TRANSFORMING EDUCATION THROUGH GENERATIVE ARTIFICIAL INTELLIGENCE (GenAI)

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Chapter 1 - Student Motivation and Generative Artificial Intelligence: A Literature Review

Kari D. Weaver, Rachael A. Lewitzky

Chapter Highlights

- Examines key theories of student motivation and how they are informing empirical research on adoption of GenAI by students.
- Presents a variety of perspectives on AI-mediated student motivation, including positive, negative, and conditional considerations.
- Provides a digestible overview of the current scholarly conversations around student motivation and GenAI.
- Suggests a direction forward for research on GenAI and student motivation.

Introduction

There are many ongoing discussions and narratives in post-secondary education with regard to the use of generative artificial intelligence (GenAI). There exist conversations questioning the usefulness of AI alongside suggestions that GenAI is changing the way in which teaching and learning occurs (Baidoo-Anu & Owusu Ansah, 2023; Warner, 2024). Likewise, there are explorations of how GenAI can be used to support post-secondary initiatives, such as helping with student enrollment and retention (Nietzel, 2022). Latham (2025) sums up this predicament: "We are awash in predictions about the impact of artificial intelligence on higher education. These accounts differ wildly in their prognoses but share the assumption that AI is not going away, and is likely to upend every facet of how universities function" (n.p.).

A report released by OpenAI in 2025 indicated that the primary use of ChatGPT by students aged 18-24 was for learning and tutoring. At the same time, Lantham (2025) suggests that students today expect a "low-friction" and "on-demand" educational experience. Moreover, the way in which teaching and learning occurs in post-secondary environments is changing due to widespread implementation of online learning and educational technologies. In this context, we may begin to wonder how student motivation influences the use of GenAI.

Guo et al. (2024) note that "Motivation has been identified as a key factor influencing students' learning methods, engagement, persistence, cognitive processes, and learning styles" (p. 1); furthermore, we might begin to ask questions about *how* and *why* GenAI is being used by students in higher education? For example, getting a job might be motivation for some students in school; yet the fact that AI is changing the workforce may make the goal of getting a job challenging (Kern & Kurtzberg, 2024).

In other words, what is the connection between the use of GenAI and student motivation? What is needed to answer these questions is a more holistic understanding of the current state of theory and empirical study on this issue to inform pedagogy and practice. In this paper, we examine common theories in motivation, such as unified theory of acceptance and use of technology, social cognitive theory, achievement goal theory, distributed cognition theory, and self-determination theory and provide an overview of the current state of discourse around AI and student motivation. By examining these theories and empirical evidence, we can start to understand the impact that GenAI has on student motivation in post-secondary contexts.

Student Motivation Theories and GenAI

As GenAI has grown to prominence in higher education, various established theories of student motivation have been explored to conceptualize its impact. While no single theory of student motivation is fully supported by empirical study, a number of potential theories have been posited as explanations for the impact of AI use on student motivation. These include The unified theory of acceptance and use of technology (UTAUT), social cognitive theory (SCT), achievement goal theory, distributed cognition theory, and self-determination theory (SDT).

Social Cognitive Theory (SCT) offers a robust framework for analyzing the impact of AI on student motivation. As Guo et al. (2024) highlight, SCT's key constructs - self-efficacy, outcome expectations, and reciprocal determinism - are particularly relevant. AI can create or tailor personalized learning experiences, which can positively impact students' self-efficacy, their belief in their ability to successfully perform a task or achieve a goal. High self-efficacy boosts confidence and engagement and students who believe they can learn the material or complete the assignment are more likely to stay motivated (Bandura, 1986; Prat-Sala & Redford, 2010; Schunk, 1991). In direct study, Shahzad et al. (2024) found that exposure to generative AI technologies like ChatGPT enhances students' belief in their own capabilities (self-efficacy), fosters creative engagement, and encourages ethical behavior, all of which positively influence learning performance. Together, these findings affirm that Social Cognitive Theory provides a valuable lens for understanding how generative AI technologies can shape students' beliefs, behaviors, and ultimately, their motivation to learn.

Unified Theory of Acceptance and Use of Technology (UTAUT) examines a student's motivation to adopt technologies in educational contexts (Venkatesh et al., 2016). While a component of the theory is the development of habits around technology adoption and use, there is recognition the theory can be adopted to emerging technologies where habit formation may not yet have occurred (Tamilmani et al., 2019). Within that context, UTAUT may be a viable theory for examination of student adoption of AI technologies in educational environments. Bouterra et al. (2024), for example, found student motivation to use ChatGPT is closely tied to the Unified Theory of Acceptance and Use of Technology (UTAUT) through key constructs such as performance expectancy, social influence, and self-efficacy. Additionally, students were more likely to adopt ChatGPT when they believed it enhanced academic performance and was endorsed by peers, aligning with UTAUT's emphasis on perceived usefulness and social norms. Strzelecki (2023) attempted to examine student habit formation, connecting use of AI to performance expectancy and hedonic motivation. The study found that students are more likely to adopt ChatGPT when they believe it enhances academic performance, enjoy using it, and have already integrated it into their study routines.

Distributed cognition theory introduces the idea that cognition is distributed across people, tools, artifacts, and the environment (Hutchins, 1995). In technology-enabled learning, it emphasizes thinking and problem-solving tasks are collaborative endeavours shaped by interactions amongst individuals and the media with which they interact (Angeli, 2008). In the context of AI technologies, they can act as external cognitive resources, helping learners offload tasks such as memory recall, information organization, and decision-making (Guo et al., 2024). By interacting with AI tools, students engage in a dynamic cognitive process where learning is co-constructed through human-machine collaboration. This distributed setup allows for tailored educational experiences, where AI adapts content and feedback based on the learner's needs, effectively extending the learner's cognitive capabilities beyond their own mind. In a recent study examining this phenomenon, Hong and Guo (2025) found that AI-enhanced multi-display language teaching systems significantly improved English as a Foreign Language, more frequently called L2, learners' motivation, cognitive load management, and learner autonomy.

Achievement goal theory, how individuals' goals and perceptions of achievement situations influence their motivation and behavior, has been applied broadly to technology-assisted learning tasks (Bardach et al., 2020; Struck Jannini et al., 2024). Recently, a small number of studies have begun to examine achievement goal theory in relation to artificial intelligence and student motivation. These include Guo et al. (2024), who indicated the ability to design content in an adaptive manner may help students develop skills and maintain interest in doing so, and Zhao (2025) who investigated the relationship between achievement goal theory, AI literacy, and student resilience. This emerging area of research indicates achievement goal theory could provide a promising framework for understanding how AI-driven personalization and skill development can support student motivation and resilience in technology-enhanced learning environments.

Self-determination theory is a theory that examines the degree to which human behavior is self-motivated and self-determined (Ryan & Deci, 2017). A particular focus of the theory is relatedness, described as the need to feel connected with others. In applying this theory to AI assisted learning, Guo et al. (2024) indicated AI technologies, "... offers continuous, student-centered support during the learning process," in addition to autonomy and immediate feedback (p. 4). Chiu and Chai (2020) conducted an early study on AI implementation in curriculum, finding teachers' motivation to design and implement AI curricula in schools is strongly influenced by their psychological needs for autonomy, competence, and relatedness, as described in Self-Determination Theory (SDT). Moving to more recent studies focused on students, Chiu (2024) found that ChatGPT-based learning activities can effectively foster self-regulated learning (SRL) by satisfying students' psychological needs for competence, autonomy, and relatedness, as outlined in Self-Determination Theory (SDT). In the most important recent study of SDT in AI enabled education, Xia et al. (2022) found the technology could support students' psychological needs for autonomy, competence, and relatedness, all core components of SDT, and that these gains were particularly prevalent for girls and low achieving students. Together, these studies demonstrate that Self-Determination Theory offers a powerful framework for understanding how AI-enabled education can foster inclusive, student-centered learning by supporting the psychological needs of both teachers and students.

When considered together, these theories of student motivation highlight several important commonalities for student motivation in an AI enabled learning environment. First, they all recognize student motivation is shaped by the interaction between the learner and their environment. UTAUT does this through consideration of how external factors affect technology adoption, SCT emphasizes the interplay of belief in self, confidence in using AI tools, and the culture of the learning environment determine how motivated students are both to succeed and to do so through the use of AI tools. Distributed Cognition Theory sees AI as part of the learner's thinking process with the potential to extend their capabilities, thereby positively impacting motivation. SDT and Achievement Goal Theory consider how learning environments support autonomy, competence, and mastery, driving individuals towards their learning goals. In sum, these theories illustrate that student motivation in AI-enabled learning environments is a dynamic outcome shaped by the interplay between personal beliefs, the broader educational context, and the AI tools themselves.

Second, many of the theories posit the perceived value and usefulness of AI tools in the academic environment is directly related to increased student motivation.For instance, both SDT and Achievement Goal Theory indicate when tools are easy to use and support learning goals, they can enhance intrinsic student motivation. UTAUT directly addresses the connection between technology performance and student effort expectancy, indicating offloading some student effort can drive motivation. SCT draws a connection between self-efficacy, the expectation of a positive outcome, and the usefulness of the technology. Together, these theories underscore that when students perceive AI as both useful and supportive of their personal learning goals, their motivation to engage with the technology in a learning environment significantly increases.

Third, AI can more easily support personalized learning experiences. This can enhance student self-efficacy according to SCT, provide adaptive content to foster mastery goals in achievement goal theory, and help learners focus on higher order thinking in Distribution Cognition Theory. Personalized paths may also support learner autonomy and competence as articulated by SDT. While the potential of these personalized learning approaches are discussed at greater length in the GenAI enhances student motivation section of this chapter, it is important to note the perspective is grounded in a variety of theoretical constructs.

Finally, these theories of student motivation recognize the importance of the social and institutional contexts in which AI is introduced. UTAUT, for instance, directly considers the impact of social influence and institutional conditions on student motivation to use emerging technologies. SCT highlights the value and importance of social modeling and feedback, both of which are served in different ways. For example, Stone (2025) found peer perceptions and AI policy clarity impact motivation. SDT highlights social relatedness in cognition supported through continuous engagement with AI.

GenAI Harms Student Motivation

While the long-term impacts of GenAI on student motivation have not been studied, there are a number of critiques and exploratory investigations that outline the potential harms. For example, GenAI can lead to “cognitive offloading” where the tools are used to reduce information processing demands on individual students. At first read, that may seem as if it could be of benefit to students, the negative impacts of reduced information processing can include decreased spacial reasoning, information or learning recall, and attention to task (Atchley et al., 2024). These harms may be compounded by the fact that the harms of cognitive offloading are not always readily apparent to the individual learner (Atchley et al., 2024). GenAI can further hinder student learning motivation by "decentering authority" (Bearman et al., 2022) and shifting sense-making agency and tasks away from students toward inanimate tools (Williamson et al., 2020).

Other criticisms of the impact on student motivation focus on learning progress and regulation. For instance, Lodge et al. (2023) note, "Generative AI does not actively co-regulate human learners based on their learning progress, nor does it engage in shared regulation with humans. Instead, humans are primarily responsible for setting standards and goals, monitoring, and evaluating their own learning and the generative AI's behaviours and responses" (p. 121-122). Individual student characteristics may also be predictive of their behaviours and perceptions toward GenAI. For example, Bouterra et al. (2024), found students with high levels of academic self-efficacy, who are often already more adept learners, tended to have increased motivation or desire to use GenAI tools. This finding may conversely be interpreted to indicate GenAI tools could negatively impact student learning motivation for students who already struggle academically. When prompted, GenAI tools themselves can readily identify potential negative impacts to learning or motivation. In one study (Baidoo-Anu, 2023), ChatGPT mentioned lack of human interaction, limited understanding, bias in training data, lack of creativity, dependency on data, lack of contextual understanding, limited ability to personalize instruction, and privacy.

GenAI Enhances Student Motivation

Over the past few years, studies have begun to uncover how GenAI may support or enhance student motivation. When prompted to identify some of the potential benefits of using GenAI for teaching and learning, ChatGPT indicated that it could be used for tutoring, automated essay grading, language translation, interactive learning, and adaptive learning (Baidoo-Anu, 2023). Further, Farrelly and Baker (2023) indicated that potential student benefits could include language tutors and individualized study material. According to Wang et al. (2023), these benefits could extend to supporting international students' learning experiences via translation, adaptive learning, and assisting with administrative tasks.

Tutoring or personalized learning, identified as an area with great positive potential for student motivation (Baidoo-Anu, 2023), has been an area of considerable study for the intersection of AI and student motivation. While this position is not new (Martin et al., 2021), the increased availability and quality of AI models has led to a dramatic increase in empirical investigation on the topic. For example, Du and Mo (2022) examined the potential of an AI supported chatbot tutor to enhance language learning student motivation, determining the chatbot could have a positive effect on motivation. Chiu et al. (2024) found chatbot tutors could enhance student motivation and autonomy but required both teacher support and student facility with the AI technology. Ng et al. (2024) found a significant impact on student motivation when autonomous tutoring systems were implemented in chemistry instruction. Guo et al. (2024) explored the use of AI generated content (AIGC) in relation to learning motivation. The authors suggest that the use of AIGC could help with feedback, creating an interactive learning environment, personalized support, and AI literacy development. Similarly, Wu et al. (2023) suggested that the use of ChatGPT could be associated with increased emotional, behavioural, and cognitive engagement when compared with search engines. In assignments with a research component, this improved engagement could ultimately enhance student performance on assessments.

At the core of AI potential around personalized learning is a focus on individual, expedient feedback. In studying this phenomenon, Hooda et al. (2022) highlight good feedback practices support self-regulated learning and directly increases engagement and motivation with AI systems playing an important role in scaling this work. In interviewing students directly, it was found AI feedback systems can enhance feelings of autonomy and competence, improving student motivation (Fahmy, 2024). While the potential of AI and computerized systems to support feedback processes predates the wide release of open AI tools (Chrysafiadi et al., 2020), their introduction into the assessment conversation does hold potential for supporting student motivation and builds on earlier, aligned considerations of learning analytics for this purpose (Jivet et al., 2020; Karaoglan Yilmaz & Yilmaz, 2021).

The ability of AI tools to enhance student motivation has also been explored specifically for second language learning (L2) and language translation. Muñoz-Basols et al. (2023) discuss the potential of AI translation to support digital literacy and critical thinking, elements which can have a positive influence on student motivation. Recently, Dinh (2025) investigated the translation capabilities of ChatGPT, finding students perceived it supportive in simplifying difficult translations, improving flow, and providing wording choices, leading to increased motivation. While Kruk & Kałużna (2025) were less overtly positive on the motivation potential for L2 learners, they still found AI had positive impacts on curiosity and excitement, which supported student motivation.

Considering student motivation more broadly, there appears to be a positive association between AI tools and student motivation. Chiu (2024) found that ChatGPT helped with competence in the self-regulated learning (SRL) model. Furthermore, in a study conducted by Hmoud et al. (2024), the authors interviewed students about their use of ChatGPT and looked at task enjoyment, reported effort, result assessment, perceived relevance, and interaction, which included both feedback and conversation, and found that the use of ChatGPT enhanced task enjoyment. While these studies emphasize the potential in higher education, others indicate positive associations for student motivation for elementary students (Pertiwi et al., 2024), high school students (Alasgarova & Rzayev, 2024), and adult learners (Lin, 2024).

GenAI May Go Either Way, But Has Major Ethical Concerns We Would Have to Overcome

Many scholars have recommended Critical AI literacy as an opportunity to broach ethical dimension of AI technologies (Bali, 2024; Goodlad & Conrad, 2024). Critical AI literacy can support learners by helping them to “resist using AI in ways that are harmful or inappropriate” (Bali, 2024, n.p.). Critical means teaching through a lens of critical theory and critical pedagogy; having an understanding of social justice issues (Bali, 2024, n.p.). This stands in contrast to the current state of AI literacy, which emphasises content and technical knowledge emanating from the field of engineering (Chiu et al., 2024).

While there have been some efforts to incorporate a critical perspective into the AI literacy discourse, most notably the work of Long and Magerko (2020), which has been frequently cited as a core publication for defining AI literacy, there lacks a consistent understanding and definition of what Critical AI literacy comprehensively entails. Bali (2024) indicates Critical AI literacy includes a combination of understanding, creativity, and evaluation. In addition to understanding how GenAI works, Bali (2024) indicates that Critical AI literacy would involve recognizing the inequalities and biases within GenAI as well as examining the ethical issues posed by GenAI. In this framework for Critical AI literacy, individuals would be able to assess appropriate uses of GenAI and be able to craft effective prompts.

Conrad (2024, n.p.) has also suggested elements composing critical AI literacy. Like Bali (2024), Conrad (2024) notes that critical AI literacy would recognize how automated and/or generative systems work. This perspective also includes knowledge of both the limitations, affordances, and opportunities presented by GenAI. Lastly, Conrad's (2024) model would include understanding the full range of known harms (environmental as well as social).

Conclusion

Synthesizing the frameworks and models explored in this piece, there are ethical, environmental, and social concerns that are interwoven with the use of GenAI. The current state of empirical study focuses much more heavily on positive associations between AI and student motivation, with negative associations and ethical concerns receiving significantly less attention. In the majority of the existing literature, the emphasis is on exploring AI-mediated student engagement rather than testing theories or hypotheses. Taking all of this together, there is a need for additional study, particularly empirical work that incorporates critical perspectives or ethical considerations and adopts a clear theoretical framework. Of the theories discussed in this chapter, the amount of interest in social cognitive theory and unified theory of acceptance and use of technology indicated they may hold the most promise as foundational theories.

Student motivation is a complex interplay of personal, social, and environmental factors. Educators and administrators concerned with the impact of AI on student motivation should look at these issues as systemic. In higher education, the environment will include peers and scholars actively using AI technologies for a variety of purposes. Students also possess a number of personal circumstances that may drive use of AI, including competing course requirements, time management needs, mental health considerations, and the social pressure to use AI if they perceive their peers are using it to positive effect. The delivery of education is also becoming increasingly AI-centric with the proliferation of GenAI into educational technologies ranging from word processing and email systems to learning management systems and assessment tools. While the current scholarship on the phenomena of AI-mediated student motivation has primarily looked at discrete educational contexts, typically an intervention in an individual course, the reality is that more study or description of these integrated factors are needed. Decision makers would be well advised to push toward institutional-level solutions that build consistency in student educational experiences. Finally, as scholars continue to examine AI's impact on student motivation, they should consider how they can examine it not in isolation but in the broader context in which it manifests.

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Chapter 2 - Harnessing Generative AI and Adaptive Learning Systems for Scalable Quality Education

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Chapter Highlights

- Presents a pilot study on the design, implementation, and evaluation of an Adaptive Learning System (ALS) for a self-paced online course on the United Nations (UN) Sustainable Development Goals (SDGs), Diversity, Equity, and Inclusion (DE&I), and work ethics, tailored to the African educational landscape.
- Integrates a Generative AI engine and a proprietary ALS to personalize learning pathways based on learners' pace, progress, and comprehension.
- Examines students' and faculty's attitudes, perceptions, and experiences, complemented by faculty and Subject Matter Expert (SME) feedback, to inform iterative improvement of ALS content and delivery.
- Highlights the critical role of Human-in-the-Loop (HITL) and Human–Machine Augmented Intelligence (HMAI) in ensuring pedagogical rigor, contextual relevance, and academic depth in AI-generated content.
- Demonstrates the applicability of established theories and frameworks, including UDL, constructivism/ZPD, constructive alignment, TPACK, and TAM, to guide the design, implementation, and acceptance of ALS in higher education.
- Identifies key challenges in usability, contextualization, and engagement, and proposes evidence-based recommendations for culturally responsive, and scalable ALS deployment.
- Provides actionable insights into institutional integration, policy support, and large-scale adoption, with early evidence suggesting that ALS has a strong potential to enhance learning efficiency and engagement and democratize access to contextually relevant quality education in Africa.

Introduction

The African higher education landscape faces significant challenges that hinder access to equitable and quality education, a goal promoted by the United Nations Sustainable Development Goal (SDG) 4, which advocates for inclusive and equitable quality education for all. Many African countries are struggling with issues related to unequal educational access, inadequate physical and digital infrastructures, overcrowded classrooms, shortage of qualified faculty, scarce learning resources, insufficient opportunities for faculty to engage in professional development activities, reliance on traditional passive pedagogical methods, and outdated curricula that are disconnected from the local context and from the needs of the job market (UNESCO, 2020; AllGoodSchools, 2025).

Home to the world's youngest population, with over 60% of its citizens under the age of 25, Africa is set to expand even more, with projections estimating Africa's total population to reach 2.5 billion by 2050 (World Economic Forum, 2023). Investing in scalable quality education is essential to unlocking the full potential of Africa's youth and to meeting the growing demand for a skilled workforce. However, expanding access to quality education across the African continent presents numerous challenges. For instance, traditional education systems, including conventional classroom settings, are often based on one-size-fits-all pedagogical approach that fails to cater to the varied students' learning paces, proficiency level, cultural contexts, and individual needs. In addition, the shortage of qualified instructors further deepens educational disparities, hindering equitable learning prospects and access to quality instruction. This shortage is particularly pronounced in rural areas, where educational institutions often struggle to attract and retain qualified educators, leading to larger class sizes and heavy faculty workload and turnover (UNESCO, 2023). These challenges call for innovative approaches to deliver personalized, accessible and scalable quality education in Africa.

Information Technology has played a leading role in addressing some of the aforementioned educational challenges in Africa. Mobile learning platforms, low-cost digital tools, and Open Educational Resources (OERs) have demonstrated potential in promoting accessibility to education. However, these solutions often suffer from a lack of contextualization, limited personalization, and inconsistent content quality, making them less effective in addressing diverse learner needs on a large scale, which hinder effective learning experiences and outcomes (McGreal, 2017; Ally and Prieto-Blázquez, 2014).

The integration of Generative Artificial Intelligence (GAI) and Large Language Models (LLMs) in education offers a transformative potential, enabling the scalable generation of high-quality, contextually relevant educational content (Brown et al, 2020). Subject matter experts can use advanced prompt engineering tools to co-create with LLMs quality learning material and assessment content, thus scaling educational content generation while ensuring that it is relevant and accessible. These models have a potential to mitigate the scarcity of subject matter experts, alleviate the workload of instructors, and revitalize course design (Wang et al, 2024).

AI-driven Adaptive Learning Systems (ALS) have a credible potential to personalize students' learning pathways at scale, ensuring that education is accessible, contextually relevant, and tailored to individual learners' profile, progress, learning pace, and competencies. An ALS is an intelligent educational platform designed to deliver a highly personalized learning experience. Unlike traditional Learning Management Systems (LMS), which often present static, one-size-fits-all content and assessments, an ALS leverages advanced AI algorithms to tailor learning paths to each student's unique profile. By analyzing individual competencies, engagement levels, performance data, feedback, learning styles, behavioral patterns, and error tendencies, an ALS ensures a dynamic and responsive approach that adapts in real time to optimize future interactions and learning outcomes. In practice, ALS continuously diagnoses current understanding and confidence to create hyper-personalized, non-linear journeys powered by constant assessment; confidence-based metacognitive assessments have been linked to greater knowledge retention and improved self-awareness, which in turn support faster skill acquisition. In fact, ALS can dynamically adjust content and teaching strategies to support diverse learner profiles and individual user characteristics (Du Plooy, 2024). ALS can also empower educators with data-driven insights into individual students' performance, thus enabling the identification of learning gaps, and enhancing academic achievement, educational outcomes and student engagement (Bond et al, 2023).

By leveraging LLMs and ALS, educational systems in Africa have the potential to overcome geographical barriers and address the prevailing constraints related to limited and varying instructional resources and capabilities. This integration can potentially democratize access to relevant quality education with a localized content and contribute towards a more equitable and inclusive educational landscape (Costa et al, 2022; Lata, 2024; Lopez-Gazpio, 2025).

This research is motivated by the fact that although the proclaimed merits and underlying challenges of integrating GAI and ALS in higher education are well covered in the literature, there is limited empirical evidence on the implementation and assessment of these systems and their impact, particularly in the African context. This study therefore seeks to address this research gap through an exploratory pilot study focused on the analysis, design, implementation and validation of an ALS, powered by GAI-generated learning materials, targeting a self-paced online course about the United Nations Sustainable Development Goals (SDGs), Diversity, Equity, and Inclusion (DE&I), and work ethics, tailored to the African educational landscape.

This pilot study was initiated by Honoris Online Academy, a digital platform crated by Honoris United Universities to equip graduates with the skills required for the modern workplace and support the development of world-class African talent. Honoris United Universities (HUU) is the first and largest pan-African private higher education network, serving a community of over 115,000 students across 76 campuses in 26 cities (Honoris United Universities, 2025). The network comprises 16 institutions, including multidisciplinary universities, specialized schools, technical and vocational institutes that offer contact, distance, and online learning programs. For this pilot project, five HUU institutions have been selected belonging to three different countries, namely Tunisia, Morocco and Nigeria.

Research Objectives and Scope

The objectives of this research are threefold:

First, this study aims to explore the use of GAI for creating robust, scalable and contextually relevant teaching materials and to explore the underlying opportunities and challenges in leveraging GAI for content generation.

Second, this study aims to examine students' attitudes and perceptions toward ALS before and after the intervention, as well as their overall satisfaction with the adaptive learning experience and outcomes. This includes key factors such as usability, engagement, content quality, personalization of learning pathways, user experience (UX), and the effectiveness of the ALS in meeting their educational needs and expectations. In doing so, it aims to uncover potential biases, misconceptions and adoption barriers while taking corrective actions to enhance the usability and boost the adoption of the ALS.

Third, this research aims to investigate to what extent an ALS, designed to personalize learning pathways, measurably enhances learning outcomes, with particular emphasis on achieving faster time-to-competency.

The scope of this pilot study is confined to a self-paced online course, designed for African learners, focused on the UN SDGs, DE&I and work ethics. These themes are very relevant for preparing learners for the demands of the 21st-centry workforce, including the need to contribute towards a more sustainable, inclusive and responsible world. In recent years, there has been a growing emphasis on incorporating the UN SDGs into higher education curricula. This includes a focus on Diversity, Equity, and Inclusion (DE&I), social justice, and work ethics. Additionally, international accreditation bodies such as ABET (2022), AACSB (2020), and AMBA-BGA (2025) have underscored the relevance of sustainable development within higher education. More specifically, they emphasize the integration of the UN SDGs into accreditation standards and evaluation criteria, compelling institutions to demonstrate how their curricula, research, and societal engagement actively advance sustainability. The 2023 HUU Employers Survey identified three critical themes, namely SDGs, Diversity, Equity, and Inclusion (DE&I), and ethics, as essential for workforce readiness. The findings revealed that 81% of surveyed employers believe graduates should receive training in sustainability and climate change, 84% consider ethical leadership a key skill for the future of work, and 87% emphasize the importance of workplace equity training.

Higher education institutions are increasingly integrating SDGs, DE&I and ethics across curricula and many universities dedicate specialized modules to these topics. This integration requires highly qualified faculty who can effectively engage students through interdisciplinary innovative pedagogical approaches, case studies, and contextualized experiential learning. However, while numerous studies (e.g., Ramirez-Mendoza et al., 2020; Desha et al., 2019; Wilson, 2019) have emphasized the importance of embedding SDGs into curricula and teaching practices, others have identified significant gaps in faculty competency in this area. For example, Barth and Rieckmann (2012) found that many faculty members lack the necessary competencies to effectively incorporate SDG concepts into their teaching. Similarly, Lozano et al. (2017) noted that integrating SDGs into higher education requires system thinking, interdisciplinary approaches, and pedagogical innovations; skills that are not yet widespread among faculty members.

We argue that leveraging LLMs to accelerate the generation of high-quality online content on SDGs, DE&I, and ethics, delivered through an ALS, represents a promising opportunity for creating high-quality, relevant content and at scale that warrants further validation. This approach not only addresses the existing gap in SDG-related competencies among faculty but also facilitates the delivery of personalized and engaging student learning experiences. Such an initiative can foster critical engagement and contribute to the broader educational and developmental goals in Africa.

Research Contribution

This chapter introduces several key contributions:

- It is the first reported study to explore students' attitudes and perceptions toward ALS.
- It provides empirical evidence of LLMs' potential to accelerate the creation of scalable, high-quality course content, addressing the need for accessible education while offering a blueprint for educational innovation adaptable to diverse contexts.
- It offers empirical evidence of the extent to which the ALS enhances student engagement and motivation to learn more about topics related to sustainability, work ethics, and gender equity.
- It highlights the critical role of human-machine collaboration, integrating human expertise and critical thinking with GAI efficiency to ensure both quality and contextual relevance in learning materials. In doing so, it reinforces the value of a human-in-the-loop approach, which enhances educational content while addressing some ethical concerns and the risks of over-reliance on technology by positioning GAI as a complementary rather than a substitute tool.
- It demonstrates how GAI and ALS can help mitigate faculty expertise shortages in crucial educational areas such as DSGs, ethics, and DE&I, facilitating the creation of high-quality, scalable, and contextually relevant learning resources that support sustainable development.

- It highlights the pedagogical and socio-technical challenges associated with integrating Adaptive Learning Systems powered by AI-generated content.
- It informs future educational policies and practices in Africa, where scalable, high-quality educational solutions are urgently needed.

The remaining of this chapter is organized as follows: section 2 provides a summary of the main related contributions. Section 3 outlines our research methodology. Section 4 presents the results of our study, while section 5 provides a detailed discussion of these findings. Finally, Section 6 presents a summary of the key research findings, while Section 7 discusses the implications of the study and offers practical recommendations.

Literature Review

The integration of Information Technologies in education, particularly through GAI, LLMs, and ALS, holds a transformative potential in creating adaptive and engaging learning materials and in enhancing and personalizing educational experiences (Bond et al, 2023; Wang 2024).

AI applications in Higher Education range from intelligent chatbot tutoring systems, AI-generated learning material, profiling and prediction, and personalized adaptive learning environments, to assessment design, and automated grading (Bond et al, 2023, Chiu et. al, 2023; Wang et. al, 2024; Crompton & Burke, 2023; Kamoun et al, 2024b). Bond et al. (2023) conducted a thorough meta systematic review of the applications of AI in Higher Education. In their study, "personalized learning" through adaptive learning systems emerged as the top reported benefit of using AI in higher education. ALS enables the creation of personalized learning environments, and the customization of educational material to meet individual student needs, thus promoting student autonomy (Algabri et al., 2021; Buchanan et al., 2021; Alotaibi, 2023). Though many studies reported in (Bond et al., 2023) mentioned the potential of ALS to positively enhance learning outcomes, very few studies provided empirical evidence of the merits of AI-generated learning materials and of the positive impact of ALS on students' motivation, engagement, and learning.

Additionally, some studies have expressed skepticism regarding the challenges associated with ALS, including ethical concerns such as data privacy, copyright infringement, algorithmic biases and errors, exclusion of underrepresented demographic groups, potential to replace human educators, and lack of accountability, transparency, and autonomy among learners and educators (Dutta et. al, 2024; Li et al., 2021; Wang et al., 2024; Golda et al, 2024; Zawacki-Richter, 2019). Technical challenges have also been highlighted, particularly issues pertaining to design complexity, digital literacy requirements, affordable Internet access, content accuracy, cultural relevance and contextual adaptability, data quality and the potential for AI-generated misinformation and hallucinations (Perrotta & Selwyn, 2020). To validate the AI-generated learning materials, and address some of the aforementioned concerns, many previous studies have emphasized the need for a Human-in-the-Loop (HITL) approach, emphasizing the collaborative aspects between human experts and AI systems, and highlighted the need for greater explainability, interpretability, and trustworthiness in GAI (Wu et al, 2022; Kamoun et. al, 2024a; Agudo et al., 2024; Baker & Xiang, 2023).

Table 1 summarizes the key reported merits of ALS as reported in the literature.

Table 1. Key Merits of ALS as reported in the Literature

Sample Reference	**ALS merit**	**Research method**
(Jose et al, 2024)	Significant improvements in student achievement	Mixed-method and quasi-experimental design
(Yang et al., 2013)	Adaptation to individual student's learning style	Case-study
(Lim et al, 2023)	Better examination score with ALS	Quasi-experimental approach
(Donevska-Todorova, et al., 2022)	Personalized learning paths	Design Research
(Papadopoulos & Hossain, 2023; Holmes et.al, 2019)	Data-driven and actionable insights for educators	Conceptual study
(Ross, et al., 2018)	Increasing student motivation and engagement	Case-study
(Vesin et al., 2018)	Addressing diverse learning needs, including those with special learning needs	Conceptual/empirical study

Sample Reference	ALS merit	Research method
(Achieving the Dream, 2021)	Support a flipped classroom model	Case study
(Shi, 2025)	Significant improvements in second language proficiency and emotional self-regulation	Mixed-method and quasi-experimental design
(Wang et al, 2023)	Capacity to mimic a one-on-one tutoring experience and addressing issues with large class sizes	Quantitative method and quasi-experimental design
(Feng et al., 2018)	Enhancing student learning outcomes	Quasi experimental design
(Imhof et al., 2020)	Enhancing student autonomy and empowering learners	Conceptual
(Liu et al., 2022)	Alleviating stress and anxiety	Empirical study
(Gyonyoru & Katona, 2024)	Inclusive education, catering to diversified learning needs, such as those of learners with disabilities.	Quantitative method
(Çağataylı & Çelebi, 2022).	Predicting academic success	Quantitative experimental study
(Smith, 2022)	Empowering students to break down complex concepts	Case study

Our research is rooted in and guided by the following established concepts, theories, and frameworks:

- Universal Design for Learning (UDL) framework (Meyer et al., 2014): It guided this research by providing a practical framework to effectively design and implement the ALS, based on UDL's key principles of (1) comprehending learners' diversity and needs (2) designing inclusive and personalized learning experiences based on continuous iterative feedback.
- Constructivism and Zone of Proximal Development (ZPD) (Vygotsky, 1978): These two concepts underscore the need for ALS to foster interactive and adaptive learning environments that personalize learning pathways based on learners' cognitive development, pace, and needs. By enhancing the adaptive capabilities of ALS, the

system can continuously keep students within their ZPD, facilitating knowledge construction and deeper engagement.

- Constructive Alignment (CA) approach (Biggs and Tang, 2011): CA emphasizes aligning intended learning outcomes, teaching and learning activities, and assessment tasks to ensure that students actively construct the knowledge and skills expected of them. This approach informed our adaptive learning design by aligning objectives, outcomes, activities, and assessments to personalize learning while preserving educational coherence.
- Technological Pedagogical Content Knowledge (TPACK) framework (Mishra and Koehler 2016): TPACK provides a comprehensive model on how the success of the proposed ALS hinges on the synergetic and coherent alignment of technology (Generative AI system) with sound pedagogical strategies, course content, and learning objectives.

UDL and TPACK provide a solid methodological base to effectively integrate ALS into students' learning experiences. Both frameworks contributed to informing our study's design approach.

- Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh and Bala, 2008): TAM provides valuable insights on designing and implementing an AI-based adaptive LMS by considering the important factors of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) and their role in shaping the students and faculty attitudes and intentions to effectively adopt ALS. While the SD theory emphasizes the motivational factors for the successful implementation of the ALS, TAM focuses on the acceptance factors. These two frameworks also guided the development of our perception survey instruments and informed the interpretation of our research findings.
- Human-machine Augmented Intelligence (HMAI) (Xue et al., 2022) and Human-in-the-Loop (HITL) Approach (Boy & Gruber, 1990): HMAI highlights the symbiotic collaboration between instructors and Generative AI in co-creating learning materials, enhancing both quality and relevance. It provided a strong contextual foundation for our research. Similarly, the HITL approach underscores the necessity of human oversight (specifically from subject matter experts) to ensure that the AI-generated content remains accurate, contextually relevant, free of bias, and aligned with ethical standards. Both approaches have also guided the interpretation of our findings.

Methodology

Research Design

This study integrates empirical research with a design science research method and comprises three key phases:

- A pre-intervention empirical study: A preliminary investigation was conducted to assess student and faculty Knowledge, Attitude, and Perception (KAP) regarding ALS before its implementation. This phase employed a quantitative approach, utilizing structured surveys as the primary data collection instrument. The methodological approach was informed by the previous work of Kamoun et.al (2024a).
- A pilot study for AI-Enabled Content Generation and ALS Development: This study was guided by the Design Science Research Methodology (DSRM) (Peffers et al., 2008). DSRM was selected due to its structured, iterative approach to developing and evaluating technological innovations in complex, real-world settings. This framework was particularly well-suited for the pilot study as it facilitated continuous refinement based on empirical feedback from multiple stakeholders. A key advantage of DSRM lies in its focus on iterative development, allowing for continuous refinement based on collected feedback from learning architects, learning engineers, SMEs, and institutions' academic leads. This approach ensures that the AI-generated content is not only technically feasible but also pedagogically sound, aligning with learning objectives and user needs. Additionally, DSRM facilitates the Human-In-The-Loop (HITL) approach, where subject matter experts (SMEs), learning architects, learning engineers, and academic leads from the participating institutions collaboratively review and enhance AI-generated educational materials, ensuring their accuracy, relevance, and contextual appropriateness.
- A post-intervention empirical study: Following the deployment of the ALS pilot study, a second empirical investigation was undertaken to evaluate the attitude, perception, and feedback of students, one intervening faculty, and two Subject Matter Experts (SMEs) regarding their experience with the system. This phase adopted a mixed-methods approach, integrating both quantitative and qualitative data collection techniques. Surveys were administered to students to gather structured responses, Feedback from the two participating subject-matter experts (SMEs) and the faculty member was collected through a structured qualitative instrument consisting of open-ended questions. This approach was designed to capture in-depth perspectives on the

merits of the Adaptive Learning System (ALS) and the challenges encountered during the pilot study.

Development of AI-Generated Learning Materials

We collaborated with a cloud-based adaptive learning software provider and assembled a multidisciplinary team comprising academics, learning architects, learning engineers, and subject matter experts (SMEs) specializing in Sustainability, Work Ethics, and Inclusion. Figure 1 illustrates the construction and workflow process employed in developing the course content and in delivering the adaptive learning solution. Additionally, Figure 2 depicts the role of various stakeholders in the course development process and highlights the critical role of the Human-in-the-Loop (HITL) approach in ensuring content accuracy, contextual relevance, and pedagogical alignment As may be seen from Figure 1, the course content generation consists of five key steps (S1-S5):

S1. Macro-Curriculum Design by Academic Team: This foundational phase entails the academic squad delineating the course structure and overarching learning objectives. The course, comprising 13 modules (see Table 2), each with a distinct macro-learning objective, follows a weekly-led format and comprises 40 hours of teaching materials, with an average of 3 to 4 hours per module.

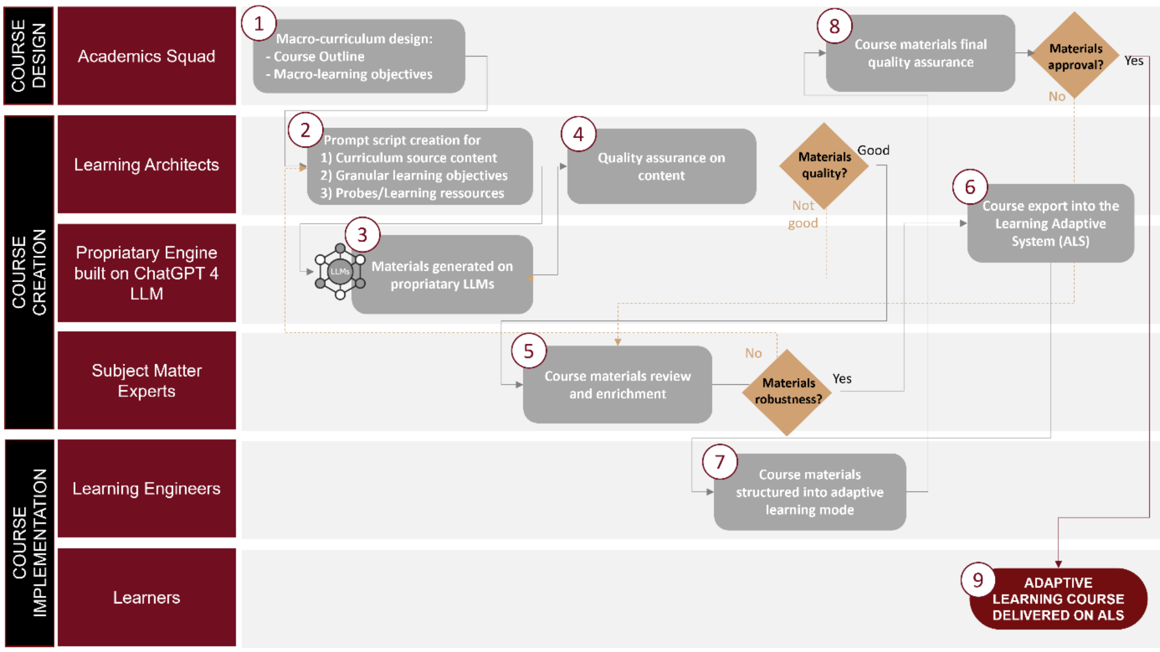

Figure 1. Workflow Process for the Pilot Course Building

S2. Prompt Script Creation by Learning Architects: Learning architects, utilizing an LLM, developed prompt scripts. These scripts encompass context, language style, and tone, tailored to the target audience and macro-learning objectives.

S3. Material Generation Using a Proprietary Generative AI Engine: Using a custom-built prompting engine based on the ChatGPT-4 LLM and validated by five subject matter experts (SMEs), this phase generated 65 to 80 nano-learning objectives per module, along with preliminary learning materials, 936 probes, and corresponding activities. In total, the 13 macro-learning objectives processed by the Generative AI engine were transformed into 1,060 nano-learning objectives, resulting in approximately 40 hours of course content.

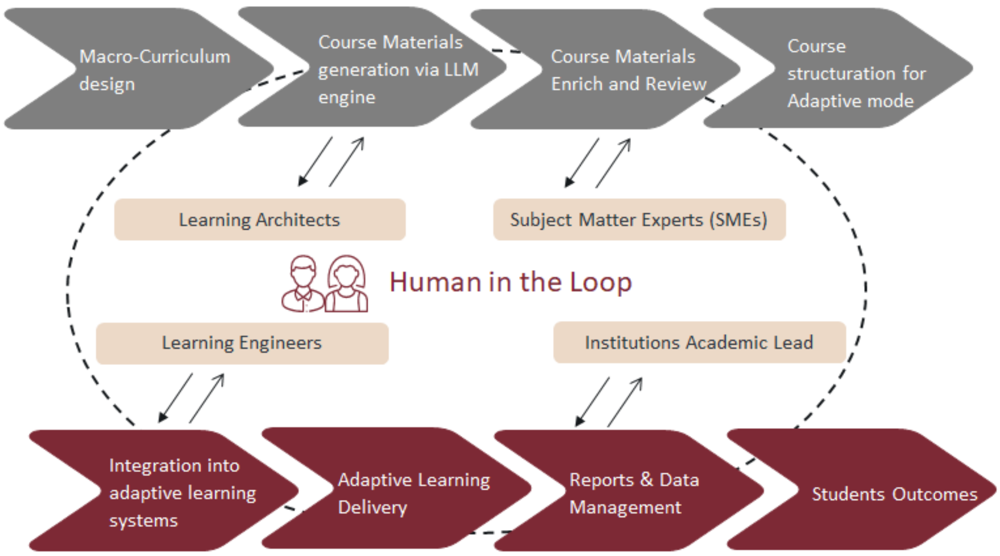

Figure 2. AI-generation of Course Materials

S4. Quality Assurance: Post-generation, the learning architects conduct a thorough quality assurance review, focusing on content clarity and relevance as per the initial scripting.

S5. Review and enrichment by Subject Matter Experts (SMEs): SMEs scrutinize and refine the nano-learning objectives and materials for accuracy and depth, enriching them with factual data, additional sources, and references to augment the AI-generated content.

Table 2. Structure of the Online Course

Week #	**Module**
1	A Green Africa: Tackling Climate Change for Environmental Sustainability
2	Assessing Progress: Metrics for Sustainable Development

Week #	Module
3	Beyond Sustainability: Unpacking Social & Cultural Dimensions
4	Building Sustainable Peace: Conflict Resolution & Peacebuilding in Africa
5	Data and Ethics: Navigating Challenges in a Digital and AI World
6	Empowering Equality: Advancing Gender and Women's Empowerment in Africa
7	Equipping Future Leaders: The Role of Education in Sustainable Development
8	Financing Africa's Growth: Sustainable Finance & Investment
9	Governing for Sustainability: Policy, Law, & Leadership
10	Leading with Integrity: Work Ethics and Decision-Making
11	Strategic Alliances: Public-Private Partnerships for Sustainable Development
12	Tech-Powered Solutions: Innovation for a Sustainable Africa
13	Unlocking Africa's Future: UN Sustainable Development Goals (SDGs)

ALS Development

As shown in Figure 1, once the course material is generated, we proceeded to the next step of delivering the course on an ALS, according to the following four steps (S6-S9):

S6. Exporting to the ALS: The SMEs' reviewed course materials are integrated into the ALS.
S7. Structuring Materials for ALS: Learning engineers structured the SMEs' approved materials into an adaptive learning schema, leveraging the Generative AI module to tailor content to the ALS framework.

S8. Materials Approval Decision Point: Following the quality assurance by SMEs, the academics squad conducted a review on the course directly on the ALS to ensure alignment with the initial curriculum design.

S9. Engagement with the course on ALS: The ALS is seamlessly integrated into the students' LMS (Blackboard or Moodle, depending on the host institution) through Learning Tools Interoperability (LTI) integration. As learners engage with the course, he system dynamically adapts the content based on performance metrics. A dashboard, displaying student progress, provides instructors with insights to inform potential adjustments in face-to-face activities.

Pre-intervention Empirical Study

This section outlines the research methodology adopted for our pre-intervention empirical study, which aimed to examine students' and faculty members' Knowledge, Attitude, and Perception (KAP) towards ALS. This pre-intervention study had two primary objectives: (1) to collect baseline data on current Attitude and Perception (AP) levels for benchmarking purposes and (2) to reinforce a user-centric design approach in guiding ALS development. This exploratory inquiry is crucial for facilitating ALS adoption beyond the pilot phase, identifying potential biases, misconceptions, and concerns, and ultimately fostering a more positive attitude towards ALS. The research methodology is based on an empirical quantitative approach, using surveys as data collection instruments. Following a similar approach as in (Kamoun et al., 2024a), we developed a survey based on structured questionnaires, consisting of closed-ended questions.

Sample Selection and Data collection Procedure

The student sample was selected via a combination of stratified sampling and convenience sampling methods. The faculty sample was selected via a census sampling approach. Student surveys were conducted via paper-based questionnaires that have been distributed during class time. Faculty surveys were conducted online, via Qualtrics.

Instruments and Measures

The instrument employed by the pre-intervention empirical study covered three main domains: Knowledge (K), Attitude (A), and Perception (P) towards ALS. The first (K) domain aimed to probe student and faculty knowledge about ALS. Each knowledge item response score was either 0 (false answer) or 10 (correct answer). The percentage of correct responses rk was computed by dividing the score by 40 or 50 as applicable and multiplying by 100%, and this measure was used to group the knowledge scores on a 5-point Likert scale as follows: $r_k < 20 = 1$, $20 \leq r_k < 40 = 2$, $40 \leq r_k < 60 = 3$, $60 \leq r_k < 80 = 4$ and $r_k \geq 80 = 5$. Knowledge scores were interpreted as follows: 1 = very low, 2 = low, 3 = moderate, 4 = high and 5 = very high. Good knowledge was regarded when the overall average score, out of 5, and across all the items is greater than or equal to 4.

The second domain (A) probed student and faculty attitudes towards ALS and contained eight 5-point Likert items (A1-A8) and six 5-point Likert items (A1-A6) for students and faculty, respectively. The responses ranged from strongly agree, agree, neutral, disagree, and strongly disagree; each weighting 5, 4, 3, 2, and 1, respectively. High index scores reflect a more positive attitude towards ALS and vice-versa. To reduce bias, we have reverse-coded some items such that a response of "strongly agree" truly represents “strongly disagree”. For these reverse-coded items, scores were also reversed and recomputed accordingly. Attitude scores were interpreted as follows: 1 = very negative, 2 = negative, 3 = indifferent, 4 = positive, and 5 = very positive. A positive attitude was noted when the overall average score, out of 5, and across all the items is greater than or equal to 4.

The third domain (P) probed student and faculty perception towards ALS and contained fifteen 5-point Likert items (P1-P15) and twenty-nine 5-point Likert items (P1-P29) for students and faculty, respectively. To reduce bias, we have reverse-coded some items such that a response of "strongly agree" truly represents “strongly disagree”. For these reverse-coded items, scores were also reversed and recomputed accordingly. A positive perception was noted when the overall average score, out of 5, and across all the items is greater than or equal to 4.

Statistical Analysis

This study used Statistical Package for Social Sciences SPSS (IBM Corporation, NY, USA, version 17) for data analysis. Demographic data was analyzed descriptively and depicted as frequencies as well as percentages. We applied the χ-square test for goodness of fit to analyze a single categorical variable. We present general KAP levels descriptively in terms of means and standard deviations and we use an independent t-test for KAP score comparisons based on demographic variables which we illustrate in terms of means, standard deviations, and p values.

Pilot Study Design and Implementation

The pilot study was conducted over a nine-month period (January–September 2024) and targeted designated classes from five institutions within the Honoris United Universities network, spanning three countries: Tunisia, Morocco, and Nigeria. While participation in the pilot was voluntary, students who completed the online training were granted bonus points and awarded the Honoris Sustainability, Work Ethics, and Gender Equity certificate, issued by the Honoris Online Academy upon successful completion of the module.

Post-intervention Empirical Study

The post-intervention empirical study pursued two primary objectives: first, to examine potential changes in students' attitudes and perceptions toward the Adaptive Learning System (ALS) following completion of the online pilot course; and second, to obtain feedback from two subject-matter experts (SMEs) and one faculty member in order to inform subsequent refinements of the system. Student feedback was also collected across four dimensions (usability, content, adaptive learning experience, and engagement and motivation) together with their overall evaluation of the pilot course.

The post-intervention research methodology employed a mixed-methods approach: a quantitative survey for students who completed the online course, and a qualitative approach for participating SMEs and faculty. The student survey was conducted online, via Qualtrics, and it utilized structured questionnaires comprising primarily closed-ended questions, with a single open-ended question at the end to gather feedback and recommendations for future improvements.

Feedback from two participating subject-matter experts (SMEs) and a faculty member was obtained through a structured qualitative instrument consisting of open-ended questions. This elicitation method was designed to capture reflective evaluations of the AI-generated content and the ALS, including its pedagogical value, technical design, encountered challenges, and areas for enhancement. The qualitative insights generated from these responses complemented the student data, thereby offering a more holistic perspective on the effectiveness of the pilot course and informing directions for system refinement.

Instruments and Measures

The student survey instrument encompassed three key domains: Attitude (A) and Perception (P) towards the ALS, as well as feedback on ALS content, adaptive learning experience, engagement and motivation, and overall user experience. The same methodological approach (including the usage of SPSS statistical package) used in the pre-intervention survey was replicated to ensure comparability of findings.

Results

Pre-intervention Results

Demographic Characteristics

One thousand one hundred sixty-one (1161) students participated in this study. Females constituted a slight majority with 53.7%. Most respondents were Tunisians (96.6%) and 63.8% of the surveyed students were aged between 18 and 22 years old. Further details are shown in Table A1 (see Appendix A).

Fifty-eight (58) faculty members participated in this study. Females constituted the majority with 79.3%, compared to 20.7% male participation. 50% of faculty have more than 2 years' working experience and 70.7% have more than 2 years' experience with online learning platforms. Further details are shown in Table A2 (see Appendix A).

Reliability and Validity of Student and Faculty KAP

Internal consistency reliability (Cronbach's α) for student and faculty KAP emerged as high for all three domains ($\alpha > 0.7$). In addition, Principal Component Factor (PCF) analysis provided evidence on the construct validity of the student and faculty KAP instruments, with most of the items being highly loaded as expected ($r > 0.4$).

General KAP Levels

The students' general AP level towards the ALS was moderately positive (mean = 3.40 ±1.08). Among the two domains, Perception emerged with a higher mean (3.47 ±1.04) than Attitude (mean = 3.31 ±1.14). Based on the mean scores, the sample of the student population demonstrated moderate positive attitudes and perceptions towards ALS and a level of knowledge that is below average (mean = 2.20 ±1.42). Refer to Table 3 for further details. The faculty knowledge and general AP levels were in the moderate positive category (mean = 3.20 ±1.34 and 3.53 ±1.05, respectively). Refer to Table 4 for further details. We also note that students and faculty members had varied opinions about the KAP as reflected by the dispersion of the responses around the mean values.

Table 3. Overall student Knowledge, Attitude, Perception, and Total KAP Level (1-5)

Domain	Mean	Standard Deviation	Interpretation
Knowledge	2.2	1.42	Low
Attitude	3.31	1.14	Moderately positive
Perception	3.47	1.04	Moderately positive
Total AP	3.40	1.08	Moderately positive

Table 4. Overall Faculty Knowledge, Attitude, Perception, and total KAP Level (1-5)

Domain	Mean	Standard Deviation	Interpretation
Knowledge	3.2	1.34	Moderately positive
Attitude	3.84	1.11	Moderately positive
Perception	3.46	1.03	Moderately positive
Total AP	3.53	1.05	Moderately positive

Knowledge Results

The knowledge level of the student sample was relatively low. On the other hand, faculty knowledge of ALS was relatively higher, as some have been exposed to this concept through research seminars and upskilling professional development courses (see Tables 5 and 6 for details).

Table 5. Student Knowledge Regarding Adaptive Learning Systems (*N*=1161)

Question	% of affirmative answers
K1-Have you heard about Adaptive Learning Systems before today?	32.8%
K2- (Before Today) I knew the difference between adaptive learning systems and traditional LMS?	32.2%
K3- (Before Today) I Knew that adaptive learning systems use data and algorithms to adapt learning content to individual student needs and abilities.	39.8%
K4-Have you interacted with adaptive learning systems in the past?	26.9%

Table 6. Faculty Knowledge Regarding Adaptive Learning Systems (n=58)

Question	% of affirmative answers
K1-Have you heard about Adaptive Learning Systems before today?	84.5%
K2- (Before Today) I knew the difference between adaptive learning systems and traditional LMS?	84.5%
K3- (Before Today) I could provide a clear explanation of what adaptive learning systems entails	51.7%
K4-I have interacted with an adaptive learning system in the past	39.7%
K5-I have gained knowledge about adaptive learning systems from reliable sources such as workshops, conferences, or academic literature	50%

Attitude Results

From Table 3, the mean student attitude score towards ALS was 3.31 ± 1.14, implying a moderately positive attitude (see Table 7 for additional details). For the case of faculty, as shown in Table 4, the mean attitude score towards ALS was 3.84 ± 1.11, implying an overall moderate positive attitude (see Table 8 for details).

Table 7. Student Attitude Towards Adaptive Learning Systems

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*
A1. I prefer using traditional platforms (e.g. Moodle) over Adaptive Learning Systems	166 14.3%	254 21.9%	412 35.5%	211 18.2%	118 10.2%	3.12	1.169
A2. I am excited about the possibilities that adaptive learning systems could offer for my learning	222 19.1%	402 34.6%	379 32.6%	95 8.2%	63 5.4%	3.54	1.059
A3. I do not trust the AI Algorithms behind adaptive learning systems	133 11.5%	299 25.8%	426 36.7%	220 18.9%	83 7.1%	3.15	1.081
A4. I would like to learn more about adaptive learning systems	291 25.1%	431 37.1%	344 29.6%	59 5.1%	36 3.1%	3.76	0.986
A5. I am open to trying adaptive	300	425	317	74	45	3.74	1.034

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*
learning systems	25.8%	36.6%	27.3%	6.4%	3.9%		
A6. I feel confident in using	182	368	443	125	43	3.45	1.000
adaptive learning systems	15.7%	31.7%	38.2%	10.8%	3.7%		
A7. I do not feel comfortable	119	184	367	301	190	2.78	1.197
asking questions to a virtual tutor	10.2%	15.8%	31.6%	25.9%	16.4%		
A8. I am afraid that adaptive	141	222	427	207	164	2.97	1.192
learning systems might be biased	12.1%	19.1%	36.8%	17.8%	14.1%		
and discriminate me							

* **SA: Strongly Agree, A: Agree, N: Neutral, D: Disagree; SD: Strongly Disagree. SDev: Standard deviation*

** Greyed cells convey negative attitude statements*

Table 8. Faculty Attitude Towards Adaptive Learning Systems

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*
A1. I am worried that adaptive	2	14	24	15	3	2.95	0.92
learning systems might be biased	3.4%	24.1%	41.4%	25.9%	5.2%		
especially on assessment part							
A2. I prefer using traditional	3	10	19	17	9	2.67	1.09
LMS platforms over new AI	5.2%	17.2%	32.8%	29.3%	15.5%		
driven approaches like adaptive							
learning systems							
A3. I am excited about the	20	29	7	2	--	4.16	0.76
possibilities that adaptive	34.5%	50%	12.1%	3.4%			
learning systems could offer to							
me and to my students							
A4. I would like to learn more	32	21	4	1	--	4.45	0.70
about adaptive learning systems	55.2%	36.2%	6.9%	1.7%			
A5. I am open to exploring and	35	19	3	1	--	4.52	0.68
integrating new technologies like	60.3%	32.8%	5.2%	1.7%			
adaptive learning systems into							
my teaching practices							
A6. I feel confident in my ability	25	27	4	2	--	4.29	0.74
to adapt and effectively use	43.1%	46.6%	6.9%	3.4%			
advanced learning platforms like							
adaptive learning systems							

*** SA: Strongly Agree, A: Agree, N: Neutral, D: Disagree; SD: Strongly Disagree. SDev: Standard deviation*

** Greyed cells convey negative perception statements*

Perception Results

Both students and faculty reported positive, though moderate, perceptions of the ALS with mean scores of 3.47 ± 1.04 and 3.46 ± 1.03, respectively (see Tables B1 and B2, Appendix B). These scores indicate a generally favorable reception of the system, suggesting that participants recognized its usefulness and potential, while also leaving room for further refinement and enhancement.

Comparison of KAP Levels Based on Demographic Characteristics

Table C1 (see Appendix C) illustrates the associations between students' key categorical demographic variables and their knowledge, attitude, and perception towards ALS, based on an independent test. p <0.05 was considered statistically significant to infer that there is significant evidence that the demographic variable under consideration influences the mean K, A, or P level. As may be seen, all demographic variables have some impact with varying degrees on student reported KAP towards ALS.

Table C2 (see Appendix C) illustrates the comparison of the reported KAP levels, for the case of faculty, based on demographic characteristics and using an independent t-test. As may be seen, gender had no significant impact on the reported KAP level, while working experience did not have any impact on the reported knowledge. University rank, on the other hand, had some impact with varying degrees on the reported KAP.

Pilot Study Results

4209 students from different fields of study (Engineering, Business, IT, Health and Creative Arts) and qualification level (undergraduate/graduate) were enrolled in the online ALS course and benefited from personalized learning experience. Among these, 1778 succeeded in obtaining their certifications. Students accessed the ALS through either Blackboard or Moodle, depending on their host institution, where the system was seamlessly integrated so that upon logging in, they were automatically directed to the ALS platform without any additional action required. Additionally, each institution was given the flexibility to select modules from the 13 available options based on their specific needs and preferences. As illustrated in Figure 3, each module comprises two key components: structured readings, divided into two units for improved assimilation, and activities that include formative assessments along with optional, self-guided supplementary readings.

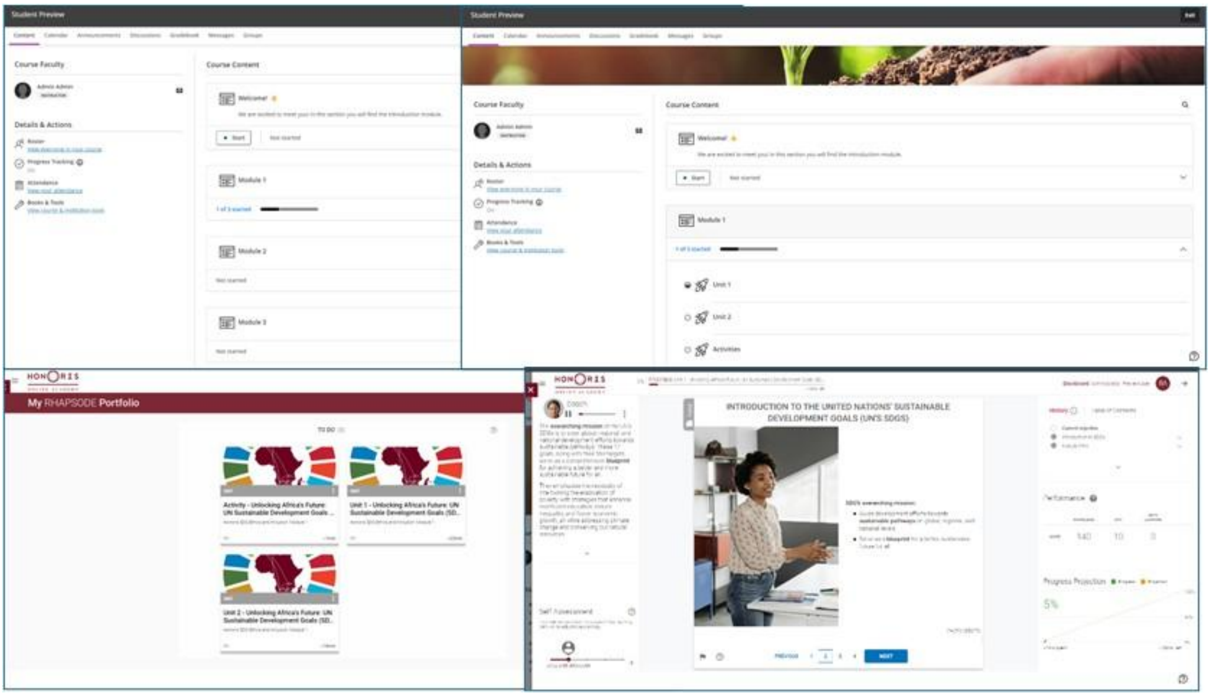

Figure 3. Samples of the ALS User Interface

If delivered in a traditional, non-ALS format, the 13-module course would require a total of 26 hours (13 sessions of 2 hours each). In contrast, subject-matter experts and the learning architects estimated that students could achieve 100% proficiency using the ALS in an average of 10 hours and 39 minutes. This corresponds to a reduction of approximately 59% in time to mastery.

Faculty members were equipped with data-driven insights to monitor student performance and progression effectively. The dashboards, designed for weekly tracking, provided more than just usage and completion statistics. They offered in-depth analytics on learning objective difficulties, time required to achieve proficiency, and metacognitive awareness, specifically distinguishing between conscious and unconscious competence or incompetence; a framework derived from the Four Stages of Competence Model (Schoonenboom, et.al, 2007). This model classifies learners into four categories:

- Unconscious Incompetence: Learners are unaware of their lack of knowledge or skills.
- Conscious Incompetence: Learners recognize their lack of proficiency and the need to learn or improve.
- Conscious Competence: Learners have acquired knowledge or skills but require

deliberate effort and concentration to apply them.

- Unconscious Competence: Learners have mastered a skill to the extent that it becomes second nature.

Our post-mortem analysis revealed that 29% of learners exhibited unconscious incompetence, meaning they were unaware of their deficiencies. This finding underscores the need for targeted instructional support to bridge knowledge gaps and enhance learning outcomes through personalized interventions, scaffolding techniques, and refined instructional strategies to improve student outcomes. Refer to Figure 4 for illustrative examples.

Post-intervention Results

Demographic Characteristics

For the post-intervention quantitative study, 215 students who successfully completed the online pilot course were invited to participate in the survey, though not all respondents completed every question. The sample exhibited a slight female majority (55.8%), with Tunisian students comprising 72.1% of respondents. Additionally, 72% of participants were enrolled in Engineering or IT programs, reflecting a strong representation from these two fields. Refer to Table D1 (Appendix D) for a detailed breakdown of participant demographics.

The survey examined three key areas: Attitude and Perception (AP) toward the ALS and the overall learning experience. The latter was assessed through multiple dimensions, including usability, content quality, adaptive learning experience, engagement and motivation, and overall satisfaction. Additionally, the final survey question invited respondents to provide suggestions for improving the adaptive platform in future iterations.

General Attitude and Perception (AP) levels

The students' general AP level towards ALS was in the moderately positive category (mean = 3.37 1.08). Based on the mean scores, the sample of the student population demonstrated moderate positive attitude and perception towards the ALS. Refer to Table 9 for further details.

Table 9. Overall student Attitude & Perception

Domain	Mean	Standard Deviation	Interpretation
Attitude	3.40	1.08	Moderately positive
Perception	3.36	1.08	Moderately positive
Total AP	3.37	1.08	Moderately positive

Attitude Results

The mean student attitude score towards the ALS was 3.40 ±1.08, implying a moderately positive attitude. Refer to Table 10 for more details.

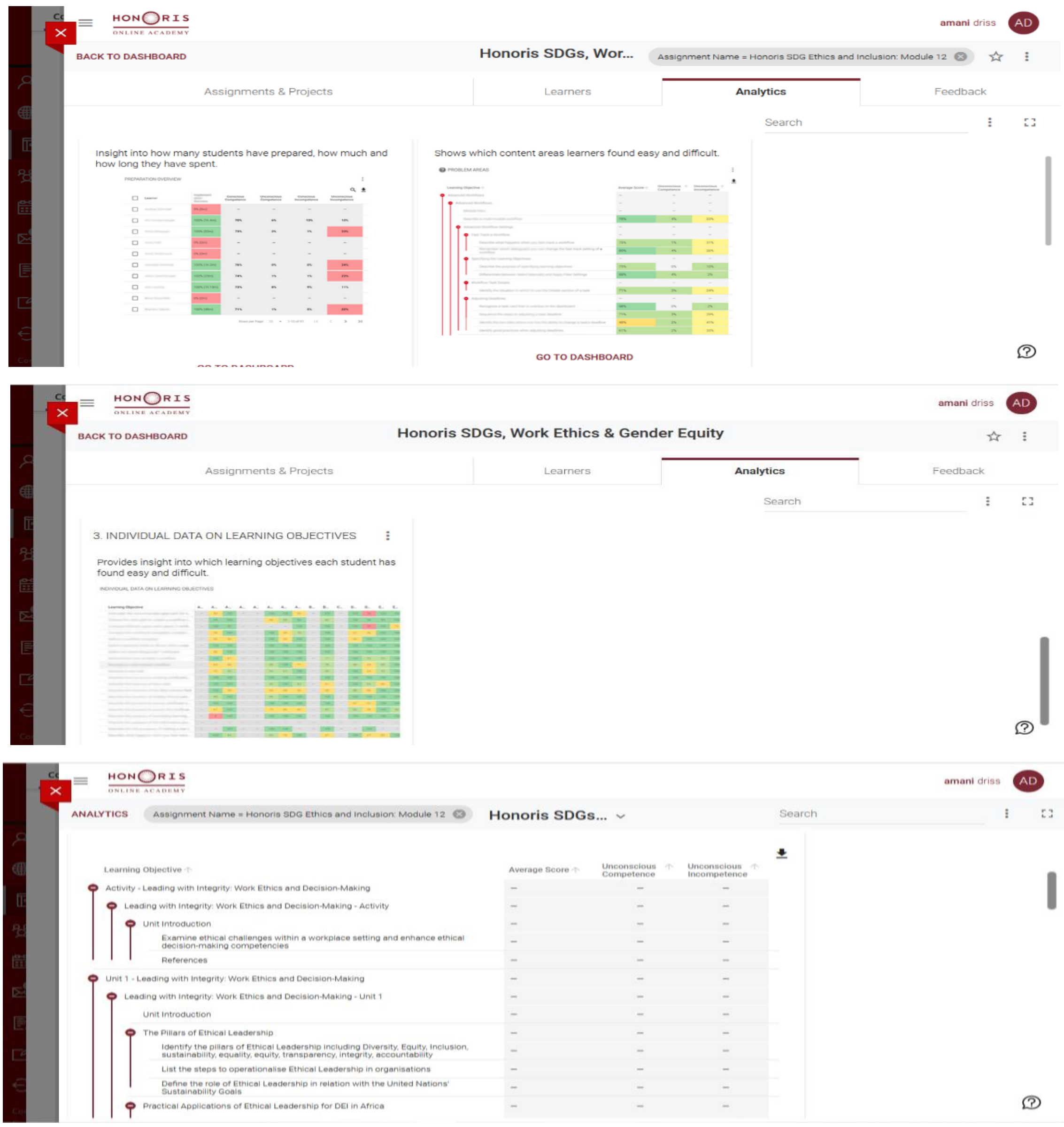

Figure 4. ALS Faculty Dashboard

Table 10. Student Attitude Towards Adaptive Learning Systems (N=172)

Statement	**5. Strongly Agree**	**4. Agree**	**3. Neutral**	**2. Disagree**	**1. Strongly Disagree**	**Mean***	**Standard Deviation***
A1. I prefer using traditional platforms (e.g. Moodle) over Adaptive Learning Systems	25 14.5%	46 26.7%	65 37.8%	23 13.4%	13 7.6%	3.27	1.10
A2. I am excited about the possibilities that Adaptive Learning Systems could offer for my learning	31 18%	80 46.5%	44 25.6%	10 5.8%	7 4.1%	3.69	0.97
A3. I do not trust the AI algorithms behind Adaptive Learning Systems	24 14%	46 26.7%	61 35.5%	28 16.3%	13 7.6%	3.23	1.11
A4. I feel confident in using Adaptive Learning Systems	29 16.9%	76 44.2%	52 30.2%	7 4.1%	8 4.7%	3.65	0.96
A5. I am afraid that Adaptive Learning Systems might be biased and discriminate me	20 11.6%	49 28.5%	56 32.6%	29 16.9%	18 10.5%	3.14	1.15

* *Greyed cells convey negative attitude statements*

Perception Results

Student perception level towards ALS was moderately positive (mean = 3.36 ±1.08). Refer to Table 11 for details.

Table 11. Student Perception Towards ALS (N=172)

Statement	**5. Strongly Agree**	**4. Agree**	**3. Neutral**	**2. Disagree**	**1. Strongly Disagree**	**Mean***	**Standard Deviation***
P1. Using Adaptive Learning Systems has enhanced my learning outcomes more effectively than traditional LMS	23 13.4%	73 42.4%	48 27.9%	17 9.9%	11 6.4%	3.4 7	1.0 5
P2. Using Adaptive Learning Systems has made it easier for me	31 18%	66 38.4%	51 29.7%	12 7%	12 7%	3.5 3	1.0 8

Statement	5. Strongly Agree	4. Agree	3. Neutral	2. Disagree	1. Strongly Disagree	Mean*	Standard Deviation*
to understand complex topics							
P3. I believe Adaptive Learning Systems would enhance my academic performance	28 16.3%	77 44.8%	46 26.7%	11 6.4%	10 5.8%	3.59	1.02
P4. Adaptive Learning Systems has provided me more control of my own learning	29 16.9%	75 43.6%	50 29.1%	8 4.7%	10 5.8%	3.61	1.01
P5. I believe that using Adaptive Learning Systems has negatively impacted my academic progress	21 12.2%	56 32.6%	44 25.6%	39 22.7%	12 7%	3.20	1.13
P6. I believe Adaptive Learning Systems has provided me a wide range of learning materials tailored to my unique needs	24 14%	70 40.7%	59 34.3%	8 4.7%	11 6.4%	3.51	1.00
P7. Using Adaptive Learning Systems has been more challenging than using a traditional online LMS	8 4.7%	10 5.8%	62 36%	69 40.1%	23 13.4%	2.48	0.96
P8. Adaptive Learning Systems have increased my motivation for learning	26 15.1%	65 37.8%	50 29.1%	18 10.5%	13 7.6%	3.42	1.10
P9. I am afraid that Adaptive Learning Systems would make me overdependent on technologies	20 11.6%	62 36%	59 34.3%	19 11%	12 7%	3.34	1.05
P10. I am concerned about the privacy issues due to the collection of personal data	29 16.9%	55 32%	64 37.2%	17 9.9%	7 4.1%	3.48	1.01

** Greyed cells convey negative perception statements*

Post-intervention Learning Experience Results

The post-intervention student learning experience survey results are illustrated in Tables 12, 13, 14, 15, 16a, and 16.b.

Table 12. Post-intervention Learning Experience Survey Results – Usability (N=167)

	USABILITY						
	1. Very difficult	**2. Difficult**	**3. Neither easy nor difficult**	**4. Easy**	**5. Very easy**	**Mean**	**SDev**
U1- On a scale from 1 to 5 (1=very difficult, 5= very easy), How would you rate the ease of navigation within the platform?	12 7%	14 8%	72 43%	44 26%	25 15%	3.34	1.06
	1. Not intuitive	2. Slightly intuitive	3. Moderately intuitive	4. Intuitive	5. Very intuitive	Mean	SDev
U2. On a scale from 1 to 5 (1=Not intuitive, 5 = Very intuitive), How intuitive did you find the platform's interface?	15 9%	14 8%	73 44%	45 27%	20 12%	3.25	1.06
	Yes, frequently		Yes, occasionally		No		
U3. Did you encounter any technical difficulties while using the platform? (select one).	44 26%		75 45%		48 29%		

Table 13. Post-intervention Learning Experience Survey Results – Content

	CONTENT						
	1. Not relevant	**2. Slightly relevant**	**3. Moderately relevant**	**4. Relevant**	**5. Very relevant**	**Mean**	**SDev**
C1- How relevant did you find the learning materials provided in the course to your current level of knowledge? (1= Not relevant, 5= Very	15 9%	17 11%	58 36%	52 32%	19 12%	3.17	1.10

relevant) N=161							
	NO			YES			
C2. Do you believe the content was well-structured and helped in understanding the concepts clearly? (Yes/No) N =161	32 20%			129 80%			
	1. Not well	2. Slightly well	3. Moderately well	4. Well	5. Very well	MEAN	SDev
C3. How well do the assessments reflect the knowledge and skills that you acquired? (1 = Not well, 5 = Very well) N=154	19 12%	11 7%	57 35%	50 31%	24 15%	3.30	1.16

Table 14. Post-intervention Learning Experience Survey Results – Adaptive Experience (N=154)

	ADAPTIVE EXPERIENCE						
	1. Not personalized	**2. Slightly personalized**	**3. Moderately personalized**	**4. Personalized**	**5. Highly personalized**	**Mean**	**SDev**
AD1- How personalized did you find the learning materials and activities based on your performance?	10 6%	10 6%	64 42%	52 34%	18 12%	3.38	0.99
	1. Poor	2. Fair	3. Average	4. Good	5. Excellent	Mean	SDev
AD2- How would you rate the quality of	11 7%	16 10%	52 34%	52 34%	23 15%	3.39	1.08

feedback provided on your performance (1=Poor, 5 = excellent)?			
	Yes, always	Yes, most of the time	No
AD3- Did the platform adjust the content to your individual learning pace and needs?	37 24%	97 63%	20 13%

Table 15. Post-intervention Survey Results – Engagement and Motivation (N=150)

	ENGAGEMENT AND MOTIVATION						
	1. Not at all	**2. Slightly**	**3. Moderately**	**4. Considerably**	**5. Yes, definitely**	**Mean**	**SDev**
EM1- Did the platform increase your interest in topics related to Sustainability, Work Ethics, and Gender Equity? (1= Not at all, 5= yes, definitely)	12 8%	14 9%	52 35%	46 31%	26 17%	3.40	1.12
EM2. Did the platform motivate you more to learn about topics related to Sustainability, Work Ethics, and Gender Equity? (1= Not at all, 5= yes, definitely)	12 8%	14 9%	52 35%	41 27%	31 21%	3.43	1.15

Table 16.a. Post-intervention Survey Results – Overall Experience (Sentiment Analysis) (N=215)

	1. Very dissatisfied	2. Somewhat Dissatisfied	3. Neutral	4. Somewhat satisfied	5. Very satisfied	Mean	SDev
O1- Overall, how satisfied were you with the platform? (1 = very dissatisfied; 3 = neutral, 5 = very satisfied)	21 10%	24 11%	41 19%	93 43%	36 17%	3.46	1.18

Table 16.b Post-intervention Survey Results – Overall Experience (Recommendation) (N=215)

	1. Do not recommend	2	3	4	5	6	7	8	9	10. Highly Recommend	Mean	SDev
O2. Would you recommend the use of this adaptive platform for other courses? (1=do not recommend, 10 = highly recommend)	23 11%	7 3%	19 9%	11 5%	41 19%	17 8%	27 13%	31 14%	22 10%	17 8%	5.81	2.69

Student Feedback and Suggested Improvements for the ALS Platform

The open-ended survey responses provided valuable insights into areas for improvement. Thematic analysis revealed three dominant themes: (1) Enhancing platform usability, (2) improving the contextualization of the content to respond to individual contexts and preferences, and (3) Improving engagement features through more interactive learning experiences. Representative student comments related to these three themes include the following:

- *"I recently used your platform for my learning journey, and while I appreciate the content provided, I found the navigation experience quite challenging. One of the main issues is the fixed screen size, which makes it difficult to engage with the material effectively. The inability to enlarge the screen or access a more spacious layout hinders my ability to view all the information comfortably on one page".*
- *"The window is too small, it's not practical at all"*
- *"Maybe make a dark mode for the platform. Staring at the screen for long can cause damage to eyes".*
- *"Improve navigation".*
- *"I think that the course content in unrelated with Tunisia, as a Tunisian, I find myself learning about things that somewhat cannot be applied in Tunisia. I think you'll need to work on the content to make it more relevant with each country".*
- *"The AI generated course is just a text that you should read, and it's not considered a revolutionary method".*

Qualitative Study Results: Faculty and SMEs Perspectives

The final phase of the empirical study employed a qualitative approach to obtain deeper insights into the effectiveness of the AI-generated course materials. Feedback from two participating subject matter experts (SMEs) and one faculty member was collected using a structured qualitative instrument consisting of open-ended questions. This instrument was designed to capture participants' initial impressions, perceptions of content quality, reflections on their interactions with the LLM, and overall experiences with the AI-generated materials.

SME *Insights*. To gain expert insights on the role of AI in course content creation, particularly in the context of Sustainability, Work Ethics, and Gender Equity in Africa, we addressed the following three key questions to each SME (hereafter referred to SME A and SME B):

1. In your expert opinion, how effectively does AI-powered content address the current needs in content about Sustainability, Work Ethics and Gender Equity I the context of

Africa?

2. Could you share your initial thoughts from your interactions with the AI-generated materials for the course?

3. Would you say that AI-generated content can be leveraged for course content creation?

AI's Effectiveness in Addressing Content Needs for Sustainability, Work Ethics, and Gender Equity in Africa

Both SMEs acknowledged that AI is a useful tool for generating foundational content on sustainability, work ethics, and gender equity. However, they highlighted some limitations in its inherent ability to provide deep, nuanced, and locally relevant insights specific to the African context. SME A pointed out that much of the AI-generated content is influenced by North American and European norms, making challenging in contextualizing African perspectives.

> "*AI provides a great foundation to get exposure to sustainability, work ethics, and gender equity more generally. However, it lacks nuance in applying these concepts to African examples*."

SME B noted that while topics like sustainability are well-documented globally, AI struggles with more complex and sensitive topics such as work ethics and gender equality in Africa, which require human expertise for accuracy and depth.

> "*AI excels at creating high-level materials on well-documented topics. However, it struggles with complex narratives that require in-depth knowledge*".

Initial Impressions of AI-Generated Course Materials

Both SMEs were impressed by the volume and structure of AI-generated content but identified gaps in depth and accuracy, particularly for specialized or region-specific subjects. SME A observed that AI-generated content often lacked key information found in academic journals and books, particularly on topics like conflict resolution and peacebuilding in Africa.

> "*There were areas where key information was not as robust as it could have been because much of the information is often found in books and academic journals*."

SME B emphasized that the suitability of AI-generated content depends on the subject matter. While sustainability-related topics were well-supported by AI, topics like work ethics and gender equality required more human refinement.

> "*Sensitive subjects like work ethics and gender equality in Africa necessitate more nuanced content creation, requiring significant human expertise*."

Additionally, SME A highlighted the importance of human intervention to ensure the accuracy of the course content.

> "*This is where I was able to add value by adding in African case studies and examples, as well as ensuring that the AI-generated content did not fall into writing about Africa using stereotypical and/or harmful language that reinforces Western-driven narratives about conflict on the continent*."

The Role of AI in Course Content Creation

Based on feedback from subject matter experts (SMEs), the use of Generative AI (GAI) in educational material development is estimated to have accelerated both creation and time-to-market by a factor of three. Both SMEs agreed that AI can be leveraged effectively for course content creation, but they emphasized the need for human intervention to ensure accuracy, contextual relevance, and academic rigor. SME A noted that AI's inability to pull from licensed academic sources presents challenges for educational integrity. However, these limitations can be mitigated if subject matter experts validate and enrich AI-generated materials.

> "*AI-generated content can provide a helpful foundation, but it is limited by its inability to pull meaningfully from academic or other reputable licensed materials*."

SME B suggested an optimal approach where AI is used for generating outlines and introductory content, while SMEs contribute deeper insights, case studies, and data.

> "*The optimal approach combines AI-generated content with human expertise. Introductory courses can leverage more AI-generated content, while advanced courses require more human oversight*."

Faculty insights. To analyze the faculty member's responses, we structured the findings into three key themes, aligning with the same questions posed to the SMEs.

AI's Effectiveness in Addressing Content Needs for SDGs, DE&I in Africa

The faculty member acknowledged that AI can be a valuable tool for structuring content on sustainability, work ethics, and gender equity in Africa. However, she emphasized that AI should not be relied upon exclusively and must be supplemented with human expertise. While recognizing AI's potential to provide insights relevant to Africa, the faculty cautioned against relying solely on it:

> "*Personally, based on this pilot experience, I find that AI can be used to guide content, particularly in terms of experiences across Africa, but we can in no way limit ourselves to it*."

Initial Impressions of AI-Generated Course Materials

The faculty member expressed a balanced perspective, acknowledging both strengths and limitations of AI-generated course content. Regarding strengths, two key benefits were highlighted:

> (1) efficiency in content creation and distribution, with AI streamlining material generation and enhancing the accessibility of e-learning; and
> (2) the production of quality learning materials that can be tailored to align with specific learning objectives and target audiences, including the capacity to generate complementary visual elements.
> "*One of the strengths of AI integration is the generation of photos in relation to the various course elements.*"

In terms of limitations, two main concerns were noted:
(1) repetitiveness in multimedia outputs, as AI-generated images were frequently reused across different topics, thereby diminishing their pedagogical effectiveness.

> "*Unfortunately, we find that these photos are repeated too often for different elements, which represents a limitation*."

and (2) insufficient depth of content, which necessitates human intervention to ensure accuracy and contextual relevance.

These observations are consistent with SME A and SME B's observations, both of whom emphasized the importance of expert validation in maintaining the quality and credibility of

AI-generated educational materials.

The Role of AI in Course Content Creation

The faculty strongly supported leveraging AI for course content creation but emphasized the importance of maintaining a balance between AI automation and human interaction.

> "*It is essential to strike a balance between AI-generated content and human interaction to achieve a holistic and complete learning experience.*"

These insights echo SME A and SME B's concerns that while AI is a powerful tool, it requires expert oversight to ensure accuracy, depth, and contextual relevance. The faculty member's perspective aligns with the SMEs' observations that AI is valuable for foundational content creation but lacks deep contextual understanding for some African-specific themes, which requires experts' intervention.

Discussion

Pre-intervention Results

Pre-intervention survey results indicated that, although surveyed faculty demonstrated a higher level of knowledge about adaptive learning systems (ALS) compared to students, nearly half of them did not have a comprehensive understanding of what an ALS entails. As shown in Table 5, nearly one third of the surveyed students have not heard about ALS before, nor can they distinguish between an ALS and a traditional LMS.

Both students and faculty exhibited a moderately positive attitude and perception towards ALS, with substantial variability in responses. Faculty reported a more positive attitude (mean=3.84) compared to students (mean = 3.31), while both maintained a similar perception level. While most students were enthusiastic about engaging with ALS, some expressed trust-related concerns associated with potential bias and reliability.

Faculty and students generally perceived ALS as an enabler of improved learning experiences, enhanced learning outcomes, and increased motivation. Usefulness and ease of use were also positively aligned with expectations, consistent with the TAM model (Davis, 1989; Venkatesh and Bala, 2008). On the negative side, a few faculty and students reported concerns regarding potential technical, trust, and privacy-related issues.

As illustrated in Table B2, surveyed faculty, in particular, expressed a positive perception of the added value of ALS for teaching and assessment but highlighted several potential challenges, including: (1) the risk of students becoming overdependent on technology, (2) the substantial time and effort required to integrate ALS effectively, (3) potential reduction in direct interactions with students, (4) the potential diminishing role of the instructor, (5) the perceived risk of being substituted by the ALS, and (6) the possibility of ALS making unreliable or incorrect decisions.

The findings suggest that while Adaptive Learning Systems (ALS) are broadly perceived as valuable for enhancing teaching and learning, their successful adoption in higher education will require deliberate strategies to balance benefits with potential risks. For instance, addressing concerns regarding trust, reliability, and the evolving role of instructors indicate that institutional policies, faculty training, and pedagogical frameworks must be established to ensure transparency and facilitate smoother change management, thereby positioning ALS not as a substitute but as a complement to human-centered education.

During the initial phase of learning materials development, preliminary observations indicated that a learning architect leveraging GAI assistance achieved a threefold increase in the speed of producing adaptive learning materials for deployment on an Adaptive Learning System (ALS), compared to manual development without the support of a GAI engine. This finding has important implications for both practice and research. From a practical standpoint, a threefold increase in development speed demonstrates the potential of GAI to significantly reduce the time and cost associated with producing adaptive learning resources, thereby enabling faster scaling of ALS-based educational interventions.

From a research perspective, it highlights the transformative role of GAI in instructional design workflows but also calls for further investigation into whether such efficiency gains compromise content quality, contextual appropriateness, or pedagogical depth. For developing countries, and particularly in Africa where educational resources are often scarce and teaching capacity constrained, such efficiency gains could help bridge access gaps and expedite the large-scale delivery of high-quality, context-relevant learning materials, supported by human-in-the-loop processes.

Post-intervention Results

Post-intervention Attitude and Perception Survey Results

Following the completion of the online course, students maintained a moderately positive attitude and perception toward the ALS. A comparison of pre- and post-intervention results (see Tables 7 and 10) revealed a slight enhancement in student attitudes ($M = 3.40 \pm 1.14$) compared to pre-intervention levels ($M = 3.31 \pm 1.08$). This improvement appears to be largely driven by greater confidence in using the ALS, a stronger recognition of its learning opportunities, and reduced concerns regarding potential bias.

In contrast, students' reported perceptions of the ALS (Tables B1 and 11) showed a marginal decline following the intervention ($M = 3.36 \pm 1.08$ compared to $M = 3.40 \pm 1.08$). While students appreciated the greater sense of control over their own learning and expressed fewer concerns about technological overdependence and privacy issues, they reported lower levels of satisfaction with ease of understanding, ease of use, perceived learning outcome achievement, and the degree of customization to their individual needs.

Taken together, these findings suggest that while exposure to the ALS improved student confidence and trust, it also revealed few usability and personalization challenges that hindered perceptions of its overall effectiveness. This highlights the importance of iterative refinement in ALS design to ensure not only trust and engagement but also alignment with diverse learner needs, cognitive preferences, and expectations of usability.

Using the UDL framework (Meyer et al., 2014), the ALS succeeded in fostering inclusivity and learner autonomy but fell short in fully addressing diverse needs through continuous feedback. From a TAM perspective (Davis, 1989; Venkatesh & Bala, 2008), students perceived greater usefulness but lower ease of use, reflecting a common tension Technology adoption and diffusion.

When examined through Constructivism and Vygotsky's Zone of Proximal Development (ZPD) (1978), the ALS enhanced learner autonomy but may not consistently supported students within their optimal ZPD through fully personalized learning pathways, potentially limiting the depth of knowledge construction and engagement, highlighting the need for more adaptive user-centric designs.

The decline in perceptions of outcome achievement indicates partial misalignment in terms of Constructive Alignment (Biggs & Tang, 2011), while the reported UX challenges point to the need for stronger TPACK integration (Mishra & Koehler, 2016). Overall, the results highlight the importance of ensuring that ALS design is simultaneously inclusive, aligned, adaptive, and pedagogically coherent.

Post-intervention Learning Experiences Results

Usability (see Table 12). The mean ease of navigation score of 3.34 ± 1.06 indicates that students generally perceived the ALS as moderately easy to navigate, although the variability in responses suggests that some students experienced challenges. This highlights the need for further refinement to ensure a more uniformly positive navigation experience, especially that the platform was primarily optimized for desktop use. This result aligns with established usability frameworks, which emphasize that system effectiveness and user satisfaction are not experienced uniformly across all learners (Nielsen, 1994). Accordingly, refinements in interface design and navigation support may be necessary to achieve a more consistently positive experience.

The mean user interface intuitiveness core of 3.25 ± 1.06 indicates that students generally perceived the system as moderately intuitive. While the average response leaned slightly toward the positive side of the scale, the variability in responses suggests that a notable proportion of students experienced usability challenges. Within the framework of the Technology Acceptance Model (Davis, 1989; Venkatesh and Bala, 2008), perceived ease of use is a critical determinant of user acceptance and subsequent adoption of technology. These findings therefore highlight the need for further refinements in system design to enhance intuitiveness, thereby strengthening user acceptance and supporting broader integration of the ALS in educational contexts.

Out of 167 students, 44 (26%) reported experiencing frequent technical difficulties, 75 (45%) encountered technical issues occasionally, and 48 (29%) reported no difficulties while using the platform. These results indicate that a substantial majority of students (approximately

71%) faced some level of technical challenges, though for most, the issues were occasional rather than persistent. From a research perspective, this highlights that while the ALS platform is generally usable, technical reliability remains an important factor influencing student experience and engagement. Addressing these technical barriers could improve overall satisfaction and support more consistent adoption, particularly in line with usability principles and the Technology Acceptance Model, where perceived ease of use directly affects user acceptance.

*Content (see Table 13)***.** The content's relevance average score of 3.17 ± 1.10 suggests that, on average, students found the learning materials moderately relevant to their current level of knowledge. While the overall perception was positive, the variability in responses indicates that some students found the materials less aligned with their prior knowledge. Accordingly, ensuring that learning materials are closely aligned with students' knowledge levels may enhance motivation, facilitate deeper learning, and support broader adoption of the ALS platform.

The fact that 80% of students found the content to be well structured and helpful in better understanding the underlying concepts implies that the ALS effectively embodied principles of Constructive Alignment (Biggs & Tang, 2011). Further, the mean assessment's adequacy score of 3.30 ± 1.16 indicates that students generally perceived the course assessments as moderately well aligned with the knowledge and skills they acquired. Although the average response is positive, the variability suggests that some students found the assessments less representative of their learning. While Constructive Alignment (CA) approach (Biggs & Tang, 2011) emphasizes that learning activities, objectives, and assessments should be coherently aligned; variability in student perceptions seem to indicate potential misalignment for some learners. These findings suggest that refining assessment design to better match learning objectives could enhance student engagement, perceived relevance, and overall effectiveness of the ALS platform.

*Adaptive Experience (see Table 14)***.** The mean personalization score of 3.38 ± 0.99 suggests that students generally perceived the learning materials and activities as moderately personalized based on their performance. While the average response indicates a positive perception, the standard deviation reflects some variability among students, with a subset experiencing less personalization. These findings suggest that the adaptive learning system provided a generally responsive learning experience, but further refinement in tailoring content and activities to individual performance could enhance perceived personalization, engagement, and learning outcomes. From a Technology Acceptance Model (TAM) perspective (Davis, 1989; Venkatesh and Bala, 2008), increasing perceived usefulness through personalized learning experiences may strengthen students' acceptance and continued use of the platform.

The average score of 3.39 ± 1.08 related to the quality of the feedback received indicates that students generally perceived the learning materials and activities as moderately personalized based on their performance. This is also backed by the fact that 87% of the respondents reported that the platform adjusted the content to their individual pace and needs. While the average response of 3.39 reflects a positive perception, the standard deviation suggests some variability among students, with a subset experiencing less tailored learning experiences. These results highlight that the adaptive learning system largely provided a personalized learning environment, but further refinements, such as adaptive content adjustments or targeted activity recommendations, could enhance perceived personalization and engagement.

The mean interest score of 3.40 ± 1.12 indicates that students generally perceived the platform as moderately effective in increasing their interest in topics related to Sustainability, Work Ethics, and Gender Equity. While the average response reflects a positive trend, the standard deviation shows some variability, suggesting that a subset of students experienced little or no increase in interest. These findings highlight that the ALS platform was generally successful in engaging students with SDGs and ethical topics; though further enhancements, such as more interactive content or contextualized examples, could strengthen engagement for all learners.

The fact that 87% of students found that the ALS platform adjusted the content to match their individual learning pace indicates that the system operationalized UDL's call for personalized learning pathways, aligned with Constructivist and ZPD principles of scaffolding within learners' developmental levels, while also demonstrating the adaptive coherence between pedagogy, content, and technology emphasized in the TPACK framework.

Engagement and Motivation (see Table 15). The mean motivation score of 3.43 ± 1.15 indicates that students generally perceived the platform as moderately effective in increasing their motivation to learn more on topics related to Sustainability, Work Ethics, and Gender Equity. While the overall perception is positive, the standard deviation reflects variability among students, with some reporting minimal increase in interest. These results suggest that the ALS platform successfully engaged most students with socially responsible and ethical topics, though further enhancements, such as more interactive content, case studies, or real-world applications, could strengthen engagement for all learners.

Overall Experience (see Tables 16a – 16b). The mean satisfaction score of 3.46 ± 1.18 indicates that students were generally moderately satisfied with the ALS platform. While the average score reflects a positive perception, the standard deviation shows some variability in responses, suggesting that a portion of students experienced lower satisfaction. The Customer satisfaction (CSAT) score of around 60% further confirms that a majority of students reported a favorable experience with the platform, although there remains room for improvement. These findings suggest that while the ALS platform successfully met the expectations of many learners, enhancements in usability, content alignment, personalization, and engagement strategies could further increase overall satisfaction.

The mean recommendation score of 5.81 ± 2.69 on a scale of 10 suggests that students' willingness to recommend the adaptive learning platform for other courses was moderate, with notable variability across responses. The Net Promoter Score (NPS) of approximately –37, calculated from 18% promoters and 55% detractors, indicates a predominance of students who were hesitant or unlikely to recommend the platform. While some students perceived the platform positively, the high proportion of detractors highlights that many learners experienced limitations, potentially related to usability, engagement, content alignment, or perceived relevance, that reduced their overall enthusiasm. From a TAM (Davis, 1989; Venkatesh and Bala, 2008) perspective, this outcome underscores the importance of enhancing perceived usefulness and ease of use to increase adoption. These findings suggest that, although the ALS platform shows potential, targeted improvements in personalization, interactivity, and alignment with course objectives are necessary to foster stronger student endorsement and sustained use across multiple courses.

Students' Qualitative Feedback

The students' feedback highlights critical areas for improving the ALS, particularly regarding platform usability, responsiveness, ease of navigation, contextual relevance, and engagement features. Issues such as navigation difficulties, limited screen flexibility, and lack of interactive multimodal elements underscore challenges in perceived ease of use, consistent with TAM (Davis, 1989; Venkatesh & Bala, 2008). Concerns about the content's applicability to local contexts reflect the need to further embed UDL principles (Meyer et al., 2014) and constructivist/ZPD frameworks (Vygotsky, 1978) to provide more personalized, culturally relevant learning pathways. For example, one student noted that creating content contextualized to Africa as a whole is challenging due to the continent's cultural diversity, suggesting that the ALS should incorporate more granular adaptation by considering the learner's country-specific cultural context.

The nearly 59% reduction in required time for students to achieve 100% proficiency, compared to the traditional non-ALS delivery format, underscores the transformative potential of ALS to enhance instructional efficiency while ensuring mastery of content. Such time compression has important pedagogical and institutional implications. At the learner level, it allows students to achieve proficiency at their own pace while freeing time for deeper engagement with other added-value activities that are often sidelined in content-heavy curricula. At the institutional level, efficiency gain translates into increased instructional capacity, enabling universities to serve larger cohorts without proportional increases in faculty workload or infrastructure costs. In resource-constrained contexts such as Africa, where access and scalability are key challenges, ALS could significantly democratize access to quality education on a large scale. Nevertheless, these proclaimed efficiency benefits must be carefully balanced with safeguarding learners' absorption capacity and the quality of learning experiences, ensuring reflective engagement, and maintaining meaningful student–instructor interactions.

SMEs Qualitative Feedback

The SMEs provided useful insights pertaining to the quality of learning materials produced by the AI generative engine. Despite extensive prompt adjustments, the output was assessed as only partially meeting the requirements of the diverse student profiles (undergraduate and postgraduate) targeted by the course. SMEs highlighted that the materials lacked sufficient depth and academic rigor, particularly for MBA-level learners. This underscores that the solitary use of an AI generative engine is inadequate for producing unique, high-quality content on SDGs in Africa that is both pedagogically robust and appropriately differentiated for varied student cohorts. While the AI engine significantly outperforms human designers in efficiency by rapidly generating large volumes of content, SME intervention remains indispensable for elevating the material to a level of scholarly and contextual relevance. The SMEs have also raised the issue of potential AI's cultural and contextual blind spots, suggesting that to avoid epistemic biases and reinforce inclusive pedagogy (Meyer et al., 2014), ALS must integrate HITL approaches where SMEs embed contextual depth and cultural relevance into AI-generated outputs, ensuring that African perspectives are authentically represented.

These findings are aligned with the Human–Machine Augmented Intelligence (HMAI) paradigm, which emphasizes the symbiotic collaboration between human expertise and machine efficiency to achieve outcomes superior to those of either agent working alone (Xue et al., 2022). The process also aligns with the Human-in-the-Loop (HITL) approach (Boy & Gruber, 1990), where human oversight, judgment, and contextual knowledge remain central to ensuring the accuracy, trustworthiness, and pedagogical rigor of AI-generated content. Such intervention requires SMEs not merely to validate and refine AI-generated outputs but also to actively co-create content with the AI system, ensuring intellectual depth, contextual sensitivity, and alignment with African realities.

The implication of these findings is that the sustainable adoption of ALS and generative AI in higher education must be anchored in HMAI and HITL principles. Institutions should view AI not as a replacement for human expertise but as an augmentation tool that accelerates production, personalization, and scalability, while faculty and subject experts ensure academic rigor, cultural relevance, and ethical integrity. Such a human–AI partnership offers a viable pathway toward innovation in education that is both efficient and contextually grounded. This observation carries critical implications for higher education in developing regions. While generative AI can mitigate resource constraints and accelerate content production, overreliance on it without substantive SME co-creation risks producing superficial or misaligned learning materials. In the African context, where contextualization of SDGs, ethics, and sustainability is central to educational transformation, human expertise must remain central to content development. The findings therefore support a hybrid model of human-AI collaboration, in which AI enhances efficiency and scalability while SMEs ensure quality, contextual relevance, and pedagogical depth. Theoretically, this contributes to emerging models of human–AI collaboration in instructional design, highlighting that optimal learning outcomes in diverse and complex educational contexts depend on the complementary strengths of AI and expert human intervention.

Faculty Qualitative Feedback

The faculty feedback echoes that of the SMEs and reinforces a nuanced perspective on the role of AI in educational content creation, particularly in the African context. While recognizing AI's efficiency in generating structured, accessible, and visually supported content, the faculty emphasized the persistent need for human expertise to ensure depth, contextual sensitivity, and credibility. This finding aligns with the HITL approach (Boy & Gruber, 1990) and the HMAI paradigm (Xue et al., 2022). Concerns about repetitiveness and insufficient depth also highlight the importance of constructive alignment (Biggs & Tang, 2011), whereby course objectives, learning activities, and assessments must be aligned through thoughtful human oversight rather than automated content generation alone.

Conclusion

This chapter presented a pilot study initiated by Honoris Online Academy focusing on the conception, design, and implementation of an Adaptive Learning System (ALS) for a self-paced online course on SDGs, DE&I, and work ethics, tailored to the African continent. The course was delivered through two AI-driven applications: the first leveraged a Generative AI engine built on a proprietary Large Language Model (LLM) to curate relevant learning materials for each nano-learning objective, while the second delivered the course adaptively, personalizing each learner's pathway based on individual pace, progress, and comprehension. A pre- and post-intervention empirical study was conducted to examine students' and faculty's attitudes and perceptions and to collect feedback from intervening SMEs and faculty, which will guide the development of the next version of the ALS.

Our findings suggest that the ALS can significantly enhance learning experiences by increasing learner engagement, promoting autonomy, and supporting individualized knowledge construction. Students and faculty reported generally positive attitudes toward the system, though challenges were noted in usability, contextualization, and content depth, highlighting the ongoing need for expert intervention and iterative system refinement. Nonetheless, several limitations must be acknowledged: the study involved a single course, with a relatively small sample of learners and faculty, limiting the generalizability of the results; the empirical findings are context-bound to the HUU pilot and may not capture all variability across disciplines or cultural settings; and the ALS and LLMs are rooted in evolving AI algorithms and technologies, with ongoing updates expected to enhance functionality, performance, and accuracy. As a future research direction, it would be interesting to use a quasi-experimental design with control and treatment groups across multiple institutions to compare the performance and engagement levels of students exposed to an ALS with those exposed to traditional teaching methods.

Despite these limitations, the pilot demonstrates the potential of ALS to impact a broader learner population. Thousands of students across the Honoris United Universities (HUU) network are expected to benefit from this evolving system, and at least one member institution has already made completion of the ALS-based course compulsory for graduation. These developments signal that, with continuous refinement and integration of Human-in-the-Loop and Human–Machine Augmented Intelligence principles, ALS can serve as a scalable, pedagogically robust, and culturally responsive solution to support quality education across diverse contexts.

Recommendations

GAI and ALS hold a significant promise to transform the landscape of higher education in Africa by fostering scalable quality education. Both are perceived as beacons of hope to democratize access to quality education in Africa. However, there is a significant work to be done to facilitate the integration of ALS in the realm of African higher education. Based on the findings from this pilot study, several recommendations can be proposed to enhance the effectiveness, scalability, and adoption of the ALS:

- Maintain a Human-in-the-Loop (HITL) Approach: Generative AI alone cannot ensure depth, contextual relevance, or pedagogical rigor, particularly for culturally sensitive or advanced topics such as work ethics and gender equity in Africa. SMEs and faculty should remain actively involved in validating, enriching, and co-creating content to ensure alignment with learning objectives, cultural context, and academic standards, consistent with the principles of Human–Machine Augmented Intelligence (HMAI) (Xue et al., 2022) and HITL (Boy & Gruber, 1990).

- Enhance Contextual Adaptation and Personalization: The learning material should incorporate more granular adaptation that accounts for country-specific cultural backgrounds and individual learner contexts, aligning with Universal Design for Learning (UDL) principles (Meyer et al., 2014) and constructivist/ZPD frameworks (Vygotsky, 1978). This would increase relevance, learner engagement, and comprehension while supporting autonomous knowledge construction.
- Improve Usability and Interactive Features: Students reported difficulties with navigation, screen layout, and lack of interactivity. Future iterations should address these usability issues and incorporate more engaging multimedia and interactive elements, guided by TPACK-informed design (Mishra & Koehler, 2016), to enhance learner motivation and perceived ease of use (TAM; Davis, 1989; Venkatesh & Bala, 2008). In particular, ALS should be optimized for mobile devices usage given their high penetration rate in Africa.
- Align the GAI Output with Constructive Alignment Principles: To ensure that ALS-generated materials effectively support intended learning outcomes, teaching activities, and assessment tasks, continued alignment is necessary. Human oversight should focus on refining content to meet the depth and complexity required for advanced learners (Biggs & Tang, 2011).
- Adopt a Tiered Implementation Strategy: Introductory courses or general content may rely more heavily on AI-generated materials, while advanced or sensitive topics should involve increased human intervention. This approach balances efficiency with academic rigor and supports the incremental scaling of ALS across the HUU network.
- Continuous Monitoring and Iterative Improvement: Feedback loops involving learners, faculty, and SMEs should be maintained to iteratively refine the ALS, ensuring that it evolves with pedagogical advances, technological improvements, and the diverse needs of learners.
- Institutional Integration and Policy Support: To maximize impact, ALS-based courses should be formally embedded into curricula, accompanied by structured training for both students and faculty to facilitate effective adoption. Strategic integration will enhance accessibility, promote sustainable use, and ensure alignment with institutional learning objectives. In addition, robust policies should be implemented to safeguard the confidentiality and security of learner data, addressing privacy concerns reported in the pilot study.

- Contextualization for African Settings, Including Rural Areas: To accommodate infrastructural limitations such as low Internet speeds, the ALS should ideally support offline access and low-bandwidth scenarios, for example through downloadable content and lightweight multimedia. Tailoring the system to local conditions will improve usability, inclusivity, and equitable access to learning opportunities across diverse regions. Additionally, the adoption of open-source platforms and scalable cloud-based solutions can reduce infrastructure costs and enable broader deployment while maintaining quality and sustainability.

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Appendices

Appendix A

Demographic Characteristics

Student Demographic

Table A1. Demographic Characteristics of Sample Student Respondents (*n*=1161)

Demographic variable	Frequency (*n*)	Percentage (%)	p value*
Gender:			0.000
Male	537	46.3	
Female	624	53.7	
Age:			0.000
18-22	741	63.8	
23-25	345	29.7	
> 25	75	6.5	
Level of Study:			0.000
Bachelor	861	74.1	
Master	300	25.8	
Nationality			0.000
Tunisian	1122	96.6	
Other	39	3.4	

* *χ-square test for goodness of fit. (Significance level p <0.05)*

Table A2. Demographic Characteristics of Sample Faculty Respondents (*n*=58)

Demographic variable	Frequency (*n*)	Percentage (%)	p value*
Gender:			0.000
Male	12	20.7	
Female	46	79.3	
University rank:			0.000
Lecturer	15	25.9	
Assistant professor	37	63.8	
Associate professor	4	6.8	
Full professor	2	3.4	
Working experience:			0.000

Demographic variable	Frequency (n)	Percentage (%)	p value*
< 2 years	29	50	
2-4 years	15	25.9	
> 4 years	14	24.1	
Experience with Online Learning Platforms:			0.000
< 2 years	17	29.3	
2-4 years	23	39.7	
> 4 years	18	31	

** χ-square test for goodness of fit. (Significance level $p < 0.05$)*

Appendix B

Table B1. Student Perception towards Adaptive Learning Systems (*N*=1161)

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	Sdev*
P1. Using Adaptive Learning Systems would enhance my learning outcomes more effectively than traditional LMS	277 23.9%	454 39.1%	306 26.4%	81 7%	43 3.7%	3.72	1.02
P2. Using Adaptive Learning Systems would make it easier for me to understand complex topics	259 22.3%	530 45.7%	256 22%	90 7.8%	26 2.2%	3.78	0.95
P3. I believe Adaptive learning Systems would enhance my academic performance	217 18.7%	455 39.2%	367 31.6%	90 7.8%	32 2.8%	3.63	0.96
P4. Adaptive learning systems would provide me more control of my own learning	149 12.8%	482 41.5%	392 33.8%	99 8.5%	39 3.4%	3.52	0.94
P5. I fear that using adaptive learning systems might negatively impact my academic progress	113 9.7%	244 21%	368 31.7%	312 26.9%	124 10.7%	2.92	1.14
P6. I believe Adaptive Learning Systems would be easy to navigate to use	171 14.7%	483 41.6%	382 32.9%	91 7.8%	34 2.9%	3.57	0.93
P7. I expect Adaptive learning systems to provide reliable learning material	170 14.6%	437 37.6%	434 37.4%	82 7.1%	38 3.3%	3.53	0.94
P8. I expect Adaptive Learning systems to provide me a wide range of learning materials tailored to my unique needs	173 14.9%	459 39.5%	391 33.7%	98 8.4%	40 3.4%	3.54	0.96
P9. I am concerned about potential technical issues when using adaptive learning systems	158 13.6%	433 37.3%	421 36.3%	91 7.8%	58 5%	3.47	0.99

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	Sdev*
P10. I worry that my personal information might be at risk when interacting with adaptive learning systems	185 15.9%	312 26.9%	399 34.4%	182 15.7%	83 7.1%	3.29	1.13
P11. Using adaptive learning systems would be more challenging than using a traditional online LMS	194 16.7%	384 33.1%	375 32.3%	137 11.8%	71 6.1%	3.42	1.09
P12. The user interface of adaptive learning systems is important for me for an effective learning experience	228 19.6%	413 35.6%	368 31.7%	103 8.9%	49 4.2%	3.58	1.03
P13. Adaptive learning systems would increase my motivation for learning	204 17.6%	367 31.6%	433 37.3%	93 8%	64 5.5%	3.48	1.04
P14. I am afraid that adaptive learning systems would make me overdependent on technologies	135 11.6%	294 25.3%	433 37.3%	192 16.5%	107 9.2%	3.14	1.11
P15. I am concerned about the privacy issues due to the collection of personal data	190 16.4%	364 31.4%	380 32.7%	165 14.2%	62 5.3%	3.39	1.08

** Greyed cells convey negative perception statements*

*** SA: Strongly Agree, A: Agree, N: Neutral, D: Disagree; SD: Strongly Disagree. SDev: Standard deviation*

Table B2. Faculty Perception Towards Adaptive Learning Systems (*N*=58)

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*
P1. Using Adaptive Learning Systems would enhance students' learning outcomes more effectively than traditional LMS	17 29.3%	30 51.7%	9 15.5%	2 3.4%	--	4.07	0.76
P2. Using Generative AI, coupled to adaptive learning systems would help me create	26 44.8%	25 43.1%	6 10.3%	1 1.7%	--	4.31	0.72

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*
teaching material more effectively							
P3. Using Adaptive learning systems would help me better tailor teaching material and assessment instruments to students 'need	17 29.3%	33 56.9%	7 12.1%	1 1.7%	--	4.14	0.68
P4. Adaptive learning systems would provide students more control of their own learning	13 22.4%	33 56.9%	8 13.8%	4 6.9%	--	3.95	0.80
P5. I anticipate that learning to use adaptive learning systems would be straightforward to me	9 15.5%	30 51.7%	15 25.9%	4 6.9%	--	3.76	0.79
P6. I expect that Adaptive Learning Systems would fit well with my current teaching and assessment educational practices	10 17.2%	32 55.2%	15 25.9%	1 1.7%	--	3.88	0.70
P7. The opinions of colleagues I respect would influence my decision to use adaptive learning systems	6 10.3%	15 25.9%	24 41.4%	8 13.8%	5 8.6%	3.16	1.06
P8. I worry that using adaptive learning systems might require significant changes in my teaching and assessment approaches	2 3.4%	20 34.5%	16 27.6%	18 31%	2 3.4%	3.03	0.96
P9. I am concerned about potential technical issues when implementing adaptive learning systems	5 8.6%	28 48.3%	16 27.6%	8 13.8%	1 1.7%	3.48	0.90
P10. I expect adaptive learning systems to provide robust and	7 12.1%	42 72.4%	7 12.1%	2 3.4%	--	3.93	0.61

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*
reliable tools for **teaching** purposes							
P11. I expect the adaptive learning systems to provide robust and reliable tools for **assessment** purposes	9 15.5%	36 62.1%	10 17.2%	3 5.2%	--	3.88	0.72
P12. I except the adaptive learning systems to help me better track individual student progress	15 25.9%	32 55.2%	7 12.1%	3 5.2%	1 1.7%	3.98	0.86
P13. The user interface of adaptive learning systems is important for me than using a traditional LMS	15 25.9%	31 53.4%	10 17.2%	1 1.7%	1 1.7%	4.00	0.81
P14. Using adaptive learning systems would be more challenging for me than using a traditional LMS	12 20.7%	24 41.4%	11 19%	11 19%	--	3.64	1.01
P15. Using adaptive learning systems would discourage contact between myself and the students	3 5.2%	9 15.5%	21 36.2%	20 34.5%	5 8.6%	2.74	0.99
P16.Using Adaptive learning systems would diminish my role as an instructor	5 8.6%	10 17.2%	15 25.9%	18 31%	10 17.2%	2.69	1.19
P17. I do not trust the AI Algorithms behind adaptive learning systems	2 3.4%	12 20.7%	19 32.8%	18 31%	7 12.1%	2.72	1.03
P18. I am afraid that adaptive learning systems would make students overdependent on technologies	9 15.5%	27 46.6%	9 15.5%	9 15.5%	4 6.9%	3.48	1.13

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*
P19. I worry that adaptive learning systems might require a significant investment of time and efforts	6 10.3%	25 43.1%	16 27.6%	9 15.5%	2 3.4%	3.41	0.98
P20. I am concerned about losing control over course content with the adoption of adaptive learning systems	4 6.9%	14 24.1%	14 24.1%	17 29.3%	9 15.5%	2.78	1.18
P21. I am concerned that adaptive learning systems might discourage students from seeking help from their instructions	4 6.9%	22 37.9%	11 19%	18 31%	3 5.2%	3.10	1.08
P22. I am concerned that adaptive learning systems might compromise the quality of student instructor interactions	1 1.7%	26 44.8%	14 24.1%	16 27.6%	1 1.7%	3.17	0.91
P23. I worry that adaptive learning systems might not accommodate diverse learning styles and needs	1 1.7%	17 29.3%	23 39.7%	16 27.6%	1 1.7%	3.02	0.84
P24. I am afraid that adaptive learning systems would substitute instructors in future	3 5.2%	18 31%	18 31%	13 22.4%	6 10.3%	2.98	1.07
P25. I am concerned about the potential privacy issues due to the collection of students' data	5 8.6%	20 34.5%	24 41.4%	5 8.6%	4 6.9%	3.29	0.98
P26. I am concerned that evaluating the effectiveness of adaptive systems might be challenging	4 6.9%	34 58.6%	15 25.9%	4 6.9%	1 1.7%	3.62	0.78
P27. I am concerned about the	4	26	19	8	1	3.41	0.87

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*
accuracy and reliability of adaptive learning systems assessments and recommendations	6.9%	44.8%	32.8%	13.8%	1.7%		
P28. I expect that Adaptive Learning Systems will save me time	11 19%	34 58.6%	10 17.2%	3 5.2%	--	3.91	0.75
P29. I consider the usage of adaptive learning systems for tracking and profiling students might be considered discriminatory and unethical	3 5.2%	12 20.7%	24 41.4%	15 25.9%	4 6.9%	2.91	0.97

** Greyed cells convey negative perception statements*

*** SA: Strongly Agree, A: Agree, N: Neutral, D: Disagree; SD: Strongly Disagree. SDev: Standard deviation*

Appendix C

Table C1. Association Between Students' Demographic Information and their KAP towards ALS (*N*=1161)

Demographic variable		**Knowledge**			**Attitude**			**Perception**		
		Mean	**SDev**	**p-value***	**Mean**	**SDev**	**p-value***	**Mean**	**SDev**	**p-value***
Gender	Male	2.2	1.423	0.004	3.1	1.190	0.001	3.2	1.020	0.004
	Female	2.1	1.421		3.2	1.188		3.1	1.015	
Age	18-22	2.9	1.328	0.000	3.3	1.189	0.000	3.1	1.011	0.000
	23-25	2.1	1.421		2.9	1.181		3.2	1.013	
	> 25	2.3	1.333		2.9	1.189		3.2	1.011	
Field of Study	Level	--	--		--	--	--	--	--	
	Bachelor	2.2	1.111	0.001	3.1	1.187	0.000	3.3	1.015	0.002
	Master	2.1	1.567		3.2	1.190		3.2	1.011	
Year of Study	1	2.3	1.421	0.000	3.3	1.191	0.000	3.1	1.010	0.001
	2	2.1	1.324		3.2	1.193		3.2	1.007	
	3	2.4	1.322		3.1	1.889		3.1	1.015	
Nationality	Tunisian	2.5	1.420	0.001	3.1	1.187	0.000	3.1	1.016	0.000
	Other	2.1	1.399		3.2	1.886		3.2	1.011	

** Independent t-test ($p<0.05$ is considered statistically significant to confirm the impact of the demographic variable on the domain)*

Table C2. Association Between Faculty Demographic Information and their KAP towards ALS (*n*=58)

Demographic variable		**Knowledge**			**Attitude**			**Perception**		
		Mean	**SD**	**p-value* intergroup**	**Mean**	**SD**	**p-value* intergroup**	**Mean**	**SD**	**p-value* intergroup**
Gender	Male	3.3	1.980	0.477	3.8	0.845	0.322	3.3	0.920	0.330
	Female	3.2	0.982		3.9	0.843		3.2	0.910	
University rank	Lecturer	3.1	1.322	0.002	3.8	0.856	0.003	3.4	0.899	0.000
	Assistant professor	3.2	1.298		3.9	0.801		3.2	0.911	

	Associate professor	3.1	0.988		4	0.837		3.3	0.889	
	Full professor	3	0.989		3.8	0.867		3	0.910	
Working experience	< 2 years	3	0.988		3.8	0.846		3.2	0.990	
	2-4 years	3.1	0.979	0.132	3.9	0.843	0.040	3.1	0.991	0.000
	> 4 years	3	1.287		4	0.844		3.00	0.899	

** Independent t-test (p<0.05 is considered statistically significant to confirm the impact of the demographic variable on the domain)*

Appendix D

Demographic Characteristics (Post-intervention Surveys)

Table D1. Demographic Characteristics of Participating Students (*N*=215)

Demographic variable	Frequency (*n*)	Percentage (%)
Gender:		
Male	95	44.2
Female	120	55.8
Age:		
18-22	94	43.7
23-25	28	13
> 25	93	43.3
Field of study:		
Management/Business	45	20.9
Engineering/IT	155	72.1
Health Sciences	2	0.9
Law	1	0.5
Architecture	4	1.9
Communication	8	3.7
Institution:		
EMSI (Morocco)	18	8.4
ESPRIT School of Engineering (Tunisia)	115	53.5
ESPRIT School of Business (Tunisia)	18	8.4
Nile University (Nigeria)	32	14.9
Université Centrale (Tunisia)	32	14.9
Nationality:		
Tunisian	155	72.1
Moroccan	18	8.4
Nigerian	32	14.9
Others	10	4.6

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Chapter 3 - Generative AI-Supported Personalized Learning: A Systematic Mapping Analysis

Abdullah Yasin Gunduz

Chapter Highlights

- This study represents the first systematic mapping analysis conducted in the field of generative artificial intelligence-supported personalized learning that emerged following the release of ChatGPT in 2022, comprehensively revealing the early developmental characteristics of the field.
- Research findings demonstrate that, unlike traditional technology leadership patterns, China and India share equal leadership positions in the field, indicating the growing influence of the Asia-Pacific region in the global educational technology ecosystem.
- The intellectual foundations of the field have been found to develop in a balanced manner across three axes: pedagogical applications, technical approaches, and conceptual frameworks, with this distribution reflecting an education-focused perspective rather than technological determinism.
- The exponential growth trend, increasing from 5 publications in 2023 to 33 publications in 2025, has been analyzed, showing that the field is rapidly emerging from its pre-paradigmatic phase and beginning to consolidate.

Introduction

The importance of personalized learning in education has steadily increased over the past twenty years and has begun to occupy a central position in modern pedagogical approaches. Research has demonstrated that traditional one-dimensional educational approaches fail to adequately respond to students' cognitive capacities, motivational characteristics, and prior knowledge levels (Peng et al., 2019; Xie et al., 2019). This situation has been observed to have negative effects on student achievement, motivation, and educational satisfaction. The idea that individual differences should be considered in the educational process rests on a broad theoretical foundation extending from Dewey's student-centered educational philosophy to Gardner's theory of multiple intelligences.

Applications of artificial intelligence technologies in education have shown significant developments, particularly over the past fifteen years. First-generation intelligent tutoring systems began to be developed in the 1970s and gradually evolved into more sophisticated adaptive learning platforms (Sleeman & Brown, 1982; VanLehn, 2011). These systems achieved successful results in monitoring student performance, identifying learning difficulties, and making basic adaptations. With the development of machine learning algorithms and the widespread adoption of big data analytics, a new era has begun in educational technologies. The field of learning analytics emerged with the aim of making sense of large amounts of data obtained from student behaviors and improving educational processes, strengthening the theoretical and practical foundations of technology-supported applications of personalized learning.

Recently emerged generative artificial intelligence technologies are creating paradigmatic changes in educational personalization. Large language models built on Transformer architecture, in particular, offer revolutionary opportunities in education through their natural language understanding and generation capabilities (Vaswani et al., 2017; Brown et al., 2020). The widespread use of models such as ChatGPT, Claude, Gemini, and similar systems in the education sector requires a fundamental re-evaluation of traditional adaptive learning approaches. These technologies enable the transition from static content presentation to dynamic interactive learning experiences, possessing the capacity to provide real-time responses to student questions, explain complex concepts at different levels, generate various learning materials, and create individual learning paths.

With the release of ChatGPT in November 2022 and the widespread adoption of similar generative artificial intelligence models, a new research period has begun in the field of educational personalization. Considering the emerging nature of this field, it is observed that scientific production is still in a pre-paradigmatic phase, with researchers attempting to define the epistemological foundations of the field. The systematic mapping of pioneering studies in this new field is critically important for understanding the early developmental stages of the field and determining future research orientations.

In this context, it is necessary to examine existing research in the field of generative AI-supported personalized learning through systematic mapping methodology and analyze the scientific development process of the field. Although the field does not possess the large datasets required by traditional bibliometric analyses due to its novelty, existing pioneering studies allow understanding of the early developmental stages and research focuses of the field. The aim of this study is to contribute to the literature through mapping pioneering studies, identifying research trends, and evaluating the future development potential of the field.

Conceptual Framework

In this study, the terms 'personalized learning' and 'adaptive learning' are consciously distinguished. While personalized learning refers to shaping the learning experience according to students' individual needs, preferences, and goals (UNESCO, 2023), adaptive learning encompasses more system-focused automatic content and difficulty level adjustments based on student performance (Brusilovsky, 2001). Although generative artificial intelligence technologies support both approaches, they offer broader opportunities particularly for personalized learning.

Theoretical Foundations of Personalized Learning

The concept of personalized learning is a paradigm with deep theoretical roots in the field of education. The philosophical foundations of this approach can be traced to John Dewey's experiential learning theory and student-centered educational philosophy (Dewey, 1897). Dewey advocated that education should be shaped according to each individual's unique experiences and interests, and this view formed the philosophical foundation of personalized learning. Developments in cognitive psychology have significantly strengthened the scientific foundations of individualized learning.

Piaget's theory of cognitive development revealed that students possess different learning capacities at different developmental stages, and this finding has gained an important place in the theoretical foundations of personalized learning approaches (Piaget, 1952). Similarly, Vygotsky's concept of the zone of proximal development holds critical importance in the theoretical framework of personalized learning (Vygotsky, 1978). This concept proposes that the gap between what a student can do independently and what they can do under guidance should be identified, and instruction should focus on this range.

Gardner's theory of multiple intelligences has significantly influenced the pedagogical foundations of individualized learning approaches (Gardner, 1983). This theory argues that the concept of intelligence is not one-dimensional and that individuals possess different capacities in different intelligence domains, emphasizing the need for diversification of instructional strategies and content presentation. Bloom's mastery learning model holds critical importance in the implementation of personalized learning (Bloom, 1968). This model advocates that all students can achieve high levels of learning success with appropriate time and support, based on the principles of individualizing learning pace, conducting continuous assessment, and providing corrective feedback.

Development of Adaptive Learning Systems

Adaptive learning systems represent a technological field that has progressed parallel to the development of computer-assisted education. The first intelligent tutoring systems began to be developed in the 1970s and gradually gained more complex adaptation mechanisms. The Scholar system stands among pioneering studies as one of the first intelligent tutoring systems capable of answering student questions in the field of history, regarding the representation of domain knowledge and adaptation to student interactions (Carbonell, 1970). These early systems represent important developments that laid the foundations for today's sophisticated adaptive platforms.

The fundamental components of adaptive learning systems have been systematically defined by Brusilovsky, with these components examined in three main categories: student model, domain model, and pedagogical model (Brusilovsky, 2001). The student model contains information about the student's knowledge level, learning preferences, performance history, and cognitive characteristics. The domain model defines the structure of the subject to be taught, relationships between concepts, and learning sequence, while the pedagogical model determines instructional strategies and adaptation rules. Traditional adaptive systems typically use rule-based approaches and predefined scenarios, with adaptation occurring through adjusting content difficulty based on student performance, presenting alternative explanations, or providing additional exercises.

Significant developments have been recorded in the field of student modeling. The overlay model represents student knowledge as a subset of expert knowledge (Carr & Goldstein, 1977), while the perturbation model systematically categorizes student errors to model misconceptions (Brown & Burton, 1978). More advanced approaches have enabled the modeling of student knowledge along with uncertainties using Bayesian networks and probability theory, and the use of these techniques has significantly increased the capacities of adaptive systems (Conati et al., 2002).

Generative Artificial Intelligence and Its Potential in Education

Generative artificial intelligence refers to machine learning systems that can produce new and original content by learning from existing data. Applications of these technologies in the field of education offer a wide spectrum and possess the potential to significantly transform traditional adaptive learning approaches (Rudolph et al., 2023). Particularly, technological breakthroughs experienced in the post-2020 period have made this potential even more evident.

Transformer architecture has created paradigmatic changes especially in the field of natural language processing and has fundamentally affected the developmental trajectory of educational technologies (Vaswani et al., 2017). The attention mechanism underlying this architecture has enabled the modeling of complex relationships in long texts, allowing GPT series, BERT, and similar models to exhibit near-human performance in natural language understanding and generation (Rogers et al., 2020). These developments have created unprecedented opportunities for personalization in education.

Large language models offer revolutionary opportunities for personalization in education. These models possess the capacity to provide instant and contextually appropriate responses to student questions, explain complex topics at different levels, generate various learning materials, and adapt content according to student needs (Kasneci et al., 2023). Models such as ChatGPT, Claude, and Gemini can establish human-like interactions through their complex structures containing billions of parameters and can simultaneously assume the roles of tutor, mentor, and content producer in learning processes.

Multimodal artificial intelligence systems can create richer and more multi-dimensional learning experiences by integrating different data types such as text, image, audio, and video. Image generation models such as DALL-E and Midjourney, along with visual understanding models such as GPT-4V, offer important opportunities for diversifying educational content and addressing different learning styles (OpenAI, 2023). Prompt engineering and fine-tuning techniques are used to adapt general-purpose models to specific educational tasks and provide more effective personalization. Through these approaches, models specialized for mathematics instruction can provide step-by-step solution processes and detect student errors to provide corrective feedback.

Following this comprehensive theoretical and technological infrastructure examination, it emerges that the field of generative AI-supported personalized learning has a multi-dimensional and rapidly developing character. Although the field is still in its early developmental stage, systematic mapping of existing knowledge accumulation and technological possibilities holds critical importance for determining future research orientations. In this context, adopting a systematic approach to analyze the current state and developmental trends of the field is necessary.

The primary aim of this systematic mapping study is to analyze research trends in the field of generative AI-supported personalized learning in depth. Considering the developing character of the field and the limited volume of existing literature, an approach of mapping pioneering studies and identifying early-period research trends has been adopted. The research questions formulated in this context are as follows:

RQ1: What are the temporal distribution and growth trends of scientific publications in the field of generative AI-supported personalized learning?

RQ2: Which authors, institutions, and countries play pioneering roles in this field?

RQ3: What are the fundamental studies referenced in research, and how do they constitute the intellectual foundations of the field?
RQ4: Based on keyword analyses, what are the dominant themes and conceptual focuses in the field?
RQ5: What is the distribution of methodological approaches adopted in existing research?

Methodology

Research Design

This study adopts a systematic mapping approach to systematically map existing research in the field of generative AI-supported personalized learning. Systematic mapping represents a methodological framework developed by Arksey and O'Malley (2005) and refined by Grant and Booth (2009), specifically used to assess the state of knowledge in developing research areas, identify research gaps, and determine priority areas for future studies. This approach envisions comprehensive analysis of existing studies and descriptive mapping of research trends rather than statistical approaches based on large datasets characteristic of traditional bibliometric analyses.

Due to the developing character of the field and the still limited research activity that emerged following the release of ChatGPT in 2022, sufficient data volume has not been reached for traditional bibliometric analyses. This situation makes the approach of systematic mapping of pioneering studies and identification of early-period research trends more appropriate. The methodological framework has been designed in accordance with systematic review principles proposed by Petticrew and Roberts (2006), adopting a pragmatist epistemological foundation that combines objective measurement approaches with thematic analysis techniques (Tashakkori & Teddlie, 2010).

Data Sources and Search Strategy

Three main academic databases were used to conduct a comprehensive literature review. Database selection was performed in accordance with the multi-database approach proposed by Gusenbauer and Haddaway (2020), considering the different strengths and coverage areas of each. Web of Science Core Collection was preferred due to its selective approach covering high impact factor journals and strong citation analysis tools. The structure of this database that prioritizes prestigious publications holds critical importance for identifying the most significant studies in the field (Falagas et al., 2008).

The Scopus database is known for its broader coverage and was selected particularly because it includes conference proceedings and multidisciplinary publications. It plays an important role in capturing publications at the intersection of educational technologies and artificial intelligence fields. ERIC (Education Resources Information Center) is a database specifically designed for educational research and was included in the study to identify publications covering the pedagogical dimensions of the field. The education-focused structure of this database enables the capture of educational scientific perspectives on the topic.

Optimized search queries were developed for each database, considering terminological variations. The basic query used in Web of Science was as follows: TI=(("personalized learning" OR "personalised learning" OR "adaptive learning") AND ("generative AI" OR "large language model" OR "ChatGPT" OR "GPT-4")). In Scopus, searching was conducted in the TITLE field with a similar approach, and wildcard characters were used to capture term variations. In ERIC, a more simplified query was applied in accordance with the database structure. The use of only the title field in the search strategy was considered a conscious choice due to the novelty of the field and the terminology not being fully standardized yet. This approach aims for high precision in accordance with sensitive search strategy principles emphasized by Booth et al. (2012).

Inclusion and Exclusion Criteria

Systematic inclusion and exclusion criteria were established to clarify the scope and boundaries of the study. Inclusion criteria were determined as the presence of specified key terms in the title, publication in English language, and being peer-reviewed journal articles or conference proceedings. Time limitation was maintained between 2020-2025, with this range selection considering the period when generative AI technologies began to become visible in the educational field.

Exclusion criteria were defined comprehensively and encompassed review articles, book chapters, thesis studies, editorial-type publications, and studies with inaccessible full texts. The inclusion of conference proceedings in the study is justified by the rapidly developing nature of artificial intelligence and educational technology fields. In these fields, researchers primarily present their current findings at prestigious conferences, and the scientific value of these proceedings is considered equivalent to journal articles (Freyne et al., 2010). Particularly, conferences such as AIED, ICML, NeurIPS, and LAK host pioneering studies in the field.

Data Collection Process

The systematic data collection process was conducted step by step according to a predetermined protocol. In the initial screening phase, 25 results were obtained from Web of Science, 78 from Scopus, and 9 from ERIC, providing access to a total of 112 publications. The literature review was completed on August 31, 2025, with data for 2025 covering the first eight months of the year. Results obtained from each database were systematically examined, and the screening process was conducted according to predetermined inclusion and exclusion criteria. At this stage, 2 review articles were removed from Web of Science leaving 23 studies, 14 book chapters and 3 review articles were removed from Scopus leaving 61 studies, and 2 theses and 2 review articles were removed from ERIC leaving 5 studies.

The process of identifying and removing duplicate records held critical importance for ensuring the methodological rigor of the study. At this stage, the duplicate detection feature of Zotero reference management software was used, and common publications across databases were systematically identified. Through the manual control process, automatically detected duplicates were verified, and the final dataset was clarified to consist of 65 unique publications. Comprehensive data extraction was performed for each publication, with author information, titles, source information, publication years, keywords, abstracts, institutional affiliations, citation counts, and geographical location information systematically recorded.

Data Analysis Methods

The data analysis process was designed with a multi-stage and multi-dimensional structure appropriate to the requirements of the systematic mapping approach. In the first stage, distribution analysis by publication years was conducted within the scope of descriptive statistics to examine the change in research activity in the field over time. Global and institutional distribution of research activities was mapped through geographical and institutional distribution analyses, and the proportional distribution of journal articles and conference proceedings was determined through distribution analysis by publication types.

Within the framework of productivity analyses, the most productive authors, institutions, and countries were identified, and their assumption of pioneering roles in the field was evaluated. Within the scope of impact analysis, the most cited publications were identified, average citation statistics were calculated, and the impact structure of the field was revealed. These analyses enabled the identification of studies and researchers who were influential in the early development of the field.

Thematic analyses constituted one of the most critical components of the systematic mapping approach and were conducted under two main headings: keyword analysis and content analysis. Within the scope of keyword analysis, frequency analysis of author keywords, word co-occurrence analysis, and word evolution analysis over time were performed. These analyses provided valuable insights for determining conceptual focuses and terminological development in the field. Content analysis encompassed thematic coding of abstracts, systematic classification of research methodologies, and categorization of application areas, thus enabling in-depth understanding of the content structure of the field.

Analysis Tools and Techniques

Integrated use of various analysis tools and techniques was adopted in the data analysis process. Excel-based data organization and basic statistical analyses were conducted for systematic organization of data and calculation of basic descriptive statistics. VOSviewer software was preferred for visualizing keyword networks and collaboration networks, and the powerful visualization capacities of this software made important contributions to understanding the conceptual structure of the field (van Eck & Waltman, 2010).

R programming language and the Bibliometrix package were used for advanced bibliometric analyses and visualizations, and the analytical capacities of these tools proved valuable particularly in revealing complex data relationships (Aria & Cuccurullo, 2017). NVivo was preferred for qualitative content analysis and thematic coding processes, thus supporting systematic coding and theme identification processes.

Methodological Limitations and Validity Assessment

The methodological limitations and validity issues of this study have been addressed in an open and transparent manner. The sample size of 65 studies may be considered relatively small for traditional bibliometric analyses, but this situation can be explained by the developing character of the field and the very recent nature of applications of generative AI technologies in education. The pre-paradigmatic phase of the field makes the approach of systematic mapping of pioneering studies more appropriate rather than large-scale statistical analyses.

The five-year period covering 2020-2025 as a time limitation may constrain the analysis of longitudinal trends, but it constitutes an appropriate choice for capturing the period when generative AI technologies became visible in education. The inclusion of only English-language publications in the study excludes potentially valuable contributions in other languages, but this limitation is at an acceptable level due to the dominant use of English as the primary language of international scientific communication. Publications outside the three selected databases, particularly studies in preprint servers such as arXiv, remained outside the scope, and while this situation limits the scope of the study, it is justified by the preference to focus on peer-reviewed publications.

Findings

The findings obtained from this systematic mapping study clearly reveal the developing character and research trends in the field of generative AI-supported personalized learning. The analyses conducted on the dataset consisting of 65 publications present important findings regarding the field's development over time, leading actors, intellectual foundations, conceptual focuses, and methodological approaches.

Temporal Distribution of Publications

Temporal analysis of publications in the field of generative AI-supported personalized learning clearly demonstrates the rapid growth dynamics and developmental process of the field. It was determined that all 65 publications in the dataset are concentrated in the 2023-2025 period and that the annual distribution exhibits a distinct increasing trend. Research activity, which began with only 5 publications in 2023, reached 27 publications in 2024, recording approximately a five-fold increase. Reaching 33 publications in the first eight months of 2025 (screening was completed on August 31, 2025) represents a 22% increase compared to the previous year and demonstrates the potential to reach 50+ publications in annual projection.

These findings clearly reflect the impact of ChatGPT's release in November 2022 on the research community. Particularly, despite the 2025 data covering only the first nine-month period, reaching 33 publications demonstrates the dynamic growth potential of the field. This trend indicates that research interest in applications of generative AI technologies in education is exponentially increasing and that the field is rapidly emerging from its pre-paradigmatic phase and beginning to consolidate. This annual growth pattern also reveals the close relationship between technological innovations and academic research activity. Despite the field having only a three-year history, the rapid growth it demonstrates reflects the high expectations in the academic community regarding the educational potential of generative AI technologies.

Analysis of Pioneering Actors

Analysis of actors playing roles in the field's development exhibits different characteristics at the levels of authors, institutions, and countries. Analysis conducted at the author level reveals that dominant researcher profiles have not yet formed in the field and that each author is represented by only a single publication. This situation can be explained by the very recent nature of the field and shows that the research community has a dispersed structure. The absence of recurring individual researchers who establish dominance in the field confirms the pre-paradigmatic character of the field and indicates that leadership is occurring at the institutional level rather than individual researchers. These findings, consistent with Kuhn's (1962) philosophy of science paradigms, show that the field does not yet possess a mature research community but researchers from various institutions are in the process of exploring the field.

Institutional-level analysis results show that universities in Asian countries, particularly, play pioneering roles in the field. Tsinghua University's prominence reveals that China's global leadership in artificial intelligence research is reflected in the educational technologies field as well. The presence of other Chinese institutions such as Ocean University of China, Shantou University, and Guangdong University of Technology demonstrates the country's systematic investment in this field. Contributions from institutions such as Saint Francis University Hong Kong and Nanyang Technological University reflect the strong character of the research ecosystem in the Asia-Pacific region. A notable finding is the presence of institutions from the African continent, such as Université Sidi Mohamed Ben Abdellah and Tshwane University of Technology, which demonstrates the global dimension of research activities. The direct contribution of technology companies such as Adobe Inc. to academic research indicates strong industry-academia collaboration in the field and suggests that bridges are being built between practical applications and theoretical research.

Analysis conducted at the country level reveals that the global research landscape exhibits a multipolar structure. China and India each sharing leadership in the field with 7 publications can be considered a reflection of these two countries' rapid developments in technology and education fields. The United States ranking third with 4 publications shows that despite traditional technology leadership, it has not yet established complete dominance in this new field. Spain, Taiwan, and Germany each contributing 3 publications with balanced contributions reflects the geographical diversity of the field and the active participation of European and Asian countries. The presence of contributions from developing countries such as Indonesia, Singapore, Saudi Arabia, Morocco, and South Africa shows that generative AI technologies have gained a central position in the global education agenda and that technological innovations are spreading rapidly. This distribution indicates that, despite concerns about digital divide, access to new technologies and research capacity are relatively balanced worldwide.

Intellectual Foundations and Influential Studies

Analysis of studies constituting the intellectual foundations of the field reveals the multidimensional structure and not-yet-consolidated character of generative AI-supported personalized learning research. The variation in citation counts of the top ten most-cited studies between 7 and 33 shows that very highly influential dominant studies do not yet exist in the field. This situation can be explained by the field's young age and indicates that intellectual foundations are still in the formation process. Dalgic and colleagues' study examining the impact of ChatGPT on learning outcomes in tourism education ranking first with 33 citations reveals that discipline-focused applications are of interest in the field. Hang and colleagues' LLM-based MCQGen framework developed for multiple-choice question generation receiving 32 citations shows that technical tool development approaches are also valued in the field.

Thematic analysis of the most influential studies reveals that the field is developing along three fundamental axes and these axes exhibit complementary characteristics. The first axis, pedagogical applications, supports interdisciplinary integration and focuses on empirical measurement of learning outcomes. Studies such as Dalgic and colleagues' tourism education study and Guo and colleagues' constructivist learning research contribute to systematic evaluation of generative AI's effectiveness in different educational contexts. This approach reflects an understanding that prioritizes technology integration based on pedagogical requirements rather than technological determinism.

The second axis, technical approaches, encompasses technological innovation and tool development studies. Development of the MCQGen system, personalized prompt engineering applications, and IoT-generative AI integrations are included in this category. Abolnejadian and colleagues' adaptive learning study through personalized prompts serves as an example in terms of combining technological possibilities with pedagogical requirements. Dong and colleagues' IoT and generative AI integration study shows that technology ecosystems should be addressed with integrated approaches.

The third axis, conceptual and critical frameworks, shows that the field is not developing only application-focused, but also that theoretical and ethical dimensions are being addressed systematically. Guettala and colleagues' study evaluating the general potential of generative AI in education and Laak and colleagues' critical evaluation regarding the non-guaranteed nature of personalization indicate that the field is developing with a mature perspective. This critical approach emphasizes the need for balance between technological optimism and realistic expectations and holds critical importance for the sustainable development of the field.

Integration of studies developing along these three axes shows that the field constitutes a healthy intellectual ecosystem. The balanced distribution of discipline-focused applications, technical innovation, and critical evaluations reveals that the field of generative AI-supported personalized learning has a multidimensional and sustainable character.

Conceptual Focuses and Thematic Structure

Thematic mapping conducted based on keyword analyses systematically reveals the conceptual focuses and terminological structure of the field. Analysis of the most frequently occurring keywords in 65 studies shows that the term "personalized learning" is in an absolutely dominant position with 52 uses. This finding indicates that the main focus of the field is shaped around personalized learning and that researchers use this concept as a central reference point. Such intensive use of the term also shows that terminological unity in the field has not yet fully formed and that researchers are in the process of developing a common conceptual language.

The second most frequent terms "learning systems" (17 times), "ChatGPT" (16 times), "artificial intelligence" (16 times), and "generative AI" (16 times) clearly reflect the technological focus of the field. Among these terms, "ChatGPT" occupying a special position shows that this technology plays a pioneering role in the field and shapes the research agenda. The frequent use of terms such as "students" (15 times), "large language model" (14 times), "adaptive learning" (13 times), and "language model" (13 times) reveals that the field exhibits both student-centered and technology-intensive characteristics.

This keyword distribution systematically reveals three fundamental thematic focuses of the field. The first theme, pedagogical focuses, encompasses concepts such as personalized learning, teaching, curricula, and student experiences. This theme focuses on adopting student-centered approaches and adapting learning experiences according to individual differences, consistent with fundamental paradigms of educational sciences. The presence of terms such as "teaching" (11 times) and "curricula" shows that technological innovations are evaluated within pedagogical contexts and focus on redesigning instructional processes.

The second theme, technology and tools category, includes ChatGPT, generative AI, large language models, and adaptive learning systems. The strong representation of this category shows that generative AI models are positioned at the center of pedagogical designs and that a different approach is adopted from traditional educational technologies. The frequent use of "large language model" and "language model" terms indicates that natural language processing technologies play a central role in the field.

The third theme, advanced computational approaches, encompasses advanced AI techniques such as federated learning, adversarial machine learning, contrastive learning, and knowledge graphs. The presence of this thematic category shows that the field is not limited only to pedagogical applications of existing technologies, but also that studies are being conducted toward adapting sophisticated AI techniques to educational contexts. The presence of discipline-focused terms such as "engineering education" (10 times) reveals that technological approaches are combined with specific domain expertise.

The multidimensional character of the thematic structure reveals that the field is being shaped from both educational sciences and computer sciences perspectives and exhibits a truly interdisciplinary nature. This finding shows that the field of generative AI-supported personalized learning is developing by balancing technological determinism with pedagogical requirements.

Methodological Approaches and Publication Characteristics

Analysis of methodological approaches adopted in field research exhibits diversity and balanced distribution characteristics. When distribution by publication types is examined, conference proceedings constitute the largest category with 41 publications and a 63% share of the total. This situation reflects the rapid development dynamics of the field and the tendency to share early findings primarily at conferences. The dominance of conference proceedings is consistent with general characteristics of AI and educational technology fields and shows researchers' desire to rapidly share current findings with the scientific community. This category encompasses studies presented at prestigious conferences such as AIED, ICML, NeurIPS, LAK and includes both methodological experiments and technical innovations.

Peer-reviewed journal articles constitute the second category with 24 publications and a 37% share, strengthening the intellectual foundation of the field with more comprehensive, theoretically-based contributions. The 2 Early Access articles included in this category indicate the field's ongoing productivity in 2025 and show the tendency to share journal articles with the research community even in pre-publication stages. The distribution of publication types reveals that in the field's academic maturation process, both rapid knowledge sharing and in-depth analytical studies are conducted in a balanced manner and that the research community adopts a multi-channel publication strategy.

Analysis in terms of methodological diversity reveals that three fundamental approaches stand out and these approaches exhibit complementary characteristics. The first approach, experimental studies, encompasses research where the impact of ChatGPT and similar generative AI tools on learning outcomes is systematically measured through controlled experiments with students. Discipline-focused experimental studies such as Dalgic and colleagues' tourism education study and engineering education applications are included in this category and are generally conducted with pre-test post-test designs, controlled group experiments, or quasi-experimental designs. The strong representation of this approach shows that the field is developing with findings supported by empirical evidence rather than just theoretical speculations.

The second methodological approach includes tool and framework development studies and exhibits characteristics consistent with the design-based research paradigm. Question generation systems such as MCQGen, adaptive prompt-based instructional frameworks, IoT-generative AI integrations, and various learning support tools fall into this category. These studies mostly find places at computer science conferences and generally include prototype development, system architecture design, performance tests, and user experience evaluations. The significant share of tool development approach reveals that the field is not limited only to testing existing technologies in educational contexts but also that studies are being conducted toward developing new technological solutions focused on education.

The third methodological approach, conceptual and theoretical studies, encompasses research focused on generative AI's potential in education, ethical limitations, personalization possibilities, and systematic evaluations. These studies are generally concentrated in journal articles and are conducted through literature reviews, theoretical framework developments, conceptual modeling, and critical analyses. Guettala and colleagues' general evaluation study and Laak and colleagues' critical perspective presentation are among examples of this category. The strong representation of theoretical approaches shows that the field is not developing only application-focused but also that conceptual foundations are being systematically strengthened.

The balanced distribution of these three methodological approaches reveals that the field of generative AI-supported personalized learning exhibits healthy diversity between both technical innovation and pedagogical application and supports its interdisciplinary character. The presence of methodological diversity shows that the field has a strong epistemological foundation by being nourished from different research paradigms in its maturation process. This finding reveals that generative AI-supported personalized learning research focuses on simultaneously exploring both technical and pedagogical dimensions in a rapidly developing field and is in the process of laying the foundations of the field with a multi-perspective approach.

Discussion

This systematic mapping study has comprehensively revealed the early developmental characteristics and research trends of the field of generative AI-supported personalized learning. The analyses conducted on the dataset consisting of 65 publications demonstrate that the field is rapidly emerging from its pre-paradigmatic phase and beginning to consolidate while exhibiting a multidimensional developmental process. In this section, the obtained findings are discussed within theoretical and methodological contexts, and evaluations regarding the current state and future potential of the field are presented.

Theoretical Evaluation of Findings

The exponential increase in research activity in the field of generative AI-supported personalized learning during the 2023-2025 period presents a meaningful picture when evaluated within the framework of Kuhn's (1962) philosophy of science paradigms. The growth pattern reaching from 5 publications in 2023 to 33 publications in 2025 reflects typical characteristics in the emergence process of a new scientific paradigm. The release of ChatGPT in November 2022 and the subsequent research explosion clearly demonstrate the power of technological innovations to shape academic agendas. This situation is also consistent with Rogers' (2003) innovation diffusion theory, showing that early adopters play an active role in the process of discovering technological potential and transforming it into academic discourse.

The shared leadership of China and India in the geographical distribution of the field reflects the changing power balance in the global educational technologies ecosystem. In educational technology research where the United States and European countries traditionally established dominance, the prominence of the Asia-Pacific region shows that these countries' strategic investments and human resource capacities in artificial intelligence are reflected in the educational field. China's leadership in the field, particularly through prestigious institutions such as Tsinghua University, reveals that the country follows an academic strategy consistent with its goal of becoming an AI superpower. India's strong representation shows that the country's software development capacity and English language advantage are being converted into academic productivity.

The three-axis development of intellectual foundations reveals that the field exhibits healthy epistemological diversity. The balanced distribution of pedagogical applications, technical approaches, and conceptual frameworks exhibits characteristics consistent with Gibbons et al.'s (1994) Mode 2 knowledge production theory. In this approach, knowledge is produced in application-focused, problem-solving, and multi-actor structures that transcend disciplinary boundaries. The field's development not only through technical innovation focus but also being shaped by pedagogical requirements and critical evaluations shows that the technological determinism trap has been avoided.

Analysis of conceptual focuses reveals that the field is in search of terminological unity but has not yet reached full consensus. The absolute dominance of the term "personalized learning" shows that researchers tend to unite around a common conceptual framework. However, the use of similar terms such as "adaptive learning," "individualized learning," and "customized learning" indicates that the conceptual clarification process continues. This situation, consistent with Lakatos' theory of scientific research programs, shows that the field is still in the process of determining its hard core and protective belt structures.

Evaluation of Methodological Approaches

The balanced distribution of methodological diversity among experimental studies, tool development, and conceptual studies shows that epistemological pluralism is adopted. This approach can be evaluated as a positive indicator for the field's maturation, considering the complex nature of educational research and the multidimensional character of generative AI technologies. The strong representation of experimental studies reveals that the field is developing with findings supported by empirical evidence rather than just technological speculations.

The 63% share of conference proceedings among publication types can be evaluated as a finding consistent with the rapidly developing nature of the field. The fact that conference proceedings have scientific value equivalent to journal articles in the fields of AI and educational technologies shows that this distribution reflects the dynamic character of the field. The 37% share of peer-reviewed journal articles indicates that the field is in the process of gaining academic legitimacy and that more in-depth analyses are also being conducted.

The significant share of tool and framework development studies shows that the field is not limited only to testing existing technologies in educational contexts. The development of systems such as MCQGen reveals that original contributions are being made toward designing education-focused AI tools. This situation, consistent with von Hippel's user innovation theory, shows that educators and researchers assume not only technology consumer roles but also technology developer roles.

Theoretical and Practical Contributions

The theoretical contributions of this systematic mapping study exhibit multidimensional characteristics. First, mapping the epistemological landscape of the field of generative AI-supported personalized learning creates an important reference point for future researchers. The identification that the field develops along three fundamental axes (pedagogical applications, technical approaches, conceptual frameworks) provides a valuable framework for researchers to position their studies and determine their contribution areas.

Second, systematically revealing the pre-paradigmatic character of the field shows how Kuhn's (1962) philosophy of science theories operate in technology-supported educational fields. The absence of dominant researcher profiles, searches for terminological unity, and methodological diversity provide important insights for understanding the natural developmental processes of new scientific fields.

Third, revealing the multipolar structure of the global research landscape shows that power balances in the educational technologies field are changing. The leadership of the Asia-

Pacific region and the presence of contributions from African countries indicate that access to technological innovations is relatively balanced despite concerns about digital divide.

When evaluated in terms of practical contributions, this study provides important guidance for education policy makers, institutional administrators, and researchers. Revealing the rapid growth potential of the field supports educational institutions in strategically planning their generative AI investments. Emphasizing methodological diversity encourages researchers to conduct multi-perspective studies by avoiding one-dimensional approaches.

Analysis of the most cited studies shows which approaches attract interest in the academic community, contributing to determining future research focuses. The identification of high impact from discipline-focused applications and technical tool development studies shows the potential for researchers prioritizing these areas to achieve higher academic impact.

Future Research Recommendations

Based on the findings obtained from this systematic mapping study, various priority areas and approaches can be determined for future research. First, considering the rapid growth and conceptual diversity of the field, conducting systematic mapping studies to be updated at regular intervals is recommended. These studies to be conducted at annual or biennial periods will enable tracking the dynamic development of the field and identifying changes in research trends.

Second, the high impact of discipline-focused applications shows that generative AI-supported personalized learning applications in different educational fields should be systematically examined. Conducting in-depth studies in specific areas such as mathematics education, science education, language education, and arts education holds critical importance for determining the unique requirements of each discipline. These studies will contribute to developing discipline-focused design principles and creating effective implementation models.

Third, the identification of methodological diversity as a strength reveals that mixed-method research should take more place in the field. Particularly, conducting studies that combine quantitative impact measurements with qualitative experience analyses will enable multidimensional understanding of generative AI-supported learning experiences. Integration of phenomenographic approaches, ethnographic studies, and design-based research will contribute to strengthening the theoretical foundations of the field.

Finally, ethical dimensions have been identified as not yet adequately addressed, and conducting comprehensive research on privacy, data security, algorithmic bias, and equity in education holds critical importance. Examining student data protection, fair behaviors of AI systems, and the effects of personalization on social justice is necessary for the sustainable development of the field.

Conclusion

This systematic mapping study has successfully mapped the multidimensional structure of the field in its rapid growth process by revealing the early characteristics of the field of generative AI-supported personalized learning. The main contributions of the study can be summarized in the following points. First, the study documents the research explosion following the release of ChatGPT in late 2022 and proves that the field is evolving from a pre-paradigmatic phase toward consolidation. Second, it emphasizes the increasing leadership of the Asia-Pacific region in the global educational technologies ecosystem and shows the close relationship between technological innovation capacity and academic research power of this change. Third, it reveals that the intellectual foundations of the field are shaped with an education-focused perspective by avoiding the trap of technological determinism. In conclusion, this study constitutes a critical reference point for understanding the early dynamics of a developing research field and determining future research orientations.

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Chapter 4 - Using Project-Based Learning to Develop GenAI Fluency for IT/Computing Graduates

Ana Hol, Vince Bruno, Margaret Hamilton, Joan Richardson, Jim McGovern

Chapter Highlights

- Student perceptions and use of GenAI
- GenAI and Assessment Integrity
- GenAI Literacy and Fluency for IT/Computing Graduates.
- Project-Based Learning and Development of GenAI Fluency

Introduction

The emergence of Generative AI (Gen AI) presents a perfect storm for higher education. Not only must educators deal with the impact of GenAI on academic work carried out by both learners and educators, but they must revise curriculum to ensure that graduates are prepared for a world where GenAI is widely used. GenAI represents a quantum leap in the ability to mimic, some would say to fake human “thinking work” (for example, Walsh 2023). This latest generation demonstrates wide ranging expertise and capabilities developed from data sets that are significantly larger than those used in the past. GenAI can interact with users to create realistic conversations, written reports, create and modify images, video and audio content. A challenge for educators is to develop competence in GenAI usage while ensuring that required learning takes place. All educators will need to play a role in developing GenAI competencies, but there is an additional challenge for classroom educators who are responsible for creating the learning environment that achieves the required unit, subject or course outcomes, and ultimately, program outcomes. There is an urgent need for change. Higher education has struggled to keep up with use of GenAI, to the point where some of the traditional roles of university education are being questioned (for example, Dodd 2025).

GenAI is broadly applicable, and its impact will be far reaching, touching all knowledge-based professions to some extent, but the most significant and immediate impact may be on the Information Technology/Computing (IT/Computing) professions. IT/Computing roles have always been subject to change as technology and methods evolve, but a recent Lightcast study (2025) shows the top seven roles on the skills change index from 2021 to 2024 have all been roles in the Information Technology and Computer Science career. These changes are in part due to developments in Artificial Intelligence (AI). In many ways, industry is ahead of higher education in adopting GenAI. Hampered by long lead times, bureaucracy, and in some cases inadequate resources, universities are playing catch up. The dilemma for many disciplines including IT/Computing is balancing the need to understand and use GenAI with the need for the technical skills to apply GenAI appropriately and effectively.

In this chapter, we argue for a greater emphasis on Project-Based Learning (PjBL) as a successful method that addresses two important challenges for higher education in general and IT/Computing in particular: 1/ ensuring that learning takes place and is demonstrated, and 2/ preparing graduates for a workplace where they will be expected to use GenAI effectively as well as to leverage its capabilities for benefit. The remainder of the chapter is divided into five sections. First, our understanding of student perceptions of GenAI and issues around their use of GenAI are discussed based on the literature, focus groups and classroom experience. Second, the issue of assessment of learning and current practices in the IT/IS discipline is reviewed. Third, a framework for developing GenAI competencies required of IT/Computing graduates is introduced. Fourth, the advantages, challenges, and success factors in PjBL are reviewed. Finally, an implementation of PjBL that aims to develop GenAI competencies is described.

Student Usage of GenAI

Studies show many students to be frequent users of GenAI (Baidoo-Anu & Ansah 2023, Chan 2023, Chan & Hu 2023, Chiu 2024, Dai, Liu & Lim 2023, Dempere, et al. 2023, Hernández-Leo 2023). Further, some students demonstrate a good understanding of GenAI technology and the issues around its use (Chan and Hu 2023) to the point where they are often more experienced and knowledgeable than their educators (Dai, Liu & Lim 2023). This may not be the complete picture however, researchers such as Kelly (2024) have found students to be over-confident and largely in need of guidance to use GenAI effectively.

This interest from students is understandable. GenAI can produce a wide variety of content including written reports and visual and multi-media content, and can provide an anytime, anywhere “assistant” that can help generate new ideas and answer their technical questions more effectively that traditional search engines, and with greater availability than their human tutors (Chan 2023; Chan & Hu 2023; Chiu 2024; Hernández-Leo 2023). Typically, students do not rely wholly on GenAI, but use it as a tool to create first drafts or first cut code, or to refine, polish or get feedback on their work before it is submitted (Smolansky, et al. 2023; Swiecki, et al. 2022).

Of particular concern in the academic domain is the production of text by GenAI. The production of text is valued above other forms of communication in education (Farrelly & Baker 2023) and is commonly used to assess learning. Writing is a hallmark of education, and for many a difficult task. There is concern that technological solutions for such a fundamental academic task will bypass an important learning process and ultimately reduce human capability (Farrelly & Baker 2023).

As Walsh points out, there is an important learning process underlying the creation of a written piece. *"…Writing an essay is much more than simply testing knowledge on the subject matter. …. it helps us become better at communicating, at evaluating evidence, and at making and critiquing arguments."* p133 (Walsh 2023). Similar issues arise for other tasks, such as coding in computing education. There are concerns that over-reliance on code generation tools will diminish the abilities of programming students to code (Denny, et al. 2024; Smolansky et al. 2023). Deep understanding of code by humans will still be important as code created by GenAI can be poorly commented, have security flaws, and breach licensing agreements (Denny et al. 2024).

From a broader perspective, GenAI facilitates independent learning and epistemic agency (Dai, Liu & Lim 2023), the ability of learners to engage in knowledge construction and development, actively and purposefully. Epistemic agency is a highly valued competency, underpinning life-long learning which will be an even more critical capability in an increasingly dynamic economy and workplace, in part driven by AI developments.

In order to inform local students' perceptions and the likely impact of GenAI on learning and assessment, the authors conducted a study based on two focus groups. At the first focus group, students were surveyed on their use of GenAI, followed by a guided discussion that was recorded and analysed. Student were given the task of writing a job application with a Curriculum Vitae (CV) using GenAI. Their experience was discussed and recorded at a second focus group. The details of the focus groups are outlined in Hol et al. (2025), but overall, the study encourages a positive view of student use of GenAI and its impact on higher education. Participants in this study considered and used GenAI as an assistant that requires oversight. Using this assistant, students were able to develop high quality outputs, without any obvious detrimental impact on the learning required by the task. In fact, the exercise of using GenAI encouraged and developed desirable analytical and critical thinking skills.

Many students are aware of the limitations, but some may have misconceptions and there is unevenness in their competencies. Their experiences encouraged them to be sceptical of GenAI output and this was central to their use. The issue here is that users may not recognise all incorrect information. While participants recognised that bias could be an issue, this appeared to come more from their perceptions than from real experience. Bias is a subtle and potentially dangerous limitation of GenAI and exercises that demonstrate this will be of value but will be more difficult to address in some assessment tasks.

Little negative impact on learning was observed, in fact quite the opposite. Participants were enthusiastic and engaged, particularly in the second focus group. The participants demonstrated valuable critical thinking and analytical skills. GenAI may encourage isolated learning. An important issue is identifying errors and bias and the lone learner will be limited in doing this. One way to address this is to encourage learners to share and discuss their artefacts created with the help of GenAI.

After their experience, participants were more focused on issues around formulating prompts and prompt literacy (Maloy & Guttupalli 2024; Ronanki, Cabrero-Daniel & Berger 2024) which is an important component of GenAI literacy. Students used different strategies in preparing their job applications and CVs and used GenAI in some unexpected ways. One, used GenAI to assess the work they had created. Another used a second GenAI product to improve the writing created by another GenAI tool. This demonstrates how GenAI literacy can encourage new and innovative uses of GenAI tools for the problem solving and generations of the better and more refined solutions.

Students were mindful of sharing personal data with GenAI, but though they were prompted to discuss ethical issues, it was not a major consideration for them. Understandably, broader issues around societal impact and ethics are not always easily included in some assessment tasks. Impact and ethical considerations can be abstract concepts to some. They also have a contextual element, and these considerations should be addressed at every opportunity.

Challenges in Using GenAI

A challenging issue for GenAI users is that it can create incorrect and conflicting output, commonly called “hallucinations” (Frey & Osborne 2023; Rudolph, Tan & Tan 2023; Walsh 2023). (It should be noted that authors such as Kowalkiewicz (2024) suggest that terms like “hallucinations” that “humanise” GenAI not be used.) Previous incarnations of AI applications, such as knowledge-based systems and robotics could be characterised by a high degree of accuracy and cosistency, but GenAI based on Large Language Models (LLMs) has traded breadth of application for accuracy to some extent. There are differing views as to how accurate LLMs can be in the long run. Some observe that they are improving quickly (Zorpette 2025), while others suggest that there will be a limit to correctness because of the inherent conflicts in the underlying data, and the re-inforcement of "hallucinations" as GenAI generated content becomes a source for future LLM training (for example, Becker 2025).

GenAI output can be very persuasive, and errors are not always easy to detect. Walczak & Cellary (2023) found that almost half of experienced student users of GenAI who claimed that they checked all content produced by ChatGPT missed clear factual errors. This was only marginally better than those students who claimed to be users who checked less thoroughly (also about half missed clear errors) and those who were not GenAI users at all (about 60% failed to pick up clear errors). It seems that students, despite their confidence, may have difficulty in detecting incorrect GenAI output. If learners rely on technology, they will engage less with their learning (Chiu 2024) and fail to develop deep understanding of subject areas and skills such as independent and critical thinking. Inaccurate output can have severe implications and the very nature of the methods of GenAI may mean that this may not be solved easily (Frey & Osborne, 2023). Critical thinking and strong discipline knowledge will be more important than ever in the age of GenAI.

Reduced Professional Skills

While GenAI can provide many practical benefits, it does not provide important experience in working with other humans. Frey & Osborne (2023) argue that communication and interpersonal skills will be even more important as GenAI takes on basic transactional interactions. For example, GenAI might create the great job application template and identify skills someone needs to meet the required job role, but it is not enough on its own and needs to be backed up with the social skills and emotional intelligence. AI can deal with high cognitive load for clear transactional interaction but lacks the ability to read the emotional and social aspects of interaction (Walsh 2023). Dependence on GenAI may hinder skills such as teamwork, problem solving, and leadership, reduce interaction with people and the development of social skills (Chan 2023; Chan & Hu 2023; Chiu 2024; Hernández-Leo 2023; Walczak & Cellary 2023). For example, dependence on GenAI to provide feedback rather than from their "expert in training" peers, reduces opportunities to interact with other humans and to learn from each other. These are skills valued in the workplace and in life in general.

Use of GenAI may also stifle creativity. The ability of GenAI to create truly new solutions or ideas is limited (Frey & Osborne 2023; Walsh 2023). While GenAI can bring together new output, it bases this on existing data. New ways of looking at existing information is a valid form of creativity, in fact an important one, but it is not the only one. GenAI may not on its own be able to create highly original solutions, make major breakthroughs or change tactics (Frey & Osborne 2023). GenAI may be good at doing what we already do or have done well, but it cannot break the mould with radical new insights. GenAI does not remove the need for the personal qualities of curiosity, critical thinking, and resilience fostered through interdisciplinary learning that focuses on authentic situations (Dai, Liu & Lim 2023).

While it could be argued that some technical skills can be left to GenAI the need for “soft” or professional skills will be increased. Employers have consistently indicated that they value many of these skills over technical skills, and higher education has attempted to improve these in graduates by mandating generic professional skills or attributes in all academic programs. Skills such as communication skills, critical thinking, curiosity, and problem solving underpin successful decision making, innovation and implementation in the face of uncertainty and complexity, as well as ethical considerations will also be more important than ever in the GenAI era.

The Impact of GenAI on IT/Computing Education

Traditionally, IT/Computing educators have introduced basic concepts like algorithmic thinking and programming, basic design, data communications and data management, before moving onto more complex concepts and large-scale application. Over the course of their academic program the complexity increases to the point where a range of technical and “soft” skills are brought together to develop skills in solving more complex, less structured problems. Often this learning is in the form of capstone course projects with industry clients or sponsors. Take for example, the learning and teaching of algorithmic thinking and programming. First year assignments are typically based around simple sorting algorithms and data structures. While some students may have always been tempted to copy, GenAI affords those so tempted to do so on greater scale, to the point of relying on students to independently complete such assignments in their own time and place (Prather et al. 2023). In extreme cases some educators report that students who turned in passing solutions to programming tasks, were unable to produce even basic code in invigilated exams. The problem here is that students who lack basic algorithmic and programming knowledge and skills will be unlikely to properly assess GenAI generated algorithms and programming solutions for more complex problems.

In an introductory data management course, the authors observed this problem first hand. Courses such as this introduce the relational model and scaffold students to develop more complex database queries through a sequence of basic SQL statements. Similarly, to the teaching of algorithms, a number of issues were identified.

Misalignment with Intended Course Learning Outcomes

The disparity between AI-generated answers and course teachings creates a disconnect in the learning process. For example, students may find themselves grappling with advanced SQL structures that far exceed the scope of their current knowledge, potentially undermining their grasp of fundamental concepts. Especially in a practical course where foundational knowledge is scaffolded with more advanced concepts from a week to week basis.

Lack of Answer Verification

When GenAI tools produce complex queries that students cannot fully comprehend or verify, it compromises the learning process. Students lack the ability to critically assess the correctness of the answers they submit. This situation undermines the educational goal of developing independent problem-solving skills and deep understanding of SQL querying. There is also an inherent trust in the answer provided by the GenAI that is not warranted.

Overcomplication of Solutions

GenAI tends to generate intricate SQL queries for straightforward questions that can obscure the direct relationship between a type of business requirements and a standard database query pattern to solve it. This additional complexity may hinder a student's ability to develop clear and efficient querying strategies for a specific class of business requirement.

Impact on Assessment and Feedback

The submission of AI-generated answers that do not align with course expectations complicates the evaluation process. Teaching staff must invest more time in evaluating and assessing these complex solutions and alternative methods, potentially reducing their ability to provide timely and constructive feedback. In a sense, the teacher requires knowledge beyond the scope of the course materials, which could make selection of qualified teaching staff more difficult.

Misinterpretation of Business Requirements

GenAI's failure to precisely address the business questions within the context of the case study may arise. The translating of the business question within the context of the case study into the technical requirements of an SQL query is a key skill for business analysts. This skill can be simulated with current AI but will fail in interpreting various nuances of business requirements of the case study.

GenAI and Assessment of Learning

Issues such as those outlined above not only subvert learning, but potentially impact on the value of awards themselves, and there has been much debate in higher education on how to protect the integrity of assessment in the face of widespread use of GenAI. The use of technology in assessment is not new (Mao, Chen & Liu 2024), nor are ways to subvert the integrity of assessment. “Plagiarism, collusion, contract cheating, falsification and the use of unauthorised resources” are all challenges for educators (Denny, et al. 2024). Technology has been used to automate pencil and paper techniques such as short answer, multiple choice questions and essays. Even for these tasks, technology can improve assessment experience through its flexibility of access and immediacy of feedback tailored to the specific learner. Students already use technology that improves submissions through tools that advise on grammar (Grammarly) and even the content and structure of reports and essays (for example Packback, MI Write). Many of these tools are being enhanced to include or work with GenAI. GenAI is yet another technology that can be used both to enhance as well as to subvert the learning and assessment process (Denny, et al. 2024; Mao, Chen & Liu 2024).

Improving Assessment

There is a considerable body of thought that assessment methods can be improved, if they are to support learning and reflect real knowledge and skills. Widely used methods such as exams, reports, development of artefacts and so on can be inauthentic, inefficient, or plain ineffective in assessing deep, higher levels of learning (see for example Swiecki, et al. 2022). For some time, methods emphasising individualised formative assessment and the use of authentic summative assessment methods that demonstrate competencies have been promoted and encouraged across a range of disciplines. Many students prefer assessment that has less focus on summative final exams, and more on formative in-class activities. In written material, the focus on understanding of supporting data and evidence should be a major focus (for example Chiu 2024). While invigilated final or mid-semester exams offer security in assessment, they may not be the best method in terms of supporting student learning. Better learning designs can enhance student learning and remove incentives to cheat (Hamilton & Richardson 2007).

The issue is not what GenAI can do to assessment, but what can be done to improve assessment overall. As Corbin, Dawson & Liu (2025) suggest, rules about the use of GenAI that are unable to be enforced will be ineffective, and what is needed is more fundamental change in assessment methods. Many educators would agree that secure, educationally sound assessment methods that will succeed regardless of the use of GenAI are already in use. They are just not as widely applied as they should be (Swiecki, et al. 2022). Assessment methods built around live presentations, demonstrations and group discussions can encourage effective learning. They do require different skills, more resources and may be more difficult to scale up. Risks around use of GenAI in assessment will be reduced by careful implementation of evidence-based methods that test learning objectives, maintain academic integrity, provide quality feedback to students, protect student data and privacy, are mindful of the quality of the student experience, and are equitable (Huber, et al. 2023; Smolansky et al. 2023).

Current Practices in IT/Computing Assessment

In a study of assessment methods in a sample of Australian MIS programs outlined for the 2025 academic year, Hol et al. (2025) found that traditional assessment methods seemed to persist, at least at the published on-line course level (see Figure 1). Assessment methods that rely on the turning in of artefacts produced independently, such as reports or those that afforded little chance of feedback and learning support, such as final exams, predominate.

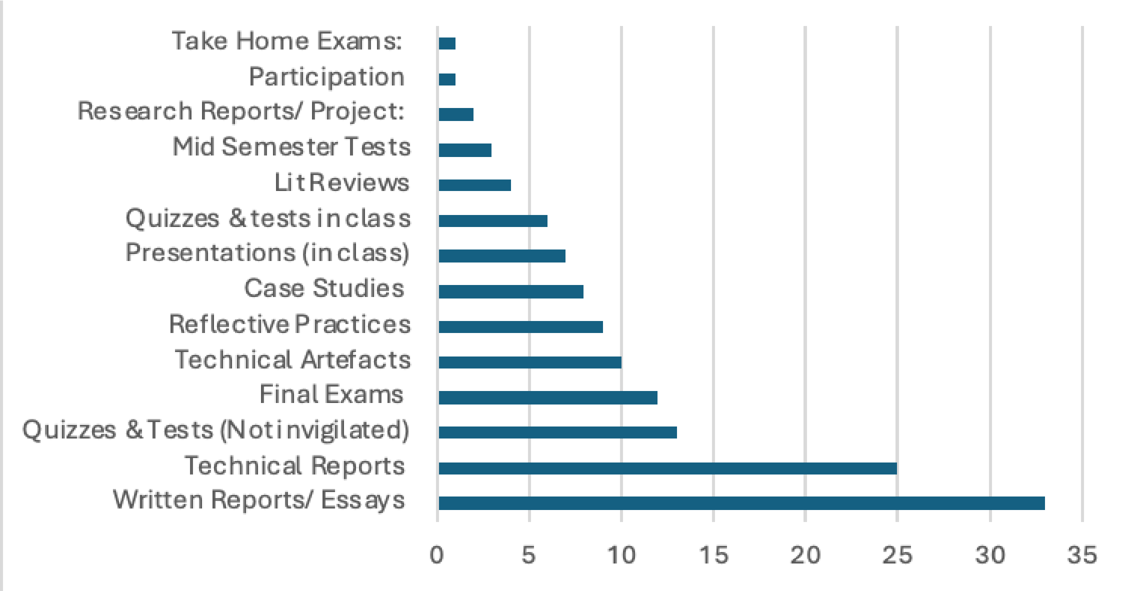

Figure 1. Assessment Types, MIS, Programs 2025

Building GenAI Competency

Many researchers and educators advocate for greater emphasis on GenAI literacy (for example, Kelly, 2024). While there has been considerable interest in AI literacy (Ng et al. 2021) for some time, this has accelerated since the widespread emergence of GenAI, and a number of tools or frameworks are being proposed or adapted from existing AI literacy frameworks. While many of these frameworks offer valuable insights into addressing GenAI literacy (for example, Bozkurt, 2025; Dal Ponte et al. 2025, Rapanta et al. 2025), Long & Magerko, (2020) provide a mature method with competency levels that can be mapped to the widely used Bloom's Taxonomy (Krathwohl 2002), as well as one that can be applied across any discipline. The model can be aligned with competency models such as that used in recent curriculum models including IS2020 (The Joint ACM/AIS IS2020 Task Force 2020), as well as the requirements of accrediting bodies such as TEQSA (n.d.) and the related AQF (n.d.). A subset of the elements of Long and Magerko's framework can be adapted for the classroom educator. Tables 1 and 2 outline a proposed GenAI competency framework aimed at a subject-based formative assessment task. This framework adapts and is compatible with the broader AI literacy framework proposed by Long & Magerko (2020) but focuses on those competencies that our research and the literature suggest as most important in such tasks. Learning design consideration and suggested implementation are separated in Table 2.

Table 1. An Assessment-based Framework for Developing GenAI Competencies

Competency Area	Competency Statement	Desirable Competency Level
Fundamentals of GenAI (non-technical explanation)	Explain how GenAI works broadly	Understand
	Explain how GenAI is limited by the data it uses	Understand
	Understand that Intelligent Agents are programmed	Understand
	Contrast the way GenAI works with human intelligence.	Understand
	Explain the limitations of GenAI conceptual knowledge.	
Limitations of GenAI Output	Explain why GenAI can produce output that is plain wrong, out of date or biased.	Understand
	Explain why GenAI may lack creativity or be otherwise limited.	Understand
	Apply frameworks that explain the different consequences of GenAI uses.	Analyse/ Apply/ Understand
Using GenAI	Use prompts to produce required output quickly.	Analyse/ Apply/ Understand
	Analyse output and detect incorrect, out of date or biased output.	Analyse/ Apply/ Understand
Broad Impact of GenAI	Assess the pros and cons of using GenAI for a particular purpose.	Evaluate/Analyse/ Apply/ Understand
	Develop and discuss views on the future possibilities and effects of GenAI.	Create/ Evaluate/Analyse/ Apply/ Understand
	Discuss the ethical and social impact of GenAI	Create/ Evaluate/Analyse/ Apply/ Understand

Table 2. Learning Design Consideration for Developing GenAI Competencies

Learning Design Consideration	**Implementation**
Discuss preconceptions	Initiate early discussion and share experiences with GenAI.
Promote honest and transparent use of GenAI.	Allow GenAI but ensure that, where needed, students acknowledge the use of GenAI.
Unveil concepts slowly	Use multi-stage approach, for example a flipped classroom approach. Introduce theory and practice slowly over time.
Design with learner's ability and maturity in mind.	Provide tasks that allow for a broad range of backgrounds but be mindful of getting students to a minimum level of competency. Material that is easy to understand without prior GenAI knowledge should be available.
Foster interaction, collaboration, teamwork and communication.	Provide GenAI group projects and foster communication of the process and the results, focusing on the data or argument and its merit.
Ensure learning activities engage learners	Ensure tasks are authentic and align with users' interests and ambitions.
Encourage new perspectives	Provide opportunities to reflect on experiences and to share these reflections.

Tasks using GenAI lend themselves to a staged approach that mirrors the focus group activity described earlier, namely an initial meeting, involving discussion preferably in small groups that addresses the tasks and allows sharing of experiences and perceptions of GenAI. Underpinning this should be resources that focus on the important elements of the literacy program: effective use of prompts, correctness, currency and bias of output, and the ethical and societal impact. On completion of tasks, there should be an opportunity for students to share their experience, and their output, and to receive feedback. Educators should be particularly cognisant of the design consideration of "Unveil concepts slowly to prevent cognitive overload".

GenAI Competencies for IT/Computing Graduates

The changes in skills required by IT/Computing professionals stem from two parts, skills in using GenAI in their work, and the abilities to leverage GenAI in applications to support the goals of their workplaces. GenAI now underpins many tools such as GitHub Copilot that support design, code generation and documentation in general (Maia et al, 2025). While GenAI will make IT/Computing professionals more productive, strong technical skills will still be needed, to be able to formulate prompts and critically analyse GenAI output.

Where IT/Computing professionals will be of most value is in working with organisations aiming to use GenAI to improve their productivity and competitiveness, and to introduce innovative services, products and processes using GenAI. Opportunities exist in a range of areas from health care to financial services (Kanbach et al., 2023) and organisations are often looking to their IT Departments to lead in exploiting these opportunities. Many CEOs report that their tenure depends on their ability to leverage GenAI (Houlne, 2025). This will require not only deep understanding of GenAI, but creativity, flexibility, problem solving and communication skills along with strong technical skills (Sidhu, 2025).

IT/Computing graduates will need to be more than simply AI literate, they will need what has been called AI fluency (Dal Ponte et al, 2025) with a deep understanding of the technology and how it can be applied. To IT/Computing graduates, fluency in AI may be as important as fluency in Java, SQL or data modelling. Like these technical skills, their development will be enhanced by authentic learning methods, such as Project-Based Learning (PjBL). From the perspective of the discipline overall, it can help develop the "why" aspects of technology, driving benefits to the community. As with many new technologies, there is a danger of adoption without full understanding of the "why" and the broader implications of their use.

Project-Based Learning (PjBL)

PjBL is a powerful student-centred teaching method based on the educational theory of active construction. In a review of literature, Rehman (2023) found that publications on the analysis of PjBL in Computer Science and the Engineering discipline had increased at a constant rate since 2010. It is likely that this is to do with employer demand for more job-ready graduates, and university imperatives around demonstration of this. PjBL will be an important tool in preparing IT/Computing graduates for the GenAI workplace by giving them experience in using GenAI tools and working with teams and "customers" to develop solutions that use GenAI.

PjBL can be implemented as part of a subject or course, as a whole course, or as a multi-semester course, such as in an IT/Computing capstone unit. While PjBL is widely implemented as capstone units, often because of accreditation requirements, we argue that it should be more widely adopted. There is a large body of work that describes the benefits, costs, risks, and the critical success factors in achieving learning outcomes from PjBL in the field of IT/Computing (e.g., McManus & Costello 2018; Pucher & Lehner 2011; Rehman 2023; Zheng et al. 2024).

Benefits of PjBL for Student Learning

Researchers have found higher levels of student engagement and motivation (Rehman 2023) and a greater sense of ownership over project work, particularly where they have chosen the project themselves (Pucher & Lehner 2011). Projects further develop the technical skills, sometimes in “messy” practical application, where there are trade-offs between elegant versus practical solutions driven by time limitations. Properly constructed projects can develop all important professional skills such as critical thinking, problem solving, leadership, time management, organisational skills, and written and oral communication.

While projects can be done by individuals, they are commonly undertaken in teams. Teamwork develops collaborative and communication skills, and introduces accountability for independent work required to deliver on parts of an overall plan. Students in teams also have opportunities to learn from each other. Projects that include or require interaction with other discipline experts are of particular value for those in the IT/IS disciplines where the professional focus for most will be working in organisational contexts. “Real world” industry initiated or sponsored projects offer particularly valuable experiences. The “real world” can be a far less structured place than students expect. Solutions may be constrained by resource or time limitations and working subsets may need to be negotiated. Valuable lessons in over-promising can be learned. Industry projects may also provide experience with industry tools, processes and methods, including those around GenAI, and develop GenAI fluency.

Challenges and Risks of PjBL

The selection of appropriate projects can be a key factor in successful implementation of PjBL. The project should be large enough and complex enough to have sub-problems. The quality of the project is important, but, dealing with this complexity can represent a real challenge for both teachers and students (Rehman 2023). While setbacks and failure are all part of learning, projects that are too complex, ill defined or become trivial may have a negative impact on student learning. The motivation of students is a key factor in the quality of the outcome and the learning experience (McManus & Costello 2018; Pucher & Lehner 2011) and providing "doable", interesting options from which to choose can keep students engaged and motivated. Students can spend much more time on projects than more traditional coursework though proponents. While some may argue that the learning from projects is well worth it, it should not detract from their other required learning.

Assessment of projects is one of the challenges of PjBL (Rehman 2023). It is difficult to fairly and consistently assess diverse projects. Pucher & Lehner (2011) found that projects originated by staff received higher grades than those that originated from students. They conjecture that there may be a bias in marking apparent here and that while measurable outcomes might be better, their observation was that students working on projects they originated themselves had a greater learning experience. Having multiple assessors and discussing other assessment at an assessor's meeting can help with consistency.

Selection of teams is important. Self-selection can lead to very different capabilities across teams. Randomly allocated teams can encourage "passengers" and poorer motivation and increase potential team conflict. Many students prefer individual assessment. Strategies to better reflect participation and contributions include assessing individual work as well as group components, and including peer assessments. Projects not only challenge students, but may also challenge teaching staff. The way educators manage their PjBL can have an impact on learning outcomes. Not all educators are capable or comfortable with project work, particularly those that involve industry. For those who are willing, but do not feel equipped for project work, professional development options should be available (Rehman 2023). Staff may also perceive projects as requiring higher time commitment than that allocated. It is important that teaching staff be allocated time that reflects the workload associated with an effective role in PjBL.

Critical Success Factors in PjBL

Successful PjBL oversight requires a good deal of interaction and communication. Gated approaches that include regular presentations are an important part of "real world" projects and are critical to PjBL. The critical evaluation of progress and outcomes, and encouragement of revisions at each stage keep students engaged, motivated and more likely to succeed. Similarly, regular weekly meetings with teaching staff where the focus is on guidance and advice, but not project management or micro-management of activity, are essential. Teaching staff guide and advise but should not project manage or micro-manage. Final presentations that include reflection not only motivate student and enhance learning but develop written and oral communication skills as well.

GenAI and PjBL

Like most knowledge based professional activities, the management and execution of IT/Computing projects will be impacted by GenAI and PjBL. GenAI will be used to assist in completing tasks that are well defined and which GenAI can assist in solving. IT/Computing professionals need a high level of fluency, and like any technical skill, they will benefit from the application of GenAI in authentic situations, and so the use of GenAI is becoming an important element of PjBL (Zheng et al. 2024). Working with industry can also provide students with opportunities to work with industry standard GenAI tools.

PjBL also addresses one of the issues of GenAI in higher education, integrity of assessment. Well implemented PjBL provides not only an effective quality learning experience for students, but also reduces risk around academic integrity. Projects with a high level of engagement and regular interaction have a much greater likelihood of encouraging student learning.

PjBL Implementation

Here we present an exemplar group-based project that challenges students to work closely with industry partners and teaching staff while addressing a complex, "real-world" business problem. The project was one of the assessments worth 30% of the final mark offered as part of a third-year course (subject) in an IT/IS bachelor's degree. The project was supported by a large organisation. This company sponsored a real life like project. The problem given to students was adapted to a classroom setting however derived from real life experiences. To solve the problem, students were required to gather data from the real stakeholders in order to consider how to solve the problem for them. To solve the problem students needed to understand the problem first and break it down to understand it (see Figure 2). As a part of their investigation students were able to utilise and apply GenAI tools, however when doing so were required to state what they used GenAI for and what they received as an output. Students were also required to technically analyse all data provided.

The student groups were required to collaborate directly with industry representatives – the process owners, the company and academic supervisor to map the current process, optimise the business process and explain the reason behind their proposal. The business problem required a structured approach encompassing problem formulation, design of solutions, testing of the proposed solution and development and the proposal for the new improved process deployment strategies.

Groups were taken through a staged approach. The first and critical step was a thorough analysis and break down of the problem to understand its components. Groups dissected the problem to understand underlying causes and technical requirements, fostering analytical rigor. This decomposition was critical not only for clarifying the scope, and setting priorities, but also for identifying aspects which would benefit from business process updates, novel technology implementations and the identification of the modules which may require further reviews and assessments. Following this, groups investigated technologies and methodologies relevant to the problem as they worked towards the solution design. Students were provided with access to domain experts, organisational data, and feedback by both the process owner and the organisation providing tools for the solution implementations. Students held regular meetings with the groups. They required agendas, clear outline of proposals and set questions. They also needed to address each group in a different way. With academics they spoke about the assessment, tools, technologies, processes. With industry they acted as one of the members working for the organisations, and industry as required provided feedback. Students were also required to initiate discussions with the teams involved so they could guide, lead and champion their project.

Once the problem was assessed and broken down, students were able to identify the GenAI tools that could be used to assist. Responsible use is emphasised through academic guidance and explicit criteria. GenAI was integrated as an enabling tool to support components of brainstorming, analysis, critical review and justifications of the proposed solution. As a part of this work students also needed to demonstrate subject mastery by critically evaluating AI-generated outputs and applying them cautiously within the context of the problem. They also needed to show that they ethically addressed when, how, what and why GenAI should or should not be used from an ethical perspective. This approach mitigates risks of superficial use of GenAI, ensures GenAI is used responsively and ensures deeper learning takes place while the students as future industry participants learn to use the tools appropriately.

GenAI was a component of the project which students were advised to apply in proposing and developing a solution. GenAI however was not a primary focus of the final artifact generation, other than any part it played in the overall solution. All outputs generated by GenAI needed to be assessed for correctness, relevance, and bias, ensuring alignment with problem requirements and organisational context. In developing GenAI fluency, all use of GenAI needed to be declared and the final report included a section that outlined GenAI contributions with a critical assessment of the use of GenAI and its output. Students were required to explicitly address potential for misinformation.

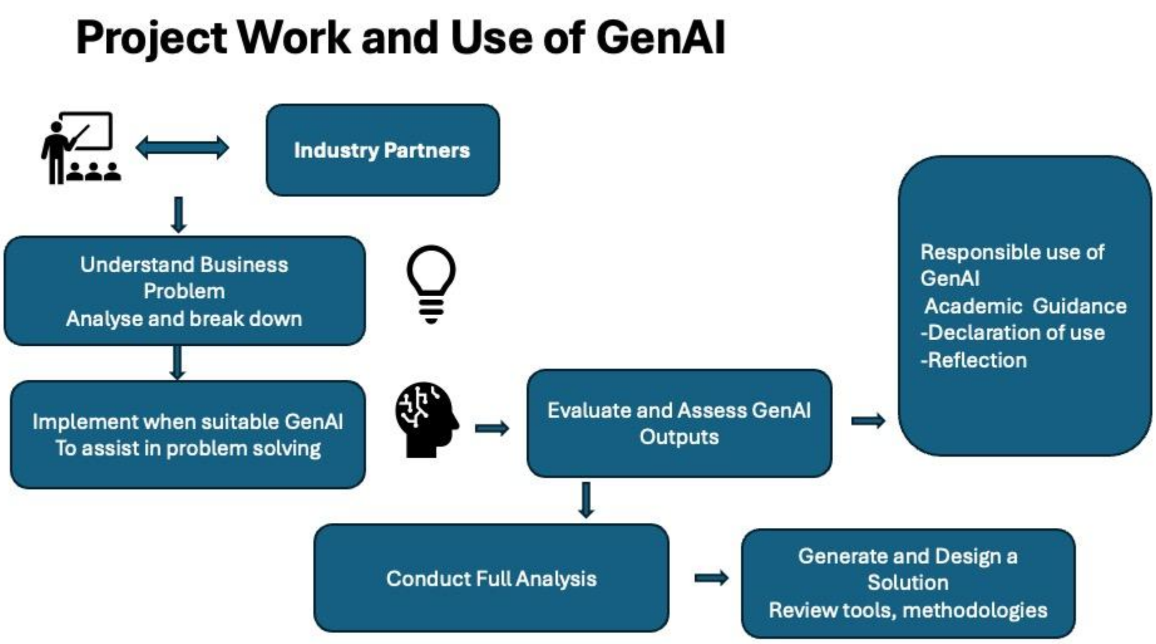

Figure 2. Project Work and Use of GenAI

Teaching staff guided reflective practices and set clear expectations on responsible uses of GenAI, as well as ensuring students met the set requirements and demonstrated understanding of the content covered. Teaching staff reviewed technical content for accuracy and completeness, and evaluated the appropriateness of the GenAI integration, team collaboration and individual contributions via peer reviews.

Continuous engagement with the student project teams was achieved by regular meetings with both industry and teaching staff. Students were required to provide evidence of scheduling, risk mitigation, planning, change management and the application of theory and practice. At each stage, these meetings also confirmed the appropriateness of problem understanding, the solution. Effective communication and understanding of the subject matter were assessed via continuous communication with industry members and teaching staff as well as via the final presentations.

Conclusion

The emergence of GenAI has presented many challenges for higher education. The IT/Computing disciplines have been impacted more than most. IT/Computing educators must deal with a technically savvy student body embracing GenAI and its impact on traditional assessment methods. The IT/Computing disciplines must also prepare its graduates for a profession that will be important users of GenAI and will have a role to play in its effective and ethical implementation.

The tools that allow educators to do this are already available. More emphasis on formative assessment and focus on authentic learning methods such as PjBL can improve student learning outcomes and reduce risks around assessment, and ultimately high education award integrity. This assessment framework offers a robust model for integrating real-world problem solving, collaborative learning, and responsible GenAI use in IT/Computing professional education. By working alongside industry partners, students develop applied skills in system deployment and management while navigating the ethical and practical challenges posed by emerging GenAI technologies. This approach prepares graduates with needed GenAI fluency to contribute effectively and ethically to digital transformation initiatives in dynamic organisational environments.

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Chapter 5 - Redefining Academic Integrity in the Age of Generative AI: Ethical Shifts, Epistemic Challenges, and the Role of Academic Libraries

Nuno Sousa

Chapter Highlights

- The rise of Generative Artificial Intelligence (GenAI) has disrupted academic norms across global higher education systems.
- This chapter argues that academic integrity must be redefined, not merely protected.
- Rather than defending outdated practices, institutions should embrace ethical co-authorship between humans and machines, rethink assessment models, and prioritize inclusive epistemic values.
- The chapter identifies academic libraries as critical hubs for AI literacy and ethical mediation, proposing an interdisciplinary approach that connects ethics, information science, pedagogy, and institutional reform.

Introduction

In 2025, institutions are still racing to adapt to the implications of GenAI. Tools such as ChatGPT, Claude, and Copilot are no longer novelties; they are foundational to how students write, reflect, and produce knowledge. The academic essay, once a symbol of independent thought and critical engagement, is now questioned for its validity and authorship. But the disruption is not merely technical — it is epistemological. GenAI challenges what we value as 'original', 'authentic', and 'human'. What does it mean for a learner to produce knowledge when the boundaries between machine-aided and human-authored work blur? In this context, the integrity of academia depends not on resisting GenAI, but on reimagining our systems in light of it.

Yet institutional responses have mostly revolved around surveillance, restriction, and punishment. AI-detection software, automated plagiarism tools, and policy reforms are reactive, often pedagogically and ethically superficial. This chapter suggests that these approaches are insufficient and even counterproductive. Instead, the path forward lies in cultivating epistemic awareness, ethical virtue, and AI literacy — and this responsibility should be shared by students, faculty, and particularly academic libraries.

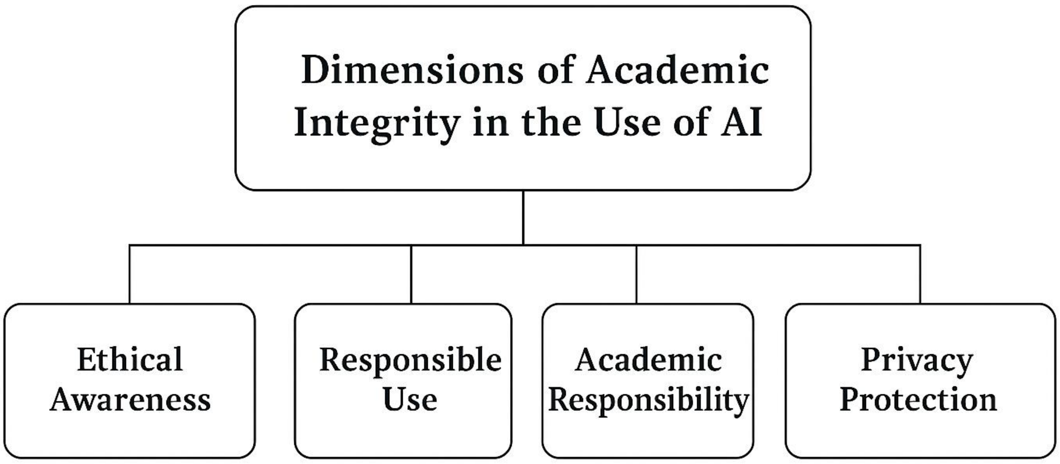

Figure 1. Dimensions of Academic Integrity in the Use of AI
Source: Artificial Intelligence

This figure outlines the evolving relationship between academic integrity and GenAI in higher education. It illustrates the shift from a punitive framework to one rooted in responsibility, agency, and ethical collaboration. The visual emphasizes the interconnected domains of institutional governance, student agency, pedagogical redesign, and technological mediation.

Methodological Aspects

This work adopts a critical-constructivist approach. Rather than aiming to measure AI use empirically, we seek to conceptually reframe how GenAI reshapes knowledge production. We build on Fricker's epistemic injustice, Vallor's virtue ethics, Lo's AI literacy framework, and the transformative pedagogies of Freire. Additionally, insights from recent work by Andrew Cox, David Lankes, Michael Seadle, and Marshall Breeding offer targeted reflections on libraries and their readiness to mediate the AI transition in higher education.

Literature Review

Epistemic Injustice and Algorithmic Bias

The intersection of GenAI and epistemic injustice raises critical concerns about whose knowledge is represented, validated, and privileged. Fricker (2007) introduced the concept of testimonial and hermeneutical injustice, where individuals are systematically excluded from knowledge-making processes. In AI systems, these injustices are encoded through biased training data and the exclusion of non-dominant epistemologies. Prinsloo and Slade (2023) warn of algorithmic systems that invisible the epistemic experiences of historically marginalized students, particularly in African and Global South contexts. These patterns reproduce what Santos (2018) termed epistemicide — the erasure of alternative ways of knowing.

Emerging critiques (Bali & Sharma, 2023; Knox, 2024) also note that dominant GenAI systems reflect neoliberal and Anglophone values, which further deepens digital colonialism in academic assessment. Addressing epistemic injustice in the GenAI era, therefore, requires more than improving datasets — it demands structural redress, curricular reform, and inclusive design principles.

Virtue Ethics, Moral Agency and Techno-Epistemologies

Beyond regulation and usage policies, scholars advocate for an ethical foundation rooted in virtue ethics. Vallor (2016) proposes that educators and institutions must actively cultivate *technomoral virtues*, such as honesty, empathy, courage, and humility, as preconditions for ethical engagement with emerging technologies. This ethical framing is being taken up in AI curricula (Williamson & Piattoeva, 2023), and supported by works like Green (2022), who insists that moral agency must be developed in parallel with technical proficiency. In higher education, particularly, the shift from compliance models to virtue-based ethics marks a deeper, more transformative pedagogical project.

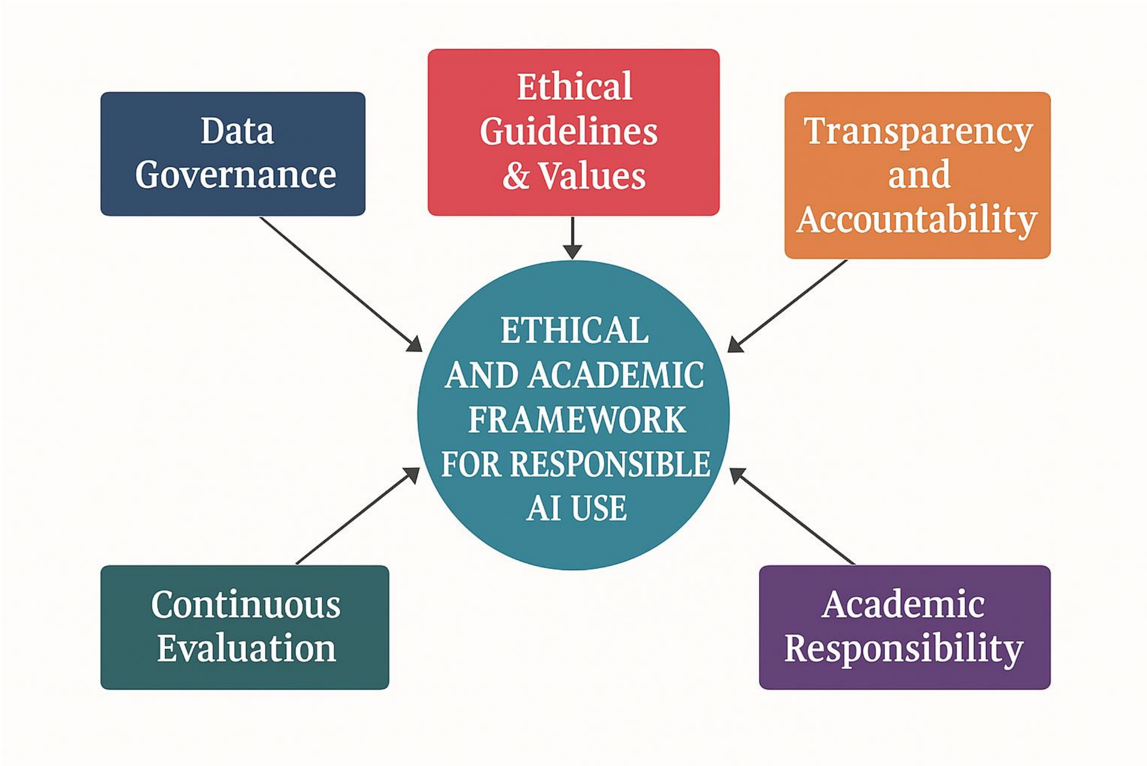

Figure 2. Ethical and Academic Framework for Responsible AI Use

Source: Artificial Intelligence

This model presents the layered dimensions that constitute academic integrity in the postdigital era. Moving beyond traditional notions of plagiarism or cheating, the figure proposes a multi-dimensional view that includes epistemic honesty, collaborative ethics, process transparency, and technological awareness.

The Strategic Repositioning of Academic Libraries

Libraries are increasingly recognized not as passive repositories but as critical mediators in the GenAI transition. Andrew Cox (2023) describes libraries as “institutional bridges” capable of integrating AI literacy, ethics, and epistemic support. Corrall and Jubb (2024) expand this vision by calling for AI-aligned library leadership, where librarians move from reactive support roles into proactive partnership with faculty and policy makers. Breeding (2023) also charts how AI is already reshaping collection development, research discovery, and information evaluation in libraries. These changes demand new competencies among staff — including ethical reasoning, algorithmic awareness, and facilitation of contested knowledge spaces. The library is thus not only a tool for navigating AI, but a site of epistemic resilience.

Literacy in AI: From Functional Use to Critical Consciousness

Contemporary discourse has moved beyond "digital literacy" to embrace AI literacy as a complex and layered capacity. Lo (2024) identifies five core domains: technical knowledge, ethical reasoning, practical skills, critical thinking, and societal awareness. However, authors such as Vallor (2016), Cox (2023), and Prinsloo & Slade (2023) argue that these domains must be situated within a critical pedagogy that confronts power, inequality, and systemic bias.". This shift echoes Freirean traditions — seeing literacy not as neutral skill acquisition, but as critical consciousness. Students and faculty must learn to interrogate AI outputs, understand training biases, and challenge institutional uses of surveillance technologies. AI literacy, then, is not only a competency — it is a democratic imperative.

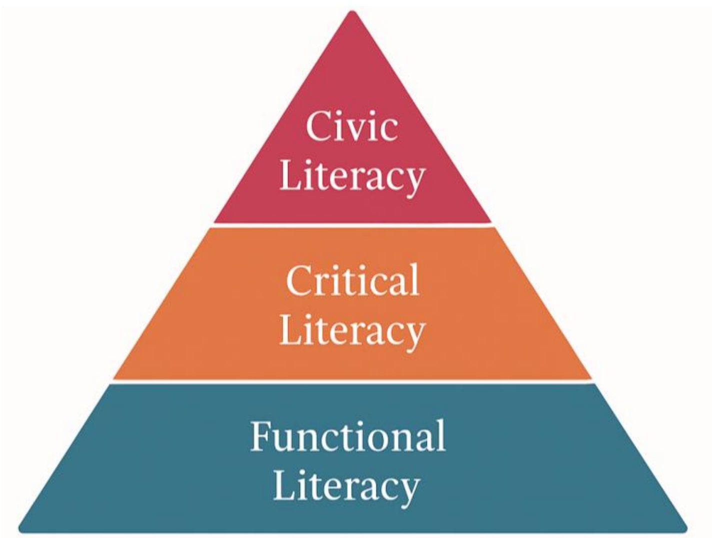

Figure 3. Literacies for Responsible and Equitable Engagement with AI
Source: Artificial Intelligence

Academic libraries occupy a strategic triadic role in the age of GenAI. This diagram illustrates how libraries act as facilitators of AI literacy, ethical mediators across disciplines, and institutional consultants shaping responsible AI policies. Their positioning at the intersection of pedagogy, policy, and digital culture gives them a critical edge in leading ethical AI integration.

Academic Integrity Reimagined in the Postdigital University

The concept of academic integrity is also evolving. Jandrić et al. (2022) position postdigital education as inherently entangled with digital systems, calling for postdigital ethics that go beyond punitive notions of cheating. Siemens & Gasevic (2023) argue for rethinking assessment, moving away from product-based evaluation toward process-oriented, collaborative, and reflexive learning designs. Recent policy work (EDUCAUSE, 2024; García-Peñalvo, 2025) shows growing institutional interest in "integrity-by-design" strategies — including co-authorship declarations, process journals, and ethical AI usage statements in assignments. These strategies offer not just defense against misconduct, but pathways to cultivate scholarly maturity and civic responsibility in a GenAI context.

Results

The integration of GenAI into higher education is no longer hypothetical — it is a lived, uneven, and evolving reality. This section outlines key patterns and institutional responses identified through a synthesis of international studies, policy reports, and recent academic literature from 2023 to 2025. The findings are organized into four thematic clusters: changing student perceptions, pedagogical redesigns, evolving institutional policies, and the expanding role of academic libraries.

Students' Perceptions: From Suspicion to Cognitive Enhancement

Where GenAI was once viewed with hesitation or as a "cheating shortcut," recent studies suggest a significant shift in student attitudes. In large-scale surveys (EDUCAUSE, 2024), over 80% of students across North American and European institutions reported using GenAI tools such as ChatGPT or Copilot as part of their academic workflow — not to plagiarize, but to clarify, structure, and brainstorm. Particularly among neurodivergent students and multilingual learners, GenAI is often framed as an accessibility tool or cognitive amplifier.

Moreover, students increasingly question the boundaries of originality and authorship in a digital age where hybrid forms of human-machine creativity are normalized in other disciplines (e.g., digital art, code generation). They call for clearer, more nuanced policies — not bans or blanket prohibitions, but guidelines that acknowledge evolving literacy, fairness, and accountability.

Pedagogical Redesign: Towards Process-Oriented Assessment

Faculty members, particularly in humanities and social sciences, are rethinking the foundations of academic evaluation. In response to GenAI, many are abandoning static essay prompts in favor of multi-step, process-based assignments that include:

- Learning diaries and reflective logs;
- Scaffolded submissions (brainstorm → outline → draft → peer feedback);
- Explicit declaration of GenAI use and critique of its outputs.

This shift aligns with calls from Siemens and Gasevic (2023) for assessment designs that evaluate epistemic practices rather than final products. Such models reward transparency, engagement, and judgment — competencies far more aligned with future academic and professional life than traditional regurgitation tasks.

Institutional Responses: Policies, Tensions, and Ethics-by-Design

While initial institutional reactions in 2023 leaned towards panic and surveillance (e.g., AI-detection software, emergency plagiarism clauses), a more nuanced trend is emerging in 2024–2025. Universities such as Stanford, University of Edinburgh, and TU Delft have begun piloting "integrity-by-design" frameworks, which include:

- Co-authorship statements clarifying AI involvement;
- Mandatory GenAI literacy workshops for students and faculty;
- Guidelines co-developed with students and librarians.

Despite these efforts, tensions remain. There is institutional inconsistency across departments and even among faculty, leading to confusion and unequal treatment. Some scholars (Prinsloo & Slade, 2023) argue that academic integrity policies risk becoming reactive instruments of control, rather than educative frameworks for responsible agency.

The Role of Libraries: Literacy, Mediation, and Innovation

Academic libraries are increasingly at the forefront of GenAI adaptation. Library and information science literature (Cox, 2023; Lo, 2024) documents a clear rise in AI-focused initiatives:

- AI Literacy Workshops embedded in first-year experience programs;
- Librarian-led seminars on evaluating GenAI output for bias, accuracy, and ethical use;
- Policy advisory roles, where librarians help draft institutional GenAI guidelines.

This is not merely a return to traditional information literacy but a repositioning of libraries as epistemic mediators. Librarians are being called upon not just to explain how tools work, but to facilitate critical dialogue, challenge assumptions, and bridge the gap between students' everyday AI use and academic standards. As Seadle (2025) notes, "libraries are no longer neutral spaces of access, but critical infrastructures of ethical knowledge navigation."

Discussion

The emergence of Generative AI is more than a technological turning point — it is an epistemic event that compels higher education to revisit the ontological assumptions underpinning teaching, learning, authorship, and assessment. This discussion synthesizes the implications of GenAI across four interrelated domains: the reframing of academic integrity, the repositioning of academic libraries, the critical pedagogy of AI literacy, and the tensions between innovation and control.

This ecosystem map visualizes the ethical forces influencing academic integrity in postdigital higher education. It highlights how values such as trust, transparency, equity, and digital fluency interact across learners, educators, and institutional systems. The circular format underscores the cyclical and interdependent nature of ethical academic ecosystems.

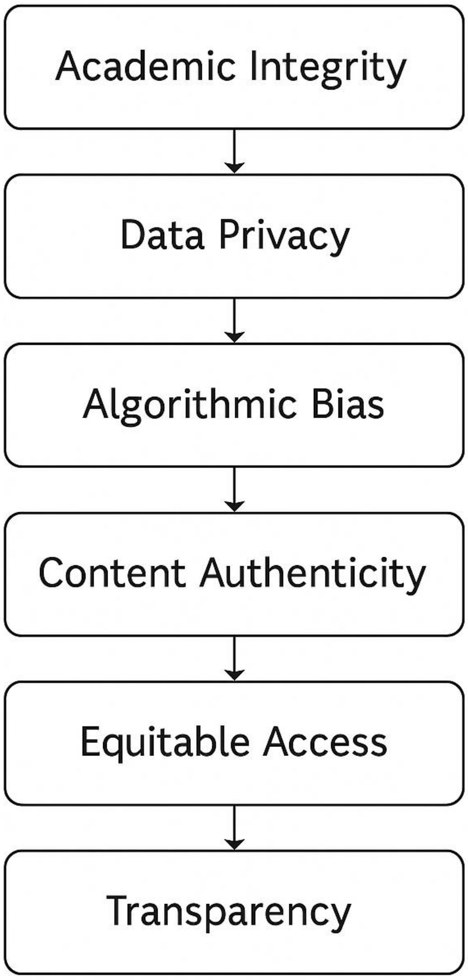

Figure 4. Ethical Implications of AI in Higher Education Libraries

Source: Artificial Intelligence

Reframing Academic Integrity Beyond Surveillance

Traditional definitions of academic integrity have relied heavily on notions of originality, individual authorship, and linear production. These principles, while historically grounded, are increasingly incompatible with postdigital practices where collaboration, remixing, and hybrid co-authorship are both common and pedagogically valuable.

Rather than anchoring integrity in surveillance (e.g., AI detection tools), institutions must redefine it as a relational and transparent process. This includes the formal recognition of GenAI as a learning partner — not an adversary — and the development of shared norms around its ethical and responsible use. Scholars such as García-Peñalvo (2025) argue that this shift from punitive to formative approaches is essential for maintaining the legitimacy of academic evaluation in the AI era.

Academic Libraries as Critical AI Literacy Hubs

Academic libraries are no longer merely support units; they are becoming active epistemic actors within the institutional AI landscape. Their unique cross-disciplinary position, institutional neutrality, and commitment to equitable access position them to lead the charge in AI literacy development.

Following Andrew Cox (2023), we suggest that libraries can assume three strategic roles:

- **Literacy Enablers:** Curating GenAI workshops, critical use guides, and integration in information literacy curricula;
- **Policy Advisors**: Participating in institutional governance, ensuring inclusive and fair policies on AI use.
- **Ethical Mediators:** Facilitating campus-wide dialogue on authorship, fairness, and epistemic justice in a GenAI-rich environment.

This triadic model moves libraries from the periphery to the center of institutional innovation and ethical deliberation.

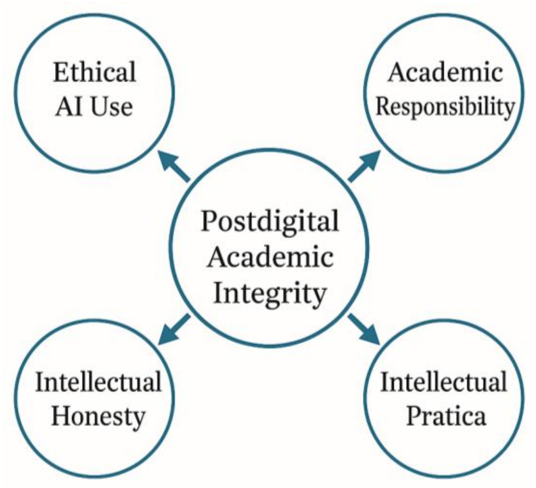

Figure 5. Ethical Ecosystem of Postdigital Academic Integrity

Source: Artificial Intelligence

This figure captures the core tensions in the integration of GenAI into academic settings. It positions creativity, learner empowerment, and generative exploration in contrast with surveillance, regulation, and institutional anxiety. The visual metaphor of opposing forces reflects the ideological and practical challenges faced by educators and policymakers.

AI Literacy as Critical Consciousness

There is a risk that AI literacy becomes reduced to technical competence — understanding prompts, basic commands, or data management. However, true literacy involves critical consciousness, drawing on Freirean pedagogy and postdigital theory.

AI literacy must therefore include:

1. **Epistemic awareness:** Understanding how AI systems encode, filter, and privilege certain knowledge forms.
2. **Ethical reasoning:** Judging when, how, and why to use GenAI in learning contexts.
3. **Social critique:** Recognizing the geopolitical, economic, and cultural forces shaping AI systems.

Institutions must resist the urge to "train" students as users and instead cultivate them as agents and critics of AI systems.

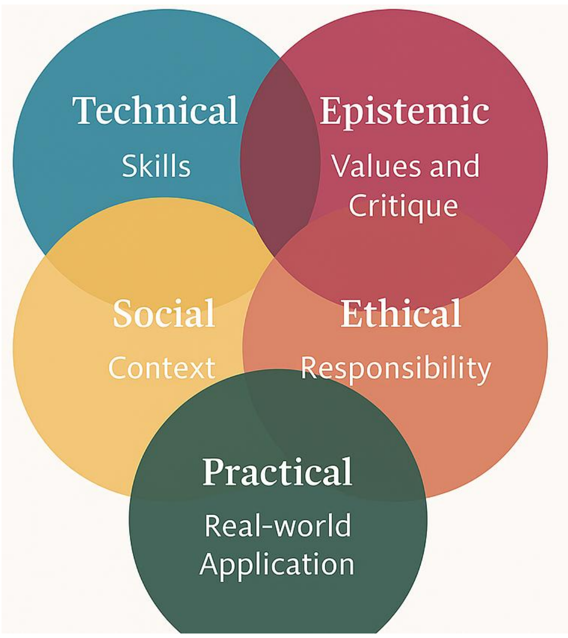

Figure 6. Principal Dimensions of Ethical AI Literacy

Source: Artificial Intelligence

This diagram maps the diverse responsibilities that academic libraries are assuming in the era of AI integration. From fostering ethical AI literacy and advising on policy to supporting inclusive pedagogy and safeguarding digital epistemologies, libraries emerge as critical infrastructures for ethical mediation and technological empowerment.

The Tensions Between Innovation and Institutional Control

The GenAI transition brings a paradox. On one hand, it invites creative, student-centered, and equitable redesigns of learning. On the other, it awakens institutional anxieties about plagiarism, standards, and control. This tension often manifests in ambivalent policies, contradictory guidance, or techno-solutionist responses (e.g., detection software over pedagogy). As Jandrić et al. (2022) argue, postdigital education cannot afford to ignore these contradictions — it must confront them. Ethical use of GenAI is not only a matter of individual behavior but of institutional culture and values. Universities must thus balance openness to experimentation with commitment to epistemic inclusivity and pedagogical justice.

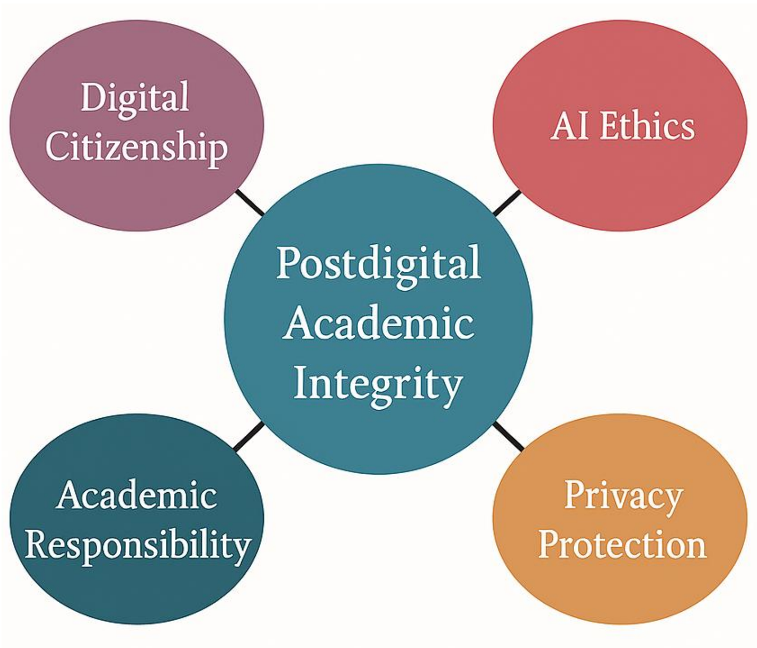

Figure 7. Expanded Ethical Ecosystem of Postdigital Academic Integrity
Source: Artificial Intelligence

The roadmap highlights key thematic directions for advancing research and institutional innovation around GenAI in higher education. It includes areas such as comparative policy studies, inclusive student voice, co-designed library practices, and longitudinal ethical assessment models—proposing an agenda grounded in critical inquiry and equity.

Limitations and Future Directions

Limitations

This chapter offers a critical and conceptual exploration of how Generative AI (GenAI) reshapes academic integrity and the role of academic libraries in higher education. However, its scope is not without limitations:

Lack of empirical data: While grounded in current literature and institutional reports, the analysis does not include original data from students, librarians, or educators. Future qualitative and quantitative studies are necessary to validate and contextualize these insights.

Global North orientation: The majority of referenced practices and policies stem from Western institutions. The experiences of universities in the Global South, where infrastructural, cultural, and policy frameworks may differ significantly, remain underrepresented.

Rapid evolution of AI tools: Given the accelerating pace of AI development, any discussion of specific platforms, capabilities, or educational uses risks becoming quickly outdated. The emphasis on principles over tools helps mitigate this, but long-term applicability remains uncertain.

Limited disciplinary scope: While this chapter focuses primarily on higher education and library sciences, cross-sectoral perspectives — including *K-12*, lifelong learning, and vocational contexts — offer rich areas for expansion.

Research and Innovation Paths

To continue building a robust and ethically grounded approach to AI in education, several research trajectories are recommended:

Comparative Policy Analysis: Systematic studies across regions and institutions can reveal how universities are implementing GenAI frameworks — comparing governance models, ethical guidelines, and institutional narratives (e.g., innovation vs. risk management);

Student Voice and Lived Experience: Investigating how students themselves perceive GenAI, navigate its use, and interpret institutional messages would provide valuable bottom-up insights. Special attention should be given to underrepresented groups, digital divides, and linguistic diversity;

Library-Led Innovation Cases: Empirical case studies of academic libraries acting as AI literacy hubs — including their design, implementation, and outcomes — could help model best practices globally. Collaborative action research involving librarians, faculty, and students would be particularly effective;

Decolonial and Intersectional AI Ethics: More research is needed into how GenAI intersects with epistemic injustice, colonial knowledge hierarchies, and global disparities. Critical scholars such as Mhlambi, Costanza-Chock, and Benjamin have laid a foundation that should be expanded into educational AI discourse;

Longitudinal Evaluation of Pedagogical Redesigns: Studies that track over time the effectiveness of new assessment models (e.g., co-authorship statements, process journals, reflective diaries) will be essential in building confidence and clarity around GenAI's place in academic integrity.

Conclusion

Generative Artificial Intelligence has arrived not simply as a new tool in the academic landscape, but as a catalyst for epistemic, ethical, and institutional transformation. As higher education grapples with its presence, the challenge is not merely to regulate AI use, but to reimagine the very frameworks that underpin how we teach, learn, and know.

This chapter has argued for a shift away from surveillance-driven models of academic integrity toward an ethics of co-authorship, epistemic inclusivity, and critical literacy. It has repositioned academic libraries as strategic hubs capable of leading this transition — not merely by facilitating access to information, but by cultivating ethical awareness, mediating complexity, and anchoring integrity in democratic engagement.

Rather than treating GenAI as a threat to traditional academic values, institutions have the opportunity to redefine integrity as an active, relational, and future-oriented practice. This redefinition demands pedagogical redesigns, interdisciplinary dialogue, and — above all — a cultural willingness to embrace complexity over control.

The path forward will not be linear. It will involve tensions, resistance, and experimentation. But it also holds the promise of a richer academic experience — one where integrity is not policed, but practiced; where libraries are not marginal, but central; and where AI is not an adversary, but a provocation to rethink what it means to be human, to learn, and to know.

As institutions move into the GenAI era, they are faced with a choice: to retreat into reactive governance or to lead with imagination, responsibility, and courage. This chapter makes a case for the latter.

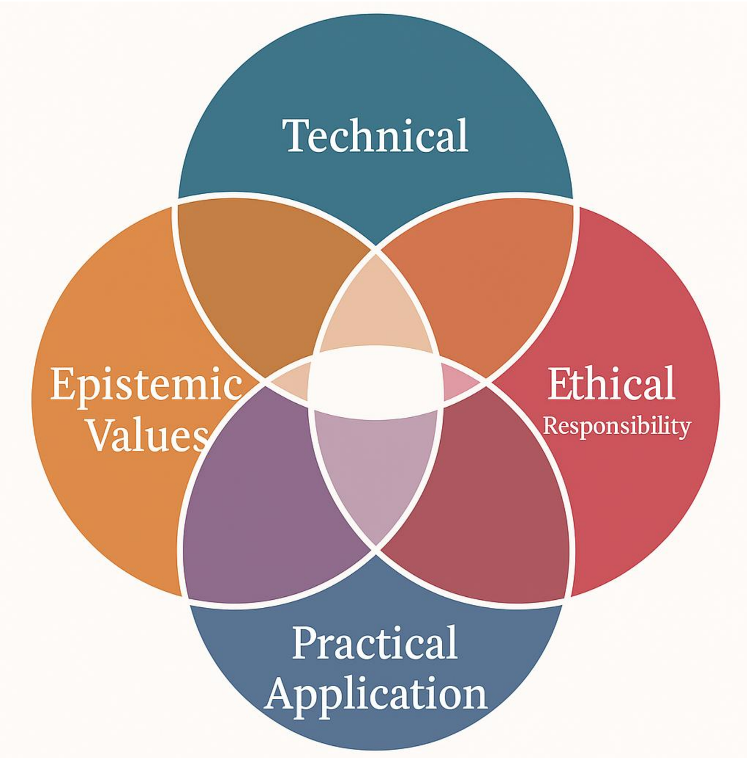

Figure 8. Principal Dimensions of Ethical AI Literacy (Consolidated View)
Source: Artificial Intelligence

This figure will illustrate the principal domains of ethical AI literacy, integrating technical, epistemic, ethical, social, and applied dimensions. It aims to present AI literacy not merely as a functional competence, but as a critical and ethical consciousness that supports meaningful academic participation.

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Chapter 6 - Preservice and Inservice Teachers' Perceptions of ChatGPT in Education

Hua Bai

Chapter Highlights

- Preservice teachers and inservice teachers both recognized the value of ChatGPT in education
- They shared some common concerns, including ethical issues associated with using GenAI, over-reliance on ChatGPT and the risk of receiving inaccurate information from AI-generated output.
- Equity issue in accessing AI, lack of confidence in using AI, and uncertainty about AI future were additional concerns expressed by preservice teachers. One inservice teacher concerned about the lack of context and personalization in ChatGPT-generated output.
- They intended to use ChatGPT to support unit and lesson planning, address pedagogical challenges and assist with administrative work.
- Training in the effective, ethical and professional use of GenAI in education is essential for both preservice and inservice teachers.

Introduction

Since the term was introduced in 1950s, artificial intelligence (AI) has evolved and increasingly become a transformative force in human society. The release of ChatGPT in November 2022 by OpenAI has marked a significant milestone, bringing generative AI (GenAI) into the spotlight and highlighting its potential to revolutionize various fields including education. In the education-specific guidance on AI integration report issued by the Office of Educational Technology (Cardona & Rodriguez, 2024), GenAI was defined as "the class of AI models that emulate the structure and characteristics of input data in order to generate derived synthetic content. This can include images, videos, audio, text, and other digital content" (p.2). GenAI tools, such as ChatGPT, have demonstrated the capability to generate human-like responses and facilitate various educational tasks. According to a global student survey conducted by the Digital Education Council (2024), 86% of university students regularly used AI in their studies and ChatGPT was the most widely used tool. As AI continues to evolve, its integration into education presents opportunities and challenges to educators and students.

GenAI and Education

AI has evolved significantly over the past decades, from symbolic AI and predictive AI to GenAI, a powerful technology capable of creating content including text, images, videos, and code (Pratschke, 2024). The rapid development of GenAI technologies has profound implications for education, motivating educators to reevaluate traditional teaching methods and consider using AI to support education. Woodruff et al. (2023) conducted a survey involving more than 4500 PK-12 educators across all 50 states. They found that, in general, the K12 educators have positive perceptions of AI, with only a small percentage of participants reporting negative perceptions. AI technologies have the potential to increase student motivation and engagement, provide individualized learning and feedback, encourage self-directed and interactive learning, and foster collaboration. AI also can help to improve teachers' instruction, support their professional development and automate administrative work including assessment and record management (Adiguzel et al., 2023; Allehyani & Algamdi, 2023; Hanover Research, 2023; Kim, 2024; Mechelen et al., 2023; Woodruff et al., 2023).

In the age of AI, it is necessary to rethink K-12 education to equip students with the knowledge and skills for a future where AI may be integrated into every aspect of their lives. Therefore, fostering students' AI literacy is essential to prepare them for the future. According to Wang and Lester (2023), "AI literacy is the ability to readily engage with AI by leveraging AI tools, systems, and framework to effectively and ethically solve problems in a wide range of sociocultural contexts (p. 231). They suggested that AI education be incorporated into every subject area in K-12 settings and that professional development on AI should be offered to teachers.

ChatGPT in Education

The GenAI chatbots use large language models to process natural language and generate human-like responses based on users' prompts. They can engage in dialogue, answer questions, provide explanations, generate content and assist users in various tasks. It has been reported that AI chatbots could have positive effects on student learning performance, motivation, interest, self-efficacy and student perceived value of learning (Wu & Yu, 2023). As an AI chatbot, ChatGPT is built on the Generative Pre-trained Transformer architecture and designed to interact conversationally based on users' inputs, which enables it to "write articles, stories, and poems, provide summaries, accommodate different perspectives, and even write and debug computer code, making it a valuable tool in education settings" (Labadze et al., 2023, p.9)

The launch of ChatGPT-3 in November 2022 sparked mixed responses in the field of education, ranging from concern to excitement. Major concerns encompassed increased cheating and plagiarism, misinformation, equity issues, bias and violation of intellectual property rights. The arguments for potential benefits included creating educational materials, developing adaptive learning strategies, personalized learning, reduced teacher workload, enhanced accessibility, and assistance in research and writing (Adiguzel et al., 2023; Labadze et al., 2023; Mishra et al., 2023; Oster et al., 2024). As a prominent example of GenAI, ChatGPT is transforming education at various levels.

The faculty in higher education were encouraged to have first-hand experience with ChatGPT to know its capabilities and shortcomings (Hanover Research, 2023). Wang (2023) tested ChatGPT's capabilities in physics education and found that it did well on interpreting simple problems coding but did not answer conceptual questions correctly. When testing ChatGPT's conceptual knowledge about material science, Daher et al. (2023) found that ChatGPT was able to solve remembering problems but encountered significant conceptual knowledge difficulties. Despite its limitations, ChatGPT had the potential to serve as a valuable companion for students who were solving chemistry problems. Yavuz et al. (2024) examined the reliability and validity of ChatGPT and Google Bard in grading EFL students' essays. They found that the two AI tools demonstrated potential for assessment but "tended to be more generous in grading good- and average-quality essays" (p. 14) than human raters. A review of the articles published between 2022 and 2023 reported that ChatGPT in higher education can support instruction, assessment innovation, remote learning, research design and development, academic writing and administrative productivity. However, there were concerns associated with its use, such as academic integrity, data security, bias and inaccurate information (Sok & Heng, 2024). After examining faculty and students' views of ChatGPT, Espartinez (2024) proposed a balanced approach, accommodating the use of ChatGPT within the educational framework while promoting ethical and responsible usage.

In K-12 settings, a survey with a nationally representative sample of 1020 teachers and 231 public school districts was conducted in Fall 2023, followed by interviews with 11 district leaders in December 2023 and January 2024 (Diliberti et al., 2024). The results revealed that as of Fall 2023, 18 percent of the teachers reported using AI for teaching and more than half had used the chatbots such as ChatGPT. Teachers have been reported to use ChatGPT to prepare and facilitate instruction, assess student learning and assist with administrative work (Oster et al., 2024). The current literature has mixed findings on teachers' perceptions of using ChatGPT in K-12 education. For example, in a survey of Missouri K-12 teachers, most participants were high school teachers, primarily teaching language arts and social sciences. Their perceptions of ChatGPT were mainly neutral, with more unfavorable responses than favorable ones. It needs to be noted that about 18% of the teachers used ChatGPT in job-related work, but only 4.5% of them actually integrated it into lessons (Hays et al., 2024). A study with 115 English language arts teachers in the Philippines, spanning elementary to college levels, found that most participants agreed that ChatGPT can enhance English language learning and improve accessibility, although they also expressed some concerns (Mabuan, 2024). In both studies, the teacher participants thought they needed knowledge and a certain level of proficiency in using ChatGPT, which indicates the necessity of teachers' professional development in using this AI tool in K-12 settings.

Teacher Education

Teachers play a crucial role in leveraging AI technologies to support instruction, student learning and the development of students' AI literacy. In teacher education, teacher educators need to model relevant practices that teacher education students can incorporate into their future classrooms. In terms of using GenAI, educators need to help teacher education students develop essential skills in GenAI tools, expose them to innovative instructional strategies and equip the students with the knowledge to use those tools ethically and effectively in K-12 classrooms. Some researchers and educators have argued the use of ChatGPT in teacher education, such as math education (Hodge-Zickerman & York, 2024; Sapkota & Bondurant, 2024; Yulia, 2024), special education (Khazanchi & Khazanchi, 2024), science education (Cooper, 2023; Küchemann et al., 2023), and language learning (Teng & Huang, 2025).

Given the growing interest in using GenAI in teacher education, it is necessary to consider how teacher education students perceive it and whether they are willing to integrate it into their teaching practice. Cun and Huang (2024) interviewed some undergraduate preservice teachers in elementary education to get their perceptions based on their life experiences using ChatGPT. They found that some preservice teachers believed ChatGPT was helpful, but some were concerned about its use in their future teaching practice. Perceived ease of use and perceived usefulness could influence preservice teachers' acceptance of AI (Zhang et al., 2023). Therefore, engaging them in hands-on learning activities with AI tools is necessary. Lee et al. (2024) conducted an experiment to examine the effect of AI chatbots on preservice teachers' responsive teaching skills in math education. The post-test results showed significant improvement in the experiment group. The preservice teachers in the experiment group had more favorable perceptions of the interaction with the chatbots.

While ChatGPT is making its way into education, limited research has explored teacher education students' perceptions after learning about and using it in learning activities. An experiment investigating the impact of ChatGPT on teacher education students' engagement in writing in English as a foreign language revealed that the students who received feedback from ChatGPT demonstrated greater affective and behavioral engagement in learning English writing but showed no difference in cognitive engagement. It is worth mentioning that when using ChatGPT, the experiment group prompted it using a pre-crafted prompt provided by the instructor (Teng & Huang, 2025). Kalenda et al. (2025) had preservice teachers critically analyze the GPT-generated lesson plans in their subject areas to see how well the plans met the standards for effective lesson plans in their field. The preservice teachers thought that AI-generated lesson plans fell short of expectations, lacking completeness and sufficient details and failing to support differentiated instruction for diverse learning needs and styles. In this study, the preservice teachers did not interact with ChatGPT themselves. The researchers recommended that future practice could have the participants prompt ChatGPT to get the intended output. In examining preservice teachers' perceptions of using ChatGPT in curriculum planning, Biberman-Shalev (2025) had preservice teachers interact with ChatGPT. Approximately half of them self-reported being unfamiliar with generative AI tools. The analysis of the preservice teachers' conversations with ChatGPT, their reflection papers and focus group interview responses showed that they generally supported integrating ChatGPT into curriculum planning and referred to it as a teacher assistant. Pesce and Blanco (2024) evaluated the preservice teachers' knowledge and prior experience in using ChatGPT when they took a course on assessment and then had them use it as an AI assistant in learning. Evidence suggested that the preservice teachers had a good understanding of ChatGPT and how it works. However, they lacked the skills to apply this knowledge in practice, highlighting the need for more hands-on experience to boost their confidence in using AI effectively.

In Spring 2023, Picciano (2024) had a group of teacher education students use ChatGPT to assist their essay writing after they received a one-hour introduction to ChatGPT specifically tailored for essay writing. Most of them had positive experiences. They valued time efficiency and idea generation when using ChatGPT in assisting with writing, viewing it as a tool that would improve student writing and support student learning in both ESL and math. They also expressed concerns, including the students' dependency on it for content and writing tasks, ethical issues and plagiarism. After learning about AI, ChatGPT and its applications, some undergraduate science teacher candidates and graduate students in the science education program of a state university in Turkey prompted ChatGPT to generate questions about environmental issues. The analysis of their interactions with ChatGPT and the interview data indicated that most of them intended to use ChatGPT in research and question creation in science teaching (Özer et al., 2024). Kurt & Kurt (2024) reported that after being trained on using ChatGPT and effective prompting techniques, the preservice teachers of English in a writing class compared feedback on their wring from three sources -

peers, the instructor and ChatGPT. They felt that using ChatGPT enabled them to receive feedback conveniently, interactively and adaptatively, but the instructor's feedback was most reliable, accurate and thorough. The rapid evolution of GenAI calls for more research on its incorporation into teaching and learning (Kaplan-Rakowski et al., 2023). To address this need, it is important to examine inservice and preservice teachers' perceptions of GenAI tools, such as ChatGPT, as their attitudes and experience will influence their classroom practice and technology integration.

Research Purpose and Questions

This research aimed to enrich the current literature on the use of ChatGPT in education by examining teacher education students' perceptions of ChatGPT after a two-week asynchronous learning unit on AI in education. Since the teacher education students include preservice teachers and inservice teachers, comparing their perceptions in the investigation is helpful. Specifically, there were two research questions.

1. How did preservice and inservice teachers' attitudes toward using ChatGPT in education differ?
2. How did preservice and inservice teachers' intentions to incorporate ChatGPT in teaching practice differ?

Methods

Context and Participants

This study was conducted in three graduate-level instructional technology classes that the same instructor taught at a mid-west university. The participants consisted of 9 inservice teachers and 19 preservice teachers. The inservice teachers were enrolled in a digital literacy class in a leadership program. The preservice teachers included 4 students from an instructional technology class for secondary education program and 15 students who took an instructional technology class for elementary and middle-level education. In each class, there was a two-week unit on AI in education. In this learning unit, students attended a self-paced lesson to learn about the concepts of AI and generative AI, how to prompt AI chatbots like ChatGPT, and how ChatGPT can be integrated into education. The lesson included the instructor's presentation, videos, external resources, quizzes and open-ended questions. In addition, the students read articles on the educational use of ChatGPT and had hands-on experience with ChatGPT. Before the AI learning unit started in each class, the students needed to do a digital storytelling project in which they created a digital story to support student learning or leadership practice. In the unit of AI, the students first prompted ChatGPT to generate a digital story script on the same topic and for the same target group of users as their own. Then, they compared the AI-generated script with their own, identifying its strengths and weaknesses. Following that, the students had ChatGPT provide feedback on their own script. They reflected on the suggestions provided by ChatGPT, considering which they agreed and disagreed with, and then revised their story script accordingly.

Data Collection and Analysis

At the end of the learning unit, all the participants completed a survey measuring their attitudes toward using ChatGPT and their intended applications in education. This survey was adapted from an existing instrument on attitudes and practices regarding the educational use of ChatGPT (Robledo et al., 2023). It comprised 13 Likert-scale items ranging from 1 (Strongly Disagree) to 6 (Strongly Agree) to assess the participants' attitudes toward using ChatGPT, along with six additional items in the same format to measure their intended use of ChatGPT in education. Additionally, three open-ended questions invited the participants to provide examples of how they planned to incorporate ChatGPT into their teaching practices, share any concerns or challenges they anticipate, and offer any comments they had about the educational use of ChatGPT.

Descriptive statistical analyses were first conducted in data analysis. When comparing the two groups' responses to the Likert scale items in the survey, statistical tests were performed to determine whether there was a significant difference in the attitudes and intentions between the preservice teachers and the in-service teachers. In addition, the two groups' responses to the open-ended questions in the survey were analyzed and coded to identify emerging themes and patterns in each group. All these analyses helped to answer the research questions.

Results

Preservice Teachers and Inservice Teachers' Attitudes

Normality tests of both groups' responses to the Likert-scale items indicated that both data sets were normally distributed. Then, the F-test for two sample variances showed that the variances of the two groups' responses were not significantly different, $F(18,8) = 1.12$, $p = 0.46$. Therefore, a two-sample t-test assuming equal variance was performed. It was found that the preservice teachers' attitudes toward ChatGPT in education ($M = 4.25$, $SD = 0.28$) were not significantly different from that of the inservice teachers ($M = 4.15$, $SD = 0.27$), $t(26) = 0.94$, $p = 0.36$, although the preservice teachers demonstrated slightly more positive attitudes.

A close examination of their responses to each item (Table 1) revealed that both groups found ChatGPT to be a helpful tool for learning, and they believed it had the potential to revolutionize the way people accessed information. In comparison, the preservice teachers slightly disagreed (M=3.68) on the item "I trust the responses provided by the ChatGPT", but the in-service teachers slightly agreed (M=4.22). While the preservice teachers slightly agreed with the statement, "I believe that using ChatGPT to complete academic assignments is unethical" (M=4.11), the in-service teachers slightly disagreed (M=3.89). Both groups disagreed (M=2.84) or slightly disagreed (M=3.22) that using ChatGPT for academic purposes should be discouraged. Both groups disagreed that it should be banned in all schools and academic institutions but agreed that its use should be regulated.

Table 1. Mean Value of Each Group's Ratings on "Attitudes" Items

Items	Preservice teachers (N = 19)	Inservice teachers (N = 9)
I find ChatGPT helpful in answering questions.	4.32	4.56
I trust the responses provided by ChatGPT.	3.68	4.22
I find ChatGPT to be a useful tool for learning.	5	4.78
I believe ChatGPT has the potential to revolutionize the way we access information.	5.53	4.78
I am concerned about the ethical implications of using ChatGPT.	4.84	4.44
I believe that using ChatGPT to complete academic assignments is unethical.	4.11	3.89
I believe that using ChatGPT for academic purposes should be discouraged.	2.84	3.22

Items	Preservice teachers ($N = 19$)	Inservice teachers ($N = 9$)
I believe that ChatGPT should be banned in all schools and academic institutions.	2.11	2.22
I believe that the use of ChatGPT for academic purposes undermines the learning process.	3.32	3
I think that the use of ChatGPT for academic purposes should be monitored and regulated.	5.58	5.22
I think people who use ChatGPT for academic purposes are cheating.	2.79	3.11
I think that schools and educators should educate students on the dangers of relying on ChatGPT for academic purposes.	5.79	5.56
I think ChatGPT is useful when used correctly and monitored accordingly.	5.37	4.89

The analysis of the participants' responses to the open-ended questions revealed some common concerns of both groups and additional concerns of each group.

Major Common Concerns

Ten out of 19 preservice teachers (53%) and 4 out of 9 inservice teachers (44%) expressed concern about the ethical issue related to the use of ChatGPT. This corresponded to the finding that for the survey item, "I am concerned about the ethical implications of using ChatGPT," the mean values of the responses were 4.84 and 4.44 for the preservice and in-service teachers, respectively. The inservice teachers' comments on this issue focused on the cheating behaviors, such as "Students are more likely to use it to cheat than use it as a learning tool" and "have concerns over student use and the ability of the AI to create a paper in seconds that the students have no real input in creating themselves." Some preservice teachers were worried that the students might not understand the concept of plagiarism and wondered about the dividing line between cheating and not cheating. One preservice teacher commented, "How much is too much? A part of me does feel like using ChatGPT is cheating, but I think as long as you still revise it and don't use it word for word then it should be okay."

Another preservice teacher stated, “I'm concerned that students wouldn't be able to recognize the line between plagiarism and original content--that being, students may take sections (paragraphs or even pages) from a ChatGPT generated text and add to it in an attempt to hide their cheating.”

For the preservice teachers, the ethical issue was related not only to student cheating but also to disrespect of intellectual property, as evidenced by the remark, “I fear that AI is able to scrub such a wide database of information, but it can be disrespectful towards intellectual property. I know this isn't chatGPT directly but dall-e (open ai) has been criticized for plagiarizing artists’ works in its image generation capabilities.”

Students' over-reliance on AI tools such as ChatGPT in learning was another common concern shared by 6 preservice teachers (32%) and 3 inservice Teachers (33%), as they thought it might undermine learning. One inservice teacher commented,

> Students will rely heavily on it without learning the skills to do the activities. Many students both general education and special education, struggle significantly in identifying implicit details in texts and then formulating CER writing. My concern is that they would utilize it without reflecting on the structure or methods of actual writing.

Similar concern was also expressed by some preservice teachers. For example, one preservice teacher pointed out, “A concern with ChatGPT would be that students will reply on it too much. I am concerned that they will depend on its efficiency and quick responses.” This common concern is also reflected by their ratings on the survey item. Both preservice teachers (*M*=5.79) and inservice teachers (*M*=5.56) agreed that schools and educators should educate students on the dangers of relying on ChatGPT for academic purposes.

In addition, 4 preservice teachers (21%) and 3 inservice teachers (33%) expressed concern about the accuracy of the information generated by ChatGPT, as one preservice teacher noted, “I would need to be extremely careful with the material ChatGPT generates, since it is not 100% accurate. The information provided by ChatGPT would need to be verified.” One inservice teacher connected the potential inaccuracy with the prompting technique, “The first and foremost concern is the validity of the information provided. Especially if I have prompted ChatGPT with vague information. It may not create an accurate response or miss the mark with what I’m trying to create.”

Additional Concerns

Besides the common concerns, three other concerns were identified when analyzing the preservice teachers' responses. One preservice teacher was concerned that not all students, especially those from underprivileged communities, may have access to AI technologies. Another preservice teacher felt unprepared to use AI with the students, "I am concerned with teaching my students how to safely and ethically use this technology. It is so new to me and I feel like I am barely beginning to understand it, but I must prepare my students for a future that is powered by AI." Moreover, one preservice teacher felt uncertain about the future of AI.

The additional concern disclosed by one inservice teacher's response was the lack of context and personalization in ChatGPT-generated output. This inservice teacher noted,

> I just feel like context is missing a lot and sometimes recommendations are very bland

or

> just an assumption of what works as a one size fits all solution. I felt like in evaluating my writing, the tool is off touch with human aspects and I think the same exists when it comes to getting ideas on how to approach an activity -- especially when thinking about the context of students.

Preservice Teachers and Inservice Teachers' Intentions

Normality tests of both groups' responses to the Likert-scale items that measured their intentions to use ChatGPT indicated that the preservice teachers' data set was not normally distributed. Given this, a Mann-Whiteney test was conducted. It was found that the two groups' responses were not significantly different ($U = 69.5$, $p = 0.4$), although the preservice teachers' responses ($M = 4.4$) were slightly more positive than those of the inservice teachers ($M = 4.2$).

Table 2 shows the mean values of each group's responses to those survey items. Both groups agreed to review and revise the ChatGPT-generated outputs before using them. They also slightly agreed that they intended to use ChatGPT as a starting point when teaching a topic and used it to make work easier and faster. Both groups slightly disagreed to use ChatGPT for educational purposes only. Regarding using ChatGPT to teach a content area and explain complicated concepts or topics in teaching, the preservice teachers slightly agreed, but the inservice teachers disagreed.

Table 2. Mean Value of Each Group's Ratings on "Intentions" Items

Items	Preservice teachers (N = 19)	Inservice teachers (N = 9)
I will review and revise the outputs of ChatGPT before using them.	5.79	5.33
I intend to use ChatGPT to teach in my content area.	4.21	3.89
I intend to use ChatGPT to get an initial idea about specific topics in my teaching.	4.53	4.33
I intend to use ChatGPT to help explain complicated concepts or topics in my teaching.	4.32	3.89
I intend to use ChatGPT for educational purposes only.	3.37	3.33
I intend to use ChatGPT to make my work easier and faster.	4.21	4.56

The analysis of the examples that the participants provided to indicate how they would use ChatGPT in teaching practice revealed three major common uses across the two groups and two additional uses by the preservice teachers

Major Common Uses

Using ChatGPT to support lesson and unit planning was intended by 11 preservice teachers (58%) and 7 inservice teachers (78%). They intended to use it to get feedback on lesson and unit plans, create assignments and assessments, or use it as a starting point to get some ideas. As one preservice teacher commented,

> I may use it to help improve or add on to lesson plans/topics I already have. I think it would be helpful for providing ideas and maybe even activities to incorporate into the lesson. I also think that with very specific and tailored prompts, I may use ChatGPT to help generate assignment topics, quizzes, or project ideas.

Similar thoughts were expressed by some inservice teachers, as one inservice teacher stated,

> refining current lesson plans to potentially increase learning and engagement. For example, if we are doing nutrition unit and some of the activities have gotten stale, asking ChatGPT to help create new activities within certain parameters and lesson objectives can help me create new activities to use during the nutrition lesson or unit.

Seven (37%) preservice teachers and 3 (33%) inservice teachers intended to use ChatGPT to address pedagogical challenges, such as creating customized materials to meet diverse student needs and explaining complex or complicated concepts. One inservice teacher explained, “I intend to use it to help me differentiate a lesson. For example, it can give me different levels of problem sets to help students with various skill levels.” One preservice teacher asserted, “I would consider using it if there is a concept that I’m trying to explain and maybe the students aren’t understanding it, I would search on ChatGPT if there are maybe other ways I can explain it.”

In addition, using ChatGPT for administrative work was shared by one preservice teacher and one inservice teacher. Both intended to use it to draft emails or letters to the parents. Notably, two (11%) preservice teachers and one (5%) inservice teacher explicitly stated that they did not intend to use the AI tools, such as ChatGPT. The inservice teacher commented, “Being a physical education teacher allows me to give students the opportunity to be active and prevent them from using any kind of technology. I think it can be difficult to use ChatGPT for my discipline and will not consider using it.” One preservice teacher claimed,

> At the moment I do not intend to use it. I still am not very familiar with it or enthusiastic about it. I already notice the students at my school have pretty weak writing stamina and I only see that becoming more and more of a problem with generative AI being such an available tool.

The other preservice teacher who did not intend to use ChatGPT thought it did “not encourage students or the teacher to think critically about the topic.”

Additional Uses

When describing how they intend to use the AI tools such as ChatGPT, 3 (16%) preservice teachers gave examples of using it to foster student engagement, as one of them would be “allowing students to go on ChatGPT to generate creative prompts to write about and also, to play around with creating works of prose and poetry generated by ChatGPT." This preservice teacher thought this would "spark the interest of students to show them that literature and language arts can be fun." Furthermore, using ChatGPT for grading was an example provided by one preservice teacher, "Today, I asked ChatGPT if I could upload scanned worksheets with answer guide and it said 'yes'. Of course, I would have to double check things and also review written questions, but imagine all the time saved as a science teacher."

Discussion and Implications

Kaplan-Rakowski et al. (2023) surveyed 147 teachers who used ChatGPT and found that over 80% of the respondents considered ChatGPT a valuable tool. The preservice teachers' positive perceptions of the use of ChatGPT were also reported in the literature (Biberman-Shalev, 2025; Kurt & Kurt, 2024; Özer et al., 2024; Pesce & Blanco, 2024; Picciano, 2024). Similarly, in this study, both preservice teachers and inservice teachers recognized the potential value of ChatGPT in education, including answering questions, transforming the way to access information and supporting learning. Overall, they had positive attitudes toward using ChatGPT for educational purposes and believed that its use in academics should not be discouraged. However, they emphasized the importance of educating students about the risks of relying on ChatGPT. Despite the fact that there was no statistically significant difference between the two groups in their responses to the survey items, a slight difference was found in some items. The inservice teachers tended not to believe that using ChatGPT to complete academic assignments was unethical, whereas the preservice teachers tended to hold this belief. This echoed their responses to the open-ended question, as the analysis revealed that more than half of the preservice teachers expressed concern about the ethical issue of using ChatGPT, however, less than half of the inservice teachers specified this concern. Also, the inservice teachers tended to trust the responses provided by ChatGPT, but the preservice teachers did not. This seemed to align with their responses to the open-ended question, as more preservice teachers than inservice teachers raised concern about the accuracy of the information generated by ChatGPT.

Regarding the intended use of ChatGPT, in general, both groups intended to use ChatGPT to get an initial idea about specific teaching topics and make their work easier and faster. Both groups agreed to review and revise the outputs before using them. There was a slight difference in their intention to use it for teaching content areas and explaining complex concepts, with the preservice teachers being slightly more positive than the inservice teachers. This finding was inconsistent with the examples they provided to indicate how they would integrate ChatGPT into teaching, as 11 out of 19 (58%) preservice teachers but 7 out of 9 (77%) inservice teachers would like to use it to support lesson and unit planning, including getting feedback on the plan, creating assignments and assessments, or brainstorming ideas. Given that there were 19 preservice teachers but only 9 inservice teachers, the unbalanced sample size of the inservice teachers probably caused the nuanced difference identified in the quantitative data analysis. Future research may need a comparable sample size to better examine the differences between the two population groups. The other common uses of ChatGPT intended by both groups included creating customized learning materials, explaining complicated concepts, and supporting administrative work. It needs to be acknowledged that only one preservice teacher planned to use ChatGPT for grading and no inservice teachers mentioned that. Perhaps the participants in this study did not see it as a proper tool for grading.

Meishar-Tal (2024) pointed out that ChatGPT may hinder the cognitive engagement necessary in the in-depth learning process and make users rely on it. The students' over-reliance on ChatGPT was a concern shared by the participants in both groups, reinforcing the findings reported by some researchers who examined the perceptions of teachers (Kim & Kim, 2022) and preservice teachers (Kurt & Kurt, 2024). After conducting a systematic literature review on the role of AI chatbots, especially the use of ChatGPT in education, Labadze et al. (2023) found that teachers are concerned about excessive reliance on ChatGPT by the students, as it could negatively affect critical thinking and problem-solving. To address this concern, teacher educators need to model the use of AI tools such as ChatGPT and help the teacher education students learn to create rules to prevent overreliance on its use in K12 settings (Mabuan, 2024). The students should be informed of the importance of gaining a strong understanding of the content knowledge. Once they have developed foundational knowledge and skills, AI tools such as ChatGPT can be a valuable resource (Hays et al., 2024). At this point, teacher educators need to prepare teacher education students to use AI tools in pedagogically sound ways. Zimotti et al. (2024) recommended “a task-based approach” (p. 20) that would help students understand when to use AI to support learning or performance and when they should not use it. The use of AI should not impede the student's growth and cognitive development.

The ethical issue related to using ChatGPT was another concern expressed by the preservice teachers and the inservice teachers in this study, focusing on student cheating behaviors. This result aligned with the findings reported in the current literature that inservice teachers (Evmenova et al., 2024; Mabuan, 2024) and preservice teachers (Labadez et al., 2023; Pesce & Blanco, 2024) took the ethical issue as a challenge when using ChatGPT in education. Whereas the academic integrity policy is in place, it alone cannot prevent students from using AI inappropriately (Zimotti et al., 2024). Teacher education students need to know the strategies that help mitigate academic integrity risks. It has been suggested that the assessment method should be changed from a product-oriented approach to a process-oriented approach. Instead of evaluating students' finished work or final performance, conducting continuous assessments through low-stake activities (Zimotti et al., 2024) or examining the student's critical thinking in the process (Eke, 2023) could minimize the likelihood of taking shortcuts by using AI. This could be coupled with written reflections, as AI may not create concrete individualized self-reflection on one's growth in the learning process (Johnson et al., 2024). Perkins et al. (2024) created an assessment scale that allows educators in higher education to determine the appropriate level of generative AI usage in assessment to address the intended learning outcome. Teacher educators could adopt this assessment scale when integrating AI into teaching practice to model the use of AI in assessment for teacher education students.

The concern regarding the possibility that AI chatbots, such as ChatGPT, could provide inaccurate information to the users has been discussed in current literature (Adiguzel et al., 2023; Labadze et al., 2023; Ng et al., 2023; Pesce & Blanco, 2024). This study reflected those findings, as the participants realized that the ChatGPT-generated output would need to be verified, and vague prompting would lead to inaccurate or unreliable information in the response. These findings emphasized the importance of not only having a solid background or content knowledge in the subject matter (Labadze et al., 2023) but also adopting a critical mindset when using AI. In teacher education, it is important to help students understand the drawbacks of AI tools, learn to prompt GenAI effectively and evaluate the output professionally, which in turn will enable them to encourage the K-12 students to think critically about AI tools to promote responsible and ethical use. Hopefully, the constant improvement **in AI chatbot performance** resulting from the **evolution** of AI technologies will diminish this concern; as Küchemann et al. (2023) mentioned, "GPT-4 can potentially provide more current information than GPT-3.5, deliver higher quality responses, handle ambiguous questions more effectively, be better at maintaining context, and have a potentially lower frequency of inappropriate content generated by the model" (p.020128-4).

Bekdemir (2024) suggested, "AI applications should be designed to be accessible to students from diverse backgrounds and abilities, fostering inclusivity" (p. 40). One preservice teacher in this study shared concerns about the equity in the accessibility of AI technologies. Such concerns highlight the need to factor in the equity issue during the development of AI technologies. As with other types of technologies, teacher education students need to be engaged in discussions about strategies for making AI accessible to all students when adopting AI to support teaching and learning. The other concerns identified in the preservice teachers' comments included a lack of teacher knowledge and the uncertainty of AI's future. In addition, one inservice teacher was concerned about the lack of context and personalization in ChatGPT-generated outputs.

It must be noted that two preservice teachers and one inservice teacher explicitly stated they did not intend to use ChatGPT. ChatGPT. As a physical education teacher, the inservice teacher thought of limiting students' screen time and engaging them in physical activities. This teacher seems to focus on the application of ChatGPT during class time rather than its use within a broader teaching framework. The preservice teachers were reluctant to use ChatGPT due to a lack of knowledge and worries about the development of students' critical thinking skills. These additional concerns and intentions not to use ChatGPT further indicated the necessity of training in GenAI in teacher education (Casal-Otero et al., 2023). The teacher education students should understand the basic concepts of GenAI and its capabilities, limits and ethical implications (Ng et al., 2023). Teacher education students should also learn to effectively and efficiently prompt AI chatbots, such as ChatGPT (Küchemann et al., 2023; Özer et al., 2024), as good prompting techniques could enable ChatGPT to generate personalized content to address specific contextual needs. To embrace the opportunities and face GenAI's challenges, "teachers need to experiment and play with these tools, seeking new pedagogical techniques in response to ongoing technological advancement and change" (Mishra et al., 2023; p. 244). Therefore, teacher training needs to develop teacher education students' AI knowledge and skills and equip them with pedagogical knowledge of AI implementation. On top of this, it may be necessary for schools or colleges of education to develop AI policies to guide educators and teacher education students' use of AI.

Limitations

This study used a convenient sampling method to ensure the participants had the same learning experience. The convenient sampling method and the small number of participants prevented the findings of the study from being fully representative of the larger population. Additionally, the unequal group sizes, with the preservice teachers' group being more than twice the size of the inservice teachers' group, may have influenced the results. Therefore, it is difficult to generalize the results to broader contexts. Another limitation of the study lies in the data collection method. All the data were collected from the survey, which consisted of Likert-scale items and open-ended questions. No interviews were conducted with any participants. Although the survey data provided helpful information, they may not capture the full depth of the participants' thoughts, limiting the ability to explore the nuances in the participants' perceptions. Future research could be conducted with larger and balanced groups of preservice teachers and inservice teachers to enhance comparability and support the generalization of the findings. Future research could also collect more qualitative data, such as interviews with focus groups, to provide a deeper and more comprehensive understanding of the topic.

Conclusion

Given the potential of using ChatGPT in education, more research should be undertaken on it (Wu & Yu, 2024). Teachers' attitudes toward AI will influence the use of AI in education (Casal-Otero et al., 2023). This study compared the preservice teachers and the inservice teachers' attitudes toward using ChatGPT in education and their intentions to integrate it into teaching practice. No significant differences between the two groups were found. They held similar perspectives and shared some common concerns and intentions regarding using ChatGPT. Hopefully, the findings of this study and the discussion of the results can help to enrich the current literature about GenAI in education and provide references for future research. A report (Weiner et al., 2024) released by the Center on Reinventing Public Education revealed that U.S. education schools were lagging in training future teachers in AI. The implications of this study's findings shed light on teacher preparation programs, emphasizing the importance of equipping teacher education students with the knowledge and skills needed to incorporate GenAI into their teaching practice effectively and ethically.

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Chapter 7 - Teacher Education and Professional Development for Generative Artificial Intelligence Readiness: The Role of Educational Leadership

Bünyamin Ağalday

Chapter Highlights

- Provides a comprehensive framework for understanding how educational leadership can support teacher readiness for generative artificial intelligence integration in diverse school contexts.
- Synthesizes current research across artificial intelligence in education, teacher education, and educational leadership to identify emerging leadership roles and responsibilities.
- Proposes a redefinition of teacher competencies in light of generative artificial intelligence, including pedagogical, ethical, and technological dimensions.
- Explores leadership-driven strategies for professional development and system-wide capacity building aligned with generative artificial intelligence demands.
- Identifies institutional and structural barriers in leadership-facilitated teacher preparation and offers actionable solutions.
- Offers evidence-based, policy-oriented recommendations for integrating generative artificial intelligence in educational systems, focusing on equity, ethics, and sustainability.

Introduction

The rapid advancement of generative artificial intelligence (GenAI) has brought about a paradigm shift across various sectors, including education. Unlike earlier forms of educational technology, which were often supplementary and procedural, GenAI tools such as ChatGPT, Claude, and Copilot possess generative and interactive capacities that challenge traditional pedagogical models, teacher roles, and leadership functions. These tools produce language and content autonomously and personalize learning, generate feedback, simulate dialogue, and aid in lesson planning. Integrating GenAI into education is not simply a matter of digital tool adoption but a transformation of the foundations upon which teaching and leadership practices rest (Giannakos et al., 2025).

At the heart of this transformation lies a dual imperative: reconceptualizing educational leadership in a GenAI-enhanced context and ensuring teacher readiness to navigate these shifts responsibly, ethically, and effectively. Educational leaders are now required to serve not only as instructional managers or policy implementers but also as digital strategists, ethical gatekeepers, and innovation architects (Dai et al., 2025). Their decisions shape institutional responses to artificial intelligence (AI) adoption and how these technologies are integrated into teaching and learning processes in equitable, sustainable, and pedagogically sound ways. This transition is not without complexity: school leaders must negotiate the tensions between innovation and regulation, efficiency and ethics, automation and humanism (Polat et al., 2025). These tensions are not abstract-they manifest in curriculum planning, professional development (PD) priorities, and technology procurement decisions. Navigating such dilemmas requires more than technical know-how; it demands ethical sensitivity and strategic foresight.

Simultaneously, teachers face mounting pressure to adapt to classrooms where AI agents may act as co-instructors, assessment partners, or content curators. GenAI challenges the long-held notion of teachers as sole knowledge transmitters and repositions them as facilitators, curators, and critical mediators of algorithmically generated content (Sperling et al., 2024). This role transformation demands significant shifts in teachers' technological pedagogical knowledge (TPACK), AI literacy, data awareness, and critical reflection skills, reflecting the multidimensional AI competence framework described by Chiu et al. (2025) and the evolving perspectives on teacher knowledge emphasized by Mishra (2019). However, studies show that many teachers remain underprepared or uncertain about how to use AI meaningfully in their practice (Wang et al., 2023; Yau et al., 2023). Without structured PD and leadership guidance, there is a risk of superficial adoption or technocentric determinism, a trend observable in the thematic gaps identified by recent bibliometric analyses of GenAI in education (Liu et al., 2024) and in empirical accounts of school-level strategies (Ng et al., 2025).

The integration of GenAI into education also intensifies existing systemic challenges. The digital divide, already a concern in many countries, may be exacerbated by uneven access to AI tools, infrastructure, and training- an issue acknowledged in global surveys of AI in education (Holmes & Tuomi, 2022). Moreover, AI applications in education often function as "black boxes," producing results through opaque algorithms that are difficult for teachers and administrators to interpret or challenge (Gillani et al., 2023). This lack of transparency introduces significant ethical dilemmas concerning student privacy, bias, surveillance, and the deskilling of educators. As such, GenAI-readiness is not only a matter of technical competence but also of ethical discernment, critical inquiry, and leadership foresight (Holmes et al., 2022).

From a policy perspective, global organizations such as UNESCO and OECD have begun issuing frameworks to guide AI implementation in education. These emphasize the importance of inclusion, human-centered design, and teacher agency in the digital transformation of schooling (Holmes & Miao, 2023; Miao & Holmes, 2021). Nevertheless, the actual implementation of these guidelines varies greatly by national context, institutional capacity, and leadership vision. In low-resource or bureaucratically rigid systems, top-down mandates may fail to equip school leaders and teachers with the localized strategies and resources necessary for meaningful integration. Conversely, in more agile systems, school leaders are encouraged to experiment with aligning innovation with learner choice and rights principles in AI-mediated environments (Berendt et al., 2020).

Therefore, educational leadership in the age of GenAI entails a complex balancing act. Leaders must support teacher learning while navigating technological trends, institutional demands, and stakeholder expectations. They must cultivate PD ecosystems beyond training in tool use and instead focus on pedagogical alignment, ethical reflection, and collaborative inquiry (Ngubane, 2025). In this context, teacher readiness is both a leadership responsibility and an indicator of systemic GenAI capacity.

Given the abovementioned issues, integrating GenAI into education is not merely a technical innovation but a profound socio-cultural, ethical, and pedagogical transformation that demands redefined approaches to leadership and teacher professionalism. The complexity of this transformation calls for a multifaceted response from education systems and actors at all levels. Leadership and teacher capacity must evolve to ensure meaningful and equitable GenAI integration.

This book chapter critically explores the complex interplay between educational leadership and teacher development in fostering institutional readiness for GenAI. Drawing on empirical studies, policy frameworks, and conceptual insights, the chapter unfolds across a sequence of interrelated themes: it first analyzes the evolving nature of teacher competencies in the GenAI era, then examines emerging strategies and models for professional development. The discussion proceeds by addressing the responsibilities of educational leadership in guiding system-wide readiness, followed by an in-depth consideration of ethical and inclusive leadership practices in teacher preparation. Subsequently, the chapter interrogates key institutional and structural barriers while highlighting opportunities for transformative leadership. Finally, it concludes with synthesized insights and presents policy-oriented recommendations designed to guide future actions across multiple levels of the education system.

By articulating the scope and complexity of leadership and teacher readiness in the GenAI era, this introduction sets the stage for a deeper investigation into how education systems can move from reactive adaptation to proactive transformation. It calls on researchers, policymakers, school leaders, and teacher educators to co-create a future where AI is not merely deployed in schools but deliberately shaped by educational values, professional ethics, and democratic participation**.** This collaborative vision is essential for ensuring that GenAI serves educational equity and human development, rather than exacerbating systemic disparities.

The Changing Nature of Teaching Competencies in the GenAI Era

The emergence of GenAI has redefined the skillset and competencies required of teachers in contemporary educational environments. Traditionally, teacher competencies have centered around subject expertise, pedagogical strategies, classroom management, and assessment literacy. However, the pedagogical affordances and epistemological challenges posed by GenAI require a fundamental shift in what it means to be a competent teacher in the digital era (Kim, 2024a; Zhai et al., 2021). As generative systems become embedded in curriculum, instructional design, and learner support mechanisms, teaching no longer revolves solely around content delivery, but rather critical mediation, design thinking, and ethical guidance.

One of the most profound changes in teaching competencies is the necessity for AI literacy. This concept includes technical fluency with GenAI tools and understanding how AI systems process data, generate outputs, and introduce bias (Sperling et al., 2024). It also involves translating this understanding into pedagogical decisions that foster student awareness, responsible use, and critical digital citizenship. Teachers must be able to critically evaluate AI-generated content, guide students in verifying its accuracy, and contextualize its use within pedagogical goals. According to Chiu et al. (2025), effective teacher AI competence encompasses multiple dimensions, including AI knowledge, pedagogical integration, assessment practices, ethics, human-centered education, and ongoing professional engagement. These dimensions collectively support teachers in responsibly and effectively integrating AI tools in education.

The TPACK framework (Technological Pedagogical Content Knowledge) has long served as a model for integrating technology into pedagogy, yet GenAI challenges the sufficiency of this model. Teachers must now engage with a new layer of human-AI collaborative pedagogy, where learning occurs through human instruction and the co-construction of knowledge with intelligent systems (Mishra, 2019). This reconfiguration demands novel competencies such as designing AI-inclusive tasks, understanding the implications of algorithmic decision-making, and supporting students' critical AI use.

Moreover, the GenAI era has introduced a demand for adaptive instructional design. Since GenAI tools like ChatGPT can generate personalized content, examples, and explanations, teachers must curate and scaffold their use appropriately within the learning environment. According to Zhang & Zhang (2024), teachers increasingly act as curators and evaluators of AI-generated content, ensuring it aligns with curriculum standards, learner needs, and cultural contexts. This also involves prompt engineering- the deliberate crafting of inputs to guide

GenAI outputs in ways that align with learning goals- a skill noted in recent studies exploring how teachers strategically interact with ChatGPT in subject-specific contexts (Beege et al., 2024). This emerging instructional design role challenges traditional planning models and necessitates teacher autonomy in navigating AI-generated content. Teachers must learn to interpret GenAI outputs and anticipate their influence on students' cognitive and emotional engagement.

In addition to technical and design-based competencies, GenAI highlights the importance of ethical discernment in teaching. With AI systems collecting and analyzing learner data, teachers must be competent in navigating privacy, consent, fairness, and transparency (Fu & Weng, 2024; Sharples, 2023). Ethical pedagogy in the GenAI era requires a keen understanding of AI governance principles and the ability to model responsible digital behavior for students. Studies show that when teachers lack confidence in these areas, they are less likely to integrate AI meaningfully in their instruction (Du et al., 2024; Wang et al., 2023).

Furthermore, the teacher's role as an affective and social anchor becomes even more critical in AI-mediated classrooms. While GenAI can personalize content delivery, it cannot replace education's relational, motivational, and humanizing dimensions (Guilherme, 2019). Teachers must thus develop competencies in fostering human-AI collaboration that centers empathy, inclusion, and dialogue. As Edwards et al. (2018) argue, emotional intelligence, adaptability, and cultural sensitivity are emerging as core teaching competencies in technologically saturated environments.

Professional identity formation is also transforming. Teachers are no longer solely content experts or facilitators, but are now expected to be AI interpreters, ethical stewards, and learning designers. This shift affects teachers' perceptions of their roles, purpose, and sense of agency. According to Moorhouse et al. (2024), some educators express anxiety or role confusion in response to AI integration, underscoring the need for leadership support and reflective PD opportunities. Without such support structures, there is a risk that the evolving demands of AI integration could erode teacher morale, confidence, and long-term professional engagement.

In response to these competency shifts, several countries and institutions have started to develop AI competency frameworks for educators. For instance, UNESCO's 2021 guidance on AI in education proposes a multidimensional model encompassing technical, pedagogical, and ethical competencies (Holmes & Miao, 2023). Similarly, recent strategic reports on GenAI integration have underscored the growing importance of frameworks like the European Commission's DigCompEdu, which is being extended in many contexts to address AI-related competences such as data literacy, algorithmic awareness, and AI-mediated assessment (Ng et al., 2025). These frameworks are essential guides but require local adaptation and contextual implementation through teacher education programs.

Empirical research also provides insight into the actual state of GenAI-related teacher competencies. Du et al. (2024) conducted an experimental study showing that targeted AI literacy workshops significantly improved teachers' confidence and capacity to integrate GenAI in the classroom. Similarly, the work of Tammets and Ley (2023) highlights the importance of ongoing, case-based learning in professional development, as it enables teachers to explore authentic dilemmas and apply GenAI tools in contextually relevant ways. These early efforts reflect a growing awareness of the need to systematize GenAI competencies. However, awareness alone is insufficient to close the implementation gap.

Despite these promising developments, significant gaps remain. Many teacher education programs lack structured modules on AI integration, and in-service training is often fragmented or overly technical (Tan et al., 2025). Moreover, disparities in access to AI tools and expertise widen the digital competency divide between schools, regions, and socio-economic groups. Without systemic investment and leadership coordination, the transformation of teacher competencies may reinforce existing inequalities rather than democratize opportunity (Ngubane, 2025; Williamson, 2024).

In conclusion, the GenAI era is reshaping teaching competence. Beyond technological skills, teachers are now called to be ethically grounded, pedagogically creative, and socially responsive actors in AI-mediated learning environments. Educational leaders, policy designers, and teacher educators must collaborate to define, support, and evaluate these new competencies in a manner that promotes inclusion, agency, and pedagogical integrity. GenAI, if critically and thoughtfully integrated, offers not a replacement of the teacher, but a reimagining of the teacher's role as a co-designer of meaningful learning in a technologically augmented world.

Rethinking Professional Development: Strategies and Structures

Having outlined the evolving competencies required of teachers in the GenAI era, it becomes essential to explore how professional development strategies must adapt to cultivate these skills effectively. In the age of GenAI, teachers' PD can no longer be confined to conventional models of skill acquisition or isolated technology training. The pedagogical integration of GenAI requires a fundamental rethinking of PD strategies that address the complexity, adaptability, and ethical challenges associated with AI-mediated teaching and learning environments (Moorhouse & Kohnke, 2024; Tan et al., 2025). This shift demands not only the reorganization of content but also the restructuring of how PD is delivered, evaluated, and institutionalized. As GenAI evolves, static or generic PD programs risk becoming obsolete, making agility and responsiveness core design principles for modern PD systems.

From Technical Training to Pedagogical Transformation

Traditional PD models often focus on tool-based proficiency, assuming that once teachers understand a technology, they will integrate it effectively into their practice. However, research has shown that GenAI necessitates pedagogical sensemaking, where teachers learn not just how to use AI tools, but when, why, and to what extent their use is pedagogically appropriate (Sperling et al., 2024; Tammets & Ley, 2023). Building on these insights, this study frames this shift as a movement from basic training toward more transformational learning experiences, grounded in critical reflection, ethical awareness, and collaborative problem-solving. In this regard, PD should enhance technical skillsets while supporting cognitive restructuring and identity redefinition in teaching with intelligent technologies.

PD should now support teachers in understanding algorithmic design, AI affordances, and the co-construction of knowledge with intelligent systems. For instance, Chiu et al. (2025) highlight the importance of contextual case-based learning, where teachers explore specific classroom dilemmas related to AI integration and develop responses grounded in their instructional realities. Similarly, Langran et al. (2024) advocate for design-based PD, where teachers co-create lesson plans involving GenAI tools and iterate them based on feedback and reflection. This collaborative and iterative approach fosters deeper pedagogical ownership and promotes a culture of experimentation among educators.

Continuous, Cyclical, and Collaborative Structures

GenAI is rapidly evolving. As such, PD must transition from one-time workshops to cyclical, continuous, and embedded learning structures**.** This means creating professional learning communities (PLCs) where teachers can share experiences, troubleshoot implementation challenges, and collaboratively explore GenAI's impact on student learning. While Du et al. (2024) do not specifically address PLCs, their findings on the benefits of targeted AI literacy workshops underscore how collaborative, context-driven learning structures can enhance teachers' readiness for GenAI integration. Similarly, the collaboration types identified by Kim (2024b) in K–12 AI integration contexts illustrate how peer networks and shared inquiry, core elements of PLCs, can foster sustainable AI adoption. These communities also serve as psychological safety nets, helping teachers cope with the uncertainty and ambiguity associated with emerging technologies.

Tammets and Ley (2023) propose a spiral AI-focused professional development (PD) model grounded in Kolb's experiential learning cycle, which engages teachers in four iterative phases. The model begins with the concrete learning phase, where teachers design real-world problems or tasks incorporating AI tools, enabling students to concretize abstract concepts. This is followed by the reflective observation phase, during which teachers evaluate students' problem-solving processes and the role of AI through reflection on past experiences. Next, in the abstract conceptualization phase, teachers develop broader understandings of collaborative problem-solving skills and adapt these insights to various teaching contexts. Finally, the active experimentation phase involves applying new instructional methods, testing theories, and assessing student engagement with AI tools. At the core of this model lies classroom orchestration, emphasizing the continuous development of teachers' professional vision and adaptive teaching skills through individual and collective reflection, experimentation, and collaboration. This cyclical approach fosters social learning and supports ongoing innovation in AI-integrated pedagogy.

Furthermore, co-teaching models involve instructional technologists, AI specialists, and pedagogical mentors, while Mishra et al. (2024) focus on the intersections of AI, teacher knowledge, and research; their emphasis on collaborative knowledge-building aligns with the rationale for distributed expertise in co-teaching arrangements. These partnerships foster cross-disciplinary learning and reduce the burden of solo exploration often placed on teachers. This form of distributed expertise not only diversifies professional input but also encourages a richer dialogue around the affordances and limitations of GenAI.

Hybrid and Multimodal Delivery Formats

As with the tools being introduced, PD must adopt hybrid, multimodal, and personalized formats, while Zhang & Zhang (2024) primarily examine the changing role of teachers in AI-mediated education, their findings on diverse instructional modes can inform the design of flexible PD delivery formats. These diverse formats allow educators to engage with content asynchronously, fostering flexibility without sacrificing depth or relevance.

One emerging practice is using AI-enabled reflection tools that help teachers evaluate their practices. For example, Phillips et al. (2023) describe a toolkit that provides feedback on teacher dialogue, engagement strategies, and AI use patterns, enabling more targeted and data-driven reflection. Similarly, generative tools can support just-in-time coaching, providing teachers with sample prompts, lesson ideas, and ethical guidelines on demand (Fu & Weng, 2024). Integrating such tools into PD scaffolds self-directed learning and supports evidence-informed instructional decisions.

Nevertheless, these innovations must be matched with human-centered support. Research shows that many teachers appreciate flexible digital formats but value structured, face-to-face discussions for deeper ethical deliberation and professional identity work (Felix, 2020). Thus, an effective PD ecosystem balances the efficiency of digital tools with the relational depth of interpersonal mentorship and community dialogue.

Ethical Capacity and Critical AI Literacy

A unique dimension of GenAI-oriented PD is the need to cultivate teachers' ethical AI awareness and decision-making skills. Beyond knowing how to use AI, teachers must understand bias, student surveillance, algorithmic opacity, and the social implications of AI deployment in classrooms (Holmes et al., 2022). These dimensions challenge the notion of value-neutral technology use and place moral reasoning at the center of AI literacy. For example, Noroozi et al. (2024) argue that teachers should be trained in recognizing hidden biases in AI-generated content and in helping students develop critical AI literacy. This has led to ethics-infused PD models, where modules on data justice, inclusivity, and algorithmic fairness are embedded alongside technical training (Fu & Weng, 2024). Such integration ensures that ethical inquiry is not an afterthought but a foundational layer of professional growth.

Furthermore, PD must create spaces for values-based dialogue where teachers can articulate concerns, share ambiguous experiences, and explore AI's humanistic dimensions in education. PD risks normalizing uncritical AI adoption or technocentric determinism without such critical reflection. Encouraging open-ended discussion allows educators to collectively grapple with dilemmas and co-create shared norms for ethical AI use.

Leadership Support and Institutional Integration

Effective GenAI-related PD is not only a matter of program design but also of institutional culture. Educational leadership is pivotal in framing AI as a pedagogical, not merely technical, priority (Arar et al., 2025). When school leaders model ethical AI use, allocate time for professional learning, and build reward structures around innovation, teachers are more likely to engage with PD seriously and sustainably. Leadership engagement also signals institutional commitment, which can significantly enhance teacher motivation and participation in PD efforts.

Moreover, PD must be integrated into broader school development plans, including curriculum reform, assessment strategies, and digital infrastructure upgrades (Dai et al., 2025). Otherwise, AI training remains peripheral or disconnected from the real demands teachers face in classrooms. This alignment ensures coherence between professional learning and day-to-day instructional realities, enhancing the transfer and sustainability of AI-related practices.

At a systemic level, policy frameworks such as UNESCO's *AI Competency Framework for Teachers* (Miao & Holmes, 2021) and the European Commission's DigCompEdu model are guiding the development of scalable, modular PD ecosystems. However, implementation must be localized and co-designed with teachers to reflect their context-specific realities. Policy without contextual grounding risks producing top-down mandates that lack practical traction in schools.

PD models to enhance teachers' pedagogical competencies for GenAI integration can only achieve lasting impact when embedded within coherent, system-level strategies supported by robust educational leadership. The innovative practices discussed in the PD context, such as spiral learning models, hybrid and multimodal formats, and ethics-oriented capacity building, can be scaled and sustained when guided by visionary leadership, strategic resource allocation, and purposeful cultural transformation. Bridging individual teacher growth with institutional and policy-level leadership strategies is a prerequisite for embedding GenAI meaningfully and ethically into the educational ecosystem.

Educational Leadership for System-Wide GenAI Readiness

While teacher-focused PD is crucial, its effectiveness depends on system-wide leadership that can coordinate, scale, and sustain AI integration across diverse educational contexts. As GenAI becomes increasingly embedded in the infrastructure of education systems, the role of educational leadership must evolve from passive facilitation to proactive orchestration. While much attention has been devoted to preparing teachers and students for GenAI tools, system-wide readiness hinges on the ability of educational leaders to develop scalable strategies, foster ethical integration, and reimagine institutional cultures (Fullan et al., 2024). GenAI is not just a technological shift-it represents a profound structural change in the knowledge ecosystem, necessitating responsive, future-oriented leadership across all levels. In this transformative context, leaders must act as cultural stewards who align technological innovation with core educational values and long-term vision.

Redefining Leadership Competencies for the GenAI Era

Traditional leadership models in education emphasized hierarchical decision-making, operational oversight, and instructional supervision. However, GenAI introduces a complex sociotechnical environment that requires leaders to possess AI literacy, data-informed strategic planning, and transformative capacity (Dai et al., 2025; Karakose & Tülübas, 2024). Wang (2021) suggests that AI-aware leadership must involve hybrid decision-making, where human judgment and machine insights are deliberately combined rather than substituted. This co-decision paradigm calls for an evolved skill set that includes critically interpreting algorithmic recommendations and foresight in shaping their application in schools.

Educational leaders are now expected to interpret algorithmic outputs, assess predictive models, and facilitate responsible school AI deployment. This requires meta-leadership- the ability to operate across disciplines, policy levels, and stakeholder interests (Milton & Al-Busaidi, 2023). Moreover, the development of AI ethics leadership is emerging as a distinct domain, involving skills in data governance, equity analysis, and digital justice (Aldighrir, 2024). Such ethical leadership must also account for the long-term societal impacts of GenAI adoption, especially regarding youth development and civic engagement.

Strategic Planning for System-Wide Readiness

Systemic integration of GenAI cannot succeed without comprehensive strategic planning. This entails aligning GenAI adoption with curriculum reform, infrastructure development, capacity-building programs, and monitoring frameworks. Dai et al. (2025) present a symbiotic leadership model, where administrators co-design AI policies with educators, technologists, and policymakers to ensure contextual relevance. These models emphasize inclusive leadership and seek to balance technological efficiency with educational purpose.

Leaders must identify key readiness indicators across the system: digital infrastructure quality, teacher competencies, student access, data security protocols, and ethical use standards. The UNESCO AI Readiness Framework (Miao & Holmes, 2021) serves as a helpful reference, categorizing readiness regarding governance, capacity, infrastructure, and data systems. However, studies show that implementation gaps persist, particularly in low-resourced contexts or decentralized governance systems (Holmes & Miao, 2023; Ngubane, 2025). Thus, strategic planning must be adaptive, equity-oriented, and supported by sustained funding mechanisms to bridge contextual disparities.

Leadership in Professional Culture and Ethical Integration

One of GenAI leadership's most under-explored yet critical dimensions is shaping an institutional culture that values criticality, inclusivity, and pedagogical ethics. School leaders must go beyond compliance to foster reflexive cultures, where AI is interrogated, debated, and adapted to meet community values (Bixler & Ceballos, 2025). This cultural shift requires leaders to create dialogic spaces where staff and students can critically examine AI's role in shaping knowledge, authority, and social dynamics.

This involves creating PD ecosystems where teachers feel supported in experimenting with GenAI tools while navigating uncertainty and risk. Fullan et al. (2024) emphasize the importance of psychological safety and collective efficacy; teachers must be empowered to make AI-related decisions without fear of failure or surveillance. Moreover, equitable access must be a central concern, as disparities in AI exposure and resources risk reproducing digital inequalities. Leadership that foregrounds trust, inclusion, and transparency can help mitigate these risks and foster a climate of pedagogical courage.

Policy Design and Regulatory Leadership

Educational leadership for GenAI readiness also requires engaging with macro-level policy structures. Leaders at district, regional, and national levels must co-develop AI governance models that set standards for data use, algorithm transparency, and ethical AI procurement (Polat et al., 2025). Arar et al. (2025) review highlights the lack of cohesive AI policies in most national education systems, particularly regarding generative AI. In response, leaders must advocate for frameworks that balance innovation with rights protection, ensuring that GenAI tools enhance rather than undermine learners' autonomy and agency. Such frameworks must be dynamic and continuously reviewed to align with fast-evolving AI capabilities. Additionally, regulation must address third-party vendors, many of whom supply GenAI tools without sufficient oversight or curricular alignment. Strategic leadership in this context involves forging accountable partnerships while maintaining educational sovereignty. This entails establishing procurement standards prioritizing transparency, accessibility, and alignment with pedagogical principles.

Distributed and Networked Leadership Models

Centralized leadership is insufficient for GenAI-era transformation. Research suggests the efficacy of distributed leadership models, where principals, department heads, IT coordinators, and teacher-leaders collaborate across hierarchical boundaries. While Ghamrawi et al. (2024) focus on teacher leadership in AI contexts, their findings illustrate how empowering teacher-leaders can be a cornerstone of leadership strategies for GenAI readiness. This enables faster adaptation, localized problem-solving, and richer knowledge flows. Such horizontal leadership practices also foster a sense of shared responsibility and ownership of innovation among staff.

Moreover, networked communities of practice across schools, districts, and countries are vital for scaling insights and sharing innovations. Global initiatives such as EDUCAUSE AI Learning Lab and OECD's AI in Education Forum exemplify how transnational collaboration can complement system-level readiness efforts. Leaders must actively cultivate these networks and facilitate cross-sector dialogue between education, tech, and civil society. Leaders can position their institutions at the forefront of ethical and practical GenAI implementation by participating in global knowledge exchanges.

Leading Ethical and Inclusive GenAI Practices in Teacher Preparation

Beyond strategic and structural readiness, leadership must embody ethical and inclusive principles to ensure that GenAI integration in teacher preparation aligns with broader social justice and equity goals. As educational systems integrate GenAI into teacher preparation programs, there is a growing imperative to reconfigure leadership frameworks to uphold ethical, inclusive, and socially responsible values. Leadership that neglects the moral implications of AI adoption may inadvertently reinforce biases, widen digital divides, or diminish human agency in teaching. This section discusses how educational leadership must be ethically grounded and inclusively oriented to ensure just, equitable, and effective GenAI integration into teacher education.

GenAI has demonstrated its capacity to transform pedagogy, assessment, and curriculum design; however, its application must be governed by ethical considerations such as transparency, accountability, and fairness (Caratozzolo et al., 2025). Leadership is pivotal in determining how these principles are translated into policy and practice within teacher education institutions. Leaders must establish technical infrastructures and foster ethical cultures that promote critical reflection and responsible innovation (Sangwa, 2025).

Equally critical is the integration of inclusive values in AI deployment. Inclusive leadership ensures that teacher education programs address the needs of all learners, particularly marginalized groups who may be disproportionately affected by AI biases or limited access to technology. Parviz and Ghorbanpour (2025) emphasize that AI-enhanced instructional systems may replicate systemic inequalities embedded in training data if left unchecked. As such, inclusive leadership requires foresight in auditing AI tools and training educators to identify and mitigate algorithmic bias.

One of the fundamental responsibilities of ethical leadership is ensuring that teacher candidates develop AI literacy that includes an understanding of moral dilemmas and social implications. Educators must be equipped to facilitate discussions around AI and equity in classrooms and to recognize when AI tools might compromise students' privacy and autonomy (Ndjama, 2025). In this regard, leadership must develop strategic capacity-building initiatives beyond functional AI skills to encompass socio-ethical competencies (Papadimitriou et al., 2025).

Institutional structures also play a role in either facilitating or hindering ethical integration. Williamson and Murray (2025) note that faculty development programs may underrepresent these critical dimensions without adequate leadership attention, focusing instead on tool use rather than pedagogical transformation. Educational leaders must invest in governance frameworks that set clear ethical guidelines for GenAI use across curricula, hiring, and student data management systems (Ghilay, 2025).

Furthermore, inclusive leadership must account for the diversity of teacher backgrounds and learning contexts. For instance, policy design should ensure that AI tools and training are accessible in rural and underfunded schools, where teachers may lack resources or digital infrastructure (Asad et al., 2024). Tailored leadership approaches can help bridge this divide, emphasizing localized support systems and culturally responsive pedagogies.

Promising ethical and inclusive leadership models emphasize participatory decision-making, stakeholder dialogue, and reflective policy formulation. In line with this perspective, UNESCO's *AI and Education: A Guidance for Policymakers* (Miao & Holmes, 2021) advocates for human-centered AI that supports equity, inclusion, and learner well-being, ensuring that values of justice and diversity inform all aspects of GenAI integration in education. Such an approach requires leaders to foster ongoing collaboration among diverse stakeholders and embed ethical considerations into every policy and practice development stage. Creating educational environments where AI tools serve all learners fairly and effectively is essential. In sum, embedding ethical and inclusive leadership practices into teacher preparation is not an ancillary concern but a foundational necessity in the GenAI era. Future-ready teacher education programs must be led by individuals who are not only technologically competent but also ethically visionary and inclusively minded. Without such leadership, the promises of GenAI may falter into new forms of exclusion and inequity.

Barriers and Opportunities in Leadership-Driven Teacher Preparation

Even with strong ethical and inclusive leadership, the integration of GenAI into teacher preparation is shaped by persistent barriers and emerging opportunities that demand adaptive, context-sensitive solutions. The infusion of GenAI into educational environments has created new demands on school systems, calling for rapid adaptation in both policy and pedagogy. Central to this transformation is the role of educational leadership in orchestrating teacher readiness. In this context, leadership is not only a facilitator of access to technology but a catalyst for cultural, ethical, and instructional change (Fullan et al., 2024; Karakose & Tülübas, 2024). However, aligning teacher preparation with GenAI integration reveals a complex terrain, defined by institutional barriers on one hand and substantial opportunities on the other.

Among the most significant challenges is the lack of strategic clarity. Many institutions still struggle to articulate how GenAI should be positioned within teaching practices, leading to fragmented implementation and inconsistent pedagogical alignment (Calderone & Wilder, 2025). Without strong vision from educational leadership, PD efforts often fail to address foundational issues such as teacher beliefs, pedagogical paradigms, and learning equity (Dai et al., 2025). Without leadership-defined AI frameworks, teachers are left navigating uncertain digital landscapes without a clear roadmap.

Closely tied to strategic ambiguity is the issue of infrastructure disparity. GenAI demands reliable internet access, computational capacity, and specialized digital platforms- all distributed unevenly across schools and regions. This digital divide is particularly salient in underserved communities where leaders struggle to provide equitable access to the tools and training necessary for GenAI adoption (Ngubane, 2025). Leaders are thus compelled to secure funding and prioritize inclusion as a design principle in teacher training programs.

Furthermore, teacher resistance poses a nuanced challenge. Resistance is not simply technophobia- it often stems from concerns about professional identity, classroom authority, and the deskilling of teaching. As Tigerstedt et al. (2024) demonstrate, many teachers view GenAI tools as overly complex or misaligned with their instructional goals, often drawing on prior negative experiences with earlier waves of technology integration, which shape their current skepticism. Educational leaders must therefore cultivate trust and agency by involving teachers in AI policy formation and pilot program design (Hoang, 2025).

Compounding these concerns are ethical and epistemological uncertainties. Teachers express discomfort with questions of authorship and originality in AI-generated content (Aldighrir, 2024; Fu & Weng, 2024). Educators must make ethical decisions independently without institutional guidelines, often contradicting evolving norms. This ethical burden can lead to avoidance, reinforcing the technological gap. Leadership must proactively establish normative and operational boundaries for GenAI usage, including governance mechanisms and feedback structures (Polat et al., 2025).

Yet, despite these persistent barriers, the GenAI transition offers considerable transformational potential, especially when mobilized through strategic and ethical leadership. One such opportunity lies in personalized PD. As Nyaaba and Zhai (2024) emphasize, leadership should move beyond generic PD models toward targeted, role-sensitive training that reflects teachers' specific disciplines, levels, and readiness stages. Such models can incorporate scenario-based workshops, AI-augmented lesson simulations, and reflective inquiry processes.

In parallel, the rise of distributed and collaborative leadership models marks a significant shift. Instead of centralizing GenAI decisions in a few hands, successful institutions are forming AI learning communities composed of teachers, tech mentors, school leaders, and external researchers. These co-leadership structures democratize innovation and foster cultural ownership (Sposato, 2025). As Cohn et al. (2025) argue, collaborative AI ecosystems reduce resistance and accelerate pedagogical experimentation.

Additionally, policy co-creation is emerging as a powerful leadership strategy. Policy relevance and legitimacy increase when educational leaders facilitate active teacher participation in local and national GenAI policy discussions. This is particularly important in contexts where centralized policies may lack cultural sensitivity or contextual fit (Arar et al., 2025). Co-creation processes improve policy outcomes and enhance teacher morale and long-term commitment.

The integration of GenAI into initial teacher education (ITE) programs represents another high-impact opportunity. Institutions such as the University of Cambridge and Stanford GSE are beginning to introduce pre-service teachers to AI concepts such as prompt engineering, machine learning basics, and human–AI collaboration (Edwards et al., 2018; Tammets & Ley, 2023). Embedding such competencies into teacher identity formation ensures that future educators approach GenAI not as a threat but as a collaborative partner.

Moreover, GenAI offers tools to enhance metacognition and teacher reflection. Platforms like reflective chatbots and AI-assisted analytics dashboards can provide teachers with feedback loops for self-evaluation, thereby increasing professional growth and reducing burnout (Phillips et al., 2023). However, successfully implementing these tools depends on leaders fostering a culture of psychological safety, where experimentation is rewarded and errors are treated as learning opportunities.

Finally, leadership in the GenAI era must take an ethics-first approach. According to Aldighrir (2024), school administrators must model ethical digital behaviors and ensure diverse voices, especially those of marginalized teachers and students, are included in AI design and governance. This entails adopting transparent AI tools, publishing data usage policies, and creating local AI review boards. Leadership thus becomes not only technical, but moral and cultural.

In sum, the pathway to GenAI readiness in teacher preparation is neither smooth nor uniform. While barriers such as resource inequality, ethical ambiguity, and pedagogical resistance persist, they are not insurmountable. When leadership is strategic, inclusive, and forward-thinking, these barriers can become catalysts for structural rethinking and pedagogical renewal. As Fullan et al. (2024) suggest, the challenge is not whether AI will be used in schools, but how wisely and humanely it will be integrated. Educational leaders are uniquely positioned to ensure that this integration strengthens the relational, ethical, and intellectual core of teaching.

Conclusion

Having examined the persistent barriers and the emerging opportunities in leadership-driven teacher preparation, it is now possible to synthesize these insights into a broader understanding of how GenAI is reshaping the educational landscape. The transformative impact of GenAI on education, while still unfolding, has already begun to challenge many long-standing assumptions about teaching, learning, and educational leadership. Across this chapter, a growing body of literature and practical observation has illuminated how GenAI is altering the foundational dimensions of teacher education and professional development. In particular, the ability of GenAI to generate content, support personalized learning pathways, provide real-time feedback, and automate routine instructional tasks is forcing educators and school systems to reimagine professional roles and organizational structures.

What emerges from this analysis is a clear understanding that teacher preparation for GenAI is not merely a technical upgrade. It is a complex professional shift that implicates ethics, pedagogical identities, leadership culture, and the very purposes of schooling. The concept of readiness must therefore be reframed, not only as technological literacy but as a profound transformation in how teachers conceptualize their roles in relation to intelligent systems. Leaders in education systems have a pivotal role in facilitating this shift. They are not simply managers of innovation but shapers of vision, builders of trust, and mediators between evolving technologies and existing professional cultures.

Leadership that fails to engage in this transformation strategically and inclusively risks creating shallow, tool-centered reforms that alienate teachers rather than empower them. The evidence suggests that teachers demonstrate greater confidence, agency, and willingness to experiment with GenAI tools where school leaders establish shared visions, support long-term professional learning, and uphold ethical values (Fullan et al., 2024; Leithwood et al., 2019; Zhang & Zhang, 2024). Conversely, where leadership is absent or overly technocratic, AI adoption remains fragmented, compliance-driven, and sometimes regressive in its pedagogical impact.

Importantly, the promise of GenAI for education will not be realized through isolated pilot projects or one-off workshops. The successful integration of AI requires systemic, sustained, and reflective action, anchored by ethically grounded and pedagogically informed leadership. The literature reveals substantial barriers to this transformation, including equity gaps in infrastructure, ethical uncertainties, institutional resistance, and the need for new teacher knowledge forms (Holmes & Miao, 2023; Kim et al., 2020). However, the opportunities are equally compelling. With thoughtful policy support, collaborative leadership structures, and purposeful professional development, education systems can evolve into learning organizations that are both digitally advanced and human-centered.

Educational leaders are uniquely positioned to bridge the space between abstract policy goals and classroom realities. Their capacity to lead through ambiguity, foster innovation, and protect pedagogical values will determine whether GenAI becomes a force for teacher empowerment or alienation. As such, this chapter closes with a series of forward-looking policy recommendations to guide educational leadership and system designers in shaping GenAI-informed teacher preparation ecosystems.

Recommendations

In light of the conclusions drawn, there is a pressing need for educational policy frameworks to move beyond a reactive stance and toward proactive, structurally embedded approaches that enable ethical and impactful GenAI integration in teacher education. First and foremost, policymakers should prioritize the development of a national framework that defines generative AI competencies for teachers. These competencies must encompass technical skills, critical thinking, ethical reflection, and the ability to evaluate AI-generated content. Countries and institutions without such frameworks risk implementing fragmented and inconsistent approaches that burden teachers with uncertainty rather than support.

In parallel, it is essential to embed GenAI literacy into all levels of teacher preparation, from pre-service education to continuous professional development. Teacher training institutions should revise accreditation standards to include AI pedagogy, prompt engineering, human-AI co-design strategies, and ethical deliberation. Rather than treating AI as a standalone topic, it must become an integrated and transversal theme across subject areas, pedagogical methods, and instructional design models.

To support this pedagogical integration, leadership models within educational institutions must evolve. Distributed and participatory leadership structures should be encouraged, where school principals, teacher mentors, curriculum developers, and even students co-design the roadmap for GenAI implementation. Policies should enable this by allocating specific funding to leadership training, school-level AI task forces, and innovation networks, allowing bottom-up experimentation and knowledge sharing.

The growing ethical complexity of AI systems also demands institutional mechanisms that can respond flexibly and transparently. Educational institutions should be encouraged to establish internal ethics committees that review AI tool usage, data privacy policies, and pedagogical impacts. Furthermore, national policy must define protocols for algorithmic decision-making, especially in student assessment and predictive analytics, ensuring that human oversight remains central.

Infrastructure and access also remain critical enablers. Equity-focused investment in digital tools, reliable internet connectivity, and secure AI platforms is foundational for inclusive GenAI integration. PD opportunities must be scaled, not only in quantity but in quality. Teachers require long-term, collaborative, and context-sensitive learning opportunities, supported by mentors, digital coaches, and reflective tools that allow them to adapt AI to their local conditions.

Additionally, research–practice integration should be made a cornerstone of policy. Institutions should be incentivized to engage in action research and publish their findings regarding GenAI integration. This builds a local knowledge base and ensures that empirical evidence rather than market trends informs practices. Policies should also encourage partnerships between universities, teacher education programs, and school districts to co-develop AI curricula, evaluation rubrics, and professional learning communities.

Lastly, an intentional effort must be made to cultivate leadership capacity around GenAI ethics, systems thinking, and foresight. Leadership development programs should include modules on AI policy, platform governance, ethical risk management, and digital transformation planning. Principals and system leaders are the architects of the educational culture in which GenAI will be normalized, and without their active, informed participation, no sustainable transformation is possible.

In conclusion, the path to GenAI readiness is both urgent and uncertain. The most effective policies will be those that position leadership not merely as implementation agents, but as pedagogical visionaries capable of guiding institutions through complexity with moral clarity, equity orientation, and systemic intentionality. By aligning policy, leadership, and teacher development, educational systems can move from fragmented experimentation to cohesive transformation, ensuring that GenAI strengthens, rather than disrupts, the core values of education.

Notes

This study is dedicated to the cherished memory of my beloved brother, Dr. Burak Ağalday, whose sudden passing has left us in deep sorrow.

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Chapter 8 - Towards the Integration of Generative Artificial Intelligence in Education: Issues, Opportunities, Ethical Challenge and Socio-Economic Impact

Hmidi Alaeddine

Chapter Highlights

- Introduces a comprehensive framework for the ethical and pedagogical integration of Generative AI (GAI) in education, emphasizing personalization, inclusion, and human–AI hybridization.
- Identifies and analyzes major ethical risks, including algorithmic bias, cognitive dependency, and the dehumanization of learning processes.
- Proposes strategic recommendations for teacher training, student AI literacy, responsible policy-making, and inclusive infrastructure development.
- Highlights real-world case studies from Finland, South Korea, and the Arab world to illustrate varied levels of GAI adoption and effectiveness.
- Advocates for a humanistic and pluralistic educational model where GAI is a tool for empowerment rather than a replacement for educators.

Introduction

Over the past decade, education systems have undergone profound transformations driven by the rise of digitalization, online platforms, and more recently, by the integration of artificial intelligence (AI) into pedagogical practices. In this context, Generative Artificial Intelligence (GAI) stands out as a major technological breakthrough, redefining the dynamics of knowledge production and dissemination (Luckin et al. 2016). GAI distinguishes itself from other forms of AI through its ability to autonomously generate original content (texts, images, videos, computer code) based on previously learned data. Thanks to large language models (LLMs) such as GPT-4 (OpenAI, 2023), these systems can simulate human-like language skills, enabling conversational interaction, information summarization, and the rephrasing of complex content.

The integration of GAI into education aligns with a broader shift toward more personalized, adaptive, and technology- enhanced schooling, as advocated by international organizations such as UNESCO (UNESCO, 2023) .and the OECD It enables the automation of certain educational tasks (writing, translation, formative assessment), the customization of learning paths according to learner levels, and the development of interactive pedagogical resources. However, the rapid emergence of these technologies raises significant epistemological, ethical, and pedagogical challenges. Several studies warn of algorithmic bias, the potential decline of essential cognitive skills among learners, and growing technological dependence in educational processes (Selwyn, 2019), (Cela et al., 2024). Additionally, unequal access to digital infrastructure in developing countries threatens to widen the existing educational divide (Olsen et al., 2022). Thus, the question is no longer whether GAI should be integrated into education systems, but how to do so in a critical, equitable, and human-centered manner. Such integration requires not only technical knowledge of the tools but also a thorough pedagogical and ethical reflection on their uses and limitations. This paper therefore aims to analyze the benefits and risks of GAI in education while proposing concrete pathways for its responsible adoption.

The rest of the paper is organized as follows: Section II introduces GAI. Section III examines the pedagogical opportunities offered by GAI. Section IV addresses the ethical and pedagogical challenges associated with its implementation. Practical strategies for its responsible integration are proposed in Section V, while real-world case studies are presented in Section VI. Section VII offers a humanistic reflection on the evolving meaning of education in the AI era. Section VIII discusses the critical perspective that artificial intelligence is not a substitute for human educators. Section IX analyzes the socio-economic impacts of GAI on education. Finally, Section X concludes the paper.

Generative Artificial Intelligence

GAI is a subset of artificial intelligence based on deep learning, particularly Transformer architectures (Vaswani et al., 2017). Models such as GPT, BERT (Devlin et al., 2019), T5, and PaLM learn complex linguistic representations from large unstructured datasets. Unlike traditional AI systems (e.g., expert systems or classifiers), GAI is distinguished by its ability to generate new, contextually coherent content that is often indistinguishable from human output. This generation relies on dynamic probabilistic pre- diction of the next element in a sequence—whether words, pixels, or code—rather than simple retrieval or replication of information (Brown et al., 2020).

Technical Functioning

GAI models typically rely on large-scale self-supervised pretraining, followed by a fine-tuning phase on specific tasks. They incorporate multi-head self-attention mechanisms, which enable them to capture long-range dependencies within sequences, making them particularly effective for natural language processing (NLP), as well as for image (e.g., DALL·E), video (Make-A-Video), or music generation (MusicLM) (Agostinelli et al., 2023).

Specific Educational Applications

In education, GAI applications are increasingly diverse and cross-disciplinary. They include:

- **Generation of personalized explanations:** GAI can create definitions, examples, or analogies tailored to a learner's level of understanding (Filiz et al., 2025).
- **Simplification of complex content:** through automatic rephrasing, summarization, or simplification.
- **Instant and contextual translation:** supporting the inclusion of multilingual and non-native learners.
- **Generation of exercises, quizzes, and automated feed- back:** personalized based on

learners' errors and knowledge gaps.

- **Assistance with academic and creative writing:** by suggesting improvements in style, grammar, or argumentative structure.

Some integrated educational platforms, such as Khanmigo (Khan Academy, 2023) (based on GPT-4), already provide these services to thousands of students, functioning as an on-demand virtual tutor .

Toward Human–Machine Hybridization

GAI is not limited to task automation but opens the door to pedagogical hybridization, where teachers and AI systems co- construct learning situations. From this perspective, some re-searchers refer to pedagogical co-agents—AI partners capable of engaging in dialogue, interacting, and even adapting their behavior based on a student's cognitive or socio-emotional profile (Christopoulos et al., 2019). However, this adaptive capacity raises major technical, ethical, and epistemological challenges, particularly regarding the relevance of generated responses, neutrality of information, and protection of personal data in interactions with learners.

Pedagogical Opportunities

GAI is not merely an incremental evolution of existing educational technologies; it represents a true paradigm shift in how knowledge is designed, delivered, and personalized. With its ability to generate pedagogical content that is automated, contextualized, and multimodal, GAI offers new possibilities for teachers, learners, and curriculum designers alike. This section highlights the key educational contributions of GAI, supported by recent empirical studies and practical experiments.

Adaptive Personalization of Learning Paths

One of the most documented benefits of GAI lies in its ability to support differentiated pedagogy by generating tailored content based on each learner's cognitive, emotional, or linguistic profile (Tan et al., 2025). Unlike traditional intelligent tutoring systems, generative models can dynamically adjust their language, abstraction level, or explanation format based on learner feedback in near real-time (Abbes et al., 2024). Platforms like Squirrel AI in China have shown that integrating generative engines into adaptive systems can significantly improve learning out- comes, especially for struggling students (Li et al., 2024).

Automated Generation of Educational Resources

GAI enables teachers to generate a wide range of dynamic teaching materials: revision sheets, self-correcting quizzes, lesson plans adapted to different levels, and remedial exercises. These resources can be created rapidly and customized based on pedagogical goals or time constraints, thereby relieving teachers of part of their administrative workload (Pablo-Huamani et al., 2024). A study by the MIT Education Lab showed that using generative tools for formative assessment design improves the diversity of pedagogical approaches while reducing teachers' preparation time by more than 40% (Gan et al., 2023).

Linguistic Accessibility and Inclusion

Thanks to their automatic translation and lexical simplification capabilities, GAI models facilitate access to knowledge for non-native speakers, learners with cognitive disabilities, or those with special educational needs. GAI can rephrase complex scientific concepts in simpler language, generate plain-language summaries, or translate content into underrepresented languages in school curricula (Shaaban, 2025). In multilingual contexts such as Canada, South Africa, or India, this becomes a crucial inclusion mechanism to democratize learning and respect linguistic diversity (Banerjee & Pan, 2024) .

Stimulating Creativity and Critical Thinking

Far from being limited to mechanical tasks, GAI can play a constructive role in developing high-level skills such as creativity, argumentation, and problem-solving. For instance, earning environments powered by generative assistants encourage students to formulate hypotheses, rephrase questions, or compare different possible answers (Arinushkina et al., 2024). Experiments con- ducted at Stanford and Harvard have shown that students using ChatGPT to co-construct argumentative essays developed better self-revision and logical structuring skills (Quratulain et al., 2025).

Human–Machine Hybridization and Augmented Pedagogy

GAI is not intended to replace the teacher, but rather to empower them in their pedagogical roles. Acting as a pedagogical co-agent, AI can provide personalized interventions during workshops, remediation, or consolidation phases, while the teacher remains responsible for the overall framework, the human relationship, and reflective assessment (Edwards et al., 2024). This augmented teaching model is currently being explored in pilot projects in Japan and Finland, where teachers work in synergy with conversational AI integrated into the classroom environment (Tooka et al., 2024).

Ethical and Pedagogical Challenges

While GAI offers considerable educational opportunities, it also raises a number of critical concerns at ethical, pedagogical, and socio-technical levels. These risks are not merely theoretical: numerous studies and experiments have revealed potential pitfalls, including the reproduction of biases, alteration of educational practices, dehumanization of the pedagogical relationship, and the worsening of the digital divide. This section explores these challenges based on recent empirical data.

Algorithmic Bias and the Reproduction of Inequalities

GAI models are trained on massive corpora from the web, open databases, or educational archives. These datasets inherently reflect existing social, cultural, linguistic, and geographic biases. Without robust control mechanisms, GAI may reproduce—or even amplify—stereotypical or discriminatory representations in the content it generates (Mittelstadt et al., 2016). For example, analyses of GPT-3 and GPT-4 revealed that outputs in educational contexts can underrepresent certain cultures or promote Eurocentric perspectives, especially in history or literature (Buolamwini & Gebru, 2018). This phenomenon, known as algorithmic amplification, threatens the cultural diversity of curricula and may marginalize local languages and references in non-Western education systems.

Cognitive Dependency and Skill Loss

Heavy use of GAI by students raises the risk of cognitive substitution, where the tool performs essential intellectual tasks on their behalf—such as writing, summarizing, argumentation, or reformulating. Several studies warn that students may gradually externalize their thinking, limiting deep learning, long-term memory retention, and metacognitive skills (Ruiz-Rojas et al., 2024), (Gerlich, 2025). A longitudinal study in U.S. high schools found that frequent use of ChatGPT for assisted writing correlated with lower performance in unaided writing assessments, calling into question the balance between technological support and cognitive autonomy (Farhan, 2025).

Erosion of the Teacher's Role and Dehumanization of Learning

The teacher's role goes beyond content delivery—it also encompasses relational, emotional, ethical, and formative functions. Unregulated use of GAI could lead to excessive delegation of certain educational tasks (e.g., grading, remediation, feedback), weakening the centrality of the human element in the learning process (Selwyn, 2019), (IEEE, 2021). Moreover, experiments with AI-based virtual tutors have shown a drop in students' intrinsic motivation when no authentic human interaction was present (Chowdhury et al., 2025).

Threats to Academic Integrity

GAI facilitates the instant generation of original texts, making it more difficult to detect cheating or plagiarism during assessments. Traditional plagiarism-detection software (such as Turnitin) struggles to identify AI-generated content, raising concerns about the validity and reliability of conventional evaluation methods (Song, 2024). Some universities have already begun rethinking their assessment methods (e.g., oral exams, reflective portfolios) to preserve the authenticity of learning and promote more student-centered evaluation approaches (Ateeq et al., 2024), (Khlaif et al., 2025).

Digital Inequality and the Educational Divide

Equitable access to GAI depends on digital infrastructure, internet connectivity, digital literacy levels, and teacher training. In many low- and middle-income countries, use of such tools remains confined to urban or privileged contexts (Becker, 2007). This imbalance risks further polarization between "connected" schools and "peripheral" ones, undermining the equity and inclusion objectives pursued by educational policies (Jibrin et al., 2024).

Strategic Recommendations for an Ethical and Inclusive Integration of GAI in Education

Given the rapid rise of GAI and its mixed impact on education, it is essential to develop pedagogical, ethical, and institutional frameworks that promote thoughtful, adaptive use. Rather than banning or blindly adopting GAI, the goal is to guide stakeholders—teachers, policymakers, and curriculum designers—toward responsible, context-sensitive integration through concrete recommendations.

Training Teachers in Critical AI Literacy

Teachers must acquire critical, technical, and pedagogical skills to evaluate GAI tools, understand their functioning, and integrate them meaningfully into their practice (Niloy et al., 2025). Initial and ongoing training modules should include:

- Principles of generative model functioning;
- Critical analysis of biases and limitations;
- Design of hybrid human–AI pedagogical scenarios.

The AI Leap 2025 program in Estonia aims to provide teachers with in-depth training on the integration of artificial intelligence in education, thus increasing their confidence and effectiveness in the pedagogical use of these tools (Eurydice, 2025).

Establishing AI Education for Students

It is essential for learners to develop a digital and algorithmic culture enabling them to understand the underlying logics of the tools they use, identify their limitations, and verify the validity of generated content (OECD, 2025). This implies introducing a transversal AI curriculum covering GAI functioning and its biases, recognition of generative hallucinations, and concepts of digital responsibility and intellectual integrity. Such initiatives are already underway in education systems in Singapore, South Korea, and the Netherlands (Su et al., 2022).

Developing Responsible Use Charters and Policies

Institutions must adopt clear policies for the pedagogical use of GAI to set boundaries, prevent misuse, and guide practices. These charters should address:

- Authorized contexts of use (e.g., writing assistance vs. full replacement);
- Transparency in the use of generated content;
- Data protection and privacy.

For example, the University of Cambridge has published a charter on the use of generative AI in assignments, encouraging thoughtful and referenced use rather than prohibition (University of Cambridge Information Compliance Office, 2025)

Adapting Assessment Modalities

GAI requires a partial redesign of assessment systems. To guarantee the authenticity of learning, it is recommended to promote:

- Oral or reflective evaluations;
- Contextualized creative productions;
- Learning journals and digital portfolios.

These process-centered assessment forms help reduce automated cheating risks while valuing critical thinking and originality.

Ensuring Technological and Infrastructural Inclusion

Access to GAI tools must be equitably distributed to avoid deepening educational inequalities. This involves:

- Investing in equipment and connectivity in rural or dis- advantaged areas.
- Developing content in local languages and culturally adapted contexts.
- Promoting free and accessible software.

Projects such as the GIGA program (UNICEF–ITU) aim to connect every school worldwide to the Internet, a prerequisite for sustainable digital inclusion (UNICEF & ITU, 2023). For a harmonious and ethical integration of GAI in education, it is crucial to clearly define the roles and responsibilities of various actors.

Examples from Global and Arab Educational Contexts

In several countries, the integration of generative artificial intelligence (GAI) into educational systems is beginning to show promising results, although realities vary significantly according to socio-economic and cultural contexts.

Case of Finland and South Korea

In Finland, GAI is notably used to improve students' writing skills. Tools based on generative models analyze in real time the texts produced by students, providing personalized suggestions for reformulation, grammatical, and stylistic correction. This approach allows immediate and adaptive support, which promotes autonomy and individual progress (Khavasi, 2025). This innovation is part of a strong national education policy focused on the responsible integration of digital technologies to enhance creativity and critical thinking. In South Korea, schools deploy systems for automatic generation of adaptive educational content, which modulate learning materials according to students' performance levels and learning pace (Kim et al., 2024). These systems rely on GAI models to produce personalized lessons, targeted exercises, and constructive feedback, contributing to large- scale differentiated pedagogy.

Situation in the Arab World

Conversely, in the Arab world, initiatives to integrate GAI in education remain largely embryonic and fragmented. Most projects focus on specific applications such as automatic translation or summary generation, without relying on a comprehensive educational strategy or quality local content. This gap limits the pedagogical impact of these technologies, especially since Arabic language resources adapted to generative systems are still scarce (Shaalan et al., 2018). Moreover, the insufficiency of digital infrastructure and the lack of specialized training for teachers constitute major obstacles to an effective and critical adoption of GAI in Arab schools (Al-Motrif et al., 2025), (Eltaiba et al., 2025). Without sustained investment in building high-speed networks, developing educational content in Arabic, and enhancing the skills of educational stakeholders, the region risks widening the technological gap with more advanced countries.

Towards a Humanistic Educational Philosophy Integrating GAI

GAI should not be viewed merely as a technical tool, but as a historic opportunity to redefine the purpose of education, the roles of teachers and learners, and the very nature of knowledge. However, this transformation cannot occur without educational policies rooted in a clear ethical and humanistic vision. Otherwise, there is a real risk of developing a technology- driven model of education stripped of human meaning.

Successful integration of GAI requires a renewed pedagogical foundation based on key educational principles:

- **Fostering critical thinking over rote memorization**: GAI should support learners in developing analysis, syn- thesis, and evaluation skills, rather than replacing cognitive effort with mechanical information reproduction (Selwyn, 2021).
- **Encouraging cooperation instead of competition**: Education in the GAI era must emphasize collaborative learning, knowledge co-construction, and the exchange of diverse ideas (Memon & Kwan, 2025) .
- **Promoting pluralism over standardization**: Even when based on large datasets, GAI must avoid reinforcing homogenizing biases and instead support pedagogies that respect cultural and cognitive diversity (Swaminathan & Danks, 2024).
- **Placing the human above algorithmic logic**: Technology should remain a means, not an end. Education must preserve human values such as empathy, creativity, and moral reasoning — qualities that algorithms cannot replicate (Noddings, 2013).

Artificial Intelligence Is Not a Substitute for Humans

Ultimately, artificial intelligence (AI) should not be conceived as a replacement for the human being, but rather as a tool designed to empower and strengthen them. A successful educational system in the AI era is not one that programs or controls everything exhaustively, but one that leaves room for surprise, error, and human experimentation (Qureshi, 2025). AI can undoubtedly help us teach more and more efficiently by automating certain repetitive tasks or providing personalized support. However, it is imperative to ensure that teaching re- mains fundamentally human, critical, and deeply rooted in our cultures and societies. Only through this thoughtful integration can education truly contribute to forming individuals capable of autonomous thinking, dialoguing with technology without becoming dependent on it, and preserving the richness of human experience (Feenberg, 2002).

Socio-Economic Impact of GAI in Education

The introduction of GAI into educational systems brings about profound transformations that go beyond the pedagogical framework to broadly influence the social and economic dimensions of societies.

Cost Reduction and Improved Access to Education

GAI enables the automation of personalized educational content production, automatic grading, and the generation of adapted assessments, which can significantly reduce the operational costs of educational institutions, especially in resource- limited countries (Ananyi & S.-Pepple, 2023). This cost reduction opens the possibility of expanding access to quality education, particularly in remote or underserved areas where human and material resources are insufficient (UNESCO, 2019).

Creation of New Skills and Jobs

The integration of GAI generates increased demand for skills in digital literacy, programming, data management, and technological ethics, thus fostering the creation of specialized jobs in these fields (OECD, 2022). Furthermore, it drives the redefinition of educational roles by valuing relational, creative, and critical skills among teachers, which could enhance the professionalization of the sector.

Risks of Exclusion and Worsening Inequalities

However, this technological revolution may also widen socio-economic divides if access to digital tools and training remains unequal. Disadvantaged populations, rural areas, or developing countries risk being marginalized, thereby exacerbating educational disparities and, by extension, economic inequalities(Ojong, 2025). This dual dynamic may create a vicious cycle where educational inequalities translate into persistent economic and social inequalities.

Effects on Productivity and Economic Competitiveness

On a larger scale, the diffusion of GAI in education pro- motes the development of a more skilled, agile, and adaptable workforce, which constitutes a key lever for national productivity and competitiveness in a knowledge-based global economy. Countries capable of effectively integrating these technologies into their educational systems could thus gain a significant strategic advantage.

Conclusion

GAI is a significant advancement poised to transform education by delivering personalized and accessible content that enhances quality and equity. However, it also raises ethical, cognitive, and social challenges, including algorithmic bias, dependency, and unequal access. Maximizing GAI's benefits while mitigating risks requires training educators and learners, establishing clear ethical and regulatory frameworks, and redesigning assessment methods. Addressing the digital divide and culturally adapting tools are also essential. GAI should be viewed not merely as a technical tool but as a pedagogical catalyst grounded in a humanistic vision, where innovation aligns with fundamental values to drive sustainable social and cognitive progress.

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