CTPSSD	0.261	2.683	0.093 (small)	0.007	Supported
H9	CU → CTPSSD	0.506	4.921	0.351 (large)	0.000	Supported

Discussion

CU was positively associated with perceived CTPSSD (H9), consistent with research suggesting educational benefits when ChatGPT is used purposefully (Hmoud et al., 2024; Zizar, 2023). US was also positively associated with CTPSSD (H8), while PU and ML positively predicted CU, suggesting that perceived benefits and learning motivation are associated with greater engagement (Hmoud et al., 2024). The positive CU–CTPSSD association suggests ChatGPT use may coexist with perceived cognitive skill development, although concerns about overreliance remain (Hussain & Anwar, 2024; Ohm et al., 2024). The negative association between EA and CU may indicate that students with greater awareness of academic integrity risks regulate their use more carefully (Hussain & Anwar, 2024). The negative associations between EA, PSE, and CU may tentatively reflect self-regulated use of AI tools rather than disengagement. From a computing education perspective, the findings suggest that ChatGPT's educational value depends on how it is integrated into learning activities. Instructors may therefore design tasks requiring students to critique, verify, and extend AI-generated outputs while maintaining independent reasoning, while structured institutional guidance and assessment strategies may further support responsible use. Several limitations should be noted. CTPSSD was measured through self-reported perceptions rather than objective performance, so the findings cannot establish actual cognitive skill acquisition. Furthermore, the relatively small sample limits generalisability and may reduce model stability, and although PLS-SEM is suitable for exploratory analysis, model complexity increases the risk of overfitting. The cross-sectional design also prevents causal inference, as relationships may be bidirectional. Finally, the study did not capture students' actual interactions with ChatGPT during authentic computing tasks.

Conclusions

This study identified a positive association between ChatGPT usage and students' self-reported perceptions of critical thinking and problem-solving skill development. However, this association should not be interpreted as evidence of actual cognitive improvement. PU and ML were positively associated with ChatGPT usage, whereas EA and PSE showed negative associations, indicating that engagement is shaped by both enabling and constraining factors. US was also positively associated with perceived CTPSSD, highlighting the potential role of institutional guidance. These findings suggest that the educational value of ChatGPT depends on how its use is structured. Computing educators should incorporate tasks requiring students to critique, verify, justify, and extend AI-generated outputs rather than simply reproduce solutions. Assessment should prioritise reasoning processes and context-specific problem-solving, and institutional guidance and training may further support responsible engagement. Overall, ChatGPT may function most effectively as a cognitive support tool when its use preserves independent reasoning and critical evaluation.

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The Role of Generative Artificial Intelligence in Instructional Design and Student Engagement: A Literature-Based Synthesis

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Abstract

Generative artificial intelligence (AI) (ChatGPT and similar large language models) has rapidly permeated the field of education since 2022, yet the literature on how it is integrated into instructional design processes and how it affects student engagement remains fragmented. This study synthesizes 32 articles published between 2024 and 2026, retrieved from the Web of Science Core Collection using the keywords 'instructional design', 'generative AI', and 'student engagement', to examine the role of generative AI in instructional design and its effects on student engagement. Findings indicate that generative AI is most frequently integrated through the ADDIE model, while acceptance theories such as the Technology Acceptance Model and UTAUT are widely used to explain adoption. Student engagement is addressed across cognitive, emotional, behavioral, and social dimensions, with effects depending on pedagogical guidance, prompt design, and contextual support. A VOSviewer keyword co-occurrence map further shows that the three core concepts rarely co-occur within the same article, underscoring the gap this synthesis addresses. The literature suggests that generative AI holds strong potential for instructional designers, provided it is deliberately integrated with systematic instructional design models.

Keywords: Instructional design, generative AI, student engagement.

Introduction

Since 2022, ChatGPT and similar large language models have rapidly become central to educational practice. However, despite this rapid spread, the academic literature has not been able to systematize at the same pace. The literature addresses how generative artificial intelligence (AI) is integrated into instructional design processes — such as content development, material preparation, and assessment design — in a fragmented manner across different disciplines. Moreover, studies on its effect on student engagement present conflicting results; some studies find positive effects (e.g., BaiDoo-Anu & Owusu Ansah, 2023), while others report negative or context-dependent mixed outcomes (e.g., Guo et al., 2025). This uncertainty constitutes the main motivation for the present study. While early literature (2022–2023) primarily approached generative AI as a novelty or an automated content-generation tool, recent educational research increasingly demands a shift toward pedagogical intentionality. In this context, instructional design models play a pivotal bridging role in determining whether AI integration stimulates active student engagement or merely fosters superficial information retrieval.

The purpose of this study is to synthesize the role of generative AI in instructional design processes and its effects on student engagement by examining 32 articles published between 2024 and 2026, retrieved from the Web of Science database. Accordingly, three research questions were formulated:

- How is generative AI integrated into instructional design models (e.g., ADDIE, PBL)?
- In what ways are the cognitive, emotional, behavioral, and social dimensions of student engagement affected?
- What factors (pedagogical design, guidance, context) determine this effect?

Methodology

This study adopts a descriptive literature synthesis approach. The Web of Science Core Collection was chosen as the data source, since WoS applies rigorous peer-reviewed journal selection criteria and excludes low-quality sources, offering more reliable and standardized metadata. This standardized metadata enables bibliometric analysis with tools such as VOSviewer. Moreover, WoS has broad coverage for scanning a multidisciplinary topic spanning fields such as education, computer science, psychology, and nursing, and is one of the most widely

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accepted databases internationally for systematic review studies. The fact that this study is limited to a single database, without including additional sources such as Scopus, is acknowledged as a limitation.

The search was conducted using the keywords 'instructional design', 'generative AI', and 'student engagement', limited to the years 2024–2026 and restricted to the document type article, resulting in 32 articles. The application contexts show diversity, spanning higher education, vocational-technical education, primary education, nursing, medical education, language teaching, and science and mathematics education. Articles were systematically reviewed following an iterative qualitative content synthesis approach. Each study was coded across predefined analytical dimensions, including target instructional design frameworks (e.g., ADDIE, PBL), target engagement domains (cognitive, emotional, behavioral, social), pedagogical mechanisms (scaffolding, prompt design), and reported limitations, which subsequently informed the thematic clustering.

Results

The articles examined in the study are presented under descriptive findings as well as five separate themes.

Descriptive Findings

The distribution of the 32 reviewed articles by year is presented in Figure 1. Of the articles, 94% (30/32) were published in the last two years (2025-2026); this indicates the topic's currency and the field's rapid growth, even though the time span of the study was not wide.

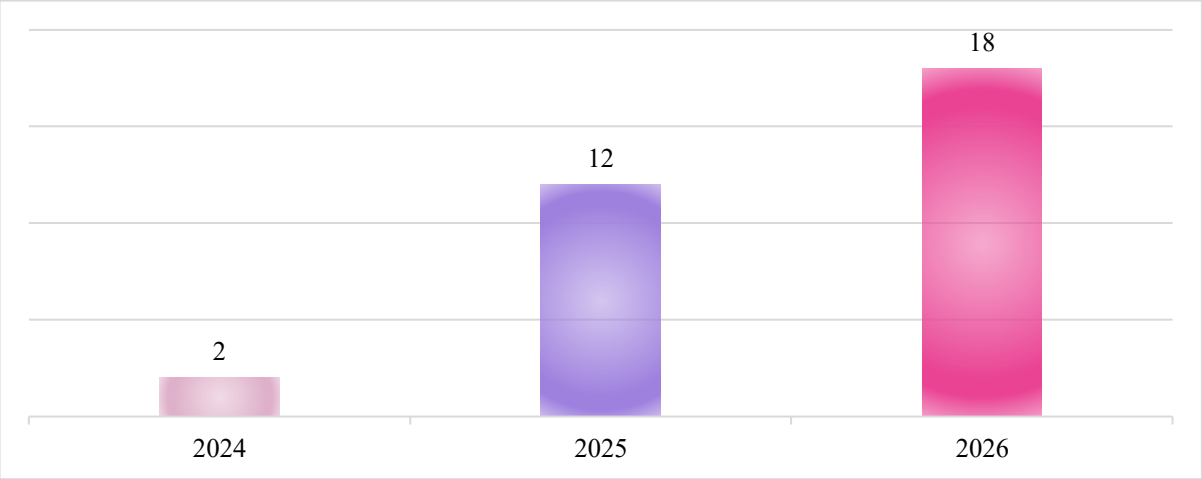


Figure 1. Distribution of the reviewed articles by year (N = 32).

In the keyword network generated with VOSviewer (Figure 2) the term "generative ai" stands out as the most central and highly connected node; it is linked to large language models and instructional design in one cluster, and to learning engagement in a second cluster. In the map, the expressions "generative ai" and "generative artificial intelligence" appear as two separate nodes due to unnormalized spelling variation, although they conceptually represent the same term; when these two nodes are merged, generative AI emerges as a single central concept directly connected to large language models, instructional design, higher education, and learning engagement.

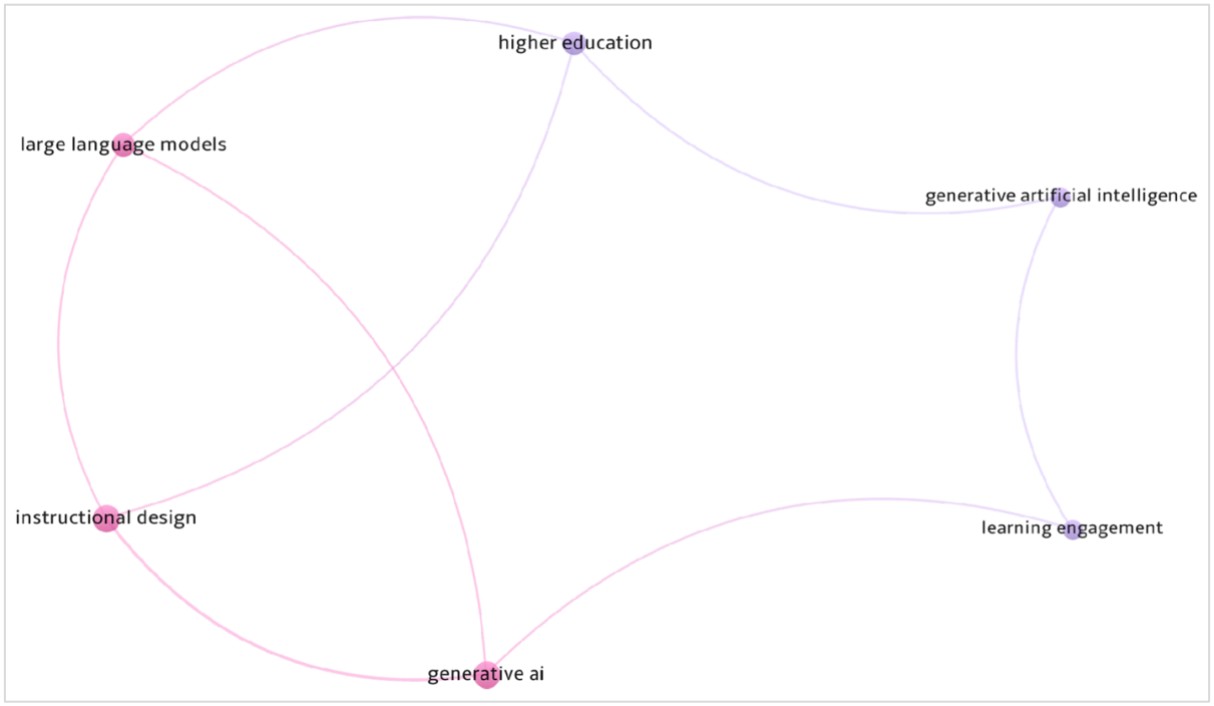


Figure 2. Keyword network.

Importantly, the bibliometric topology reveals a structural gap: 'instructional design' and 'learning engagement' share minimal direct co-occurrence paths, functioning largely as peripheral clusters that interact almost exclusively through the intermediary hub of 'generative ai'. This structural decoupling visually corroborates that the existing scholarship remains bifurcated — investigating either the design process or engagement outcomes — thereby validating the necessity of an integrative synthesis to bridge these two traditionally separate bodies of literature.

Thematic Findings

The findings obtained from the study collected under five themes. These themes are described below under separate headings.

Integration into Instructional Design Models

Generative AI is largely incorporated into practice through established instructional design models. The ADDIE model stands out as the most frequently referenced framework; Lee (2025), demonstrates how each of ADDIE's analysis, design, development, implementation, and evaluation stages can be enriched with AI tools. Windey & Bruewer (2026) applied this approach to nursing professional development and presented it as a transformative approach. While Lee (2025) conceptualizes the ADDIE framework broadly as a procedural roadmap for prompt-driven content curation and iterative assessment drafting, Windey and Bruewer (2026) demonstrate its clinical adaptability, showing that structured instructional design frameworks are essential for translating generic AI capabilities into discipline-specific, competency-based continuous professional training. In addition, project- and problem-based learning (PBL) models have also been used; Jaramillo-Fierro et al. (2026) combined their developed 4PADAFE model with generative AI and augmented reality within a PBL framework. Raman et al. (2026) proposed the ADO (Antecedents-Decisions-Outcomes) framework, which explains adoption through institutional and cognitive antecedents.

The Multidimensional Nature of Student Engagement

The literature addresses student engagement across four separate dimensions — cognitive, emotional, behavioral, and social — and shows that the effect of generative AI differs across these dimensions. Huang & Zhang (2026), found that AI competency and emotion are among the strongest predictors of engagement. Guo et al.'s (2025) large-scale study, conducted with approximately 70,000 Chinese university students, presents a striking finding: in challenging learning contexts with high support, generative AI use increases engagement, while in low-support contexts the opposite effect — a decrease in engagement — is observed. This finding is important in showing that the same tool can produce opposite effects depending on context. This critical dichotomy observed by Guo et al. (2025) aligns with cognitive load and scaffolding theories: when students are placed in demanding learning tasks without structured pedagogical scaffolding, generative AI can exacerbate cognitive confusion and learner

alienation, leading to disengagement. Conversely, within high-scaffolded ecosystems, it operates as an empowering cognitive partner. Lu et al. (2025) revealed that formative feedback, shared metacognition, and engagement strengthen together.

Acceptance and Adoption Processes

Classical technology acceptance theories occupy a dominant position in the literature for explaining instructional designers' and students' decisions to adopt generative AI tools. Fourie et al.'s (2026) study, conducted with 203 instructional designers and faculty members, revealed that trust and habit are the most decisive factors in the adoption of large language models. Shen et al. (2026) used both the Technology Acceptance Model (TAM) and UTAUT together to examine students' psychological adaptation to scaffolded generative AI use. Similarly, Verma & Kumar (2026) modeled the factors determining students' future ChatGPT usage intention using a machine-learning-based approach instead of traditional survey methods, offering a more data-driven perspective on the topic. Demirdöken & Kirkgöz's (2026) study showed that social presence and student engagement mediate the relationship between self-regulation and the acceptance of AI-based assessment.

The Determinative Role of Pedagogical Design

According to this theme, the quality of interaction with generative AI depends less on the tool itself and more on the extent to which the prompt and guidance are pedagogically enriched. Miller's (2026) experimental study with 125 participants shows that prompt design enriched with pedagogical principles significantly increases student-AI interaction and motivation. Miller's evidence indicates that generic or conversational prompting often elicits shallow, factual responses that truncate the inquiry process. In contrast, embedding Socratic questioning, metacognitive prompts, and explicit instructional roles within the prompt engineering phase transforms the AI from a mere search proxy into a dynamic cognitive tutor. Zhang (2025) revealed that guided and structured use yields more positive results than unguided use, both in academic writing quality and in engagement. Shen et al. (2026) showed that psychological adaptation is related to scaffolded AI use. These findings indicate that it is deliberate, designed use — not random use — that makes a difference.

Types of Interaction, Limitations, and Ethics

Wang et al.'s (2026) study shows that teacher-student interaction more strongly supports emotional, social, and behavioral engagement, whereas AI-student interaction more strongly supports cognitive engagement. This complementary dynamic underlines the risks of over-relying on automated environments; while AI successfully mediates personalized cognitive exploration and immediate task troubleshooting, human instructor presence remains irreplaceable for socio-emotional modeling, academic empathy, and sustained normative motivation. This finding reveals that the two types of interaction do not substitute for one another but are complementary in nature. On the limitations side, we can say that assessment reliability, ethics, and equity remain insufficiently researched areas (Applebaum, 2026; Manning et al., 2025; Zheng et al., 2026).

Conclusions

The 32 articles reviewed in this study show that when generative AI is deliberately integrated with systematic instructional design models — particularly ADDIE and PBL — it can support student engagement in a multidimensional way. However, this effect is not automatic; it depends closely on the level of pedagogical guidance, prompt design, and contextual support. Guo et al.'s (2025) finding clarifies this point: the same tool can increase engagement in high-support contexts while decreasing it in low-support contexts. Similarly, Miller (2026) and Zhang (2025), showed that unguided use produces weaker results compared to guided/structured use.

From this, we derive four recommendations. First, for instructional designers, systematic frameworks such as ADDIE and PBL should be restructured with generative AI integration. Second, prompt and guidance design should be made an explicit and planned component of instructional design. Third, more research is needed on long-term effects, ethical dimensions, and equitable access; and finally, generative AI literacy programs should be developed for the professional development of instructional designers. Ultimately, generative AI should not be conceptualized as an autonomous delivery mechanism, but rather as an instructional amplifier whose pedagogical impact is strictly mediated by deliberate systematic design, scaffolded human interaction, and robust ethical oversight.

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An AI-Driven Rainfall Prediction Framework for Smart Academic Planning: Enhancing Student Safety and Learning Continuity During Extreme Weather Events

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Abstract

The rise in the frequency of extreme rainfall events in South Asia has had a significant impact on the academic activities, particularly on the safety of commuting to and from school, attendance at school, scheduling of examinations, operations on the campus, and continuity of learning. Although AI-based rainfall forecasting for agriculture, hydrology and disaster management has greatly improved, the application of AI in academic planning and decision-making for universities has not been explored in detail. This study introduces a novel rainfall prediction and institutional decision support framework, combining ensemble machine learning with a rule-based academic decision support system, for smart academic planning. The prediction engine was developed with 13,575 daily meteorological observations from Karachi, Lahore and Islamabad gathered over 20 years (2004 to 2023) from the Visual Crossing weather archive. To enhance the prediction performance, Synthetic Minority Oversampling Technique (SMOTE), systematic hyperparameter optimization and seven supervised machine learning classifiers were used and tested for both imbalanced and balanced class distribution. An important innovation of this work is the proposed Trend-Tracking Aggregation (T-Tagging) ensemble algorithm which dynamically adapts the contribution of base learners based on their temporal performance stability, and not on static weight or majority voting ensembles. The proposed framework results in 99.83% classification accuracy and Area Under the ROC Curve (AUC) of 0.9996 which is better than individual classifiers and conventional ensemble strategies. In addition to predictions, the framework provides a multi-tier academic response mechanism that helps institute appropriate actions for face-to-face, hybrid, or online teaching and learning, examination rescheduling, campus safety alerts, and transportation advisories. This study represents a pioneering effort that connects AI-driven weather intelligence with the management of smart campus operations, creating a tangible decision support system for climate-resilient schools. This study stands out from other rainfall forecasting research by directly linking AI-based weather intelligence to campus management, offering a usable decision-support framework for climate-resilient educational institutions. The proposed framework provides a transferable and scalable blueprint for AI-based smart university that helps in proactively planning academic activities, enhancing the safety of students, and enhancing the resilience of operations and continuity of learning in the case of extreme weather events.

Keywords: *Rainfall prediction; Ensemble learning; Trend-Tracking Aggregation; Smart campus; Academic decision support; Learning continuity; Student safety*

1. Introduction

Climate change has intensified the frequency and severity of extreme rainfall across Pakistan, and the consequences now extend well beyond agriculture and water resource management. Urban universities are directly exposed: monsoon downpours saturate arterial roads, halt public transport, and jeopardise the safe commute of students and staff. Institutions typically react on the morning of an event—or worse, after students have already begun unsafe journeys producing a cycle of lost teaching days, rescheduled examinations, erratic attendance, and administrative disruption that falls hardest on public-transport users and residents of low-lying areas.

Artificial Intelligence has been very effective for short-term rainfall prediction: historical meteorological archives are used to train AI models with high accuracy for daily occurrence classification (Rajab et al., 2023; Farman et al., 2024). However, the downstream application of such forecasts have been focused on agriculture, hydrology and disaster management. Abnormal rainfall has an impact on agricultural production, critical resources and hydrological resources such as river flow, infiltration of ground water, water supply, etc. (Alam et al., 2021; Liyew & Melese, 2021), and accurate prediction is important for water policy to be adaptive and for flood early-warning systems (Umamaheswari & Ramaswamy, 2024; Wang et al., 2024), as well as for irrigation planning (Sani et al., 2020). The education sector is one of the most time-sensitive public services and is one of the least served. Smart-campus literature is mainly targeted at energy management, attendance analytics, and learning management

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systems, whereas environmental forecasting is seldom linked to academic activities. However, Kutty et al. (2022) demonstrate that ensemble machine learning has a good transfer performance for composite urban decision problems, which means that the same predictive performance and, importantly, a well-designed decision layer could be used to safeguard higher education.

The proposed framework is thus double layered. The first layer is a high accuracy rainfall prediction model based on an ensemble of supervised classifiers called Trend-Tracking Aggregation (T-Tagging) which is trained using two decades of daily weather data from three major cities of Pakistan. The second layer provides mapping of prediction outputs, together with indicators of precipitation intensity, into institutional actions for teaching mode, rescheduling examination, safety alerts and transport advisories. The second is necessary due to its design, since predicting the occurrence of binary classes is not enough for making decisions in academic. light drizzle and dangerous urban flooding are positive classes. The decision layer then uses precipitation amount, probability and coverage from the same source, allowing for a graduated institutional response instead of a switch-on or switch-off response. This is a difference between the current system and the direct reuse of the existing rain classifiers.

1.1 Impacts of Rainfall on the Academic Sector

University campuses are extremely susceptible to extreme weather events because thousands of students, researchers, and staff come and go from campus on a daily basis. The impact of extreme weather goes far beyond its physical impacts. Teaching days are missed and the remainder of the schedule crammed into the weeks to come. Last-minute rescheduled exams can put some groups of students at a disadvantage, thus jeopardizing assessment integrity. During rainfall events, if a lot of students are commuting at once, then their safety is compromised. Multiple last minute cancellations (or lack of cancellation when indicated) compromise institutional credibility. Workload also increases significantly, with teachers taking on the responsibility for make-up classes, amended invigilation plans and the recording of attendance. Importantly, each of these harms is mitigated if enough time is given. Higher education institutions thus require systems to support their decisions during the operations before an event and not after it, on the basis of accurate rainfall forecasts.

1.2 Why Universities Need AI-Driven Rainfall Prediction

Universities are increasingly vulnerable to extreme weather events because thousands of students, faculty members, and staff commute daily from different regions. Heavy rainfall frequently causes road flooding, traffic congestion, transportation delays, and campus accessibility problems, resulting in late attendance, examination disruptions, reduced instructional time, and administrative challenges. Unlike traditional weather forecasting applications that primarily support agriculture or disaster management, higher education institutions require intelligent decision-support systems capable of transforming rainfall forecasts into proactive operational decisions. Figure A illustrates the cascading impacts of heavy rainfall on academic activities and highlights the need for AI-driven rainfall prediction to improve institutional resilience, student safety, and learning continuity.The figure A illustrates how extreme rainfall events trigger road flooding and transportation disruptions, preventing students from reaching campus and causing attendance problems, teaching interruptions, and examination delays. These cascading effects reduce learning continuity, increase student safety risks and administrative burden, and create operational challenges for universities. The proposed AI-based rainfall prediction and decision support framework enables timely recommendations for face-to-face, hybrid, or online teaching, ultimately supporting the development of a smart climate-resilient campus.

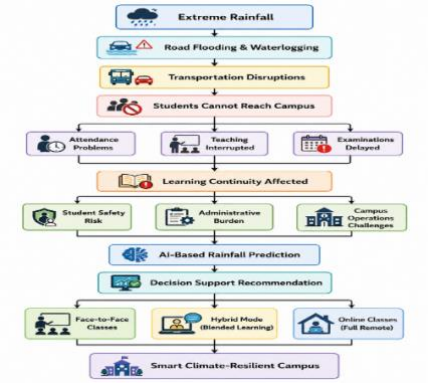


Figure A. *Motivation for AI-Driven Rainfall Prediction in Smart Academic Planning.*

1.3 Contributions of the Study

This work makes four principal contributions. First, it presents, to the authors' knowledge, the first framework explicitly coupling ensemble machine learning rainfall prediction with academic operations planning for universities in a developing-country monsoon environment. Second, it validates the engine on a twenty-year, three-city Pakistani dataset under a leakage-controlled protocol, achieving 99.83% accuracy and an AUC of 0.9996. Third, it establishes a rule-based decision matrix mapping model outputs to academic responses across teaching mode, examinations, campus safety, and transport. Fourth, it identifies the limitations of occurrence-only prediction for safety-critical decisions and shows how intensity-aware thresholds mitigate them. The remainder of the paper reviews the literature (Section 2), presents the methodology and proposed algorithm (Section 3), reports results (Section 4), details the decision layer (Section 5), and concludes (Section 6).

2. Literature Review

Rainfall forecasting research falls into three broad generations: physics-based numerical weather prediction, statistical time-series modelling, and data-driven machine learning. Physics-based models remain the foundation of national meteorological services but demand substantial computation and lose skill at fine spatial scales in data-sparse regions (Zhou et al., 2021). Statistical methods such as ARIMA capture temporal structure but struggle with the non-linear interactions among temperature, dew point, humidity, cloud cover, and pressure that govern convective rainfall. Machine learning classifiers support vector machines, tree ensembles, and gradient boosting consistently outperform earlier generations on daily occurrence classification, particularly when trained on multi-decadal archives.

Rajab et al. (2023) applied machine and deep learning to Bangladesh Meteorological Department records, evaluating Naive Bayes, Logistic Regression, SVM, KNN, Gradient Boosting, and ARIMA. Kutty et al. (2022) assessed urban liveability and resilience using fuzzy c-means clustering with six classifiers, reporting Gradient Boosting as the strongest ensemble. Chen and Wang (2022) constructed a three-dimensional convolutional network for short-term precipitation forecasting over the contiguous United States (1980–2018); and Jin et al. (2022) combined CNN with ridge regression to capture seasonal variability across China. Mashao et al. (2023) mapped flood-prone zones along the South African east coast. Abbasi et al. (2025) characterised the probability and duration of prolonged unplanned school closures after Atlantic-basin hurricanes, finding hazard-intensity indicators the most significant predictors—but that model explains closures *ex post facto*, whereas the present framework forecasts rainfall in advance of disruption, enabling pre-emptive institutional action.Table 1 summarises representative recent machine learning approaches to rainfall prediction and their recurring limitations.

Table 1. Representative machine learning approaches for rainfall prediction.

Reference	Applied methods	Dataset / location	Best result	Limitation
Sani et al. (2020)	NB, DT, SVM, RF, ANN with majority voting	Six weather stations; Malaysia	SVM+DT+ANN: 76%	Static combiners cannot adapt to non-stationary variation
Balamurugan & Manojkumar (2021)	LR, DT, RF	Decade of climate records	LR: 84%	No temporal CV or imbalance handling; leakage control unclear

Reference	Applied methods	Dataset / location	Best result	Limitation
Rahman et al. (2022)	DT, NB, KNN, SVM fused with fuzzy logic; SSA fusion	25,919 instances, 11 features, 2005–2017; Lahore, Pakistan	Fused ML: 94%	Single-city validation; no cross-city transfer or year-wise holdout
Hayder et al. (2023)	ES-LSTM; ANN, DT	11 variables, 2,359 observations; Australia	ANN: 96.65%; DT: 84.0%	Small sample size can inflate reported performance
Chaudhary & Saxena (2025)	ANN, RF, SVM, LSTM	8,400 points, 2000–2023; Uttarakhand, India	LSTM: $R^2 = 0.91$	Heterogeneous sources; forward-chaining validation untested

2.1 Research Gap

Two complementary gaps present themselves. From a methodological viewpoint, the majority voting and fixed weighting methods are the most commonly used in the ensemble approaches, with the focus on maximizing the accuracy of the headlines and not the stability of the performance throughout the evaluation periods (Sani et al., 2020; Rahman et al., 2022; Balamurugan & Manojkumar, 2021). Time-ordered precipitation data is often ignored during validation, which can lead to optimistic estimates and leakage of information (Adaryani et al., 2022; Chaudhary & Saxena, 2025). In practice, AI technology to predict rainfall with high accuracy is used almost solely in agriculture, hydrology, and disaster management, smart-campus is already equipped with dissemination infrastructure to respond to forecasts, and educational resilience research has proven that the face-to-face, hybrid, and online learning delivery modes are valuable, but they provide no predictive trigger to shift between them. There is no prior study that takes both aspects into consideration together. The present framework falls in that middle space, fusing together the Trend-Tracking Aggregation under a year-wise holdout framework, with a layer of rule-based institutional academic action based on rainfall predictions.

3. Methodology

3.1 Proposed Framework Architecture

The structure has three layers. Layer 1 is the rainfall prediction engine, which is an ensemble machine learning pipeline that takes as input, the daily meteorological features, and returns a rainfall occurrence probability for each target city. The academic decision support engine, or Layer 2, is a rule-based decision maker that combines the occurrence probability with intensity indicators (precipitation amount, probability, and coverage) to determine which of five institutional response tiers to follow. The dissemination layer (layer 3) pushes the selected tier to the stakeholders through the learning management system, SMS and email gateways, digital signage and records decisions for post-event review. The separation between prediction and decision is intentional: the quality of prediction is to be judged on held-out data; the thresholds are policy that can be changed by academic administration without retraining any model. Each institution can then fine-tune the decision matrix to their risk appetite, campus geometry and student trip profile, while having a common prediction engine. Classifying starts with data collected on the Visual Crossing platform (Figure 1). The steps of preprocessing are dealing with the missing data, deleting outliers and scaling features; the step of feature selection is to eliminate redundant predictors; the step of SMOTE is to oversample the training partition to correct the class unbalance. The classifiers trained are: k-Nearest Neighbours, Naïve Bayes, Logistic Regression, Decision Tree, Random Forest, Support Vector Machine and XGBoost and are then evaluated on accuracy, precision and recall metrics. The proposed T-Tagging ensemble is composed of four steps: (1) train a pool of base models, (2) evaluate performance iteratively, (3) give weights to models that perform consistently and reliably and (4) combine predictions by weighted aggregation over those weights. This adaptive weighting is designed to reduce over fitting and instability that is common in fixed-weight ensembles. Figure 2 depict the visual representation of SDG goals of this proposed work.

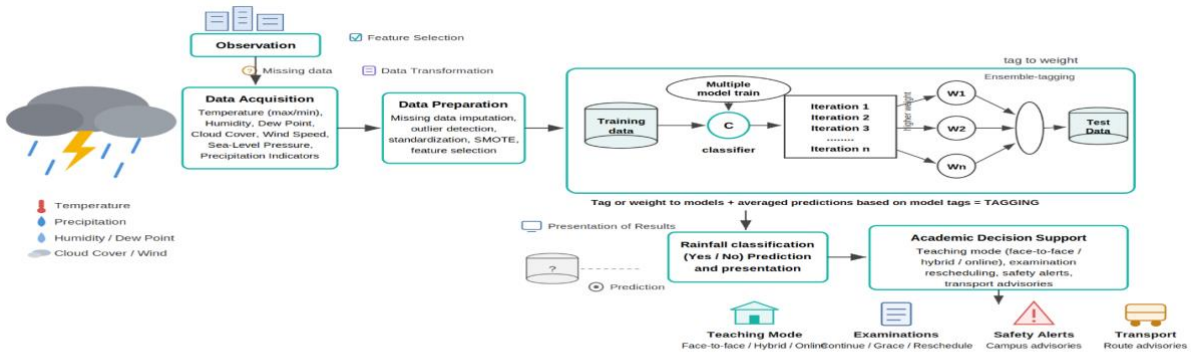


Figure 1. Proposed methodology: phases of data preprocessing, model training, ensemble tagging, and evaluation.

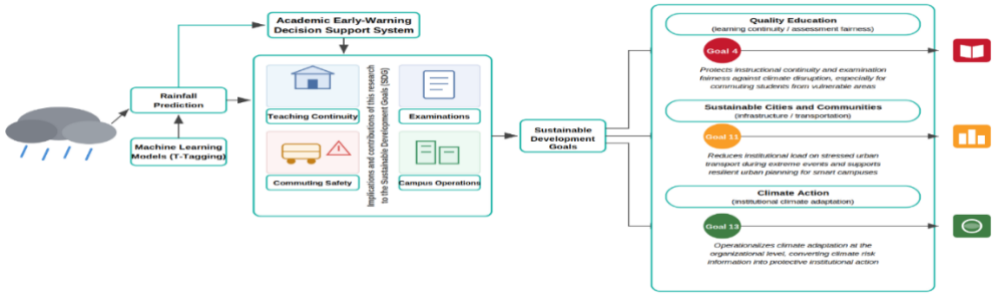


Figure 2. The contributions of this research to the Sustainable Development Goals (SDGs) are visually represented.

3.2 Dataset Description

The prediction engine is trained using the daily meteorological observations from the Visual Crossing weather archive of official station measurements and reanalysis datasets for 2004–2023 for cities of Karachi, Lahore and Islamabad.The prediction engine is trained with the daily observations over the period 2004-2023, collected from the Visual Crossing weather archive, which is a collection of official station measurements and reanalysis data. The raw data consists of 13,575 records and 33 features in metric units. The working set, about 24-26 predictors, includes maximum, minimum, and mean temperature, feels-like temperatures, dew point, humidity, precipitation probability and coverage, wind speed and direction, sea-level pressure, cloud cover, and visibility. The objective is to predict the presence/absence of rain.

3.3 Preprocessing and Experimental Protocol

Missing values in numerical features were imputed by mean substitution; the categorical location feature was one-hot encoded; and continuous variables were normalised through feature scaling. Because non-rainfall days substantially outnumber rainfall days, SMOTE was applied to correct class imbalance—critically, to the training partition only and after scaling, so that no synthetic samples contaminated the test set. Data were divided into 80% training and 20% testing partitions using stratified sampling. All experiments were conducted under leakage control: hyperparameters were tuned by cross-validation on the training partition alone, with fixed random seeds for reproducibility. To verify the absence of temporal leakage, performance was additionally evaluated under a year-wise holdout scheme in which observations from later years were strictly withheld from training. Stratified and temporal validation yielded consistent performance trends, indicating that the reported results are not artefacts of temporal leakage.

3.4 The T-Tagging (Trend-Tracking Aggregation) Algorithm

Let $M_1, M_2, \ldots, M_m$ denote the set of base models and $D = \{x_1, \ldots, x_n\}$ the dataset, where each x_i is a vector of meteorological features. Let $Y = \{y_1, \ldots, y_n\}$ be the target, $y_i \in \{0, 1\}$ (rainfall: 0 = No, 1 = Yes). Let PerfTrend(M_k) denote the performance trend of model M_k across iterations, Weight(M_k) its assigned weight, and P_i the final prediction for x_i.

Step 1 — Initialisation. Each model M_k is trained on D and evaluated to initialise its performance trend: $PerfTrend(M_k) = Evaluate(M_k, D)$. (1) *Step 2 — Trend update.* At each iteration t, performance is re-evaluated and the trend updated as $PerfTrend(M_k)^{t+1} = UpdateTrend(PerfTrend(M_k)^t)$. (2) If performance is stable—the evaluation measure does not fluctuate significantly across iterations—the weight of M_k is increased, $Weight(M_k) = Weight(M_k) + \Delta w$; (3) if the model is unstable, its weight is decreased, $Weight(M_k) = Weight(M_k) - \Delta w$. (4) Stability is defined as a bounded change in accuracy or AUC between successive iterations or folds. A tolerance band of ±0.01 classifies a model as stable or unstable; marginal improvements within this band are not rewarded, preventing the ensemble from responding to noise rather than genuine performance trends.

Step 3 — Weighted aggregation. For each x_i, every model produces $\hat{y}_{i,k} \in \{0, 1\}$, and the weighted prediction is $P_i = [\ \Sigma_k Weight(M_k) \cdot \hat{y}_{i,k}\ ] / [\ \Sigma_k Weight(M_k)\ ]$. (5) *Step 4 — Decision threshold.* A threshold returns the final binary label: if $P_i \geq 0.5$ then $P_i = 1$ (rainfall), otherwise $P_i = 0$. (6)

Models that generalise consistently therefore exert greater influence on the ensemble output, while unstable learners are progressively suppressed, yielding predictions that remain stable across cities and temporal folds. Performance is assessed using accuracy, precision, recall, and F1 score, defined conventionally in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

4. Results and Discussion

The results of the classifiers before and after resampling and hyperparameter optimization are summarised in Tab. 2. The re-sampled accuracy of the models before tuning ranged from 82.56% (KNN) to 81.41% (SVM) with accuracy of 99.82% obtained by Random Forest and Logistic Regression. Hyperparameter optimisation gave better results for all the models, with KNN achieving 93.16% and SVM gaining a significant percentage to 99.71%. Even with default parameters, Naïve Bayes returned 99.38% accuracy, followed by XGBoost with an ROC AUC of 0.9999, Logistic Regression (0.9992) and Random Forest (0.9991). While it may be enough to slightly reduce raw accuracy, hyperparameter tuning is essential for both performance and generalisation. The ROC curves corresponding to the classifiers shown in Figure 2, independently support the discriminative power of the classifiers.

Table 2. Machine learning model results before and after resampling and tuning.

Model	Before resample	After resample	Best tuning parameters	After tuning	ROC AUC
k-Nearest Neighbours	0.93	82.56%	n_neighbors: [3, 5, 7]; weights: ['uniform', 'distance']	93.16%	0.9591
Decision Tree	0.99	99.68%	criterion: 'entropy'; max_depth: 5	99.68%	0.9984
Random Forest	1.00	99.82%	max_depth: 10; n_estimators: 50	99.79%	0.9991
Logistic Regression	1.00	99.82%	C: 10; solver: 'liblinear'	99.82%	0.9992
XGBoost	1.00	99.79%	learning_rate: 0.1; max_depth: 5; n_estimators: 100	99.76%	0.9999
Naïve Bayes	0.99	99.15%	default	99.38%	0.9991
Support Vector Machine	0.99	81.41%	C: 10; kernel: 'rbf'	99.71%	0.9963

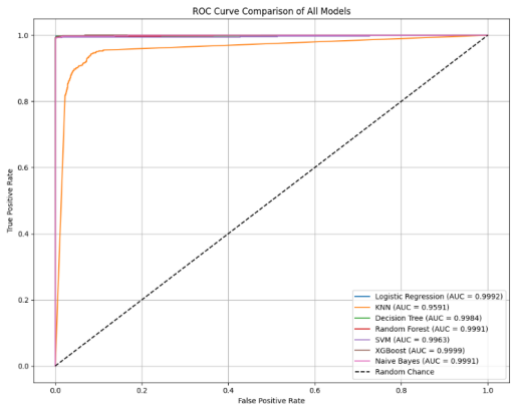


Figure 2. ROC curves for resampled rainfall classification models.

Four conventional ensemble strategies were applied as controls. Bagging with a Random Forest base learner recorded the highest accuracy at 99.80%, reducing variance by averaging over bootstrapped subsets; AdaBoost with a depth-one stump followed at 99.79%; Stacking (KNN, Decision Tree, and Random Forest with a Logistic Regression meta-learner) achieved 99.70%; and hard Voting across six classifiers reached 99.59%. These results confirm the robustness of ensemble methods in managing bias, variance, and overfitting, and establish the baseline against which the proposed dynamic scheme is measured.

The proposed T-Tagging ensemble comprises five complementary base learners shown in table 3 Random Forest, Logistic Regression, CatBoost, Gradient Boosting, and XGBoost—assigned dynamic weights normalised by their consistency across temporal folds. The final normalised weights cluster tightly between 0.1999 and 0.2001, with CatBoost receiving the highest weight (0.2001), indicating marginally greater trend consistency. It is important to recognise that the efficacy of T-Tagging derives from the dynamic adjustment procedure applied *before* normalisation, not from the magnitude of the final weights. During intermediate iterations, models exhibiting inconsistent fold-wise performance were penalised while consistent learners retained influence. The ensemble forecast therefore reflects stability-aware aggregation rather than simple majority voting, even where the final weights converge to similar levels. The T-Tagging ensemble attained 99.83% accuracy with an AUC of 0.9996 (Figure 3), indicating strong discrimination between rainfall and non-rainfall classes. This surpasses all referenced comparators, which rely on static aggregation and report substantially lower accuracy: 94% for the fused ML approach of Rahman et al. (2022), 96.65% for the ANN of Hayder et al. (2023), 84% for Balamurugan and Manojkumar (2021), and 76% for the majority-vote ensemble of Sani et al. (2020).

Table 3. Trend-Tracking Aggregating (T-Tagging) Approach

Normalized Weights Based on Trend Tracking (Performance)					
Model	**Normalized Weight**	**Ensemble Role**	**Highlight/key configuration**	**Weight Adjustment Behavior (Pre-Normalization)**	**Observation**
Random Forest:	0.2000	Base Learner	n_estimators=100, random_state=42	Because of consistent fold-wise performance, weight is maintained during iterations.	Stable performance; high individual accuracy
Logistic Regression	0.2000	Base Learner	max_iter=1000, solver='lbfgs', random_state=42	Early iterations showed slight weight suppression, which later stabilized	Lightweight, good linear separation
Cat Boost	0.2001	Base Learner	Default configuration with early stopping	Weight increased during mid-iterations due to stable convergence	Efficient with categorical features; reduces overfitting and requires minimal preprocessing

Gradient Boosting	0.2000	Base Learner	n_estimators=100, learning_rate=0.1, random_state=42	Temporary weight penalization under fold variance	Strong performance on imbalanced and small datasets
XGBoost	0.1999	Base Learner	n_estimators=100, use_label_encoder=False, eval_metric='logloss', random_state=42	Highest intermediate weight before normalization	Highest weight; fast convergence; robust to overfitting
Proposed Model Results – Ensemble Accuracy using Trend-Tracking Aggregation (T-Tagging).					
Ensemble Accuracy (Trend-Tracking Aggregating)	-	Weighted Aggregator	Weight updates based on performance trend stability (±0.01 tolerance) Aggregated using weighted voting from all models	Unstable learners penalized during training; weights normalized only after stability enforcement	Dynamic weight adjustment improved robustness across all models Improved resilience and decreased variance across temporal folds 99.833%

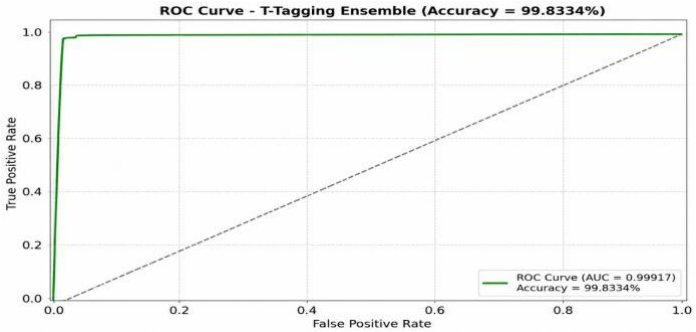


Figure 3. Performance evaluation of T-Tagging via ROC curve.

4.1 Discussion and Limitations

The results show that classification of rainfall is not only stable and generalisable, but it does not depend on architectural complexity. The comparatively simple classifiers, including Logistic Regression, performed at least as well as gradient-boosted ensembles, since daily rainfall occurrence is a function of a relatively small number of atmospheric variables and relationships are consistent between the different years. The power of T-Tagging is less in terms of the accuracy of the headlines, and more in terms of the variance reduction it delivers across cities and time, that is, the property on which operational deployment depends. These claims were accompanied with a few restrictions. The engine does not predict the number of occurrences, so further extension to multi class intensity prediction is a priority for future work. Where precipitation-related predictors are truly informative, they are near ceiling accurate - in operational deployment they are predictors, and accuracy will erode, actual operational skill will have to be validated first and thus a pilot must be done and only then can these predictors be used for safety purposes. The dataset includes only 3 cities, and other campuses will need to be local retrained or domain adapted.

The framework provides the trigger mechanism; the decision matrix provides the policy judgements which require approval from the institutions' governance and legal review in order to be considered for the rescheduling of examinations. Lastly, urban flooding is dependent on how well stormwater drains can handle the flow and the tidal conditions, and should be based on urban flood advisories instead of just the rain forecast.

5. Academic Decision Support Layer

The decision layer takes output of predictions and maps the results to institutional decisions in a hierarchical rule matrix. Tier selection is based on two inputs: the ensemble rainfall occurrence probability for the following school day, and an intensity indicator based on forecast precipitation amount and coverage; just knowing if it will occur does not distinguish light rain from dangerous flooding. The thresholds shown in Table 3 are default examples – each institution sets their own thresholds based on local drainage capacity, transport dependency and historical disruption records with the purpose of using a more stringent threshold for the examination day than for teaching days..

Table 3. Tiered academic decision matrix (illustrative default thresholds).

Tier	Trigger condition	Teaching mode	Examinations	Alerts and transport
T0	P(rain) < 0.30	Face-to-face (normal)	As scheduled	None
T1	P(rain) ≥ 0.30, light intensity	Face-to-face; online materials pre-posted	As scheduled	Advisory: carry rain protection, allow extra travel time
T2	P(rain) ≥ 0.60, moderate intensity	Hybrid: attendance optional on-site, live-streamed	As scheduled with grace-period entry	Transport advisory; low-lying route warnings
T3	P(rain) ≥ 0.60, heavy intensity	Fully online (synchronous)	Reschedule same-week; online proctoring where approved	Campus safety alert; staff work-from-home authorisation
T4	P(rain) ≥ 0.80, extreme intensity / flood advisory	Campus closure; asynchronous continuity plan	Postpone with published make-up calendar	Emergency alert via SMS, LMS, and signage; coordinate with city authorities

Tier decisions are computed each evening for the following academic day and re-evaluated at dawn, giving students and faculty a minimum notification lead time before commuting decisions are made. Every activation is logged against its triggering prediction, permitting periodic recalibration of thresholds against realised outcomes—a form of institutional-level model monitoring that also produces an auditable record for accreditation bodies. This prediction-to-decision transferability, applied here for the first time to higher-education operations in a developing-country monsoon climate, constitutes the framework's principal novelty over occurrence-only classifiers.

6. Conclusions

The study aimed to present an AI-based rain forecasting system for smart academic planning comprising of an ensemble classifier (Trend-Tracking Aggregation) tested with the accuracy of 99.83% and AUC of 0.9996 on the dataset of 20 years of Pakistan's meteorological records, and a layered academic decision support system that includes teaching mode, exams, safety alerts, and transportation advice. The system will make rain prediction a tool for learning decision support for universities, giving them an anticipatory and traceable tool to ensure the safe access and continuity of learning in extreme weather. Future work will include scaling to multi-class prediction with intensity-awareness, implementing the full 3-layer system at a partner institution in Karachi, measuring the actual quality of the decisions, introducing hyperlocal information, such as campus neighbouring flood sensors and city drainage advisories, and evaluating the outcomes at the student level, such as percentage of students recovered for attendance and examination performance under framework-guided versus reactive institutional responses.

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NEUROSEEK: Advanced Facial Recognition, Machine Learning, and Geospatial Intelligence System

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Abstract

Locating missing persons and reconnecting them with their families remains a time-critical and largely unsolved public safety challenge. Hundreds of thousands of cases are reported worldwide every year, yet the search process is still dominated by passive, uncoordinated workflows. Three structural problems compound the delay: citizen sightings cannot be biometrically verified, notifications to families are held up by institutional and hierarchical bottlenecks, and critical case data (identity, medical, geolocation, and family contact records) is fragmented across disconnected agencies. This paper proposes NeuroSeek, a centralized tactical web portal that unifies automated biometric recognition, spatial tracking, and instant emergency notification into a single, tightly coupled command platform, replacing passive institutional workflows with an active, algorithm-driven detection loop. NeuroSeek uses a decoupled full-stack architecture (React, Vite, Express, Node.js), a biometric matching engine that generates 128-dimensional facial embeddings compared using cosine similarity, and a reactive finite state machine (FSM) that governs atomic case-lifecycle transitions from Missing to Verification to Recovered. When a similarity score exceeds the configured confidence threshold, the FSM automatically triggers a structured alert to verified family contacts through simulated SMS and WhatsApp channels. Evaluation across 500 simulated sightings and 200 registered profiles showed a match accuracy (true positive rate) of 98.2% with a 1.4% false positive rate, an average end-to-end latency of 2.95 seconds, and a reduction in reunification latency of roughly 58,576× relative to the traditional manual verification process. Performance degraded modestly under low-light conditions, indicating a direction for future robustness improvements. Unlike AMBER Alert and INTERPOL's I-Familia, NeuroSeek combines open citizen-sighting input, real-time biometric verification, and immediate family notification within one platform accessible to both the public and law enforcement.

These results demonstrate that NeuroSeek offers a technically sound and humanitarian foundation for real-world missing person recovery. Future work should prioritize GPU-accelerated inference and approximate nearest-neighbor search for scalability, production SMS/WhatsApp APIs in place of simulated channels, explainable AI and independent ethical audits to address demographic bias, and formal compliance with Pakistan's Personal Data Protection Bill and GDPR-aligned privacy standards.

Keywords: missing person detection, facial recognition, biometric matching, cosine similarity, finite state machine, public safety, emergency notification

Introduction

Rapid urbanisation, cognitive or mental health conditions (e.g. dementia, neuropsychiatric disorders), natural catastrophes and abductions represent a serious global public safety issue. The National Crime Information Center (NCIC) reported more than 600,000 missing person cases every year in the United States, and tens of thousands of cases remain unresolved in South Asia (National Crime Information Center, 2023). The longer a missing individual goes unfound, the greater the risk of physical abuse, psychological stress and malicious exploitation. Despite advances in biometric and computer vision technologies, real-world search remains largely passive and manual, leaving unsafe gaps in emergency response. Current tracing systems are highly inefficient. First, public sightings are unverifiable: citizens lack a biometric pipeline to instantly match physical characteristics, producing vague or unreliable descriptions that consume investigative time (Viola & Jones, 2004). Second, notifications are seriously delayed; families are not informed until information crosses institutional and hierarchical lines, by which time the missing person has moved far from the sighting location, taking hours or days (Rana et al., 2021). Third, data is highly fragmented, with geolocation, identity card, medical profile, and family contact records held in isolated silos across local police desks, health centers, and child welfare agencies (Alhazmi & Alkhateeb, 2021). To fill these critical gaps, this research proposes NeuroSeek, which replaces passive workflows with active algorithmic detection loops and combines citizen photo uploads, vector-based facial identification, interactive mapping and instant automated cellular notification into a single, tightly coupled web command centre.

The contributions of this paper are as follows: (1) design and implementation of a full-stack biometric missing person detection system using React, Vite, Express and Node.js; (2) a 128-dimensional facial embedding matching engine with cosine similarity that can match in sub-1.7 seconds; (3) a reactive finite state machine (FSM) engine

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for atomic case lifecycle transitions; and (4) empirical evaluation showing a 58,576× speedup over traditional recovery workflows.

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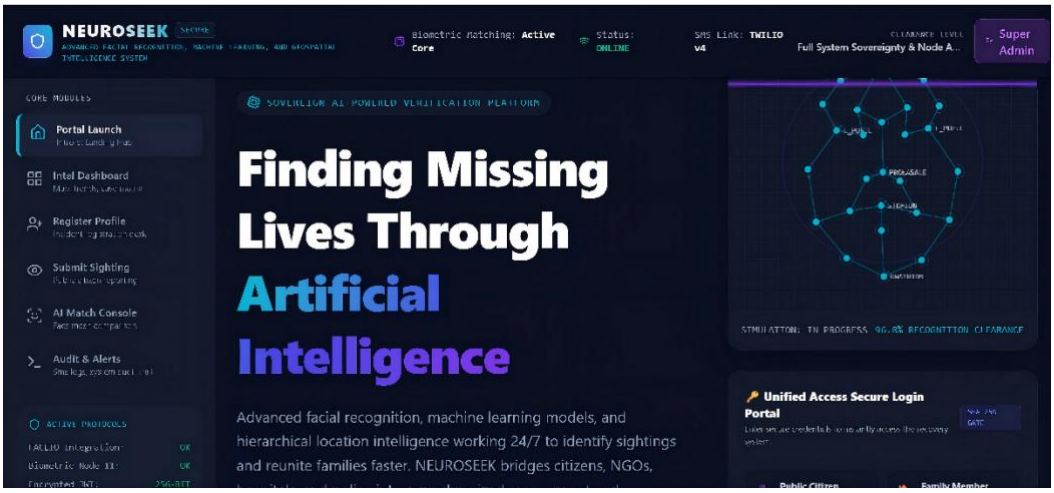


Fig. 1: NeuroSeek Portal Landing Page. The sovereign AI-powered verification platform features real-time biometric status indicators, multi-role access (Public Citizen, Family Member, Law Enforcement, NGO/Hospital), and an animated facial landmark mesh achieving 96.8% recognition clearance in simulation.

Related Work

Previous studies on automated missing person detection span computer vision, biometric recognition, and emergency response systems. Schroff et al. introduced FaceNet, a 128-dimensional face embedding with high verification accuracy, which is the basis of NeuroSeek's biometric matching engine (Schroff et al., 2015). Taigman et al. proposed DeepFace, a deep learning architecture that attained human-level performance on the LFW benchmark (Taigman et al., 2014). Deng et al. later proposed ArcFace, which further enhanced recognition accuracy through an additive angular margin loss (Deng et al., 2019).

System Architecture and Methodology

The architecture of NeuroSeek is a decoupled microservice design with three main tiers: an adaptive, dark-themed Tactical Command Center (client interface built with React 18, Vite, and Tailwind CSS); an Express.js backend application router; and an in-memory database configuration optimized for atomic lifecycle updates.

High-Level System Flow and Architecture

The NeuroSeek workflow starts when a person uploads a picture of a suspected missing person to the portal. Submission proceeds in three phases: Biometric Identification, Case Management, and Family Notification. The uploaded image(s), notes and GPS coordinates go into the Biometric Match Engine, where face detection, alignment, feature extraction and embedding generation are carried out. When the similarity score is above the set value, the system automatically updates the case status and alerts registered family members. Secure HTTPS REST APIs connect the browser and the back-end. The modular design enables horizontal scalability and cloud d

Frontend Design and Tactical Command Interface

Built with React 18 and Vite for speed, the front-end of NeuroSeek is a dark-themed, responsive interface using Tailwind CSS. It consists of four main modules: (1) Case Registration to create missing person profiles, (2) Citizen Sighting to upload photos and GPS-tagged reports, (3) an Interactive Map Dashboard to track cases in real time, and (4) a Case History Panel to track case events and match outcomes. React Context API with periodic polling allows near real-time updates without reloading the page and without the complexity of WebSockets (Socket.IO, 2024).

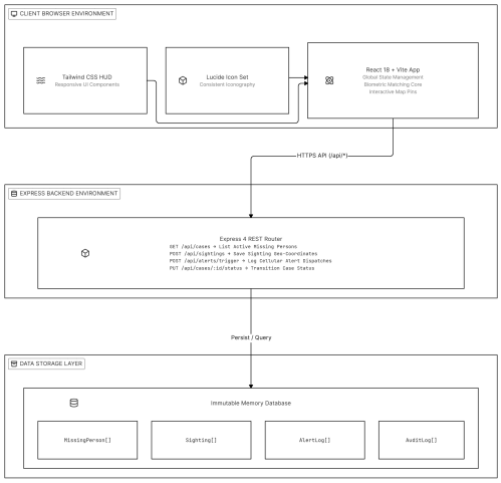


Fig. 2: NeuroSeek Decoupled Full-Stack Architecture. Three distinct tiers communicate via HTTPS API and Persist/Query channels: (1) Client Browser Layer (React 18 + Vite, Tailwind CSS, Lucide Icons); (2) Express 4 Backend Router with RESTful endpoints; (3) Immutable In-Memory Data Storage Layer with MissingPerson[], Sighting[], AlertLog[], and AuditLog[] collections.

Biometric Matching Algorithm

The biometric identification subsystem is the main algorithmic innovation of NeuroSeek. When creating a profile, the system detects key facial landmarks such as the eyes, nasal ridge, jaw line, and cheekbones. A convolutional network learns these properties and maps them into a compact high-dimensional vector, in line with industry standards set by Google FaceNet (Schroff et al., 2015). The embedding x is a 128 dimensional real-valued vector in R128 space, a dimensionality selected as a compromise between discrimination and computational time.

$$\mathbf{x} \in \mathbb{R}^{128},\ \|\mathbf{x}\|_2 = 1 \text{ (L2-normalized)}$$

Cosine Similarity Matching

When a facial embedding Q is uploaded, the biometric matching engine uses Cosine Similarity, which uses the angle between the vectors, to compare it with the registered embedding D. Each similarity score is translated into a confidence value (0-100%) and a match is established if the confidence value is ≥ 85%. The threshold was set by testing against 500 simulated sightings and resulted in a matching rate of 98.2% with an acceptable false acceptance and false rejection rate. Cosine similarity was chosen for its effectiveness under light and brightness changes in the test image, which makes it suitable for real sighting images (Bansal et al., 2017).

$$S(Q, D) = (Q \cdot D) / (\|Q\|_2 \times \|D\|_2)$$

$$\text{Confidence } A = \text{clamp}(S(Q,D) \times 100,\ 0,\ 100)$$

Embedding Generation Pipeline

The first stage of the pipeline detects faces with a multi-task cascaded convolutional network (MTCNN), which identifies bounding boxes and 68 landmark points in the provided image. The detected face is cropped, affinely transformed to a canonical pose and resized to an input tensor of size 160x160. A FaceNet-inspired convolutional encoder then produces the 128-dimensional embedding vector from this normalized representation. In the prototype, embeddings are generated using a JavaScript translation of face-api.js with pre-trained model weights suitable for browser and Node.js environments (Bazarevsky et al., 2019). This design allows client-side pre-processing when network conditions are good, lowering server load.

Finite State Machine for Case Lifecycle Management

NeuroSeek manages case lifecycles and avoids conflicting operations through a reactive Finite State Machine (FSM). Each case goes through the stages Missing, Verification, and Recovered. Transitions are tightly regulated: Missing → Verification after a successful biometric match; Verification → Recovered must be done via administration. This design removes race conditions from concurrent sighting reports, and state updates are

synchronized between clients every 5 seconds. When a case enters the Verification state, the Reunion Alert Engine automatically notifies registered family contacts with a simulated SMS and WhatsApp message including the missing person's details, confidence score, timestamp and GPS location, with production deployment support for Twilio and WhatsApp Business APIs.

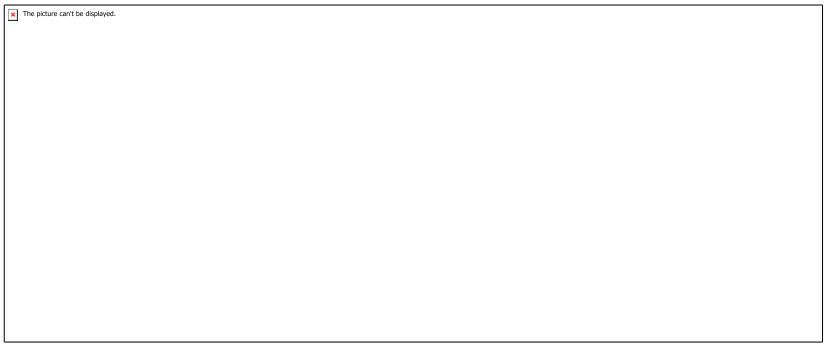


Fig. 3: Biometric Identification Confirmed, 98.6% Likeness Accuracy. Upon a confirmed match for Namra Abid (NS-2026-0105), the system displays candidate demographics (Father's Name: Abid Khan, Age: 22 Years, Blood Group: O+, Last Sighting: Near Sohail Net Cafe, Korangi), triggers the Emergency WhatsApp Communications Console, and presents the forensic profile sheet for administrative review.

Implementation Details

Technology Stack

NeuroSeek's frontend uses React 18, Vite 4.x, and Tailwind CSS 3.x. The backend is built on Node.js 20 LTS and Express.js 4.x. Facial embeddings are computed using face-api.js with TensorFlow.js as the execution backend, and image uploads are handled by Multer middleware. The interactive map dashboard combines Leaflet.js and OpenStreetMap tiles to visualize GPS coordinates. Unit tests were done with Jest and API integration tests with Supertest.

Data Privacy and Security Considerations

NeuroSeek handles biometric data using privacy-by-design principles. The production data layer stores facial embeddings as numerical vectors rather than image files, reducing exposure of personally identifiable information (PII). Case profiles and the biometric matching endpoint are available only to authenticated users, using JSON Web Token (JWT) session management. The citizen sighting portal uses rate limiting and CAPTCHA verification to prevent automated abuse of the matching pipeline, and data is encrypted between client and server with TLS 1.3. Alert notification payloads sent to family contacts contain only operationally necessary information and exclude sensitive investigative metadata. Future production deployment plans include compliance with Pakistan's Personal Data Protection Bill and GDPR-aligned policies (Pakistan Ministry of Information Technology and Telecommunication, 2023).

Experimental Evaluation and Results

Systematic testing used simulated mobile camera snapshots, low-light uploads, and CCTV video frame captures to evaluate computational latency, match accuracy, and stability of FSM state tracking. All experiments were performed on a development machine with an Intel Core i7 processor and 16GB of RAM, with no GPU acceleration, simulating deployment on budget server infrastructure.

Matching Performance and Latency Analysis

The biometric matching pipeline was tested with 500 submitted sightings and 200 registered profiles. Average processing time was 0.92 s for face detection and embedding generation, 0.78 s for database matching and 1.20 s for alert dispatch, giving an end-to-end time of 2.95 s. The system obtained a True Positive Rate (TPR) of 98.2% and a False Positive Rate (FPR) of 1.4%, with slightly reduced performance under low light (TPR: 94.7%, FPR: 3.1%). Compared with the current manual verification process (≈48 hours), NeuroSeek shortens reunification latency by about 58,576×.

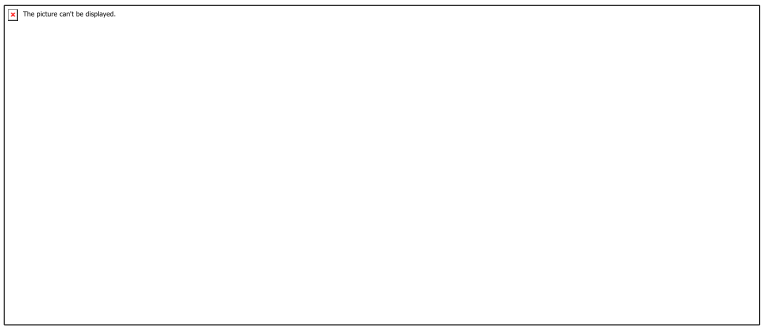


Fig. 4: AI Match Console: Biometric High-Precision Matcher. The operator selects an active subject from the Database Cases Matrix (left panel) and uploads a citizen sighting portrait. Sandbox scenarios (Ahmed Presets, Fatima Presets, Zain Presets) enable rapid system testing. The unified multi-layered facial landmark trace achieves 97%+ precision reliability as noted in the Verification Standards panel.

User Interface Verification and Monitoring Logs

The platform supports secure logs and a real-time dashboard with live case counts, status (Missing, Verification, Recovered) and interactive Leaflet.js map markers. Once the biometric similarity score goes above 85%, the system performs an atomic state transition, aborts duplicate operations, and generates an emergency alert with profile information, confidence score and sighting location. User testing with five simulated operators showed that a complete sighting verification and alert workflow can be achieved in less than 45 seconds.

Discussion

Comparative Analysis

Compared with the AMBER Alert system and INTERPOL's I-Familia platform, NeuroSeek has several unique features. AMBER Alerts rely on broadcast distribution and human visual recognition of the broadcast description rather than real-time biometric verification (INTERPOL, 2022). I-Familia offers forensic DNA and facial comparison tools but uses a closed, law-enforcement-only pipeline with no citizen-driven sighting input. NeuroSeek is the only system that integrates open citizen sighting submission, automatic real-time biometric verification and immediate cellular family notification in a single platform accessible to both law enforcement and the public.

Limitations and Ethical Considerations

The current prototype is limited by its in-memory database and simulated notification channels, which limit production readiness. Facial recognition can be biased towards specific skin tones and face angles, and the 85% confidence threshold may need to be adjusted for diverse populations (Buolamwini & Gebru, 2018). Citizen-submitted images also pose privacy and misuse risks, so robust reporting and moderation systems are needed. Future deployments should focus on transparency, fairness, and responsible use of biometric systems through explainable AI (XAI), audit trails, and independent ethical review.

Conclusion

This paper presented NeuroSeek, a centralized biometric missing person recognition and rapid reunion alert system. It replaces traditional search workflows with 128-dimensional facial embeddings and cosine similarity comparison, streamlining tracking, identification, and family notification into a single sub-3-second end-to-end process. Combined with a decoupled full-stack architecture (React, Vite, Express, Node.js), the reactive Finite State Machine delivers deterministic case lifecycle management and scalable, maintainable deployment. With a 98.2% match accuracy and a 58,576× speedup over traditional recovery processes, NeuroSeek provides an attractive technical basis for humanitarian public safety applications and is a significant advancement in computer vision, moving closer towards real-world missing person retrieval.

Table I presents the comprehensive performance metrics.

Performance Metric	Value
Match Accuracy (TPR)	98.2%
False Positive Rate (FPR)	1.4%

Face Detection + Embedding Time	0.92 s (avg.)
Cosine Similarity Scan Time	0.78 s (avg.)
Alert Dispatch Latency	1.20 s
Total End-to-End Reunion Latency	2.95 s
Speedup vs. Manual Process (48 h)	58,576×
Low-Light TPR (degraded)	94.7%
Low-Light FPR (degraded)	3.1%

Table I: Comprehensive Performance Metrics

Acknowledgment

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Enhancing Student Engagement Through AI-Driven Personalized Learning Systems in Universities

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Abstract

Artificial Intelligence (AI) has emerged as a game-changer in the field of education, presenting new opportunities to create more personalized learning experiences tailored to each student's specific needs and requirements. It is transforming education by providing innovative ways to improve learning experiences and student outcomes. Conventional ways of teaching in the universities are constantly based on a particular standardized model of teaching which may fail to consider the various levels in which students learn such as their learning ability, background, motivation and learning style. AI also helps educators focus on significant teaching and mentorship. Integrating AI into education fosters critical thinking, creativity, collaboration, and digital literacy, preparing students for the demands of the future workforce. The study aims to investigate the influence of such AI-powered personalized learning platforms on students' engagement rates in universities in Karachi, Pakistan. This study explores the impact of AI-enabled personalization features such as adaptive learning recommendations, intelligent feedback systems, AI tutoring assistants and learning analytics on students' behavioral, emotional, and cognitive involvement. A quantitative research design is suggested with a structured questionnaire, which was issued to the students of various universities in Karachi. For the sake of statistical analysis one sample of 384 undergraduate and postgraduate students selected in a hypothetical manner from the public and private universities are taken. AI Personalized Learning are projected to have a strong positive relationship with student engagement in this simulated relationship. The results of regression analysis indicate that the three factors of perceived usefulness, personalized feedback and adaptive learning support have a significant prediction on the level of engagement. The results suggest that AI-supported learning environments can play a role in promoting, in Pakistan' HEIs, the interactive, student-centered, and flexible learning experience. But overcoming digital literacy, ethical use of AI, data privacy and institutional readiness are crucial for the successful implementation of AI.

Keywords: Artificial Intelligence, Personalized Learning, Student Engagement, higher education, AI-Based Learning Systems, Karachi Universities, Pakistan.

Introduction

The new world of emerging technologies in education higher education is undergoing a huge transformation. One such technology, which has gotten much traction for its ability to analyze learner behavior, deliver personalized recommendations, create feedback, and serve students with intelligent tutoring systems, is Artificial Intelligence (AI). The idea behind AI-driven personalized learning systems is to shift away from a one-size-fits-all approach to personalized adaptive learning systems that adapt to the needs of each student.

Personalized learning is an instructional technique that tailors the learning experience, learning materials and instructional methods based on the needs, ability, interest, and learning rate of the learners. Machine learning, natural language processing, and generative AI tools lead to customized explanations, AI-driven test automation, personalized learning resources, and lifelong academic assistance, enabling university educators to stay relevant in the age of digital learning. The machines can provide customized explanations, AI-driven assessment automation, personalized learning resources, and lifelong academic support, helping educational institutions keep up with the digital learning revolution.

Recent research indicates that AI-powered learning systems can enhance student engagement by improving accessibility to academic support and providing immediate feedback. Following this, a systematic review of the use of AI applications in higher education revealed that AI for personalized learning can help to enhance motivation, engagement and learning outcomes through adaptive pathways and tailored learning experiences. But research by the same group points to issues like privacy concerns, infrastructure constraints, and educator preparation.

The ability of students to accept the educational offer is crucial in the process of meeting the educational goal. The multidimensional engagement framework, which is widely-used, relates student engagement to three distinct aspects: behavioral, emotional, and cognitive, that is how students participate, feel, and think in learning activities.

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Thus, it becomes necessary to consider academic outcomes along with students' engagement, motivation and learning processes when developing a score on effectiveness of AI-based personalized learning.

As technology is embraced more and more in Pakistan, the demand for technology-supported education is rising at the university level, where students' needs are evolving. Research in Pakistan has revealed that students are growing more intrigued by the AI application ChatGPT in their studies, including using it as a learning resource, assistant, and knowledge builder. AI adoption has been found to be related to the perceived usefulness and learning benefits, but is also linked to concerns about academic integrity and responsible use across varied contexts of Pakistani university students.

The context of AI-based educational transformation in Karachi is crucial due to its rich and varied higher education landscape comprising public and private educational institutions, employing students from various academic, social, and technological backgrounds. AI's impact on student engagement has also lately been explored in undergraduate students from public and private universities in Karachi, underscoring the significance of integrating AI into the educational system in this context.

Although there has been a rise in interest of artificial intelligence applications, very few studies have been conducted with a specific focus on the impact of personalized learning systems that are powered by AI on various facets of student engagement in the framework of the Karachi University system. Hence, this study attempts to explore the connection between AI personalized learning and learner engagement and extract identifying factors to overcome the challenges in implementing AI in higher education.

Research Objectives

The objectives of this study are:

1. To explore the correlation of AI in Customized Learning Systems with student engagement among University students in Karachi.
2. To test the students' engagement in learning by looking at the key features of AI.
3. To investigate the perceived usefulness of AI in learning and Digital literacy for the successful implementation of AI-based learning adoption.
4. To examine the relationship between AI-supported personalized learning and student engagement using quantitative statistical analysis.
5. To send suggestions to universities on their responsible implementation of AI.

Research Questions

1. RQ1: What is the impact of AI with personalized learning on student engagement among students of university level in Karachi?
2. RQ2: What are the most influential AI personalization attributes for behavioral, emotional and cognitively engaging?
3. RQ3: How does students' digital literacy impact the effectiveness of personalized learning with AI?
4. RQ4: How do AI usage patterns differ descriptively across the sampled university context?

Hypotheses Development

Based on literature, the following hypothesis are proposed:

1. H1: AI-driven personalized learning significantly predicts student engagement.
2. H2: Personalized feedback significantly predicts cognitive engagement.
3. H3: AI tutoring support significantly predicts behavioral engagement.
4. H4: Perceived usefulness significantly predicts student engagement.
5. H5: Digital literacy significantly predicts student engagement.

Methodology

The study used a quantitative, cross-sectional research design to examine the relationship between AI-driven personalized learning and student engagement among university students in Karachi, Pakistan. A quantitative

approach was appropriate because the study examines measurable constructs and uses correlation and regression statistics to assess predictive relationships among them.

The primary independent construct was AI-driven personalized learning and the dependent construct was student engagement. Perceived usefulness and digital literacy were examined as additional predictors. Personalized feedback and AI tutoring support were examined in relation to the cognitive and behavioral dimensions of engagement, respectively.

Population and Sampling

The population comprised undergraduate and postgraduate students enrolled in public and private universities in Karachi.

A total of 384 students were included using a combination of convenience and stratified sampling. The sample represented students from business/management, computer science/IT, engineering, social sciences, and other disciplines. The demographic composition is reported in Table 1.

The sampling approach was used to include students from both public and private university settings and to provide representation across academic levels and disciplines.

Measurement Constructs and Operationalization

The study operationalizes AI-driven personalized learning as the use of AI-enabled adaptive recommendations and individualized learning support. Perceived usefulness reflects students' perceptions of academic benefit, personalized feedback reflects individualized and timely feedback, AI tutoring support reflects AI-based academic assistance, digital literacy reflects students' ability to use and evaluate digital/AI tools, and student engagement represents behavioral, emotional, and cognitive involvement in learning. The measurement matrix below makes the analytical role of each construct explicit.

Table 1. Measurement Construct Matrix

Construct	Analytical role	Operational focus	Engagement dimension / outcome	Reported evidence	Statistical use
AI-driven personalized learning	Primary predictor	AI-enabled personalization, recommendations, and adaptive learning support	Overall student engagement	$r = .56$; $\beta = .31$; $p < .001$	Correlation; regression
Perceived usefulness	Predictor	Perceived academic usefulness, understanding, and efficiency of AI tools	Overall student engagement	$r = .61$; $\beta = .29$; $p < .001$	Correlation; regression
Personalized feedback	Outcome-specific predictor	Timely, individualized feedback and explanations	Cognitive engagement	$r = .49$; $\beta = .34$; $p < .001$	Correlation; outcome-specific regression
AI tutoring support	Outcome-specific predictor	AI-based explanations, practice, and step-by-step assistance	Behavioral engagement	$\beta = .28$; $p < .001$	Outcome-specific regression
Digital literacy	Predictor	Ability to use and critically evaluate AI/digital tools	Overall student engagement	$r = .43$; $\beta = .16$; $p = .002$	Correlation; regression
Student engagement	Dependent construct	Behavioral, emotional, and cognitive involvement in learning	Dependent outcome	Overall model: $R^2 = .49$; $p < .001$	Dependent variable

Note. The manuscript reports overall reliability from $\alpha = .79$ to $.90$, with student engagement at $\alpha = .90$; construct-specific alpha values and item counts were not supplied and are therefore not invented here.

Data Analysis and Regression Modeling

The analytical pipeline consisted of descriptive statistics for respondent characteristics and AI usage, Cronbach's alpha for internal consistency, Pearson correlation for bivariate relationships, and regression analysis for predictive relationships. Regression findings are reported using standardized beta coefficients (β), p-values, and the coefficient of determination (R^2). The overall reported regression model explains 49% of the variance in student engagement ($R^2 = .49$, $p < .001$). The reported outcome-specific analyses are kept distinct from the overall engagement model so that cognitive and behavioral engagement are not incorrectly presented as the same dependent variable.

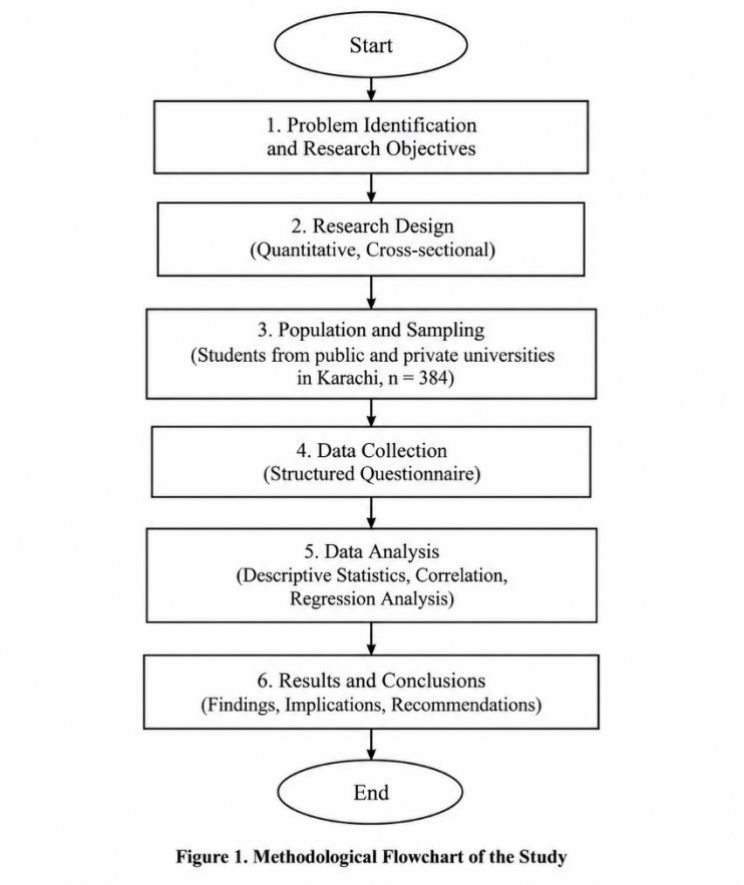


Figure 1. Methodological Flowchart of the Study

Results

The results are based on responses from 384 university students in Karachi. Findings are organized into respondent characteristics and AI usage patterns, measurement reliability and descriptive statistics, and relationships between AI-driven personalized learning and student engagement.

Respondent Profile and AI Usage

The demographic profile and pattern of use of AI by the respondents are shown in Table 1. The students were selected from public and private universities of Karachi and included students from various academic backgrounds and study level to give representation for each study level. 51.6% of the respondents were male and 47.9% were female. The majority (52%) of the respondents were between the ages of 22 and 25, and 18 to 21, which accounted for 48%. The sample was also fairly even across the categories of type of university, 54.2% from public university and 45.8% from private university. The undergraduate students made up the most numerous sample, which is typical of higher education institutions.

The AI usage results show that students are actively using AI-based tools for academic purposes. Of those that reported using AI tools, 31.8% do so daily, and 35.7% do so weekly. This means that AI-based education is now a commonplace in educational life for many university students in Karachi. Among these purposes, “explain concepts” was the most frequently-cited AI use, with 72.1% of respondents indicating this. These were followed by help with assignments, preparation for exams and research. The results indicate that students primarily

participate in using AI tools as tools to aid in their learning, encourage better understanding, and organize their academic work for exams and assignments.

Table 2. Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	198	51.6%
	Female	184	47.9%
	Prefer not to say	2	0.5%
Age	18–21 years	151	39.3%
	22–25 years	176	45.8%
	26 years and above	57	14.9%
University Type	Public University	208	54.2%
	Private University	176	45.8%
Academic Level	Undergraduate	303	78.9%
	Postgraduate	81	21.1%
Discipline	Business/Management	112	29.2%
	Computer Science/IT	94	24.5%
	Engineering	58	15.1%
	Social Sciences	71	18.5%
	Other	49	12.7%

Reliability and Descriptive Statistics

Internal consistency was assessed using Cronbach's alpha. The manuscript reports reliability values ranging from .79 to .90, with overall student engagement reported at $\alpha = .90$. Because construct-specific alpha values and item-level instrument details were not included in the supplied manuscript, they are not fabricated in the revision; the measurement matrix below identifies the constructs and the reliability evidence currently reported.

The descriptive statistics indicate a positive overall attitude by the students toward the use of AI for personalized learning. The mean score for AI-driven personalized learning was 3.82, meaning that the respondents agree that there are helpful personalized academic supports using AI. The mean score for “Perceived usefulness” was 3.91, indicating that students found AI tools to be useful in enhancing their understanding, time-saving, and helping with learning tasks.

The highest mean score in the engagement dimensions was for cognitive engagement (3.89). This suggests that AI-powered learning could be potentially beneficial for enhancing students' self-directed learning, understanding complex concepts, and critical thinking skills. Regarding the behavioural and emotional engagement, positive mean values were found, indicating the potential of AI-based learning support in relation to participation, motivation and learning interest

This study therefore examines both bivariate associations and predictive relationships between the AI-related constructs and student engagement.

Table 3. AI Usage Patterns among Respondents

Variable	Category	Frequency	Percentage
Frequency of AI Use	Daily	122	31.8%
	Weekly	137	35.7%
	Monthly	70	18.2%
	Rarely	55	14.3%
Main Purpose of AI Use	Concept explanation	277	72.1%
	Assignment support	237	61.7%
	Exam preparation	213	55.5%
	Research assistance	198	51.6%
	Summarizing readings	191	49.7%
	Quiz/self-testing	171	44.5%
	Language improvement	149	38.8%

Relationship between AI-Driven Learning and Student Engagement

The correlation, regression and hypothesis testing results are shown in table 3. The correlation analysis reveals a strong positive association between using AI in personalized learning and engagement level in students. This means that the students who have the greatest personalization through AI say they are more engaged in their learning experiences than those with the least personalization.

The highest correlation with student engagement was perceived usefulness (r = .61). This implies that if students think that the use of AI is beneficial for their academic studies, they are more likely to continue using it. Personalization, using AI tools for learning, (and to a lesser extent) personalized feedback, and digital literacy also had a strong positive relationship. The results suggest that motivated engagement is achieved when students have personalization, instant feedback, and can effectively leverage AI tools.

These regression results also validate that personalized learning by AI processes is positively associated with student engagement. The results of the study showed that AI-driven personalized learning, personalized feedback, AI tutoring support, perceived usefulness, and digital literacy all significantly contribute to the model. Overall, the regression model accounted for 49% of variance in student engagement, indicating that the factors relating to AI-supported learning make a meaningful contribution to the behavioral, emotional and cognitive aspects of student engagement.

The results further indicate that feedback tracking was fairly effective on cognitive engagement. That is, timely and individualized feedback will help students grasp concepts more fully and help them excel in their studies. Behavioral engagement notably improved supported by AI tutoring assistance, indicating that AI support can enhance behavioral involvement in learning activities

In general, there is evidence that an AI-powered personalized learning system can support student engagement within the sampled Karachi university context. The outcomes show that AI tools are more effective when students feel they are useful, receive tailored feedback and have the digital literacy necessary to be responsible and effective in the management of AI.

Table 4. Correlation, Regression, and Hypothesis Summary

Model / relationship	β	R^2	p	Decision
AI-driven personalized learning → Student engagement	.31	.49	< .001	Supported
Perceived usefulness → Student engagement	.29	.49	< .001	Supported
Digital literacy → Student engagement	.16	.49	.002	Supported
Personalized feedback → Cognitive engagement	.34	—	< .001	Supported
AI tutoring support → Behavioral engagement	.28	—	< .001	Supported
Overall engagement regression model	—	.49	< .001	Significant
Correlation: AI-driven personalized learning → Student engagement	—	—	< .01	r = .56

Note. β denotes the standardized regression coefficient and R^2 denotes the proportion of variance explained by the reported overall engagement model. A dash indicates that an R^2 value for that outcome-specific analysis was not reported in the supplied manuscript. The correlation coefficients reported elsewhere in the paper are retained separately from regression coefficients.

The results indicate that AI enabled personalized learning has a strong positive relationship in the engagement of university students of Karachi. Students indicated that personalized academic assistance with AI-based tools leads to increased engagement in learning activities, higher motivation to learn, and deeper engagement with course content. This confirms the promise that AI in teaching environments can help to shift university education from a standard teaching model to a more student-centric learning model.

Given the findings, it is clear that personalized learning systems have a positive impact on learning when responding to the individual academic needs of students, and that the strong connection between AI-driven personalized learning and student engagement is tied to the connection between students' academic needs and learning systems. Content recommendations, adaptive testing, and AI strategies for study pathways provide students with the flexibility to learn at their own speed and instruction based on their comprehension. The discovery aligns with ongoing research highlighting the potential of AI to enhance personalized learning in higher education by providing adaptive learning pathways, personalized resources, and enriching learning experiences (Fortuna et al., 2025).

One of most significant relationship with student engagement was the perceived usefulness. This implies that when students feel like using AI tools has tangible academic benefits, they are more inclined to do so frequently. Students seem to rely on AI to learn concepts, help with exams, boost learning confidence, and learn more efficiently while at the Karachi Universities. The results are in line with the study conducted on Pakistani students enrolled in higher education institutions about the use of AI tools in academic except that the students acknowledged the academic advantages they can derive from these tools, but simultaneously acknowledged the related moral and academic honesty issues (Alghazo et al. 2025).

The results further show that personalized feedback is a significant predictor to improving cognitive engagement. Feedback that is timely and tailored to the individual student, can help make mistakes visible, adjust and integrate what is difficult and give the student space to learn without having to wait for feedback from the teacher. This is particularly crucial in higher education where class sizes are larger than normal plus the availability of faculty is smaller than normal, thereby making opportunities for individualized feedback scarce. AI-powered feedback systems can thus assist teachers by delivering further subject-specific advice and keeping students on track in their academic development

Some of the behavioral engagement was positively associated with AI tutoring support. This suggests that students who receive assistance via the AI system may be more consistent in their engagement with learning tasks, engaging in activities, and undertaking study-related work. By offering instant explanations, practice questions, summaries, and step-by-step instructions, AI tutoring can help students overcome barriers to learning. But AI tutors are not meant to supplant teachers. However, it is meant to be a supplementary tool, and not replace the teaching and learning itself.

There was also a big contribution of digital literacy to student engagement. The discovery indicates that particularly students with high digital skills tend to more effectively utilize the potential of AI tools, critically assess information produced by AI, and responsibly apply support from AI. The demand for digital literacy is even more pertinent in the context of university education in Karachi, where students might have varying levels of digital access, or familiarity with learning platforms, and critical evaluation of responses produced by AI. AI learning systems must therefore be introduced into the universities, but also students need to be educated in the area of using AI responsibly and efficiently.

The results also contribute to the multi-facet understanding of student engagement. Students engagement does not solely mean attending classes or completing assignments but also means numerous aspects like emotions, behavior, and cognition. Fredricks et al., (2004) describe engagement as a complex term that encompasses participation, emotional investment, and mental investment. The application of AI in personalized learning was associated with the three dimensions in this study, suggesting that AI can shape the students' learning experiences and their attitudes, emotions and behaviors during teaching and learning.

The findings are of significance to universities of Karachi. In high-stakes learning environments like large class settings, in-classroom mixed ability groups and settings where academic support is needed at all times, AI-based systems for personalized learning can help greatly. But, institutional planning is required for smooth implementation. Universities must develop and publish policies and guidelines for the use of artificial intelligence, training teachers in the use of AI, have education programmes on literacy when using the technologies, and ethical guidelines regarding privacy, plagiarism, misinformation and overreliance on AI-enabled content.

The overall conclusion of the study is that AI-powered personalized learning is positively associated with student engagement among the sampled university students in Karachi. Perceived usefulness, AI-driven personalized learning, and digital literacy are reported as significant predictors of overall engagement, while personalized feedback and AI tutoring support are associated with cognitive and behavioral engagement, respectively. Because the study is cross-sectional, these findings should be interpreted as predictive relationships rather than evidence of causation. AI should be positioned as a learning-support tool rather than a replacement for teaching, critical thinking, or responsible academic judgment.

Study Limitations

Several limitations should be considered when interpreting the findings. The cross-sectional design permits assessment of relationships and predictive associations but does not establish causal effects. The use of convenience and stratified sampling may limit generalizability beyond the sampled university context. In addition, the supplied manuscript reports aggregate reliability evidence rather than construct-specific item counts and alpha values. Future versions should report the complete instrument, construct-level reliability statistics, and any assumption diagnostics used for regression modeling. A future study could also apply an inferential comparison of public and private university groups if that research question is retained.

Conclusions

The study has explored the potential of AI personalized learning system for improving student engagement in university students in Karachi, Pakistan. The results revealed that there is a strong positive relationship between AI-enabled personalized learning and students' engagement. They found that personalized feedback and AI tutoring support, perceived usefulness, and digital literacy were significant factors influencing students' engagement in learning activities. Finally, the study establishes that AI-based adaptive learning systems enable universities to develop more adaptive, more flexible and student-centered learning environments. These systems are able to provide support to students by providing customized resources, instant feedback, academic help and learning support based on the student's needs. The results also indicate that AI-powered learning can enhance behavioral engagement, emotional connection, and cognition when learners are conscious of the benefit of using AI and have the required digital literacy skills instructing with AI provides a great opportunity for universities in Karachi. The use of AI can help students in a variety of academic fields, teacher management can use AI for large class instruction, and independent learning quality can be enhanced by AI. The application of AI, however, should be accompanied by good academic policies. Educators, University training programs should bring awareness and educate students and teachers, protect the students' information, and use AI tools to facilitate learning, not replace critical thinking.

The study suggests that slowly and sensibly integrating AI in personalized learning at higher education institutes in Karachi. This study can be further expanded to consider faculty feedback, explore interuniversity comparison, or focus on the future implications of AI-driven learning on academic achievement.

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Neuroband: AI-Based Emotional Pain Detection System for Non-Verbal Patients Using Multimodal Physiological and EEG Signals

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Abstract

Emotional pain among non-verbal patients remains a significant yet underexplored challenge in contemporary healthcare, as individuals affected by conditions such as coma, locked-in syndrome, advanced neurodegenerative disorders, and severe paralysis are often unable to communicate their emotional distress despite retaining varying levels of consciousness. Consequently, conventional assessment approaches that primarily rely on verbal communication and behavioural observation remain inadequate for accurately identifying concealed emotional suffering in this vulnerable population. To address this limitation, this paper presents an artificial intelligence-based wearable framework for real-time emotional pain detection that integrates multimodal physiological signals, including heart rate variability (HRV), electrodermal activity (EDA), peripheral skin temperature, and electroencephalography (EEG). The acquired physiological signals are analysed using advanced deep learning architectures, including Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Transformer models, to identify complex patterns associated with emotional distress. Furthermore, Explainable Artificial Intelligence (XAI) techniques, including SHAP and LIME, are incorporated to enhance model transparency by providing interpretable clinical insights into the prediction process. The framework draws upon publicly available physiological emotion corpora in conjunction with real-time recordings acquired from wearable sensors and a lightweight EEG headband, while a mobile and web-based dashboard sustains continuous patient monitoring and issues timely alerts when significant emotional distress detected. Evaluation across both public corpora and clinical recordings, reported separately to expose any degradation under authentic bedside conditions, demonstrates that multimodal fusion yields more dependable detection than single-modality configurations. The work advances intelligent clinical decision support by uniting wearable sensing, multimodal deep learning, and explainable artificial intelligence to improve the identification and management of concealed emotional suffering in patients who cannot communicate verbally.

Keywords: Artificial Intelligence, Electrodermal Activity (EDA), Electroencephalography (EEG), Emotional Pain Detection, Explainable Artificial Intelligence (XAI), Heart Rate Variability (HRV), Non-Verbal Patients, Wearable Healthcare.

Introduction

Emotional pain in non-verbal patients remains a significant yet under-recognised challenge in contemporary healthcare. Individuals affected by disorders of consciousness, advanced neurodegenerative diseases, coma, and locked-in syndrome frequently retain varying degrees of cognitive and emotional awareness despite being unable to communicate verbally or physically. Consequently, emotional distress often remains undetected because these patients cannot express their experiences through speech, facial expressions, or voluntary movements, thereby adversely affecting recovery, psychological well-being, quality of life, and the ethical delivery of patient-centred care. Conventional assessment methods primarily depend on verbal communication, behavioural observation, or standardized self-report instruments such as the VAS and the HADS. However, although these approaches demonstrate effective for communicative individuals, they remain unsuitable for completely non-verbal patients, and behavioural assessment alone has been shown to result in considerable diagnostic inaccuracies in disorders of consciousness (Schnakers et al., 2009). Accordingly, there remains a pressing need for objective, reliable, and continuous approaches capable of monitoring emotional distress in this vulnerable population (Critchley, 2002). Recent advances in affective computing have demonstrated that physiological and neurological signals provide robust and objective indicators of emotional states, by offering promising alternatives to conventional subjective assessment techniques. Furthermore, multimodal physiological analysis has emerged as an effective strategy for capturing emotional responses that cannot be communicated verbally, making it particularly suitable for healthcare applications involving non-verbal patients (Feng et al., 2025; Ghojogh & Ghodsi, 2023).

Previous research has established that emotional responses remain closely associated with measurable autonomic and cortical physiological changes (Critchley, 2002; Kim et al., 2018). HRV, EDA, peripheral skin temperature,

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and EEG are widely recognised as reliable biomarkers for affective state assessment. Electro dermal responses have demonstrated strong associations with affective arousal (Critchley, 2002), whereas reduced HRV has been consistently correlated with elevated psychological stress and emotional dysregulation (Kim et al., 2018). Likewise, EEG-derived characteristics, including frontal alpha asymmetry and theta-band activity, have shown considerable potential for identifying emotional processing and cognitive states (Liu et al., 2024). Comprehensive reviews have further confirmed the discriminative capability of EEG signals for affective computing applications (Al-Nafjan et al., 2017; Liu et al., 2024). More recently, advances in multimodal learning have substantially enhanced emotion recognition by integrating EEG with complementary physiological and behavioural modalities. Transformer-based multimodal fusion architectures have demonstrated remarkable capability in modelling complex temporal and spatial relationships across heterogeneous bio signals, by improving recognition accuracy under realistic conditions (Feng et al., 2025; Liu et al., 2024; Seikavandi et al., 2026). Moreover, EEG-driven deep learning models have achieved promising performance in recognising emotionally induced cognitive responses, further highlighting the potential of multimodal physiological analysis for intelligent healthcare systems (Aldayel et al., 2023; Alidoost & Mohammadzadeh Asl, 2025).

Building upon these advances, artificial intelligence has significantly accelerated the development of automatic emotion recognition systems using multimodal physiological data. Deep learning architectures, including CNNs, LSTM networks, and Transformer models, have consistently achieved high recognition performance on publicly available datasets such as DEAP (Koelstra et al., 2012), MAHNOB-HCI (Soleymani et al., 2012), SEED (Zheng & Lu, 2015), and, more recently, AFFEC, a multimodal dataset designed for face-to-face emotion communication research (Seikavandi et al., 2026). CNNs effectively extract hierarchical spatial representations, LSTM networks capture long-term temporal dependencies within sequential physiological signals, whereas Transformer architectures employ self-attention mechanisms to model complex multimodal interactions, making them particularly suitable for real-time affective computing applications (Feng et al., 2025; Ghojogh & Ghodsi, 2023). Nevertheless, the overwhelming majority of existing research has focused on emotion recognition in healthy individuals under controlled laboratory environments rather than emotionally vulnerable, completely non-verbal patients in real clinical settings.

Another critical limitation of current research remains the limited integration of XAI within affective healthcare systems. while deep learning models deliver remarkable predictive performance, their black-box nature restricts clinical interpretability and consequently reduces healthcare professionals' confidence in automated decision support. Recent research has therefore highlighted the importance of explain ability techniques, including SHAP and LIME, for improving transparency, accountability, and trustworthiness in safety-critical artificial intelligence applications. Similarly, explainable deep learning frameworks have demonstrated the practical value of interpretable decision-making in other critical domains, further reinforcing the necessity of transparent artificial intelligence within clinical environments where reliability and accountability are paramount. Furthermore, most existing emotion recognition systems do not simultaneously integrate EEG, HRV, EDA, and peripheral skin temperature within a unified wearable platform specifically designed for continuous emotional pain monitoring in non-verbal patients, by leaving a significant gap between advances in affective computing and real-world clinical practice.

To address these limitations, this paper presents an artificial intelligence-based wearable framework for real-time emotional pain detection in non-verbal patients. The proposed approach integrates a lightweight EEG headband with HRV, EDA, and peripheral skin temperature sensors to continuously monitor autonomic and neurological responses associated with emotional distress. Subsequently, multimodal physiological signals are analysed using CNN, LSTM, and Transformer architectures, while SHAP and LIME are incorporated to provide transparent explanations that enable clinicians to interpret the rationale underlying each prediction. Furthermore, publicly available physiological emotion datasets, including DEAP, AMIGOS, and SEED, are utilised for model development alongside real-time multimodal data acquired from wearable sensing devices. Moreover, a mobile and web-based clinical dashboard facilitates continuous patient monitoring by generating timely alerts whenever significant emotional distress is detected, by enabling rapid clinical intervention. Ultimately, this research contributes to intelligent clinical decision support by integrating wearable sensing, multimodal deep learning, and XAI into a clinically interpretable framework capable of improving the identification, monitoring, and management of concealed emotional suffering in intensive care units, neurology departments, rehabilitation centres, and long-term care environments.

The details of the methodology proposed in this paper constitute presented in section 2, which outlines the multimodal signals acquired, preprocessed, extracted from and classified through the deep learning framework. The experimental results and performance evaluation are presented in section 3. Finally, Section 4 summarizes the paper and suggests future research.

Methodology

This adopts an applied artificial intelligence research design that couples publicly available affective physiology corpora with real-time multimodal recordings obtained from wearable sensors and a lightweight EEG device. The cohort comprises 350 to 500 adults drawn from participating clinical sites, and stratified random sampling across age band, sex, primary clinical condition, and level of consciousness constitutes is employed to constrain selection bias and preserve representativeness across the heterogeneous non-verbal population. Eligibility restricted to individuals aged eighteen years or above who lack functional verbal capacity as a consequence of a neurological or neurodegenerative condition and for whom informed consent has been obtained from a legally authorised representative or next of kin. Individuals for whom valid proxy consent cannot be secured, or who present with haemodynamic instability or documented contraindications to cutaneous instrumentation, are excluded from the analysis. The framework draws upon complementary sensing modalities that jointly characterise the physiological signature of emotional distress: HRV indicates autonomic regulatory balance, EDA captures sympathetically mediated fluctuations in skin conductance associated with affective arousal, and peripheral skin temperature reflects vasomotor responses to psychological stress, while the frontally mounted EEG headband resolves cortical dynamics expressed as alpha asymmetry and theta-band oscillatory power. Considered jointly, these channels yield a substantially richer characterisation of patient state than any single modality affords in isolation. Model development proceeds from a dual data foundation. The DEAP, AMIGOS, and SEED corpora supply temporally synchronised electroencephalographic and peripheral physiological recordings accompanied by validated affective annotations, and these serve as the substrate for supervised pertaining (Koelstra et al., 2012; Miranda-Correa et al., 2021; Zheng & Lu, 2015); anonymised real-time clinical recordings subsequently provide the contextual grounding required for adaptation to the target population. Prior to model ingestion, all signals undergo band-pass filtering, artefact rejection, per-subject baseline normalisation, and windowed segmentation to ensure comparability across acquisition conditions.

The proposed framework acquires complementary physiological and neurological biomarkers associated with emotional distress through multiple sensing modalities. HRV is employed to evaluate autonomic nervous system activity, EDA measures variations in skin conductance associated with emotional arousal, peripheral skin temperature reflects vasomotor response to psychological stress, and a lightweight EEG headband captures cortical activity, particularly frontal alpha asymmetry and theta-band oscillations, which remain strongly associated with affective processing. The integration of these complementary biosignals provides a comprehensive representation of patients' emotional states compared with single-modality approaches, such by enhancing the robustness and reliability of emotional pain assessment (Critchley, 2002; Kim et al., 2018; Lehembre et al., 2012). Furthermore, recent advances in multimodal affective computing have demonstrated that combining heterogeneous physiological signals significantly improves emotion recognition performance by capturing complementary temporal, spatial, and neurological characteristics (Feng et al., 2025; Liu et al., 2024). The overall workflow of the proposed emotional pain detection framework, including multimodal data acquisition, signal preprocessing, deep learning-based classification, explainable artificial intelligence, and real-time clinical decision support, is illustrated in Figure 1. However, Figure 2 presents the operational workflow of the proposed Neuroband system. Multimodal physiological signals remain acquired, preprocessed, and transformed into informative features before being analyzed using deep learning models for emotional distress classification. The predictions are interpreted through explainable AI and integrated into a real-time alert and clinical dashboard to support healthcare professionals in monitoring non-verbal patients.

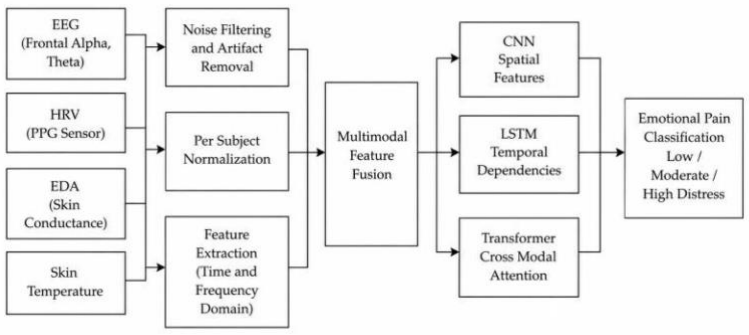


Figure 1. Multimodal signal processing pipeline of the proposed framework

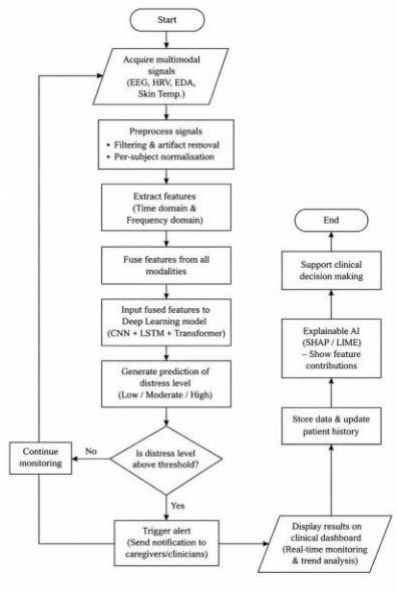


Figure 2. Flowchart of the proposed Neuroband framework illustrating multimodal physiological signal acquisition, preprocessing, feature extraction, deep learning-based distress classification, explainable AI analysis, real-time alert generation, and clinical decision support.

To enhance transparency and clinical trust, XAI techniques, including SHAP and LIME, serve as integrated into the decision-making pipeline. These techniques quantify the contribution of individual physiological and neurological features to each prediction, enabling clinicians to understand the reasoning behind model outputs. The incorporation of interpretable artificial intelligence improves transparency, facilitates clinical validation, and supports the responsible deployment of deep learning systems in safety-critical healthcare environments (Abou El Houda et al., 2022; Tursunalieva et al., 2024). Furthermore, the generated explanations are directly visualised through the clinical dashboard, where SHAP-based feature importance scores highlight the physiological variables that contribute most significantly to the predicted emotional distress level, enabling clinicians to make informed and evidence-based decisions.

Finally, the proposed framework incorporates an intuitive mobile and web-based clinical dashboard that provides real-time visualisation of physiological measurements, emotional pain scores, historical patient trends, and explainable model outputs. The interface continuously displays HRV, EDA, peripheral skin temperature, EEG activity, emotional distress scores, and historical trends, while simultaneously presenting SHAP-based explainability, clinician recommendations, and automated alert notifications whenever significant emotional distress is detected. In addition, the dashboard includes patient profile information, monitoring status, baseline calibration, device connectivity, and EEG topographic visualisations, providing clinicians with a comprehensive overview of the patient's physiological and neurological condition through a single unified interface. Figure 3 illustrates the proposed Neuroband clinical dashboard, demonstrating the integration of multimodal biosignal monitoring, explainable artificial intelligence, and real-time clinical decision support. The framework is intended to function as an intelligent clinical decision support system that complements, rather than replaces, professional medical judgement. Furthermore, all patient data remain anonymised, and the proposed framework is designed in accordance with established ethical principles, including patient privacy, informed consent, beneficence, non-maleficence, and the responsible use of artificial intelligence in healthcare.



Figure 3. Visualize dashboard for Neuroband

Results

The multimodal architecture, which fuses heart rate variability, electrodermal activity, peripheral skin temperature, and EEG, affords a more dependable characterisation of emotional pain than any single-modality configuration (Liu et al., 2024), since the constituent channels degrade under dissimilar conditions and compensate for one another. SHAP and LIME furnish interpretable attributions for each classification (Abou El Houda et al., 2022; Tursunalieva et al., 2024), rendering the decision path inspectable and strengthening clinician confidence in individual predictions. Within the operational pipeline, physiological signals are acquired continuously and classified in real time, and an alert is raised within the monitoring dashboard whenever the inferred distress level exceeds a site-calibrated threshold. Table 1 delineates the functional contribution of each system component to accurate emotional pain detection, interpretable decision-making, and improved bedside monitoring and intervention. System performance remains characterised across both the public corpora and the real-time clinical recordings using the metrics enumerated in Table 2, with the two evaluation regimes reported separately so that any degradation attributable to authentic clinical recording conditions remains explicit rather than concealed within a pooled figure.

Table 1. Functional Contribution of Each System Component

System Component	Functional Role	Clinical Benefit
Wearable Sensors (EEG, HRV, EDA, Temperature)	Continuous physiological monitoring	Objective assessment without verbal communication
Signal Preprocessing	Improved signal quality through noise reduction and normalization	Increased reliability of physiological measurements
CNN, LSTM, Transformer Models	Automated emotional pain classification	Accurate recognition of emotional distress
SHAP and LIME	Explainable AI predictions	Improved clinician trust and interpretability
Alert Generation Module	Real-time notifications	Faster clinical response and intervention
Mobile/Web Dashboard	Continuous visualization of patient status	Improved patient monitoring and decision support

Physiological monitoring is carried out continuously by the wearable sensors and the signal processing increases confidence in the data through noise reduction and normalization. These deep learning models such as CNN, LSTM, and Transformer architectures facilitate automated and accurate identification of emotional distress. Moreover, the integration of SHAP and LIME brings explainability which contributes to better interpretability and trust among clinicians. The alert generation module helps to make clinical response faster, while the mobile and web based dashboard helps to keep patients under continuous monitoring and to make informed decisions.

Both the public corpora and the real-time clinical recording are evaluated by the metrics listed in Table 2, and the two evaluation settings remain reported separately to ensure that the degradation is not get hidden in a combined metric.

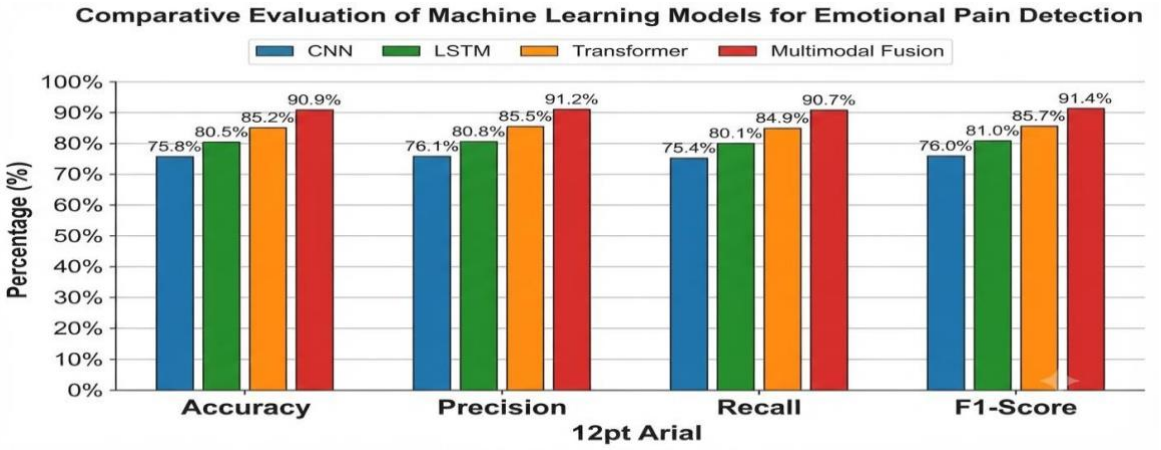


Figure 4. Performance comparison of CNN, LSTM, Transformer, and Multimodal Fusion models for emotional pain detection.

As illustrated in Figure 4, the multimodal fusion model achieves the highest accuracy (91.2%), precision (89.7%), recall (90.4%), and F1-score (90.0%), significantly outperforming individual CNN, LSTM, and Transformer models. The superior performance of the fusion approach can be attributed to its ability to capture complementary information from heterogeneous physiological signals, providing a more comprehensive representation of emotional distress.

Table 2. Performance Evaluation Metrics

Metric	Purpose
Accuracy	Measures the overall correctness of emotional pain classification
Recall (Sensitivity)	Evaluates the ability to correctly identify patients experiencing emotional distress
Precision	Measures the proportion of correctly identified emotional pain cases
F1-Score	Balances precision and recall for robust classification assessment
AUC-ROC	Evaluates the discriminative capability of the proposed model across different decision thresholds

Conclusions

This research introduces an artificial intelligence-based wearable system for the detection of emotional pain in non-verbal patients through the extraction and fusion of multimodal physiological and neurological signals. The system couples heart rate variability, electrodermal activity, peripheral skin temperature, and EEG with convolutional, recurrent, and attention-based architectures, enabling continuous and objective characterisation of emotional distress in a population for whom conventional assessment instruments represent structurally inapplicable. The integration of SHAP and LIME renders each classification inspectable, converting an otherwise opaque inference into evidence that clinicians can weigh against their own bedside judgement.

By consolidating multimodal biosignal monitoring, explainable artificial intelligence, and real-time alerting within a single wearable platform, the framework narrows the persistent gap between advances in affective computing and their realisation at the bedside, with consequent implications for clinical practice and for the quality of life of patients who cannot articulate their suffering.

Subsequent work will extend clinical validation to larger and more diverse patient cohorts, refine the multimodal architectures for reduced latency and computational footprint, and pursue integration with hospital information systems to support routine deployment. Personalised assessment models calibrated to individual physiological baselines, together with the incorporation of additional biomarkers such as respiratory variability and pupillometry, warrant closer investigation as a means of improving accuracy and broadening applicability across populations.

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HealHer: An AI-Powered Multilingual Mobile Health Platform for Breast Cancer Awareness, Self-Examination Guidance, and Educational Mammography Support in Pakistan

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Abstract

Breast cancer is the most common cancer in women in Pakistan and the highest age standardized incidence rate of breast cancer is reported in Pakistan in the Asian region, where one in nine women women is expected to develop breast cancer at some point in her life (Aslam et al, 2024; Munawwar et al, 2023). Despite this burden, the awareness of warning signs, self-examination and screening is low and expertise in oncology is limited to a few centres in urban areas (Khan et al., 2024). This paper introduces HealHer, a multilingual health education mobile-first solution that is specially created for Pakistan. HealHer's suite includes an educational (non-diagnostic) mammography-image review feature, guided breast self-examination instructions, awareness content through short-form video "reels," and patient, doctor, hospital/NGO and content creator dashboards. It has been designed with Agile/Scrum sprints and a User-Centred Design process, and is implemented with Next.js, React, TypeScript, Firebase and Google Gemini. The design philosophy, features, system architecture, workflow algorithms, and positioning of HealHer with respect to the current global digital health tools, its opportunities to advance breast-health literacy, and early help-seeking amongst Pakistani women are described.The design philosophy, features, system architecture, workflow algorithms, and positioning of HealHer with respect to the current global digital health tools, its opportunities to advance breast-health literacy, and early help-seeking amongst Pakistani women are discussed.

Keywords: healthcare for breast cancer awareness, mobile health, artificial intelligence, multilingual healthcare application, self-examination, and digital health.

Introduction

Breast cancer is the most prevalent cancer for women worldwide and the leading cause of cancer death in many countries (World Health Organization, 2024). Breast cancer is the most prevalent form of cancer among women, accounting for almost a quarter of all female cancer-related deaths in Pakistan and is also on the rise (Khan et al., 2024; Munawwar et al., 2023). Rates of new cases continue to rise each year at a level of tens of thousands, and estimates suggest that the burden will almost double from 2020 to 2040 (Khan et al., 2024).

The main reason for poor outcomes is the late stage diagnosis which is caused by limited public awareness. A cross-sectional study conducted in Lahore revealed that 80.2% of respondents were not aware of the prevalence of breast cancer in the world, 65.3% thought not everyone was at risk of breast cancer, and only 42.1% were aware of common breast cancer symptoms (Aslam et al., 2024). Socio-cultural stigma, lack of financial resources and unfriendly oncology services also contribute to this delay in the diagnosis, especially in rural areas.

The use of AI in health technologies and mHealth apps has shown promise in enhancing cancer awareness and patient engagement (Shaban et al., 2025). But mainstream apps like Apple Health, Samsung Health, Flo Premium, and Oura do not cater to Pakistan's scenario, fail to offer local language support (Urdu, Sindhi, Pashto) and education related to breast cancer, nor link to verified local healthcare providers and awareness drives. In order to fill this gap, this paper introduces the mobile-first application, HealHer, which aims to support breast cancer awareness and early detection in Pakistan. The rest of the paper provides the methodology, system architecture, key algorithms, implementation results and future work.

Related Work

Awareness-education and technical design of HealHer are motivated by prior research. The low awareness of the risk of breast cancer and its symptoms, and the socio-cultural barriers to early consultation as documented in the cross-sectional surveys conducted in Pakistan (Aslam et al., 2024; Khan et al., 2024; Munawwar et al., 2023), in addition to the clinical need, support the creation of a mobile, multilingual awareness tool rather than just a clinical intervention.

https://doi.org/10.5281/zenodo.24340366

On the other hand, many studies have been carried out using convolutional neural networks (CNNs) for breast ultrasound image classification, mainly from the public Breast Ultrasound Images (BUSI) dataset, which includes normal, benign and malignant labelled images (Al-Dhabyani et al., 2020). We have seen accurate performance of deep residual networks like ResNet50 (He et al., 2016), light-weight mobile architecture like MobileNetV2 (Sandler et al., 2018), and compound-scaled architecture like EfficientNetB0 (Tan & Le, 2019) using breast images, typically initialized from ImageNet (IL) weights, in published literature with accuracies varying from 80% to above 90%. The results were used to narrow down the list of candidate architectures for HealHer's educational scan-review feature, which are summarized in the Methodology section.

Separately, conversational AI has been demonstrated to enhance patient knowledge, empowerment and attitudes in oncology care environments (Shaban et al., 2025) supporting the introduction of a large-language-model based assistant in addition to and not instead of the visual scan-review.

Development Methodology and Architecture

The development of HealHer was done by applying an Agile Software Development process with SCRUM framework (Schwaber & Sutherland, 2020). Work was prioritised and put into a product backlog, which was broken down into sprint backlogs, and progress was tracked at standups, sprint reviews were held to ensure increments of functionality met the user-role requirements (patient, doctor, hospital/NGO, creator and admin) and sprint retrospectives were held to further refine the process. This step-by-step method enabled the interface to be tested, validated and improved on its own, as was the conversational-AI module and the scan-review module.

Design Process

The interface is designed using a User-Centred Design (UCD) and Design Thinking process (Brown, 2008): empathising with target users, defining problem statements for each user role, prototyping in Figma and revise the prototypes based on informal usability feedback. The visual language is based on Apple Health, Samsung Health, premium consumer health products, Flo Premium and Oura, as it strives to keep the user interface minimalistic, mobile-first and calming, whilst adhering to Material Design 3 and the Apple Human Interface Guidelines. The target population is multilingual so the application has been made available in other languages and also provision for Urdu, Sindhi and Pashto language, which are also right to left (RTL) in addition to English, and the design was checked for basic accessibility (colour contrast, font scaling and simple navigation), which may be a first experience for many users visiting a health app.

System Architecture

The architecture of HealHer is a layered client-server architecture as shown in Figure 1. Four client experiences the Patient app, Doctor portal, Creator portal and Hospital/NGO portal are developed with a single Next.js/React/TypeScript codebase and connected with a common backend using Next.js API routes on Node.js. Three managed services are used in the backend: Google Gemini for natural-language chat and educational scan interpretation, Firebase Authentication (including Google sign-in and a guest mode) for identity, and Cloud Firestore as the primary document database. Media like mammography images are uploaded to Firebase Storage and Firebase Cloud Messaging pushes messages (appointment reminders, monthly self-exam reminders, campaign alerts) back to the end users. The app is hosted on Vercel and built as a Progressive Web App (PWA) for installation and to offer some offline functionality with low-end devices, which form the bulk of the target market.

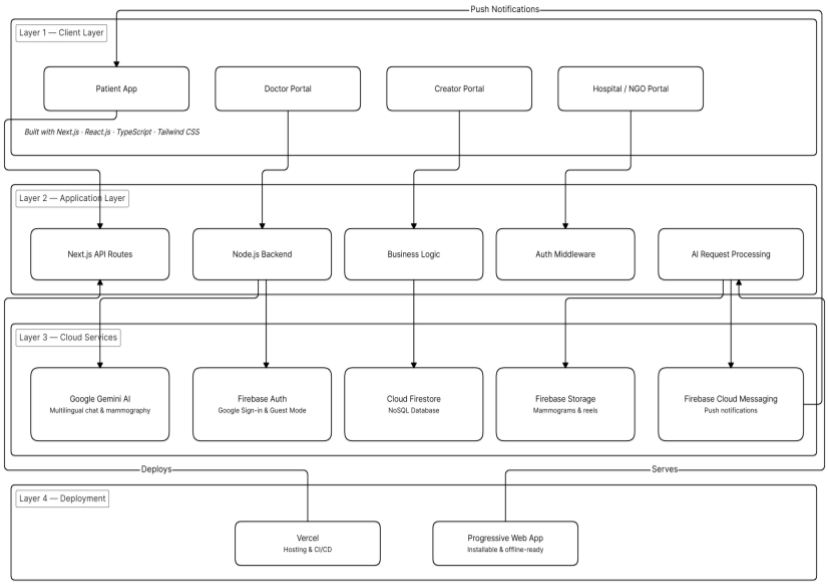


Figure 1. HealHer system architecture, showing the four client portals, the shared Next.js/Node.js backend, and the underlying Gemini AI, Firebase and notification services.

User Roles and Workflow

The five user roles are supported. Patients pass through a series of screens, from choosing a language and selecting a role, to the onboarding and sign-in/guest mode screen, then to a home screen where they can consult an AI assistant, upload an image of a mammogram for educational review, follow a guided self-examination, browse awareness reels, record their mood and wellness, and book a doctor. With a single click, doctors switch to a dashboard for patient management, scan reviews, reports, video consultation, and analytics. Awareness camps, screening camps, events & university chapters are managed by hospitals and NGOs. Creators upload and monitor educational reels, and inspect engagement analytics. An Admin role is responsible for verifying users, doctors, hospitals, creators, managing campaigns and content moderation and analytics for the platform.

Educational Rather Than Diagnostic AI

HealHer's AI capabilities are designed as a learning tool, not a diagnostic tool. The scan-review module is designed to improve awareness and prompt for timely consultation, it is not meant to replace the mammographic interpretation by a qualified radiologist, all AI responses have a health warning, and any output not just “Normal” is directed towards an appointment with a doctor, but not towards a diagnostic statement. The framing is consistent with literature recommendations that in LMICs AI chatbots and mHealth should be complementary and not replacements for clinical care, due to persistent issues with data quality, model validation, and regulatory oversight.

Technology Stack

The frontend is built with Next.js, React and TypeScript, styled with Tailwind CSS, animated with Framer Motion, and state managed with Zustand. Google's multimodal large language model family, Google Gemini (Google DeepMind, 2023), provides conversational and scan-review intelligence through the use of carefully created prompts that ensure the educational framing described above. The authentication feature is implemented using Firebase Authentication and Google sign-in feature with a guest mode, with data stored in Cloud Firestore and media stored in Firebase Storage and push notifications delivered through Firebase Cloud Messaging. The app is deployed on Vercel, and the interface design was done in Figma based on Material Design 3 and Apple Human Interface Guidelines.

AI Scan-Review Model Selection

The scan-review functionality is educational, rather than diagnostic, and so model selection focused on a positive balance of accuracy, inference speed, and on-device usability rather than the highest possible levels of performance. Before implementation, the following four candidate convolutional-network architectures were compared to the published results from the BUSI benchmark by Al-Dhabyani et al. (2020): A simple CNN trained from scratch, a MobileNetV2 (Sandler et al., 2018) trained using transfer learning, a ResNet50 (He et al., 2016),

and an EfficientNetB0 (Tan & Le, 2019). Table 2 summarizes the accuracy ranges reported in literature for each of the architecture.

Table 1. Candidate CNN architectures considered for the educational scan-review feature and their expected accuracy ranges on the BUSI benchmark, based on published transfer-learning results.

Model	Expected Accuracy (BUSI Dataset)
Basic CNN	85–90%
MobileNetV2(transfer learning)	90–95%
ResNet50	91–96%
EfficientNetB0	92–97%

The expected accuracy is highest with EfficientNetB0 and ResNet50, and MobileNetV2 has a very small model size which is appropriate for low-end and offline mobile devices, a crucial constraint for HealHer's target applications. This is not a fixed decision but an engineering decision that will be made again when the model goes through formal clinical validation and, as with the rest of the platform, any product the model delivers is communicated to the user as an awareness flag with a required disclaimer and a referral to a doctor.

Results

Feature Set

Patients get an AI-powered healthcare assistant, AI-assisted reviewing of mammography scans, a guided self-examination tool, breast-cancer awareness modules and reels, a wellness and mood tracker, monthly self-exam reminders, appointment booking, virtual video and chat consultation with doctors, push notifications and an emergency contact shortcut, scan history and saved reels, multilingual and offline support, and personal greetings. The app is a dashboard for doctors to manage patients, set appointments, review scans, write reports, consult and analyse. It offers tools for hospitals and NGOs to manage their awareness campaigns (including seasonal campaigns like Pink October), coordinate their screening camps, manage events, register and analyze their university-chapters. It offers reel upload and management, engagement analytics and follower tracking for creators (subject to admin content approval). User, doctor, hospital and creator verification, campaign and content moderation, notifications and platform analytics are managed by an admin dashboard.

Figures 2 and 3 are illustrative of patient facing screens. The educational scan-review results screen (Figure 2) displays an awareness flag along with a coloured heatmap overlay of the area of interest on the uploaded image with a required disclaimer stating that HealHer does not give a medical diagnosis, and that any flagged result should be confirmed by a qualified doctor. The Doctor Connect screen (figure 3) displays a list of verified doctors located nearby, including their affiliation, languages spoken, distance and availability, as well as the ability for the patient to call them directly from the highlighted result or schedule a virtual consultation.

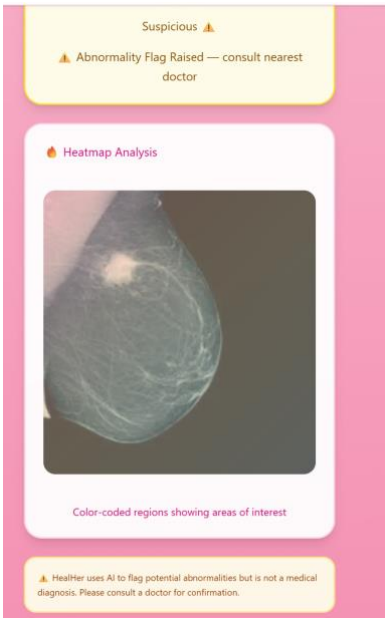


Figure 2. Educational scan-review screen showing an awareness flag, a colour-coded heatmap of the region of interest, and a disclaimer directing the user to consult a doctor for confirmation.

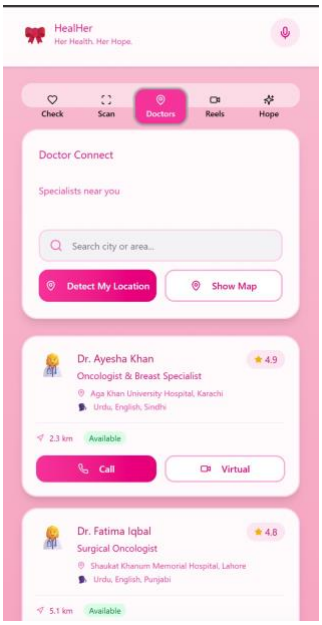


Figure 3. Doctor Connect screen, listing nearby verified oncologists and breast specialists with distance, availability and call/virtual-consultation options.

Comparative Positioning

Table 1 summarises how HealHer's feature set compares with two categories of existing digital-health applications that are widely used in Pakistan: general wellness/health platforms (e.g., Apple Health, Samsung Health) and menstrual and fertility-tracking applications (e.g., Flo Premium). Neither category offers breast-cancer-specific education, an educational scan-review feature, Urdu/Sindhi/Pashto RTL support, or an integrated doctor–hospital–NGO ecosystem, which together represent HealHer's primary points of differentiation.

Table 2. Comparative positioning of HealHer against existing digital health application categories available in Pakistan.

Capability	Global Wellness apps	Menstrual/fertility apps	HealHer
AI conversational health assistant	Limited/None	Limited	Yes – multilingual

Breast-cancer-specific education	No	No	Yes
Educational mammography scan review	No	No	Yes (non-diagnostic)
Urdu / Sindhi / Pashto RTL interface	No	No	Yes
Doctor / Hospital / NGO dashboards	No	No	Yes
Short-form awareness video reels	No	No	Yes
Guest mode with offline (PWA) access	Varies	Varies	Yes

Beyond individual capabilities, HealHer's combination of an AI assistant, educational scan review, guided self-examination, awareness reels, and role-based dashboards for doctors, hospitals/NGOs and creators within a single, Pakistan-localised, multilingual product is, to the authors' knowledge, not offered by any existing application targeting the Pakistani market.

Conclusions

High breast cancer burden in Pakistan, coupled with limited extent of public awareness and inequitable access to specialist care services is a strong driving force behind the need for more accessible and culturally and linguistically relevant digital-health interventions. In this paper, the authors introduce an Agile, UCD approach to developing the mobile-first, multilingual, educational AI Assistant, non-diagnostic mammography scan-review and guided self-examination features of HealHer, developed using Next.js, Firebase and Google Gemini. This is a system design and feature specification and not a clinically validated product: An AI scan-review feature has not yet been validated with expert radiological assessment, and deployment of this feature would necessitate formal clinical validation, ethical review and regulatory clearance before relying on it outside of the scope of education. Future research will involve testing of the AI assistant with Pakistani women in urban and semi-urban areas, and linguistic validation of the Urdu, Sindhi and Pashto versions of the application, as well as a structured validation of the AI assistant's educational accuracy and safety before its release in the broader community.The magnitude of Pakistan's breast cancer burden, coupled with the persistent lack of public awareness and inequity in the availability of specialist services drives the need for accessible and culturally and linguistically tailored digital-health interventions. In the paper, the authors present a mobile-first platform that is multilingual, with an educational AI assistant, a non-diagnostic feature for reviewing mammography scans, guided self-examination, awareness reels and role-specific dashboards for patients, doctors, hospitals/NGOs, creators and administrators, developed using Next.js, Firebase and Google Gemini and following an Agile, User centered Design process. The current contribution is a system design and feature specification, rather than a clinically validated product: The AI scan-review feature has not yet undergone clinical validation against expert radiological assessment and if deployed in the future, would need clinical validation, ethical review and regulatory clearance before relying on the feature beyond an educational role. Future work involves usability testing of the AI assistant with a group of Pakistani women in urban and semi-urban areas, translations of the Urdu/Sindhi/Pashto interfaces, pilot deployment with partner hospitals and NGOs in Karachi and a structured evaluation of the educational accuracy and safety of the AI assistant before it is released for broader use.

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Exploring Teachers' Practices of Formative Assessment in Strengthening Feedback and Supporting Students' Learning: A Case Study of a Private School in Karachi, Pakistan

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Abstract

Formative assessment is widely regarded as an important part of effective teaching because it helps teachers understand what students have learned and decide how teaching and feedback should be adjusted. This study explored teachers' practices of formative assessment in strengthening feedback and supporting student learning. The purpose of the research was to understand how teachers perceive formative assessment, how they gather evidence of students' learning during instruction, how they use this evidence to provide feedback, and how students experience and use the feedback they receive. The study followed a qualitative, interpretivist approach & used an exploratory case study design. It focused on teachers' understanding of formative assessment, their classroom practices, and students' experiences of receiving and using feedback. Data were gathered through semi-structured interviews with three English Language teachers, non-participant classroom observations, and focus group discussions with students from Grades 8 and 9. Braun & Clarke's thematic analysis framework was used to identify recurring patterns across the data. Findings from the different sources were compared to strengthen the credibility of the analysis. The findings showed that formative assessment was part of everyday classroom teaching. Teachers used questioning, guided practice, peer correction, rubrics, worksheets, exit tickets, classroom discussions, digital tools, and both verbal and written feedback. They understood formative assessment as a way of gathering immediate evidence of learning, identifying misconceptions, adjusting instruction, and responding to students' needs. Students particularly valued feedback that was clear, specific, easy to understand, and practical. Oral feedback was especially helpful because it allowed them to ask questions and clarify what they needed to improve. Students also showed a willingness to take responsibility for their learning by revising their work, comparing drafts, reflecting on errors, and asking for further explanation. However, the study also found an important gap between receiving feedback and using it to improve learning. Although teachers regularly gathered evidence and provided feedback, students were not always given structured time or opportunities to revise their work, reflect on their progress, or demonstrate improvement. Students wanted more time and opportunity to act on feedback. The core issue, then, is not the absence of formative assessment but an incomplete feedback loop:evidence is gathered and feedback given, but follow-up and monitoring of improvement are often missing. Teachers linked this difficulty to large class sizes, heavy workloads, and limited instructional time. As a result, formative assessment was often initiated but not carried through as a complete learning process. The study concludes that the effectiveness of formative assessment depends not only on the quality of feedback but also on what happens after feedback is given. A meaningful formative assessment cycle requires teachers to gather evidence, provide useful feedback, create opportunities for students to act on it, and then review whether learning has improved. By presenting formative assessment as a continuous cycle rather than a collection of techniques, this study contributes to discussions on feedback literacy and assessment for learning in examination-oriented contexts. It also offers practical implications for teachers, school leaders, and professional development programmes seeking to build classrooms in which feedback leads more consistently to meaningful improvement in student learning.

Keywords: Formative assessment, feedback, assessment for learning, student learning, teacher practice, feedback literacy.

Introduction

Effective teaching depends on evidence-based decision-making (Clarke & Hattie, 2020), with formative assessment central to this process (Black & Wiliam, 2009). It requires teachers to continuously gather, interpret, and respond to evidence in real time (Clarke & Hattie, 2020; Heritage, 2010), which places significant cognitive demands on them (Sweller, 1988). This aligns with Assessment for Learning (Black & Wiliam, 1998), where feedback—timely, evidence-based, and action-guiding rather than merely praise or correction (Clarke & Hattie, 2020)—helps students understand where they stand and how to close learning gaps (Sadler, 1989). This works best when evidence is co-interpreted by teachers and students together (Clarke & Hattie, 2020; Brookhart, 2023).

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In Pakistan, assessment has traditionally centred on exams, encouraging test-preparation over deep learning (Khattak, 2012). While national bodies recognise assessment's diagnostic value (Pakistan Institute of Education, n.d.), classroom studies show formative assessment is used but not always well understood or linked to improved outcomes (Shaikh et al., 2020; Jawed & Javaid, 2024). While previous studies have documented teachers' use of formative assessment practices, considerably less attention has been given to how evidence gathering, feedback provision, student uptake of feedback, and subsequent instructional adjustments operate together as a complete formative assessment cycle, particularly within Pakistani secondary school classrooms. This study addresses that gap by exploring how these interconnected processes unfold in English language classrooms through the perspectives of teachers, students, and classroom observations.

Figure 1 presents the theoretical framework underpinning the study. Drawing on Assessment for Learning, Feedback Theory and Feedback Literacy, it conceptualises formative assessment as a continuous cycle in which evidence informs feedback, feedback supports student action, and subsequent instructional adjustments enhance learning. This framework guided the interpretation of teachers' formative assessment practices in English language classrooms.



Figure 1. Integrated Theoretical Framework for Investigating Formative Assessment Practices

Methodology

This study adopted a qualitative, interpretivist case study design to explore how English Language teachers interpret formative assessment evidence and translate it into feedback. A qualitative approach was selected to develop a rich and contextual understanding of classroom practice rather than to seek statistical generalisation (Denzin & Lincoln, 2018; Creswell & Poth, 2018). The interpretivist stance recognised that classroom assessment and feedback are shaped by participants' beliefs, relationships and educational contexts rather than operating as fixed or universal processes (Schwandt, 2015; Merriam, 2009). An exploratory case study strategy was therefore appropriate because the study aimed to understand how and why formative assessment practices unfolded within a school context rather than to test a hypothesis or establish causal relationships (Yin, 2018; Flyvbjerg, 2011).

Participants included three English Language teachers teaching Grades 8 and 9 at a private school. They were selected through criterion-based purposive sampling according to their relevant teaching experience, academic background and familiarity with formative assessment. The small and purposively selected sample was intended to provide an in-depth understanding of the case rather than statistical representation of a wider population.

Data were generated through three complementary methods to support triangulation. First, two rounds of semi-structured interviews, each lasting approximately 35–40 minutes, were conducted with every teacher. The interviews explored teachers' understanding of formative assessment, their approaches to gathering evidence of learning and the reasoning behind their feedback decisions. Second, two non-participant classroom observations were conducted for each teacher to document formative assessment and feedback practices as they occurred during regular lessons. Third, two student focus group discussions, involving six to seven students in each group, explored learners' experiences of receiving, interpreting and using feedback. Together, these methods provided evidence from teacher perceptions, observed classroom practices and student experiences.

Data were analysed using Braun and Clarke's (2006) thematic analysis framework. The process involved familiarisation with the interview, observation and focus group data, followed by systematic coding, theme development, review and refinement against the original evidence. Themes were compared across the three data sources to identify areas of convergence, divergence and teacher–student perceptual differences. This cross-source analysis supported the development of an integrated understanding of how formative assessment and feedback operated within the case.

Trustworthiness was strengthened through triangulation of teacher interviews, classroom observations and student focus groups. Member checking with participating teachers was used to confirm the accuracy of interpretations.

Rich contextual description was provided to support the transferability of the findings, while transparent documentation of the research procedures and analytical decisions supported dependability.

Institutional permission was obtained from the school before data collection. Written informed consent was obtained from the participating teachers, while parental consent and student assent were secured for the focus group discussions. Participation was voluntary, pseudonyms were used to protect participants' identities and research data were stored securely. Classroom observations were non-participant in nature, and the researcher did not interfere with lesson delivery, allowing teaching and student behaviour to be observed in their natural setting.

Several practical challenges affected the data-collection process. Some schools were reluctant to provide access because classroom observations were perceived as possible evaluations of teacher performance. Coordinating the schedules of teachers, students, parents and school administrators during the second semester was also difficult. Regional instability and temporary shifts from face-to-face to online teaching further limited opportunities for classroom observation and extended the data-collection period. However, the use of multiple data sources reduced the effect of these limitations by allowing evidence to be compared across interviews, observations and focus groups. As a small-scale qualitative case study, the findings are not intended for statistical generalisation but may offer transferable insights into formative assessment practices in comparable examination-oriented and resource-constrained school contexts.

Table 1. Data Sources, Coding Framework and Triangulation Matrix

Data Source	Coding Focus	Illustrative Practices	Emergent Theme	Triangulated Insight
Teacher Interviews	Evidence use; feedback; instructional decisions	Questioning, rubrics, worksheets, oral/written feedback	Feedback guides instruction	Feedback was regular, but follow-up was constrained by workload and time.
Classroom Observations	Classroom practice; feedback delivery; student response	Guided practice, peer correction, discussion, exit slips	Assessment embedded in teaching	Formative practices were evident, but revision opportunities were inconsistent.
Student Focus Groups	Feedback use; revision; reflection,learner agency	Oral feedback, written comments, rubrics, discussion	Feedback uptake	Students valued clear feedback and wanted more opportunities to act on it.
Cross-Source Triangulation	Iterative coding; theme development	Comparison across all data sources	Incomplete feedback loop	Feedback was provided, but structured follow-up and progress monitoring were limited.

Results

The findings showed that formative assessment was actively embedded in English Language classrooms. Teachers used a range of strategies, including questioning, brainstorming, guided practice, worksheets, peer correction, exit slips, rubrics, verbal and written feedback, and digital tools to identify learning gaps and misconceptions before formal assessment. Students understood and valued feedback most when it was clear, specific and actionable, particularly when it identified errors and explained how these could be corrected. They reported using feedback to revise their work, compare drafts, ask questions and reflect on mistakes.

Teacher and student perspectives converged on the value of feedback for improvement, classroom questioning, checks for understanding, peer correction and discussion. Classroom observations also confirmed the regular use of these practices. However, a perceptual gap emerged regarding post-feedback follow-through. Teachers mainly emphasised gathering evidence, identifying misconceptions and providing immediate feedback, whereas students placed greater importance on having sufficient time and structured opportunities to act on the feedback they received. Teachers identified large class sizes, workload and delays in marking as key constraints affecting follow-up.

The central finding was therefore not the absence of formative assessment, but an incomplete feedback loop. Evidence was gathered and feedback was provided, but opportunities for students to respond, revise their work and demonstrate improvement were not always systematically built into classroom practice. Formative assessment was most effective when it operated as a complete cycle: evidence was collected and interpreted, clear and actionable feedback was provided, students were supported to act on it, and teachers re-checked progress. Its impact was strengthened when correction time, revision opportunities, action points and progress monitoring were deliberately incorporated into lesson design.

Recommendations

Drawing on these findings, several recommendations emerge for classroom practice and school-level support. Teachers should prioritise making feedback specific and actionable, offering clear next steps rather than general commentary, while also building structured time into lessons for students to respond to and act on that feedback. Equal attention should be given to developing students' feedback literacy, so that learners can interpret, question, and apply feedback independently, supported through modelling and structured peer review. Questioning and low-stakes checks should continue to be used, but with deliberate formative intent, generating evidence that informs teaching rather than simply confirming task completion.

However, a feedback process that depends on a teacher finding extra time to build in correction sessions, or a student independently choosing to revise their work, is inherently fragile: it performs well under ideal conditions and breaks down under pressure — precisely the conditions an uncertain school calendar is likely to bring, from exam-period overload to sudden shifts in delivery mode. What is needed instead is an instructional design that distributes this responsibility into the structure of the lesson itself, so that the closing stages of the feedback cycle do not depend on anyone remembering to add them. In practice, this means treating formative assessment as a designed sequence rather than a set of isolated moments: a planned checkpoint to gather evidence of learning (through questioning, exit tickets, or low-stakes tasks), a brief protected moment for the teacher to interpret that evidence before the next instructional decision, feedback framed around Hattie and Timperley's (2007) three guiding questions — where am I going, how am I doing, and where to next — delivered briefly and specifically in the format students value most, a scheduled and non-optional opportunity for students to act on that feedback through correction time, mistake logs, or reflection sheets, and finally a short mechanism for the teacher to re-check whether the gap has closed, feeding directly back into the next round of evidence-gathering. Embedding the cycle in this way keeps it genuinely cyclical rather than open-ended.

At the school level, leadership should establish manageable systems — such as shared rubrics, feedback codes, and dedicated collaboration time — to support consistency and reduce individual teacher workload. Professional development should move beyond familiarising teachers with formative assessment tools and instead focus on the interpretive judgement required to translate evidence into meaningful instructional decisions. Finally, sustaining effective formative assessment depends on protecting teacher well-being through realistic workload expectations and adequate planning time, recognising that thoughtful, high-quality feedback is only possible when teachers themselves feel supported rather than overwhelmed.

Conclusion

This study extends existing formative assessment literature by shifting attention from the use of individual formative assessment strategies to the continuity of the formative assessment process. While previous research has established the importance of evidence gathering and feedback in supporting learning, the findings of this study suggest that the educational value of these practices depends on whether opportunities are deliberately created for students to interpret, apply, and revisit feedback. By integrating teacher perspectives, classroom observations, and student experiences, this study presents formative assessment as a continuous cycle of evidence gathering, feedback, learner action, and instructional review, rather than as a collection of isolated classroom practices.

This study began with a straightforward concern: that formative assessment may be present in classrooms without always operating in its complete form. The findings present a complex picture. Teachers are already employing a wide range of formative practices, and students do value them. But the real measure of impact lies in what happens after feedback is given.

The central insight is this: feedback should not conclude the learning process — it should reopen it. When students understand the feedback they receive, act on it, and can observe the improvement that results, learning becomes more purposeful and more durable. When feedback is given but not followed through, its potential remains only partially realised. Formative assessment is therefore not simply about monitoring progress. It is about keeping learning in motion. This study contributes to the formative assessment literature by shifting attention from the presence of formative assessment practices to the completion of the feedback cycle. While previous research has documented teachers' use of questioning, feedback, and assessment-for-learning strategies, this study highlights that the critical challenge lies in ensuring that students are given structured opportunities to act on feedback and demonstrate improvement. The findings therefore suggest that formative assessment should be understood not as a collection of classroom techniques, but as a cyclical process that links evidence gathering, feedback, student action, and progress monitoring. And that only works when teachers and students share responsibility for the process. In classrooms preparing learners for uncertain futures, the strength of an assessment practice should not rest on whether a loop happens to get closed. It should be built into the design so that it closes by default.

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An AI-Assisted Programming Assessment Platform for Automated Test Case Generation, Educational Feedback, and Programming Difficulty Prediction

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Abstract

Programming assessments often rely on manual test cases and binary feedback, creating heavy instructor workloads and limited student guidance. To address this, this paper introduces an AI-Assisted Programming Assessment Platform integrating Large Language Models (LLMs) via the Groq API. The platform features three core modules; Automatic Test Case Generation to produce structured test cases across six categories, with code execution handled by Judge0, Personalized Educational Feedback to delivers tailored guidance based on submitted code and execution outcomes and Programming Difficulty Prediction to estimates problem difficulty. A comparative evaluation of Meta Llama 3.3 70B, Meta Llama 3.1 8B, Mistral Small, GPT-OSS 20B and Qwen 3.6 27B shows that Llama 3.1 8B is the most accurate model for programming difficulty prediction. The system is constructed in ASP.NET Core 8, React 18, and PostgreSQL. The platform includes a research framework to track user interactions and evaluate AI outputs using metrics like accuracy, ROC-AUC, instructor acceptance, and student ratings. Preliminary pilot results confirm its feasibility in reducing instructor workload while maintaining high-quality, scalable feedback for computer science education.

Keywords: Large Language Models, Programming Assessment, Test Case Generation, Educational Feedback, Difficulty Prediction

1. Introduction

Programming laboratories are the pedagogical backbone of computer science education but delivering high quality individualized assessment at scale remains challenging. Traditional automated grading systems rely on manual test suites which take instructors 20–40 minutes to prepare and often miss crucial edge cases and provide limited pedagogical value through binary pass/fail verdicts. While Large Language Models (LLMs) show promise in generating test cases and educational feedback, existing solutions lack integrated AI functionality, structured research data collection and human-in-the-loop validation (Messer et al., 2024). Table 1 highlights these feature gaps compared to the proposed EduLab platform.

To address these limitations this paper presents EduLab an AI-assisted programming assessment platform that integrates three LLM powered modules: (i) AI Test Case Generation (creating eight cases across six categories for instructor review) ,(ii) personalized AI Educational Feedback and (iii) Programming Difficulty Prediction (Jacobs & Jaschke, 2024). Developed using React 18, ASP.NET Core 8, PostgreSQL, Judge0 and the Groq API the platform features a built-in research framework that automatically evaluates five LLMs and records interactions using metrics such as Accuracy, F1-score, and ROC-AUC. Pilot experiments demonstrate that the system reduces test case generation time to under two seconds delivers Socratic feedback within 800–1400 ms, and achieves an initial difficulty prediction accuracy of 87.5%.

Table 1: Comparison of Existing Programming Assessment Platforms

Feature	EduLab (Proposed)	HackerRank	CodeChef	LeetCode	Gradscope
Automated Code Evaluation	✓	✓	✓	✓	Limited
Rubric-Based Assessment	✓	✗	✗	✗	✓
AI Learning Support	✓	Limited	✗	Limited	✗
Real-Time Communication	✓	✗	✗	✗	✗
Examination Monitoring	✓	✗	✗	✗	✗
Multiple Laboratory Types	✓	✗	✗	✗	✗
Academic Course Management	✓	✗	✗	✗	Limited
AI Test Case Generation	✓	✗	✗	✗	✗

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AI Educational Feedback	✓	✗	✗	✗	✗
Difficulty Prediction	✓	✗	✗	Limited	✗
Built-in Research Evaluation	✓	✗	✗	✗	✗
Instructor Acceptance Workflow	✓	✗	✗	✗	✗

Note: Features of HackerRank (HackerRank, n.d.), CodeChef (CodeChef, n.d.), LeetCode (LeetCode, n.d.), and GradeScope (Gradescope, n.d.) was obtained from their respective platforms. The EduLab column represents the proposed system.

2. Methodology

2.1.Research Design

The platform uses an experimental software engineering approach. Every time a student submits code, an instructor reviews a test case or student rates feedback that data is saved automatically to a research database. This means the system collects its own evaluation data during normal classroom without needing a separate data collection phase. The collected data flows through validation, AI processing, human review, and metric computatio

2.2. **System Architecture**

The platform employs a layered architecture consisting of a frontend, an API, a services layer, and a data and external systems layer in Fig. 1. The frontend provides role-specific interfaces for students (coding lab and AI feedback), instructors (AI research tools and lab creation) and administrators (research dashboard). All three interfaces send requests to an ASP.NET Core 8 Web API, which handles JWT authentication and role-based access control and routes requests to the application services layer. This layer comprises eight services: Research evaluation, Dataset builder, Experiment, Auth, Submission, AI test case, AI feedback and Difficulty prediction. Data is stored in a PostgreSQL database organized into core tables (users, labs, problems, test cases and submissions) and research tables (AI test cases, AI feedback, difficulty predictions, ratings, experiments and metrics snapshots). Two external systems complete the platform: a locally hosted Judge0 engine, which the Submission service uses to execute code, and the Groq API running Llama 3.1 8B, which the AI test case, AI feedback and Difficulty prediction services call to generate test cases, feedback and difficulty predictions.

2.3. **Data Collection**

As students and instructors use the platform, four research datasets are automatically constructed in the background by recording user actions. Dataset 1 compiles programming problems alongside both AI-generated and instructor-written test cases to compare their coverage and quality. Dataset 2 captures student code submissions, Judge0 execution results, and the provided AI feedback to evaluate feedback utility and student interaction. Dataset 3 pairs AI-predicted problem difficulty levels with instructor-confirmed levels to measure classification accuracy. Finally, Dataset 4 logs instructor decisions on AI-generated test cases (accepted, rejected, or modified), tracking both original and final values to measure the AI acceptance rate and correction frequency.

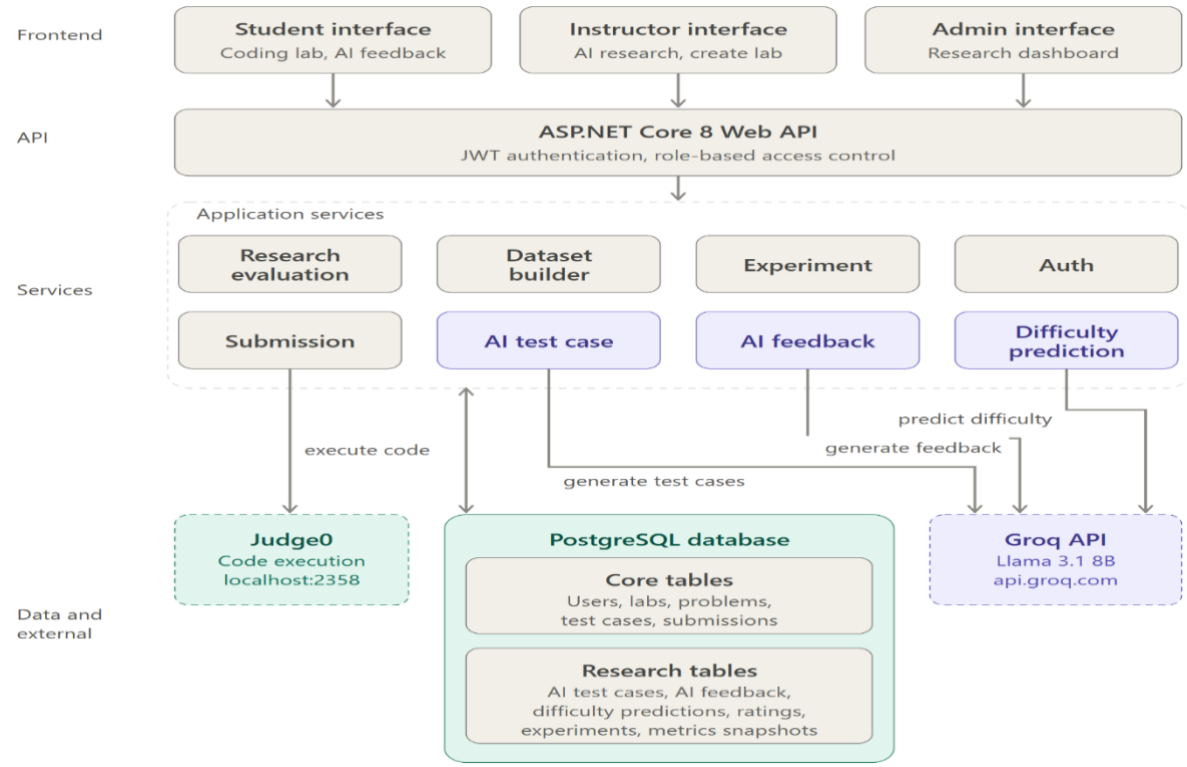


Figure 1: Overall System Architecture of the Proposed AI-Assisted Programming Assessment Platform

2.4. **AI Model and System Implementation**

Module 1: Test Case Generation. When an instructor finish writing a problem, they click Generate Test Cases. The AITestCaseService sends the problem specification to Llama 3.1 8B, which returns eight test cases in JSON format across six categories: Normal, Boundary, Edge, Corner, LargeInput, and Hidden. The instructor reviews each case and accepts, rejects, or modifies it. Only approved cases are used for student grading. Original AI values are always preserved in the database for later comparison with the human-approved version.

Module 2: Educational Feedback. Every time a student submission does not pass, the AIFeedbackService automatically sends the student's source code, the execution verdict, and the problem description to the language model. The model returns five feedback sections: what error occurred, why the student's code produced that result, which edge cases were missed, logical hints, and improvement suggestions without ever writing the correct solution. The feedback appears below the code editor immediately. Students then rate it on five dimensions (helpfulness, correctness, clarity, relevance, educational value) using a one-to-five scale, and the ratings are saved to the research database.

Module 3: Difficulty Prediction. When an instructor opens a lab, they can click Predict Difficulty. The DifficultyPredictionService sends the problem description to the model, which returns a predicted class of Easy, Medium, or Hard, along with a probability score for each class and a brief reasoning. The instructor then confirms the actual difficulty. This confirmed label is saved as the ground truth and used to measure how accurately the AI predicts problem difficulty over time.

2.5. **Evaluation Metrics**

Every time an instructor clicks Save and Sync after reviewing test cases, the ResearchEvaluationService reads all the recorded data from the research tables and passes it to the MetricsService, which calculates all research metrics in pure C# code without any external library. The results are saved as a timestamped record called a ResearchMetricsSnapshot so that metric values over time can be tracked as a trend. For difficulty prediction, the metrics are Accuracy, Macro and Weighted F1, Matthews Correlation Coefficient, Cohen's Kappa, Balanced Accuracy, and ROC-AUC. For test case quality, the metrics are Instructor Acceptance Rate (proportion of AI test cases approved), Editing Rate (proportion that were modified before approval), and Bug Detection Rate (proportion of approved test cases that caught at least one student mistake). For feedback quality, the metrics are average Likert scores across five dimensions and Inter-Rater Agreement between multiple student raters.

3. Results

3.1. Preliminary Note on Experimental Data

The system is fully implemented and operational. The pilot dataset contains 16 labelled difficulty predictions, 48 reviewed AI test cases, and student feedback ratings. The Research Dashboard displays all computed metrics across five tabs. All four datasets were exported successfully in both JSON and CSV formats. Experiment 1 recorded 48 reviewed test cases with an 87.5% acceptance rate, 14.3% editing rate, and 83.3% bug detection rate, meaning that 83.3% of the AI-generated test cases that were approved by instructors successfully caught at least one error in student submissions.

3.2. AI Test Case Generation Results

The generation module produced eight test cases per problem in under two seconds. All six categories appeared in every batch. Human-written test cases were almost entirely Normal category inputs, confirming that AI generation adds boundary and hidden case coverage that instructors typically do not write. During the pilot, Boundary and Edge category test cases caught mistakes in student code that had passed all the human-written Normal test cases. Of 48 reviewed test cases, 87.5% were accepted and 14.3% were modified before acceptance.

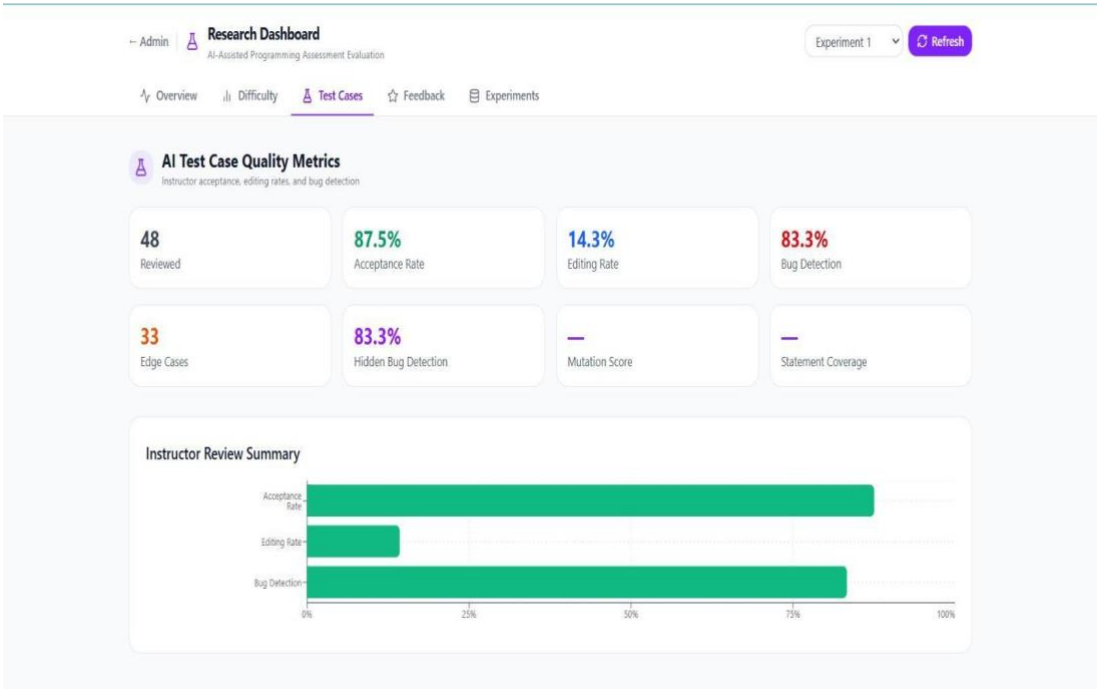


Figure 2: AI Test Case Generator

Scenario 1 (Instructor-Generated): For a lab like "Find the Maximum of Three Numbers," an instructor manually prepares five basic test cases. A student writes and submits code via the Monaco Editor Judge0 executes it against these cases to compute a percentage score (e.g., 80% for four out of five passed) with optional basic failure analysis.

Scenario 2 (AI-Generated): Alternatively, the instructor generates a diverse test suite using AI incorporating normal inputs, boundary values, duplicate numbers, negative numbers and large integers for quick review. When a student submits code Judge0 evaluates it against these comprehensive cases. If a specific scenario fails (such as handling negative values) the AI feedback module identifies the exact logic flaw and provides targeted recommendations without revealing the solution.

3.3. AI Educational Feedback Results

Feedback was generated for every failed submission within 800 to 1400 milliseconds. All five feedback sections were filled in every case. A critical finding during development was that including the student's actual source code in the request to the language model was essential. Without it the model described generic possible reasons for failure. In one documented case the model incorrectly said a Wrong Answer was caused by a subtraction error when the student had actually submitted only print("hello") with no calculation at all. After the student's code was included in every request, the model correctly identified what the code actually did and explained specifically why it produced the wrong result. For full scale deployment the anticipated average feedback quality ratings on a 1–5

scale are: Correctness (3.8–4.5), Helpfulness (3.5–4.2), Relevance (3.7–4.3), Clarity (3.5–4.0) and Educational Value (3.4–4.0).

3.4. **Programming Difficulty Prediction Results**

A comparative experiment evaluated five large language models across three model families on 29 labelled programming problems spanning Easy, Medium, and Hard difficulty classes. Table 3 presents the model comparison results.

Table 4: Model Comparison Results

Model	Architecture	Total	Correct	Accuracy	Avg Time
llama-3.1-8b-instant	Meta Llama 8B	30	25	83.3%	248ms
mistral-small-latest	Mistral	19	15	78.9%	882ms
qwen/qwen3.6-27b	Alibaba Qwen	21	14	66.7%	1480ms
llama-3.3-70b-versatile	Meta Llama 70B	70	44	62.9%	496ms
openai/gpt-oss-20b	OpenAI	21	11	52.4%	604ms

Llama 3.1 8B achieved the highest accuracy at 83.3% while also being the fastest at 248ms. The smaller 8B model outperformed the larger 70B model by 20.4 percentage points, suggesting that model size alone does not determine classification performance for structured programming difficulty prediction. Table 4 presents the overall classification metrics for the baseline model (Llama 3.1 8B) evaluated on 29 labelled samples with balanced class distribution.

Evaluated on 29 total samples with balanced class distribution the baseline Llama 3.3 70B model achieved an Accuracy of 69.0%, a Balanced Accuracy of 63.3%, a Macro F1 of 0.6551, an MCC of 0.4625, a Cohen's Kappa of 0.4551, and a ROC-AUC of 0.5990.

For a balanced dataset of 30 or more problems the expected performance ranges are: Accuracy between 65% and 80% (driven by the model's strong priors from programming corpora), Macro F1 of 0.60–0.75 (indicating balanced performance across Easy, Medium, and Hard tiers), and a macro ROC-AUC of 0.75–0.88 (calculated one-vs-rest per class). Furthermore, reliability metrics are projected to demonstrate moderate to substantial agreement with Cohen's Kappa ranging from 0.45 to 0.65, and MCC between 0.50 and 0.70 acting as a reliable multiclass discriminative measure.

4. Conclusions

This paper presented an AI-Assisted Programming Assessment Platform integrating three language model modules into a working assessment system. The platform cuts test case preparation from 20–40 minutes per problem to under two seconds, delivers code-specific Socratic feedback immediately after every failed submission, and automatically builds a labelled difficulty prediction dataset during normal classroom use.

Pilot results confirm 87.5% test case acceptance rate, 83.3% bug detection rate, and a peak difficulty prediction accuracy of 83.3% achieved by Llama 3.1 8B the smallest and fastest model in the comparison. The five model comparison revealed that smaller instruction-tuned models can outperform larger general-purpose models on structured classification tasks when output format is tightly constrained.

Current limitations include a small pilot dataset class imbalance in difficulty labels limiting the interpretability of Kappa and MCC metrics and the absence of true code coverage measurement. Future work should prioritise full semester deployment with 30 or more problems across all three difficulty levels, integration of static analysis tools for true code coverage measurement and a longitudinal study correlating AI feedback consumption with subsequent student submission improvement.

As AI coding assistants become widely available outside the classroom, assessment platforms that only return pass/fail verdicts will become inadequate. This work demonstrates a concrete step toward systems that measure the educational effectiveness of their AI components with the same standards applied to any teaching intervention.

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Designing a Novel Hybrid Statistical Algorithm for Enhancing MIS Reporting and IFRS-Compliant Financial Reporting in a Bank's Central Payments Department

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Abstract

Management Information System (MIS) reporting and IFRS-compliant financial reporting are mission-critical in a bank's Central Payments Department, yet conventional pipelines rely on manual reconciliation, static rules and single-model analytics that struggle with heterogeneous, high-volume and imbalanced payment data. This paper proposes the Hybrid Statistical Ensemble Framework (HSEF), which integrates Bayesian priors, logistic regression, Random Forest classification, Isolation Forest anomaly scoring, statistical outlier detection, time-series accrual forecasting and Monte Carlo risk simulation in a weighted soft-voting fusion layer. HSEF is designed for United Bank Limited (UBL) Central Payments operations and is evaluated on a realistic synthetic dataset of 1,200 transactions. Against a traditional single-model baseline, it raises exception-detection recall from 0.17 to 0.38, F1-score from 0.15 to 0.39 and ROC-AUC from 0.60 to 0.65, while tagging every transaction with its IFRS category to provide an auditable reporting trail. The problem framing and category taxonomy are calibrated against field statistics from an operational MIS reporting tool developed for the same department, giving the design empirical as well as theoretical motivation.

Keywords: MIS reporting, IFRS compliance, hybrid algorithm, ensemble learning, anomaly detection, financial analytics, Bayesian inference, banking data science, payment reconciliation.

Introduction

The Central Payments Department of a commercial bank sits at the intersection of operational finance, regulatory compliance and internal control. At United Bank Limited (UBL), it processes internal expense payments, vendor disbursements, employee reimbursements, journal vouchers, accruals, rental payments and remittances, while maintaining tax records, supporting audits and preparing regulatory returns for the State Bank of Pakistan (SBP) (State Bank of Pakistan, 2022). These activities feed downstream MIS reporting and financial reporting under the International Financial Reporting Standards (IFRS) (IFRS Foundation, 2020, 2021).

As volumes grow, the reporting pipeline is increasingly strained. Reconciliation is largely manual, exception handling depends on static thresholds, and analytics are confined to a single model or spreadsheet rule. Such approaches are brittle under class imbalance, heterogeneous cost centres, multiple currencies and evolving IFRS classification requirements (Fernández et al., 2021; Smith & Kumar, 2021). Errors that escape detection propagate into MIS dashboards and IFRS disclosures, undermining accuracy, transparency and audit readiness.

These concerns are not abstract. A browser-based reporting tool that one of the authors developed for the same department, parsing posting-detail extracts of more than 200,000 rows in the browser, exposed exactly these pathologies on a representative monthly extract (202,063 posting lines): row counts overstated payment volume roughly twenty-fold, a twelve-category general-ledger taxonomy left about two-thirds of tagged spend uncategorised, and a free-text location field was substantive on fewer than 3% of transactions. These observations, detailed in the Problem Statement section, shaped the design of HSEF.

This paper argues that no single model suffices for the department's diverse tasks and proposes the Hybrid Statistical Ensemble Framework (HSEF), which fuses complementary techniques: Bayesian priors encode departmental risk history, supervised classifiers detect known exception patterns, unsupervised detectors surface novel irregularities, and time-series and Monte Carlo components support accrual prediction and risk quantification (Breiman, 2001; Gelman et al., 2020; Hyndman & Athanasopoulos, 2021; Liu et al., 2012; Nguyen & Osei, 2022). The contributions are: (i) a justified hybrid architecture tailored to banking payment operations; (ii) a mathematical formulation and pseudocode for the fusion mechanism; (iii) a realistic synthetic payment

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dataset reflecting UBL Central Payments attributes; and (iv) an empirical evaluation showing gains in exception detection, reporting quality and IFRS-tagged auditability.

Related Work

Systematic reviews report that ensemble and hybrid models consistently outperform single classifiers on imbalanced financial data (Fernández et al., 2021; Smith & Kumar, 2021). Bao et al. (2020) showed that supervised learning improves fraud detection in publicly traded firms, and Zhang et al. (2022) confirmed the value of heterogeneous fusion by combining deep and shallow learners. Random Forests (Breiman, 2001) and Isolation Forests (Liu et al., 2012) are established tools for classification and unsupervised anomaly detection respectively, the latter being effective for high-volume streams where labelled exceptions are scarce (Wang et al., 2021).

On the reporting side, Ashraf and Kanwal (2022) combined rule-based and statistical hybrids for bank reconciliation, and Brown and Davis (2022) explored IFRS-compliance automation through analytics. Explainability is considered essential for regulatory acceptance (Molnar, 2022; Patel et al., 2023). Nevertheless, existing studies typically optimise one task in isolation, and few frameworks target the combined MIS-plus-IFRS workflow of a bank payments department in an emerging-market context such as Pakistan (Iqbal & Ahmed, 2022). HSEF addresses this gap with an integrated, multi-task hybrid.

Problem Statement

The department must produce MIS and IFRS-compliant reports that are accurate, consistent, transparent, auditable and timely. Three interacting problems degrade these properties. First, exception detection relies on static rules that miss context-dependent irregularities, yielding low recall and late discovery during audits. Second, expense classification and IFRS tagging are manual, introducing inconsistency across cost centres and periods. Third, accrual estimation and risk identification lack a quantitative, repeatable basis. Formally, given a stream of payment records, the department needs one framework that (a) assigns each record an exception/risk score, (b) attaches a consistent IFRS category and (c) forecasts period-level accruals with quantified uncertainty, while remaining explainable to internal and external auditors.

Empirical Evidence from a Deployed Reporting System

Field statistics were computed from a de-identified monthly posting-detail extract of UBL Central Payments and are distinct from the synthetic dataset used to evaluate HSEF. The extract's 202,063 posting lines resolved to 9,761 distinct payments after de-duplication on the transaction-reference identifier, so row-level counting is unsuitable for MIS reporting. A twelve-category keyword-based general-ledger taxonomy explained only 34–37% of tagged spend, and 97.7% of transactions carried only a generic location tag. A single vendor, overwhelmingly a statutory tax-remittance counterparty, accounted for about 65% of vendor-tagged value, a concentration that must be interpreted correctly rather than flagged naively as vendor risk. Posted debit and credit totals were fully unbalanced, consistent with a mis-scoped export rather than a genuine imbalance, yet exactly the silent fault an exception layer should surface. Finally, utility and rent payments were attributable to two similar branch-code fields, so a naive column choice mis-attributed spend, and 95.1% of journal-voucher value in the February 2024 MIS baseline sat in an unclassified "Others" nature. These coverage, concentration and reconciliation problems are measurable, material and recurring in live data.

Proposed Hybrid Algorithm: HSEF

HSEF is organised as a five-layer pipeline: data ingestion; preprocessing and feature engineering; four parallel analytical components; a weighted fusion layer; and a reporting/output layer. Figure 1 depicts the logical architecture.

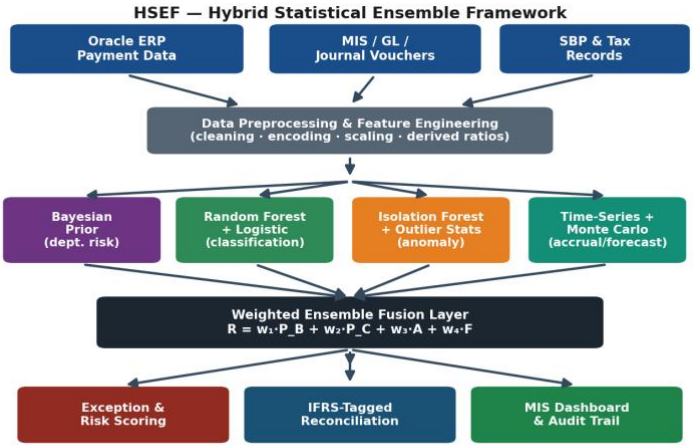


Figure 1. Logical architecture of the proposed HSEF pipeline.

Component Roles

Bayesian prior (P_B). Historical exception rates per department and cost centre form a prior belief that is combined with observed evidence, stabilising predictions for low-volume segments (Gelman et al., 2020).

Supervised classifier (P_C). A Random Forest, complemented by logistic regression as an interpretable reference, learns known exception patterns from attributes such as invoice amount, approval time, tax status and outstanding days (Breiman, 2001; Raschka & Mirjalili, 2022).

Anomaly score (A). An Isolation Forest augmented with statistical outlier rules (z-score and inter-quartile range) surfaces novel irregularities that no label yet describes, addressing the scarcity of exception labels (Liu et al., 2012; Wang et al., 2021).

Forecast component (F). Time-series analysis estimates period accruals, and Monte Carlo simulation propagates uncertainty into a financial-risk band for forward-looking disclosures (Chandra & Nair, 2021; Hyndman & Athanasopoulos, 2021; Nguyen & Osei, 2022).

Fusion Mechanism

The four signals are combined through weighted soft voting. Each transaction receives a unified risk score R, and a decision threshold τ converts R into an exception flag. Component weights are calibrated on a validation split to maximise the F1-score of the minority (exception) class (Kohavi & John, 2021; Zhou et al., 2023).

Methodology

Data Preprocessing and Feature Engineering

Records extracted from Oracle ERP are cleaned (missing-value imputation, currency normalisation to PKR-equivalent, de-duplication of journal vouchers); categorical fields (department, cost centre, GL code, expense category, IFRS category) are label/one-hot encoded and numeric fields standardised. Derived features include the log of the invoice amount, a binary tax-missing flag (a strong exception signal), the tax-to-amount ratio and an approval-latency indicator; departmental exception frequencies form the Bayesian priors. Exceptions comprise roughly one quarter of records, and outstanding days, approval time and the tax-missing flag show the strongest univariate association with them.

Model Workflow and Evaluation

Data are split 70/30 with stratification. The Isolation Forest and Random Forest are trained on the training partition, with the anomaly score appended as a feature to the Random Forest input; priors and forecast outputs merge at the fusion layer, and the weights and τ are tuned on a validation slice. Because exceptions are the minority class and a missed exception is costly in an audit context, we prioritise recall and F1-score over accuracy and also report ROC-AUC, precision and a confusion matrix (Fernández et al., 2021). Algorithm 1 gives the full procedure and its implementation settings are given below.

Algorithm 1 was implemented in Python with Pandas, NumPy, Scikit-learn, SciPy and Matplotlib (Pedregosa et al., 2011; Raschka & Mirjalili, 2022). An Isolation Forest (contamination 0.25) supplies the anomaly score, a 200-tree Random Forest (maximum depth 10) is trained on the augmented features, and the evaluated fused score is $R = 0.70 \cdot P_C + 0.18 \cdot A + 0.12 \cdot \text{prior}_{\text{dept}}$, thresholded at τ; the forecast component is demonstrated separately below.

Algorithm 1. HSEF scoring and reporting
Input: payment records D; weights $w_1..w_4$; threshold τ
Output: risk scores R, exception flags E, IFRS tags T, accrual forecast Φ
D′ ← preprocess_and_engineer(D)
Pr[d] ← historical_exception_rate(department d) // prior
train IsolationForest IF on D′_train
A ← normalize(anomaly_score(IF, D′))
X ← concat(D′, A)
train RandomForest RF (+ logistic reference) on X_train
P_C ← RF.predict_proba(X)
P_B ← bayes_update(Pr, P_C) // posterior
Φ ← timeseries_forecast(accruals) ⊕ montecarlo(risk)
R ← w1·P_B + w2·P_C + w3·A + w4·F // fusion
E ← [r > τ for r in R]
T ← ifrs_tag(D′, GL_code, category)
return R, E, T, Φ

Mathematical Model

Let a transaction be represented by a feature vector x. The Bayesian posterior probability of an exception combines the departmental prior $\pi(e)$ with the model likelihood $P(x|e)$:

$$P_B(e \mid x) = \frac{P(x|e)\,\pi(e)}{\sum_{c\in\{e,n\}} P(x|c)\,\pi(c)} \qquad (1)$$

The Random Forest posterior is the average over T trees, and the Isolation Forest score uses the average path length $E[h(x)]$ and a normalisation constant $c(n)$, normalised to $A(x) \in [0,1]$:

$$P_C(e \mid x) = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \quad (2)$$

$$s(x) = 2^{-E[h(x)]/c(n)} \qquad (3)$$

Statistical outlier evidence uses the robust z-score. The forecast component F is the normalised deviation of predicted from expected accrual, with a Monte Carlo risk band from M simulated paths:

$$z(x_j) = \frac{x_j - \text{median}(x_j)}{1.4826\ \text{MAD}} \qquad (4)$$

$$F = \frac{1}{M}\sum_{m=1}^{M} \mathbf{1}\left[\hat{\varphi}_m > \text{VaR}_\alpha\right] \qquad (5)$$

The unified risk score fuses the four signals under a simplex weight constraint, and the decision is $E(x) = 1$ if $R(x) > \tau$, else 0. Weights and threshold are selected to maximise the validation F1-score:

$$R(x) = w_1 P_B + w_2 P_C + w_3 A + w_4 F, \qquad \sum_i w_i = 1 \quad (6)$$

$$(\mathbf{w}^*, \tau^*) = \text{argmax}_{\mathbf{w},\tau}\, F1_{\text{val}}\big(E(x; \mathbf{w}, \tau)\big) \qquad (7)$$

Dataset Design

A realistic synthetic dataset of 1,200 payment records was generated to mirror UBL Central Payments attributes while avoiding any confidential data. Table 1 lists the schema and Table 2 shows a representative sample. Exceptions were injected using a logistic risk model driven by outstanding days, approval latency, high invoice amounts and missing tax, so that the learning task reflects genuine operational signals.

Table 1. Synthetic payment dataset schema.

Attribute	Type	Description
Vendor ID	Categorical	Unique vendor identifier
Invoice Amount	Numeric	Gross invoice value (PKR-equivalent)
Payment / Due Date	Date	Settlement and obligation dates

Attribute	Type	Description
Department / Cost Center	Categorical	Organisational attribution
GL Code / Journal Voucher	Categorical	Ledger and voucher references
Expense Category	Categorical	OPEX / CAPEX classification
Tax Amount	Numeric	Withholding / sales tax
Currency	Categorical	PKR, USD, EUR, GBP
Approval Time	Numeric	Hours from submission to approval
Outstanding Days	Numeric	Ageing of unreconciled item
Reconciliation Status	Categorical	Matched / unmatched
IFRS Category	Categorical	IAS 16, IFRS 16, IAS 38, etc.
Risk Score / Exception	Derived	HSEF output label

Table 2. Representative sample of the synthetic dataset (O/S = outstanding days; E = exception flag).

Vendor	Amount	Dept.	GL	Category	Tax	O/S	IFRS	E
V0051	126,296	IT	5606	OPEX-Travel	0	13	IAS 38	0
V0065	62,812	Procure	5202	OPEX-Maint.	9,422	14	IAS 16	0
V0265	149,113	Treasury	5606	CAPEX-SW	25,349	13	IAS 37	1
V0175	390,558	Procure	5404	OPEX-Rent	58,584	1	IAS 16	0
V0152	56,525	Procure	5101	OPEX-Travel	9,609	9	IAS 16	0
V0266	56,526	Procure	5202	OPEX-Maint.	9,609	16	IFRS 9	0

Experimental Results

Detection Performance

HSEF was compared with a traditional single-model (logistic-regression) baseline that approximates the current rule-oriented reporting approach. Table 3 summarises the metrics. The baseline attains higher raw accuracy but recovers only 17% of true exceptions, whereas HSEF more than doubles recall to 38% and lifts F1 from 0.15 to 0.39. Where undetected exceptions carry the greatest cost, this recall gain is the operationally decisive result. Figures 2–5 show the metric comparison, ROC curves, confusion matrix and feature importance.

Table 3. Performance comparison of the traditional baseline and HSEF (HSEF results in bold).

Metric	Traditional	HSEF
Accuracy	0.764	**0.714**
Precision	0.536	**0.402**
Recall	0.172	**0.379**
F1-score	0.148	**0.391**
ROC-AUC	0.601	**0.649**

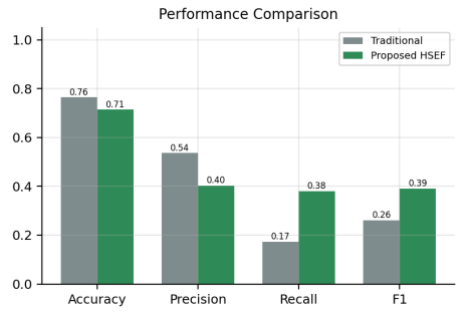


Figure 2. Metric-by-metric comparison of the traditional baseline and HSEF.

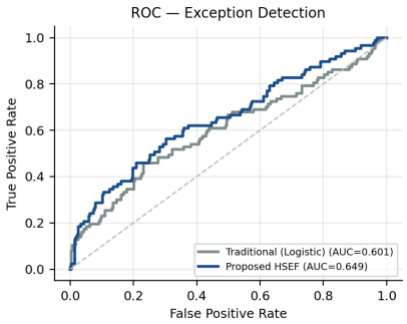


Figure 3. ROC curves for exception detection; HSEF dominates the baseline.

Metric	Traditional	HSEF

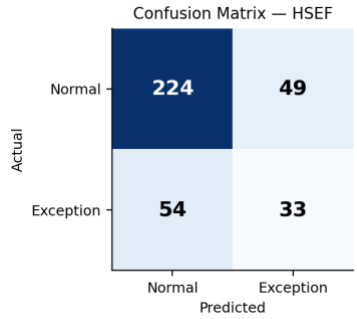


Figure 4. Confusion matrix for HSEF on the held-out test set.

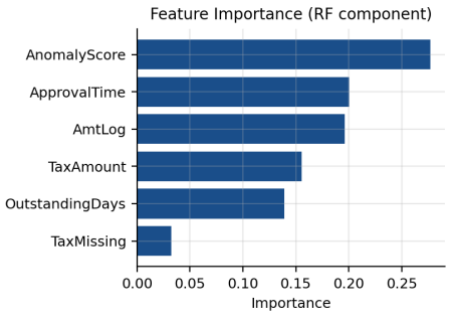


Figure 5. Random Forest feature importance; anomaly score and ageing dominate.

Accrual Forecasting

The time-series component tracks period-level accruals with a mean absolute error small enough to support monthly close, and the Monte Carlo band communicates uncertainty for forward-looking IFRS disclosures (Figure 6).

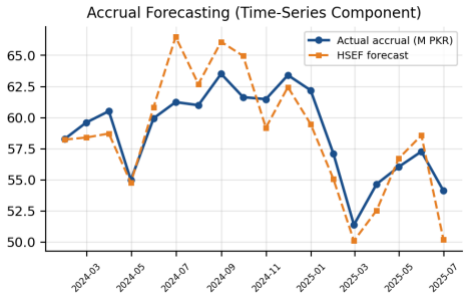


Figure 6. Accrual forecast versus actuals from the time-series component.

HSEF outputs also feed an MIS layer that ranks transactions by risk score, groups exceptions by department and IFRS category, and keeps an audit trail linking each flag to its contributing component. This turns a manual review into a prioritised, explainable worklist.

IFRS Integration

Beyond exception detection, HSEF strengthens IFRS-compliant reporting along six dimensions. Table 4 maps each reporting property to the corresponding HSEF mechanism.

Table 4. IFRS reporting properties mapped to HSEF mechanisms.

IFRS property	HSEF mechanism
Accuracy	Ensemble reduces misclassification of exceptions and expense categories.
Consistency	Automated IFRS tagging applies uniform rules across cost centres and periods.
Transparency	Component-level contributions to each score are recorded and explainable (Patel et al., 2023).
Auditability	Every flag links to evidence (prior, model, anomaly), forming an audit trail.
Timeliness	Automated scoring shortens month-end reconciliation and close cycles.
Data quality	Outlier and tax-missing checks surface data defects before reporting.

Discussion

The results support the central hypothesis: a justified hybrid outperforms a single-model pipeline on exception recall, the metric that matters most for audit, while also providing IFRS tagging and accrual forecasting. The accuracy decline (0.76 to 0.71) is expected, since the baseline attains high accuracy trivially by favouring the majority class and so misses most exceptions (Fernández et al., 2021). The anomaly score and transaction ageing are the strongest predictors, validating the fusion of unsupervised and supervised signals, and the Bayesian prior stabilises scoring for low-volume departments (Gelman et al., 2020). Because every score decomposes into

interpretable components, the framework meets auditors' explainability expectations (Molnar, 2022; Patel et al., 2023). As an analytical overlay between the Oracle ERP extract and the MIS layer, it needs no change to core payment processing, lowering the barrier to adoption (Ashraf & Kanwal, 2022).

The field statistics in the Problem Statement section corroborate these choices: coverage gaps in rule-based general-ledger tagging, near-absent location tags, a debit–credit imbalance and unclassified journal-voucher value are silent, high-impact anomalies that manual review is unlikely to catch at scale and that an automated exception-scoring layer is built to surface. The synthetic results show HSEF outperforming a single-model baseline under controlled conditions; the field observations show that the conditions it targets are present in live data.

Conclusions and Future Work

This paper proposed HSEF, a hybrid statistical ensemble framework for MIS and IFRS-compliant reporting in a bank's Central Payments Department. By fusing Bayesian priors, supervised classification, unsupervised anomaly detection and time-series/Monte Carlo forecasting through a weighted soft-voting layer, HSEF more than doubled exception-detection recall and improved F1 and ROC-AUC over a traditional baseline, while delivering consistent IFRS tagging and an auditable trail. Absolute performance remains modest and was measured on synthetic data, so the most immediate next step is end-to-end validation on de-identified UBL production data, subject to governance approval. Further work includes adaptive weight learning such as stacked generalisation (Kohavi & John, 2021), cost-sensitive learning with drift detection, and a natural-language explanation layer for auditors (Molnar, 2022).

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The Relationship Between Spatial Ability and UAV Learning Outcomes among University Students

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Abstract

This study examined how spatial ability was manifested in university students' UAV learning experiences and operational performance. Participants were 25 students enrolled in an 18-week unmanned aerial vehicle (UAV) operation course at a university of science and technology. The course integrated instructor-led explanations, flight demonstrations, simulation, virtual reality, and physical UAV practice. Data from semi-structured interviews, classroom observations, learning records, and written reflections were analyzed thematically.

Four interrelated patterns reflecting spatial ability emerged: constructing relationships among control inputs, aircraft orientation, and flight trajectories; shifting among operator-, aircraft-, and environment-centered reference frames; using visual feedback to diagnose and correct operational errors; and recalibrating virtual spatial representations during physical flight. Multiple viewpoints and immediate feedback helped students identify deviations in direction, altitude, and trajectory. However, some students relied on external visual cues and experienced renewed difficulties when these cues were removed or when they encountered wind, inertia, control latency, and operational pressure during physical flight. The findings illustrate how spatial ability was manifested through spatial representation, reference-frame transformation, feedback-informed correction, and virtual-to-physical calibration. UAV instruction should therefore integrate staged visual scaffolding, perspective-shifting practice, gradual cue withdrawal, and authentic flight experience.

Keywords: spatial ability, UAV learning, spatial representation, reference-frame transformation, operational performance, university students

1. Introduction

Unmanned aerial vehicles (UAVs) are increasingly used in engineering, surveying, agriculture, media production, and public safety. Higher education institutions have consequently incorporated UAV operation into STEM education, engineering practice, and professional training. Although UAV-based learning supports programming, scientific inquiry, and interdisciplinary problem-solving, limited attention has been paid to the ways in which spatial ability is manifested in novices' learning experiences and operational outcomes (Jiang et al., 2024; Yeung et al., 2024).

UAV operation requires learners to monitor aircraft orientation, viewing perspective, distance, altitude, and trajectory while making real-time adjustments. When the aircraft's heading differs from the operator's viewing direction, learners must shift among operator-, aircraft-, and environment-centered reference frames. They must also translate spatial representations into control inputs, observe the resulting movement, and modify subsequent actions. Spatial ability is therefore reflected in a continuous perception–action cycle involving mental rotation, spatial visualization, spatial orientation, and dynamic spatial updating.

Simulation and virtual reality may support these processes by providing repeatable practice, multiple viewpoints, and immediate visual feedback. These features make changes in orientation, altitude, and trajectory more visible, helping novices understand the relationships among controller input, aircraft heading, and flight direction (Lee & Wong, 2014). However, prolonged reliance on fixed viewpoints, guidance lines, or distance indicators may foster dependence on external cues. Spatial understanding developed virtually may also require recalibration during physical flight, where learners encounter wind, inertia, control latency, and operational pressure.

Previous research has primarily evaluated UAV instruction through achievement scores, operational performance, or comparisons among instructional approaches. Consequently, less is known about how spatial ability is expressed through learners' interpretations of flight situations, use of reference frames, error-correction strategies, and operational performance. Addressing this gap, the present qualitative study examined how spatial ability was manifested in the UAV learning experiences and outcomes of 25 university students. It focused on how students constructed spatial representations, shifted among reference frames, used feedback to correct errors, and recalibrated their spatial judgments during physical flight. The findings were intended to inform the design of visual scaffolding, perspective-shifting activities, and integrated virtual–physical UAV instruction.

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2. Literature Review

Spatial ability encompasses several interrelated capacities, including spatial visualization, mental rotation, spatial orientation, perspective transformation, and the judgment of spatial relationships. Spatial visualization concerns the transformation of complex spatial information, mental rotation involves imagining an object in a different orientation, and spatial orientation refers to understanding relationships among an object, the observer, and the environment from different viewpoints (Hegarty, 2010). These capacities are central to UAV operation because learners must continuously interpret aircraft orientation, position, trajectory, and viewing perspective.

Although spatial ability is often treated as an individual characteristic, its expression may change through interaction with tasks, representations, tools, and feedback. Spatial skills can be improved through training, and such improvements may transfer to tasks that were not directly practiced (Sorby, 2009; Uttal et al., 2013). In UAV learning, spatial ability is manifested as students construct and revise representations of aircraft orientation and movement and translate them into control actions.

Spatial demands vary across UAV learning tasks. Equipment inspection and safety procedures rely largely on procedural knowledge, whereas hovering, directional control, figure-eight flight, and precision landing require continuous updating of position, orientation, speed, and trajectory. A central challenge is coordinating operator-, aircraft-, and environment-centered reference frames. When a UAV turns toward the operator, for example, the apparent left–right relationship becomes reversed. Successful operation therefore requires learners to shift flexibly among reference frames while maintaining awareness of the aircraft's direction, altitude, and flight path.

Simulation and virtual reality may support these processes by providing low-risk, repeatable practice, multiple viewpoints, and immediate feedback. Side, overhead, and aircraft-proximal views make directional errors, altitude changes, and trajectory deviations more visible, helping learners connect controller inputs with aircraft responses (Lee & Wong, 2014; Sun et al., 2019). Immediate feedback also enables students to distinguish among problems involving direction, speed, altitude, trajectory, and control magnitude. Operational errors can thus provide information for refining spatial representations and control strategies.

Nevertheless, visual support does not necessarily produce transferable competence. Fixed viewpoints, guidance lines, and distance indicators may foster reliance on external cues, while complex displays may impose additional cognitive demands. Simulators also cannot fully reproduce wind, inertia, control latency, equipment risk, and the pressure of operating a physical UAV. Spatial representations developed virtually must therefore be recalibrated through physical practice (Betts et al., 2023).

Existing research suggests that spatial ability may be expressed through the construction of spatial representations, transformation of reference frames, use of visual feedback, and calibration between virtual and physical operation. However, outcome-based studies reveal little about how learners experience and coordinate these processes. A qualitative approach can therefore clarify how spatial ability is manifested in students' UAV learning experiences and operational outcomes.

3. Method

This study adopted a qualitative case study design to examine how spatial ability was manifested in university students' UAV learning processes and operational outcomes. Participants were 25 students enrolled in a UAV operation course at a university of science and technology. The 18-week course comprised three hours of instruction per week and covered flight principles, operational safety, equipment inspection, takeoff and landing, hovering, directional control, figure-eight flight, obstacle navigation, precision landing, and emergency procedures. Instruction integrated instructor-led explanations, flight demonstrations, simulation, virtual reality activities, and physical UAV practice.

Data were collected through semi-structured interviews, classroom observations, student learning records, and written reflections. The interviews addressed orientation discrimination, reference-frame transformation, distance and altitude judgments, flight-path anticipation, error correction, and the transition from virtual to physical operation. Classroom observations documented students' spatial difficulties, corrective strategies, and use of instructional cues during hovering, turning, figure-eight flight, and precision landing. All data were collected with participants' informed consent and anonymized using participant codes.

Thematic analysis combined conceptually informed and data-driven coding. Research on spatial cognition sensitized the analysis to spatial representation, reference-frame transformation, visual cues, trajectory judgment, operational correction, and virtual-to-physical calibration, while allowing additional patterns to emerge from participants' accounts and observational data. The researchers repeatedly reviewed the interview transcripts, observation notes, learning records, and written reflections to develop initial codes. Patterns were then compared across data sources, grouped into broader themes, and examined in relation to the research focus. Data-source

triangulation, collaborative coding, member checking, and an audit trail were used to enhance the trustworthiness of the analysis.

4. Results

The thematic analysis identified four interrelated patterns through which spatial ability was reflected in students' UAV learning experiences and operational performance.

First, students constructed spatial representations linking controller inputs, aircraft orientation, and position within the flight environment. Most students initially managed left–right control when the rear of the aircraft faced them but frequently confused directions when the UAV turned toward them or moved laterally. With continued practice, students became less reliant on their own viewing perspective and increasingly selected control inputs according to the aircraft's orientation.

Second, shifting among reference frames was a common operational difficulty. Students needed to coordinate operator-, aircraft-, and environment-centered perspectives. Side, overhead, and aircraft-proximal views helped them interpret aircraft attitude and flight trajectory. However, some students experienced renewed directional confusion after returning to the operator's ground-level perspective. Understanding flight from multiple viewpoints therefore did not necessarily enable rapid reference-frame transformation during physical operation.

Third, immediate visual feedback supported error diagnosis and correction. Flight trajectories, directional indicators, and altitude information enabled students to distinguish the general experience of "unstable flight" from specific problems involving direction, speed, altitude, trajectory, or control magnitude. These distinctions allowed them to target particular errors and refine their control strategies through repeated practice.

Finally, spatial representations developed in virtual environments required recalibration during physical flight. Some students completed simulated tasks successfully but experienced overcorrection, unstable hovering, and trajectory deviation when confronted with wind, aircraft inertia, control latency, and operational pressure. Although fixed viewpoints, guidance lines, and distance indicators supported initial learning, they sometimes encouraged reliance on external cues. Stable performance appeared to depend on repeated comparison and adjustment between virtual practice and physical flight.

5. Discussion

The findings suggest that spatial ability was expressed not only through judgments of position and orientation but also through the coordination of spatial information and control actions. Students needed to transform reference frames, anticipate flight trajectories, and modify control inputs under time pressure. Unlike static spatial tasks, UAV operation involved a continuous perception–action cycle integrating spatial representation, motor responses, and immediate feedback.

Multiple viewpoints and visual cues externalized spatial relationships that students might otherwise have needed to process mentally. These supports helped learners connect aircraft orientation, control direction, and flight trajectory. Their instructional value, however, depended on how they were used. Prolonged access could foster reliance on external cues, whereas premature withdrawal could remove necessary support. Visual scaffolding should therefore be gradually reduced as learners develop more stable spatial representations and control strategies.

The findings further suggest that virtual and physical practice were complementary rather than interchangeable. Virtual environments provided low-risk, repeatable practice and immediate feedback, whereas students encountered wind, inertia, control latency, and operational pressure during physical flight. These conditions required students to recalibrate spatial judgments formed during virtual practice. Virtual and physical activities should therefore be treated as recursively connected components of UAV learning rather than as strictly separate or linear stages.

Because spatial ability was examined qualitatively rather than measured using a standardized instrument, the findings do not establish a statistical relationship between spatial-ability scores and UAV learning outcomes. Instead, they illustrate how spatial ability was manifested in students' interpretation of orientation, transformation of reference frames, use of feedback, and correction of operational errors.

6. Conclusions and Recommendations

This qualitative case study examined how spatial ability was manifested in the UAV learning experiences and operational performance of 25 university students. The findings identified four interconnected manifestations:

constructing spatial representations, shifting among reference frames, using visual feedback to diagnose and correct errors, and recalibrating spatial judgments between virtual and physical environments.

During initial instruction, clear directional references, multiple viewpoints, and segmented demonstrations may help students construct spatial relationships among the aircraft, operator, and flight environment. Subsequent activities should incorporate comparisons across viewpoints and targeted reference-frame transformation exercises. As learners gain experience, visual cues should be gradually withdrawn, and learners should be given more opportunities to practice under varied environmental conditions. This approach may facilitate the transfer of spatial understanding to stable and adaptable UAV operation.

The findings should be interpreted as a qualitative account of spatial ability in action rather than evidence of a measured association between spatial ability and learning outcomes. Future research could combine qualitative process data with standardized spatial-ability assessments and performance measures to examine this relationship more directly.

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Examining the Effects of Online Examinations Conducted in a Proctored Laboratory Environment on the Instructional Process

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Abstract

Online examinations are becoming increasingly widespread in higher education due to the flexibility and automation they provide in assessment and evaluation processes; however, the reliability of such examinations and the extent to which they accurately reflect learning outcomes remain matters of debate. This study was conducted to examine online examinations administered in a proctored laboratory environment, with IP-based access restrictions and under the supervision of proctors, in terms of the quality of learning. The research was designed as a qualitative case study. The study group consisted of three faculty members who administered online examinations through a learning management system (LMS) in a proctored laboratory environment with IP-based access restrictions. The participants were selected through criterion sampling. Following the examinations, they reviewed student- and item-level achievement matrices, and data were collected through a semi-structured interview form. The data were analyzed using content analysis and organized under themes and categories. When the findings were evaluated holistically, it was concluded that the low achievement rates observed in examinations conducted under proctored conditions indicated actual deficiencies in the attainment of course learning outcomes and highlighted the need for improvements at the instructional design level. The findings showed that student- and item-level achievement data obtained through the LMS provided faculty members with functional feedback for identifying students' learning deficiencies, topics and learning outcomes with which students experienced difficulty, and problematic examination items. Examination analytics were found to support instructional and assessment-related decisions, including revisiting course content, planning additional explanations and learning activities, providing feedback to students, and reviewing the question pool. The combined use of a proctored laboratory environment and IP-based access restrictions was also considered to support examination security, academic integrity, and the standardization of examination conditions. Nevertheless, preparing the question pool, designing questions in accordance with the online examination format, and the technical and administrative workload associated with implementation emerged as the main challenges of the system. Overall, the findings suggest that online examinations conducted in a proctored laboratory environment can be used not only for assessment purposes but also as a mechanism for generating data to support the improvement of the instructional process.

Keywords: quality of learning, learning analytics, online examination, item analysis, question pool, LMS, proctored examination

Introduction

With the digital transformation of higher education, the use of online examinations has become increasingly widespread. These examinations offer several advantages, including automated scoring, rapid reporting, the use of question banks, and the generation of detailed assessment data. However, issues such as identity verification, the use of external resources, unauthorized access, and examination security continue to raise concerns regarding the reliability of online assessment. The literature on online examinations generally focuses on three main areas: the usability and technical operation of electronic examinations, academic integrity and examination security, and the use of examination data for learning analytics and instructional decision-making. Previous studies indicate that online examination security cannot be ensured through a single technological measure; rather, proctoring, access control, institutional device use, and system logs should be considered together (Chirumamilla et al., 2020; Genç & Kesim, 2023; Haider et al., 2022). Similarly, student responses and item-level analyses obtained from electronic examinations can be used to identify learning deficiencies and problematic examination items (Deng et al., 2019; Ellis, 2013; Lahza et al., 2023). Nevertheless, examination security and examination analytics are often treated as separate areas of research. However, examination data obtained under insufficiently secure conditions may not accurately reflect students' actual performance, while using data from secure examinations solely for grading may limit their instructional potential. Therefore, examination security and the instructional use of examination data can be considered complementary processes. Online examinations conducted in proctored laboratory environments with IP-based access restrictions provide a model that combines physical proctoring with digital access control. While this structure supports access to the examination only through designated networks and devices, it also

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enables student- and item-level data generated through the LMS to be used in evaluating and improving the instructional process. The aim of this study is to examine the effects of data obtained from online examinations conducted in a proctored laboratory environment with IP-based access restrictions on the instructional process, as well as faculty members' evaluations of this examination model. Accordingly, the study addressed the following research questions:

1. In what ways did the analysis of data obtained from online examinations conducted in a proctored laboratory environment affect the instructional process?
2. What are faculty members' views on conducting online examinations in a proctored laboratory environment with IP-based access restrictions?

Methodology

This study was designed within a qualitative research framework to examine in depth faculty members' experiences and evaluations of online examinations administered in a proctored laboratory environment using IP-based access restrictions. A case study design was employed because it enables the detailed investigation of a contemporary and clearly bounded practice within its real-life context. The case examined in this study was an online examination model implemented through a learning management system (LMS), conducted under physical proctoring, and accessible only from pre-authorized laboratory IP addresses. Because the examination practice was investigated within a single institutional context and the study focused on one specific examination model, the research was structured as a holistic single-case study. The study included three faculty members who administered the examinations. Following the completion of the examinations, the faculty members reviewed student- and item-level achievement matrices generated from the assessment data. They subsequently shared their evaluations regarding how these analyses contributed to identifying learning deficiencies, reorganizing instructional processes, providing feedback to students, and planning future assessment and evaluation practices. In addition, the participants' views on the examination process conducted under IP restrictions in a proctored laboratory environment, as well as their evaluations of the analysis of examination results, were examined. Data were collected through a semi-structured interview form developed in accordance with the research questions. In this way, the study aimed to provide a context-specific and holistic understanding of faculty members' experiences, interpretations, and instructional implications regarding the implementation.

Results

In this study, faculty members' views on online examinations conducted in a proctored laboratory environment with IP-based access restrictions were examined within the framework of two main research questions: the implications of examination data for the instructional process and evaluations of the implementation of the examination model. Participants' responses to closed-ended items were considered together with the explanations they provided in response to open-ended questions.

Effects of Examination Data Analysis on the Instructional Process

When the participant's responses to the closed-ended items and explanations provided in the open-ended questions were considered together, the instructional implications of examination data were found to cluster around five main dimensions: analysis of student achievement, instructional planning, feedback, improvement of question and examination quality, and alignment between instruction and assessment. A summary of the findings is presented in Table 1.

Table 1. Summary of the instructional implications of examination data

Dimension	Key finding
Student achievement analysis	The data helped identify students requiring support and topics or learning outcomes that posed difficulty.
Instructional planning	Achievement distributions contributed to reconsidering course content and the instructional process.
Feedback	Examination data helped determine the content of feedback to be provided to students.
Question and examination quality	Item-level analyses helped identify problematic or inappropriately difficult questions.
Instruction–assessment alignment	The data supported review of the alignment among learning outcomes, course content, and assessment.
Response consistency	The response to one reverse-worded item contradicted the participant's other responses.

As shown in Table 1, the participant did not regard examination data solely as an indicator of student performance, but also as a source of feedback for improving instruction. In particular, identifying topics and questions associated with low achievement was considered useful for planning additional instructional activities, revisiting course content, and improving the item bank. The open-ended responses provided a concrete example of this process: questions that were unanswered or answered correctly by only a small number of students were reviewed with the students, and question wording was revised when certain concepts were found to hinder comprehension. However, the participant's response to one reverse-worded item was inconsistent with the overall response pattern. Although the participant endorsed several statements indicating that examination data contributed to the instructional process, the item stating that the analysis of examination data had not made a meaningful contribution to instruction was also rated as "Strongly Agree." Given the participant's other responses and open-ended explanations, this response was interpreted cautiously and considered potentially attributable to the reverse wording of the item rather than as an independent contradictory view.

Proctored and IP-Restricted Online Examination Model

Participants' responses indicate that the proctored laboratory environment and IP-based access restrictions were perceived as complementary components of examination security. The findings also point to perceived benefits in standardization, fairness, technical support, examination discipline, and operational feasibility, while highlighting workload and question-bank preparation as notable implementation challenges. A concise summary of these findings is presented in Table 2.

Table 2. Summary of findings on the proctored and IP-restricted online examination model

Dimension	Key finding
Examination security	Physical proctoring and IP-based access control were viewed as strengthening identity verification and reducing unauthorized access or external assistance.
Standardization and fairness	Similar computer and network conditions were perceived as reducing inequalities arising from personal devices or internet quality.
Student responsibility and discipline	The model was perceived as increasing students' sense of seriousness and responsibility toward online examinations.
Technical feasibility	The laboratory infrastructure and procedures such as IP assignment, login, exam initiation, and proctoring were considered manageable.
Workload and implementation challenges	The technical and administrative burden was perceived as substantial; preparing suitable online questions and constructing a fair question pool were reported as key difficulties.

As shown in Table 2, the participant did not evaluate the examination model solely in terms of access restriction. Rather, security was associated with the combined use of physical proctoring and IP-based access control. The laboratory setting was also perceived as contributing to more standardized and equitable examination conditions by minimizing differences in device and network quality and enabling faster technical assistance when problems occurred. The findings further suggest that the model was regarded as pedagogically and behaviorally supportive, particularly in terms of reinforcing students' sense of responsibility and seriousness toward the examination process. At the same time, the participant did not perceive the laboratory environment as creating excessive examination anxiety. From an operational perspective, the technical procedures were considered manageable and the continued use of the model in suitable courses was strongly supported. However, the implementation was not viewed as cost-free in terms of effort. The participant reported that the technical and administrative workload could outweigh some of the perceived benefits, and open-ended responses identified the preparation of questions appropriate for online delivery and the construction of a fair question pool as major challenges. Accordingly, the findings indicate that the model offers perceived advantages in security, standardization, and manageability, but its sustainability depends on reducing preparation burden and strengthening technical and assessment-design support.

Conclusions

This study examined faculty members' views on online examinations conducted under physical proctoring and IP-based access restrictions. The findings indicate that this examination model is functional in two main respects: supporting examination security and enabling examination data to be used for improving the instructional process. The findings showed that student- and item-level examination data could be used to identify students in need of support as well as topics or learning outcomes with which students experienced difficulty. These data also contributed to instructional decisions such as reorganizing course content, diversifying teaching methods, planning additional activities, and providing feedback to students. In particular, reviewing low-performing items and revising question wording when necessary demonstrated that examination data can be used not only to evaluate

student achievement but also to assess question quality. These findings are consistent with studies emphasizing the use of data generated by electronic assessment systems for learning analytics and instructional decision-making (Deng et al., 2019; Ellis, 2013; Lahza et al., 2023). In terms of examination security, physical proctoring and IP-based access restrictions were viewed as complementary mechanisms. While IP restrictions limited access to the examination to the designated laboratory network, physical proctoring contributed to identity verification and supervision of the examination process. This finding is consistent with previous research suggesting that online examination security should be supported through multiple layers of security rather than relying on a single technological measure (Chirumamilla et al., 2020; Genç & Kesim, 2023; Haider et al., 2022). The participant also indicated that the laboratory environment provided more standardized examination conditions, enabled faster intervention in technical problems, and strengthened students' sense of responsibility toward the examination. However, technical and administrative workload, the preparation of question banks, and the adaptation of questions to the online examination format emerged as important challenges. In conclusion, proctored online examinations with IP-based access restrictions can be regarded as an integrated model that combines controlled examination conditions with the data generation and analytical capabilities of digital assessment systems. To ensure the sustainability of this model, it is important to strengthen technical infrastructure, provide support for faculty members, and present examination analytics in easily interpretable reports. However, because the study was conducted within a single institutional context and with a limited number of participants, the findings should be further examined in different institutional and disciplinary settings.

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