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Artificial intelligence and communication technologies in academia: faculty perceptions and the adoption of generative AI

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Abstract

Artificial intelligence (AI) is ushering in an era of potential transformation in various fields, especially in educational communication technologies, with tools like ChatGPT and other generative AI (GenAI) applications. This rapid proliferation and adoption of GenAI tools have sparked significant interest and concern among college professors, who are dealing with evolving dynamics in digital communication within the classroom. Yet, the effect and implications of GenAI in education remain understudied. Therefore, this study employs the Technology Acceptance Model (TAM) and the Social Cognitive Theory (SCT) as theoretical frameworks to explore higher education faculty's perceptions, attitudes, usage, and motivations, as the underlying factors that influence their adoption or rejection of GenAI tools. A survey was conducted among full-time higher education faculty members ($N = 294$) recruited from two mid-size public universities in the US. Results found that college professors' perceived usefulness of AI predicted their attitudes and intention to use and adopt the technology, more than their perceived ease of use. Trust and social reinforcement strongly influenced college professors' GenAI adoption decisions and acted as significant mediators to better understand the relationship between TAM and SCT. Findings emphasized the power of social dynamics in shaping professors' self-efficacy, attitudes, and use of GenAI. Trust enhances peer influence and affects how perceived usefulness shapes users' willingness to adopt technology, whereas self-efficacy has a minimal impact. This research provides valuable insights that inform higher education policies aimed at improving the educational experience for college students in an AI-driven workforce.

Keywords: Artificial intelligence, Communication technology, Higher education, Technology adoption, Faculty, Trust, Self-efficacy, Social influence

Introduction

Generative AI (GenAI) has quickly become particularly consequential in higher education. Recent research indicates that 43% of adults aged 18–29 have used ChatGPT (McClain, 2024). This is up from 33% just nine months earlier. Higher education faculty face a rapidly changing classroom dynamic as these widely used, multimodal tools raise numerous opportunities and challenges. This study investigates these opportunities and challenges by exploring the current use and perspectives of higher education faculty regarding GenAI, the most recent additions to the educational communications and media technologies toolbox.

Generative AI (GenAI) is defined as a technology that leverages deep learning models to generate human-like content (e.g., images, words) in response to prompts (Lim et al., 2023). Examples of interactive text-based GenAI include OpenAI's ChatGPT, Google's Gemini, Anthropic's Claude, and Meta.AI. Multimodal GenAI tools are also becoming more widespread and are changing the landscape of educational media creation. Image development tools like DALL-E or Midjourney can be used to create visual content. Video development is rapidly advancing with tools such as Open AI's Sora and RunwayML. Taken together, the potential for creating more engaging and diverse digital educational materials is substantial.

Like most arenas, applications in the higher education context are rapidly emerging, and ever-increasing capabilities make it difficult to identify the most salient use cases. Teaching examples include the development of case studies and assessment items for a given topic. Research examples include support for qualitative data analysis. Logistical support includes the capacity to generate captions for images and videos. The latest LLM models have also introduced an incredible leap in the accuracy of speech-to-text transcription.

While artificial intelligence is not new and has been studied for years (decades in some fields), the rapid proliferation and adoption of GenAI tools have generated widespread concern and interest among educators and researchers (Yusuf et al., 2024). This interest has moved AI implications beyond the original academic disciplines such as computer science, information management, and other STEM fields. The implications for communication and education technologies beyond the academy's STEM disciplines are now garnering greater attention and are the target of this study. Our focus is on the implications for non-STEM fields where academicians likely do not have a deep grasp of the underlying technology. While this limits the generalizability, it provides valuable insights into the emerging impact of artificial intelligence on disciplines that have traditionally been less influenced by such technologies.

Literature review

AI in higher education

Artificial Intelligence is not a new phenomenon; its applications in higher education have been studied for decades (Hartley et al., 2024). Recent advances in the technology underlying AI applications have dramatically improved general capabilities (Mollick, 2024). These advances have introduced numerous new challenges and opportunities for higher education faculty (Yusuf et al., 2024).

The role of GenAI in academia and its implications for faculty are emerging and complex. One researcher conceptualizes the use of GenAI as 'co-intelligence' (Mollick, 2024), which is consistent with the admonition that these new tools are best conceived as assistants or collaborators. Researchers have also identified its paradoxes, as it can be viewed as supportive and adversarial, effective and inaccurate, popular and banned (Lim et al., 2023). Academic tasks such as teaching, service, and research all intersect with GenAI. Early research utilizing GenAI to accomplish tasks such as providing writing feedback has fallen short compared to human evaluators (Steiss et al., 2024). However, the tools are improving rapidly as is our understanding of how and when to utilize ChatGPT. The study noted above utilized ChatGPT version 3.5. A study comparing ChatGPT version 3.5 with 4.0 on the United States Medical Licensing Exam found marked improvement. 3.5 demonstrated an accuracy of 47.7%, while 4.0 leaped to 87.2% (Shieh et al., 2024). Whether or not this improvement translates into higher scores for students remains unclear.

Faculty and student perceptions of AI

Some have argued that the responsibility of preparing students for the future dictates preparation for a "society powered by AI" (Chiu, 2024). A rapidly expanding body of research has provided initial insights into GenAI's import to higher education. In a comparison of faculty and student perceptions of writing with AI tools, researchers found disagreements regarding the acceptable use of GenAI (Barrett & Pack, 2023). Interestingly, these differences indicated a more positive view of GenAI by teachers than students. Work prior to the introduction of ChatGPT indicates that positive views of GenAI for learning might be justified. In a meta-analysis of the use of text-based chatbots in education, researchers found numerous advantages for students (Labadze et al., 2023). More recent work has supported the finding of improved performance in the short-term, however, there are also reasons to believe that GenAI use is better viewed as a 'crutch' that, when removed, can result in decreased understanding in the longer term (Lim et al., 2023). A common concern among educators is the potential for Gen AI to result in a decline in student's cognitive and logical skills (Yusuf et al., 2024).

Technology adoption

To understand the interaction between higher education faculty and GenAI, it is useful to look at technology adoption frameworks. The Technology Acceptance Model (TAM) suggests that technology acceptance is strongly influenced by its perceived ease of use (PEU) and perceived usefulness (PU) (Davis, 1989; Granić & Marangunić, 2019; Venkatesh et al., 2003). Faculty perceptions of ease of use and usefulness are thus essential avenues to explore GenAI's implications for higher education. Another relevant framework is the Unified Theory of Acceptance and Use of Technology (UTAUT), which acknowledges the value of TAM constructs, and adds social influence and facilitating conditions to drive behavioral intention to use a technology (Venkatesh et al., 2016). To explore the social and personal factors, the Social Cognitive Theory (SCT) serves as another theoretical framework that explains the technology acceptance process (Bandura, 1999). In this study, we combine TAM and SCT to have a better understanding of college professors' uses of GenAI.

In brief, the behavioral intention to use technology will be directly related to the attitude towards the technology, which is in turn influenced by the perceived ease of use (PEU) and the perceived usefulness (PU) of the technology. In addition, other factors discussed below will contribute to the adoption equation.

Attitude

The user's attitude towards the technology and innovation can significantly influence the adoption of new technologies. Users' attitudes towards technological advancements are crucial in determining whether or not they will embrace innovations (Davis, 1989; Granić & Marangunić, 2019). Regarding AI, individuals' attitudes and comfort levels can greatly influence acceptance and integration into various aspects of the education system (Bower et al., 2024). Preliminary studies suggest that faculty attitudes toward Gen AI are mixed (Bower et al., 2024). While a majority of faculty perceive the potential for major impact, these same faculty are more familiar with the technology.

PEU/PU

One's attitude towards technology can be influenced by its perceived ease of use and its perceived usefulness (Davis et al., 1989; Granić & Marangunić, 2019). These factors become critical as higher education faculty consider the adoption and inclusion of communication technologies.

The arrival of ChatGPT in November 2022 was significant in part because it introduced an approachable avenue for people to interact with an advanced large language model. Prior to this, Generative AI application users were largely limited to those with coding knowledge or domain-specific expertise. However, the perceived ease of use is somewhat limited in that the early interfaces were predominantly text-based. As the interfaces have developed to better match user needs, perceptions have and will improve. For example, ChatGPT, Claude and Gemini can now display preview windows that include working drafts of images, charts, tables, or code, substantially improving the ease of use (Gupta et al., 2024).

Self-efficacy

When considering attitudes and perceptions of new technology, a helpful framework is Bandura's social cognitive theory, which postulates the importance of content-specific self-efficacy in pursuing knowledge (Bandura, 2002; Venkatesh et al., 2003). Self-efficacy refers to an individual's belief in their ability to succeed in a given context or content area. Technology self-efficacy can play an essential mediating role in technology acceptance (Granić & Marangunić, 2019; Holden & Rada, 2011). For example, perceived ease of use was associated with self-efficacy in undergraduate students engaged in technology-supported self-directed learning (Pan, 2020). The intention to use and adopt GenAI tools is likely similarly influenced by self-efficacy for these emerging technologies. Users who have committed significant time to its use will be more likely to confidently use GenAI compared to those who have had limited engagement.

Social reinforcement

Research has also addressed the important role of social reinforcement. This can be defined as the degree to which users believe that their social networks feel it is important that they adopt a particular technology (Marikyan et al., 2023). While a recent meta-analysis concluded that the social influence association with behavior was non-significant, it did find an overall significant impact on attitudes (Marikyan et al., 2023). The rapid adoption of GenAI, major investments by major corporations, and extensive media coverage have resulted in substantial direct and indirect pressure on individuals toward adoption. These influences, of course, vary between cultures and disciplines. For example, the impact of GenAI on college composition courses has garnered substantial negative attention. Social cognitive theory acknowledges our enhanced capacity for observational learning and the vital role of social interactions (Bandura, 1999). This capacity, combined with the widespread discussion, will likely influence users' perceptions, attitudes, and self-efficacy toward using GenAI. In line with prior work in technology adoption (Venkatesh et al., 2016), we operationalize social influence as social reinforcement, reflecting the impact of others' opinions and behaviors on an individual's decision to use the technology.

Trust

Trust becomes a key consideration when investigating the adoption of new technologies. Trust can be described as the willingness of an individual to accept information from another, with the expectation that the information provider is accurate (Wu et al., 2011). A meta-analysis of technology adoption studies identified trust as strongly associated with PEU and PU (Marikyan et al., 2023). For example, Choung et al. (2022) explored the role of trust in adopting AI voice assistant technology, and found trust significantly influenced both perceived usefulness of the AI voice assistant and users' attitudes toward it, which subsequently elevated usage intention. Similarly, Tanantong and Wongras (2024) examined the use of AI in recruitment by human resources and found that while trust does not affect intention directly, it significantly influenced both perceived usefulness and ease of use. These findings underscore that trust has a significant impact on perceived ease of use, perceived usefulness, and attitudes toward GenAI.

Social networks and trust are integral for the diffusion of new technologies (Busken, 2020). According to Busken, once individuals recognize the potential benefits of a technology, it is necessary to build trust that the innovation will deliver the promised advantages. To achieve this, continuous reinforcement from social circles are key for developing trust in technology. This suggests that social reinforcement can influence trust perceptions which in turn influence the likelihood of technology adoption, particularly in the context of GenAI. Overall, trust becomes uniquely important when it comes to GenAI adoption, given the widespread concerns about the propensity towards hallucinations in the major models.

Current study

The purpose of this study is to improve our understanding of higher education faculty's perceptions, usage, and attitudes toward GenAI, with a focus on identifying motivations and barriers through the framework of existing research and technology adoption theories. In particular, we investigate the technological, social and psychological factors that have been demonstrated as relevant. These factors include those identified in TAM and SCT in addition to perceptions of Trust (Fig. 1).

Proposed research questions and hypotheses

RQ1: Does the TAM model perform similarly with GenAI as it does with other technologies?

H1 (a) Perceived Usefulness and (b) Perceived Ease of Use will positively influence College Professors' attitudes towards GenAI.

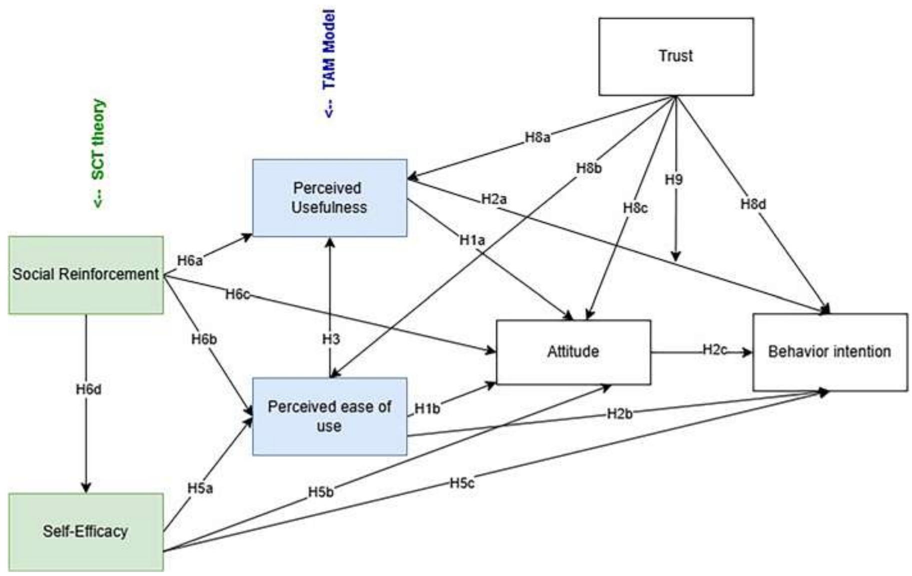

Fig. 1 Conceptual Framework and Hypotheses Summary

H2 (a) Perceived Usefulness, (b) Perceived Ease of Use, and (c) College Professors' attitudes will positively influence behavioral intention to use GenAI.

H3 Perceived Ease of Use will positively influence College Professors' Perceived Usefulness of using GenAI.

H4 College Professors' attitudes toward GenAI will mediate the relationship between (a) Perceived Usefulness and (b) Perceived Ease of Use on their Behavioral Intention to Use GenAI.

RQ2: What is the relationship between the TAM model (PU and PEU) and the SCT (self-efficacy and social reinforcement) in understanding GenAI adoption?

H5 GenAI self-efficacy positively influences (a) Perceived Ease of Use, (b) College Professors' attitudes, and (c) behavioral intention to use GenAI.

H6 Social Reinforcement positively influences (a) Perceived Usefulness, (b) Perceived Ease of Use, (c) College Professors' attitudes, and (d) self-efficacy toward GenAI.

H7 Social reinforcement will mediate the relationship between (a) Perceived Ease of Use, and (b) Perceived Usefulness on college professors' behavioral intentions to use GenAI.

RQ3: How does Trust influence the relationship between the TAM model (PU and PEU) and the SCT (self-efficacy and social reinforcement) in understanding GenAI adoption?

H8 Trust in GenAI positively influences (a) Perceived Usefulness, (b) Perceived Ease of Use, (c) attitudes, and (d) behavioral intention toward GenAI.

H9 Trust will moderate the relationship between Perceived Usefulness and college professors' behavioral intentions to use GenAI.

H10 Trust will mediate the relationship between social reinforcement and college professors' behavioral intentions to use GenAI.

Methods

This study employed a survey design to explore higher education faculty's perceptions, attitudes, uses, and experiences regarding GenAI. The primary objective was to examine the potential motivations, barriers and factors underlying the adoption or rejection of GenAI tools among university professors.

Participants

An online survey was designed using Qualtrics with full-time higher education faculty members recruited from two mid-size public U.S. universities, one on the East Coast and one in the Southwest, to participate in this study. The sample represented all faculty members in the social sciences and humanities disciplines as they use GenAI in a similar manner that differs fundamentally from its application in STEM disciplines.

Procedures

The study procedures started by creating an email list for all faculty members obtained from the email directory available online, then filtered by discipline to include only social sciences and humanities. Using Qualtrics email distribution, we sent an email inviting them to participate in the study with a link to the survey. Upon clicking the link, they begin by giving their consent and answering a filter question about whether they have ever used GenAI; if they say no, we ask questions about why, current perceptions, concerns about AI, and any future intention, followed by some demographics questions then the survey is terminated. If they said yes, they have used GenAI, they continue to the main survey, where they start by reporting their comfort with technology, their use of GenAI technology in teaching, research, and service, and their views and concerns about GenAI. Then, it covered the main TAM theoretical constructs, followed by some demographic questions. Also, a couple of attention-check questions were added to the survey to ensure respondents were paying sufficient attention and avoid speeding through the survey or giving random answers that could harm data quality. Data collection took place from January to March 2024.

Measures

All the theoretical constructs in this study used existing measures, adapted to fit the AI context and measured using multi-item scales validated in previous research.

Behavior Intention, is the intention level to adopt GenAI, was measured using a five-point likert scale adapted from (Youk & Park, 2023) with four statements such as "I will be willing to use the AI technology in the future" (α = 0.957).

Perceived Usefulness. The degree to which a person believes that using GenAI technology would enhance his or her job performance (Davis et al., 2024). This construct was measured using a five-point Likert scale adapted from both (Holden & Rada, 2011; Youk & Park, 2023) with seven statements such as "Using the Gen. Technology improves my performance in my job" (α = 0.906).

Perceived ease of use, is the degree to which a person believes that using GenAI would be free from effort, was measured with a nine-item, five-point Likert scale adapted from (Holden & Rada, 2011) including statements such as "I find it easy to get the technology to do what I want it to do" (α = 0.874).

AI self-efficacy is the users' personal confidence towards successfully and purposefully using the GenAI technology. The scale is adopted from (Holden & Rada, 2011). The construct used a ten-point Guttman scale (1 = not at all confident to 10 = totally confident) such as "I could complete any desired task using GenAI technology if there was no one around to tell me what to do as I go." (α = 0.931).

Attitudes toward GenAI, refers to an individual's overall affective and cognitive evaluation of a new technology. This was measured with a four-item using a five-point Likert scale adapted from (Choung et al., 2022) including statements such as "I feel positive toward GenAI" (α = 0.931).

Social Reinforcement refers to the extent that technology was encouraged by others within their reference group or social networks. This was measured with a seven-item using a five-point Likert scale adapted from (Compeau & Higgins, 1995) and composed of five statements such as Respondents were asked to assess to what extent the use of GenAI was encouraged by "your job, manager, peers, friend, family, co-workers, subordinates." (α = 0.858).

Trust assesses the psychological state of having positive expectations about GenAI (Choung et al., 2022). We adapted a scale from Huh et al., (2005) that asked respondents to rate GenAI on four items using a five-point scale (believable, trustworthy, credible, and reliable) (α = 0.870).

Comfort with technology measures the acceptance, use and overall level of comfort with technology. Here, it was measured using a five-point Likert scale adapted from (Rosen et al., 2013) that consisted of six items such as "I feel that I get more accomplished because of technology" (α = 0.820).

Finally, AI concerns included nine items obtained from media reports and discussions with many practitioners. Each item was assessed on a five-item scale and the measure was obtained by averaging the score of the nine items (e.g., plagiarism, copyright, accountability, originality etc.) (α = 0.842).

Sample characteristics

A total sample size of 294 higher-education faculty completed the survey. The sample consisted of Full Professors (24.5%), Associate Professors (23%), Assistant Professors (19%), Faculty in residence (7.5%), Adjunct Faculty (6.5%), and Visiting Faculty (6.5%). Of the sample, 82% did not hold an administrative position. They had multiple years of experience, 35% for 20+years of experience, 21% between 9 and 14 years, 20% between 4 and 8 years, 15% between 15 and 20 years. Participants were Females (45%), Males (43%), Prefer not to answer (6%), and Non-binary/others (2%). Participants identified as Caucasian (69%), Black or African American (7%), Asian or Pacific Islander (7%), Hispanic (6%), Mixed race and others (3%). Their age ranged from 41–50 (25%), 51–60 (23%), 31–40 (21%), 61–70 (15%). Only 66.4% of college professors have reported that they used GenAI before.

Research questions

RQ1: Does the TAM model perform similarly with GenAI as it does with other technologies?
RQ2: What is the relationship between the TAM model (PU and PEU) and the SCT (self-efficacy and social reinforcement) in understanding GenAI adoption?
RQ3: How does Trust influence the relationship between the TAM model (PU and PEU) and the SCT (self-efficacy and social reinforcement) in understanding GenAI adoption?

Results

A series of statistical analyses were conducted to test the study hypotheses. The first research question involves evaluating the hypotheses related to the TAM with GenAI technology. For the first hypothesis, a multiple regression was run to predict College Professors' attitudes toward using GenAI from (a) Perceived Usefulness (PU) and (b) Perceived Ease of Use (PEU). Results found that both variables statistically significantly predicted the attitude to use GenAI [F (2, 188) = 108.476, $p < 0.001$, $R^2 = 0.536$], accounting for 54% of the variance. The PU [$\beta = 0.655$, $t(188) = 12.221$, $p < 0.001$] and PEU [$\beta = 0.163$, $t(188) = 3.040$, $p < 0.01$] were found to positively predict the attitude to use GenAI. Hence, H1 (a,b) was fully supported (see Table 1).

Similarly, for the second hypothesis, a multiple regression was run to predict College Professors' behavioral intention to use GenAI from (a) PU, (b) PEU, and (c) attitudes. Results indicated that the model explained 58% of the variance and that the model was a significant predictor of behavioral intention to use GenAI [F (3, 187) = 85.84, $p < 0.001$, $R^2 = 0.579$]. Only the PU [$\beta = 0.347$, $t(187) = 5.07$, $p < 0.001$] and attitude [$\beta = 0.462$, $t(187) = 6.6307$, $p < 0.001$] were found to positively predict behavioral intention to use

Table 1 Multiple regression with TAM

	Attitude		Behavioral Intention	
	β	*Sig*	*β*	*Sig*
Perceived usefulness	0.655	0.000	0.347	0.000
Perceived ease of use	0.163	0.003	–	0.645
Attitude	–	–	0.462	0.000

GenAI, but PEU was not significant ($p=0.645$). Hence, H2 (a, c) were only supported (see Table 1).

The third hypothesis predicted College Professors' PU of using GenAI from PEU. Results found that the model was significant [F (1, 193) $=30.112$, $p<0.001$, $R^2=0.135$], accounting for 14% of the variance, and PEU [$\beta=0.367$, $t(193)=5.487$, $p<0.001$] was found to positively predict Perceived Usefulness to use GenAI. Hence, H3 was supported.

To test the H4 hypothesis, we conducted a mediation analysis using the SPSS PROCESS macro (Hayes, 2017) to examine whether attitudes mediate the relationship between (a) PU and (b) PEU on college Professors' behavior intention to use GenAI. Using model 4, we ran a bootstrap analysis with the default 5000 iterations. For PU, results indicated that the model was a significant predictor of attitude [$F(2, 188)=129.20$, $p<0.01$, R2 $=0.58$] with 58% accounting for the variance. Results showed that attitudes mediated the relation between PU and behavior intention ($B=0.39$, 95% CI of 0.24 to 0.56). While for PEU, results indicated that the model was a significant predictor of attitude [$F(2, 188)=102.49$, $p<0.01$, R2 $=0.52$] with 52% accounting for the variance. Results showed that attitudes mediated the relation between PEU and behavior intention ($B=0.41$, 95% CI of 0.27 to 0.58). Thus, only H4 (a,b) was fully supported (see Fig. 2).

The second research question and its corresponding hypotheses aims to integrate and examine the TAM model with SCT theory. The fifth hypothesis is about self-efficacy. A multivariate multiple regression was run to assess how self-efficacy influences Professors' (a) PEU, (b) attitudes and (c) behavioral intention to use GenAI. Results found that GenAI Self-efficacy statistically significantly predicted PEU ($b=0.131$, $p<0.001$, 95% CI [0.090, 0.172]), but neither predicted attitude ($p=0.113$), nor behavioral intention to use GenAI ($p=0.571$). Thus, only H5a is supported (see Table 2).

For the sixth hypothesis, a multivariate multiple regression was run to examine the influence of social reinforcement on PU, PEU, attitude and self-efficacy. Results found that Social Reinforcement statistically significantly predicted all the variables; PU ($b=0.348$, $p<0.001$, 95% CI [0.220, 0.477]), PEU ($b=0.161$, $p<0.01$, 95% CI [0.055, 0.268]), attitude ($b=0.335$, $p<0.001$, 95% CI [0.185, 0.485]), and self-efficacy ($b=0.357$, $p<0.05$, 95% CI [0.013, 0.702]). Thus, all H6 (a,b,c,d) was fully supported (see Table 2).

To test the seventh hypothesis, we conducted a mediation analysis using the SPSS PROCESS macro (Hayes, 2017) to examine whether social reinforcement mediates the relationship between (a) PEU and (b) PU and College Professors' behavioral intention to use GenAI. Using model 4, we ran a bootstrap analysis with the default 5000 iterations. For PEU, results showed that the model was significant [$F(2, 189)=15.19$, $p<0.01$, $R^2=0.14$] and that social reinforcement mediated the relation between PEU and

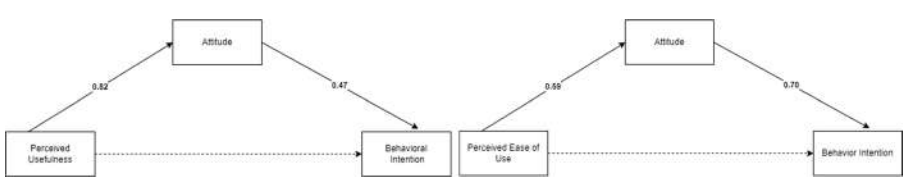

Fig. 2 TAM Mediation Analysis (H4)

Table 2 Comparison of Factors affecting Technology Adoption

	Self-efficacy		Social reinforcement		Trust	
	B	***Sig***	***B***	***Sig***	***B***	***Sig***
Perceived usefulness	–	0.551	0.348	0.000	0.525	0.000
Perceived ease of use	0.131	0.000	0.161	0.003	0.316	0.000
Attitude	–	0.113	0.335	0.000	0.630	0.000
Behavior intention	–	0.571	0.238	0.003	0.503	0.000
Trust	0.072	0.011	0.232	0.001	–	–
Self-efficacy	–	–	0.357	0.042	0.466	0.011
Social reinforcement	0.061	0.042	–	–	0.254	0.001

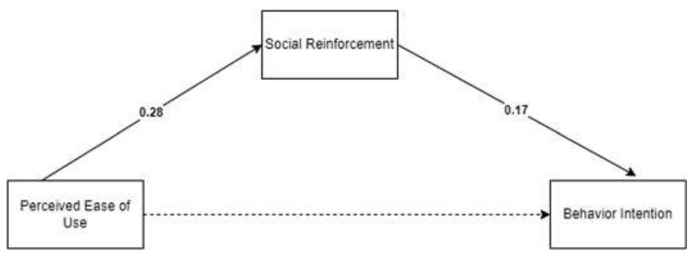

Fig. 3 Social Reinforcement Mediation Analysis (H7)

behavior intention ($B = 0.05$, 95% CI of 0.00 to 0.12) (See Fig. 3). However, for PU, mediation was not established because the regression coefficient between social reinforcement and behavior intention was not significant at ($p = 0.49$) and the Zero falls within the confidence interval range (− 0.07 to 0.03). This is explained by the direct effect ($B = 0.79$) being nearly identical to the total effect ($B = 0.78$), suggesting there was no indirect effect. Hence, H7a was only supported.

The third research question and its corresponding hypotheses address trust perception. For the eighth hypothesis, a multivariate multiple regression found that Trust statistically significantly influenced PU ($b = 0.525$, $p < 0.001$, 95% CI [0.402, 0.648]), PEU ($b = 0.316$, $p < 0.001$, 95% CI [0.212, 0.421]), attitude ($b = 0.630$, $p < 0.001$, 95% CI [0.493, 0.768]), and behavioral intention to use GenAI ($b = 0.503$, $p < 0.001$, 95% CI [0.354, 0.652]), as shown in Table 2. Thus, H8 (a,b,c,d) was fully supported (see Table 2).

Since Trust was one of the strong factors that influenced the TAM model, and to answer the ninth hypothesis, we conducted a moderation analysis using model 1 with the SPSS PROCESS macro (Hayes, 2017) to assess whether Trust moderates the relation between PU and behavioral intention towards GenAI. For PU, results indicated that the overall model was significant [$F(3, 191) = 68.41$, $p < 0.01$, $R^2 = 0.52$]. The interaction between PU and Trust was significant ($B = -0.21$, $SE = 0.06$, $t = -3.81$, $p < 0.05$), indicating that the relationship between PU and behavior intention depends on the level of Trust. Analysis revealed that the simple slopes at different levels of Trust (e.g., low, medium, and high levels) are all positive, indicating that the PU has a positive effect on the behavior intention at all levels of Trust. However, the magnitude of this positive effect decreases as the Trust increases. Thus, the relationship between the PU on behavior intention was stronger when the Trust was low ($B = 0.85$, $SE = 0.08$, $t(191) = 11.21$,

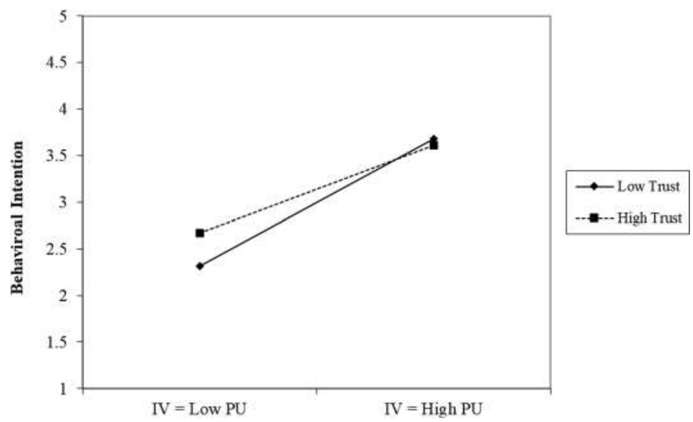

Fig. 4 Moderation with Trust

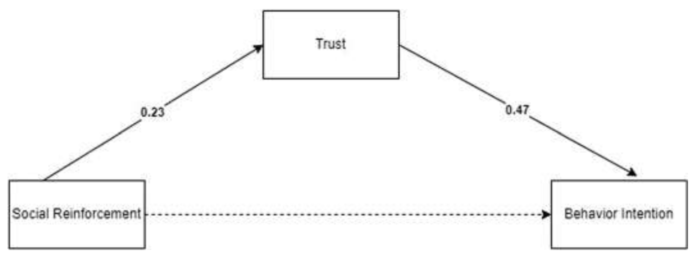

Fig. 5 Mediation with Trust

$p < 0.001$) compared to when it was high ($B = 0.48$, $SE = 0.09$, $t(191) = 5.24$, $p < 0.001$). Thus, H9 was supported (see Fig. 4).

For hypothesis ten, we conducted a mediation analysis using the SPSS PROCESS macro (Hayes, 2017) to examine whether Trust mediates the relationship between social reinforcement and behavior intention to use GenAI. Using model 4, results indicated that the model was significant [$F(2, 189) = 24.20$, $p < 0.01$, R2 = 0.20] and that trust mediated the relation between social reinforcement and behavior intention ($B = 0.11$, 95% CI of 0.04 to 0.19). It is worth noting that only the indirect effect was significant, while the direct effect was not significant ($p = 0.079$). Hence, H10 was supported (see Fig. 5).

Discussion

By integrating the TAM model and SCT theory, this study explored higher education faculty's perceptions, attitudes, and experiences regarding GenAI. It also examines the potential benefits and drawbacks, motivations and concerns, and factors behind adopting or rejecting GenAI tools. Overall, our results offer theoretical support for the proposed model to evaluate GenAI adoption decisions among college processors (see Table 3).

Table 3 Study hypotheses summary

Hypothesis number	Hypothesis paths/relations	Beta	P value	Result
H1—TAM	PU → Att	0.655	$P<0.01$	Supported
	PEU → Att	0.163	$P<0.01$	Supported
H2—TAM	PU → BI	0.347	$P<0.01$	Supported
	PEU → BI	–	$P=0.645$	Not supported
	Att → BI	0.462	$P<0.01$	Supported
H3—TAM	PEU → PU	0.367	$P<0.01$	Supported
H4—Mediation	Att mediates			
	PU → BI	0.39	$P<0.01$	Supported
	PEU → BI	0.41	$P<0.01$	Supported
H5—Self-Efficacy (SE)	SE → PEU	0.131	$P<0.01$	Supported
	SE → Att	–	$P=0.113$	Not Supported
	SE → BI	–	$P=0.571$	Not Supported
H6—Social Reinforcement (SR)	SR → PU	0.348	$P<0.01$	Supported
	SR → PEU	0.161	$P<0.01$	Supported
	SR → Att	0.335	$P<0.01$	Supported
	SR → SE	0.357	$P<0.05$	Supported
H7- Mediation	SR mediates			
	PEU → BI	0.05	$P<0.01$	Supported
	PU → BI	–	$P=0.49$	Not Supported
H8—Trust (T)	T → PU	0.525	$P<0.01$	Supported
	T → PEU	0.316	$P<0.01$	Supported
	T → Att	0.630	$P<0.01$	Supported
	T → BI	0.503	$P<0.01$	Supported
H9—Moderation	T on			
	PU → BI	−0.21	$P<0.05$	Supported
H10—Mediation	T mediate			
	SR → BI	0.11	$P<0.01$	Supported

TAM

All hypotheses derived from the Technology Acceptance Model (TAM) were found to be statistically significant. Results indicated that perceived usefulness exerts a considerably stronger influence on attitudes and, specifically, on behavioral intentions compared to perceived ease of use. This highlights the importance of demonstrating the practical benefits of GenAI technology to encourage its adoption.

Notably, while PEU did not demonstrate a direct significant effect on college professors' behavioral intentions to use GenAI ($p=0.645$), it exhibited a significant indirect mediation effect on behavioral intentions through attitudes. Specifically, mediation analysis revealed that of the total effect ($B=0.498$), the indirect effect accounted for ($B=0.413$), whereas the direct effect was relatively minor, at ($B=0.085$). Thus, the indirect effect predominantly explains the relationships within the model. These findings suggest that perceptions of ease of use of GenAI alone are insufficient to drive adoption among professors, but when these perceptions are coupled with positive attitudes toward GenAI, they can significantly enhance the likelihood of adoption. This indicates that professors may need compelling reasons and motivations to engage with GenAI. In contrast, perceived usefulness (PU) demonstrates a strong influence on behavioral intentions to use GenAI, both directly and indirectly through attitudes.

Trust

Overall, trust emerges as the most significant predictor influencing all factors (PU, PEU, SR, SE, Att) related to the decision to adopt GenAI technology, closely followed by social reinforcement. In this study, trust refers to perceptions of believability, credibility, reliability, and trustworthiness. Findings show that trust in technology has a direct effect on Professors' belief that it will enhance their performance, i.e., perceptions of usefulness. It can also foster a sense of simplicity, which, in turn, boosts their self-efficacy—their confidence in their ability to effectively utilize the technology. Increased trust can lead to more positive attitudes and stronger intentions to adopt GenAI technology. This is particularly relevant in light of the prevailing concerns surrounding this controversial technology (Gupta et al., 2024); professors' level of trust can dispel their concerns and significantly shape their perceptions, attitudes, and subsequent decisions regarding its adoption. Thus, educational institutions need to offer clear information while addressing any misinformation to alleviate fear and skepticism about GenAI and build trust.

Moderation analysis revealed that trust significantly influences the relationship between perceived usefulness and the intention to adopt GenAI technology. However, this effect is conditional, with the impact becoming weaker at higher levels of trust. This suggests that when professors have a high level of trust in the technology, they may rely less on its perceived usefulness or prioritize their trust over perceived usefulness to determine their intention to adopt it. Conversely, when trust is low, professors will need clearer and more compelling reasons for adoption, leading them to rely heavily on perceptions of usefulness as a motivating factor to encourage them to adopt the technology. Overall, this highlights trust as a strong factor that can potentially overshadow other essential factors like perceived usefulness.

Social reinforcement

The results indicate that social reinforcement serves as another significant predictor for most factors that affect the decisions to adopt, particularly because social reinforcement is a common factor across the Social Cognitive Theory (Bandura, 1999) and various technology adoption theories (Granić & Marangunić, 2019; Venkatesh et al., 2016). This finding is consistent with similar investigations in other fields such as healthcare (Roppelt et al., 2024) and journalism (Trang et al., 2024). This underscores the critical role of social interactions and social environments in shaping professors' perceptions, attitudes, and decisions regarding the adoption of GenAI technology. Specifically, results found that social reinforcement has a direct and positive influence on perceptions of usefulness and ease of use, fostering favorable attitudes and encouraging the overall decision to adopt the GenAI technology. Additionally, reinforcement from one's social circles can positively influence professors' belief in their own ability to use and adopt the GenAI (self-efficacy); the belief that "if others can do it, so can I" serves to motivate and facilitate adoption among peers. Therefore, these findings suggest that social dynamics play a big role in decisions to adopt GenAI technology. This effect is important given that GenAI technology is associated with various ethical concerns, prompting many individuals to approach it with caution. Thus, social interactions with peers, conversations and positive feedback and experiences shared by others within their social groups, and discussion within the departmental, college and university levels can all influence perceptions, attitudes and use of the technology. This suggests that expectations and behaviors of a social group can influence one's disposition toward GenAI technology and its perceived value. If using a particular technology becomes common within a community, individuals are more likely to adopt it.

Additionally, mediation analysis showed that with social reinforcement as a mediator, there was no mediating indirect effect between perceived usefulness and behavior intention, only a direct effect. This means that once professors perceive GenAI technology to be useful, they will use it. They do not need further reinforcement from their social networks. This explains why the direct effect was nearly identical to the total effect. On the other hand, for perceived ease of use, there was a significant mediation effect on behavioral intention to use GenAI. This suggests that perceptions of easiness are amplified when reinforced by others within social circles who have used it or hold positive attitudes towards the new technology, leading to a higher likelihood of adoption.

Trust and social reinforcement

The mediation analysis showed there was no direct effect from social reinforcement in behavioral intention, but there was a significant indirect effect of trust mediating the relationship between social reinforcement and behavioral intention. This means that while social reinforcement alone does not directly influence intention, it enhances trust, which subsequently increases the likelihood of technology adoption. This is because such social interactions can be a validation and reinforcement that enhance one's trust, as well as it can help reduce uncertainty or alleviate doubts, thus feeling more confident to use it. However, simply receiving social reinforcement does not directly lead to an intention to use the technology because it depends on the credibility of the source and pre-existing views that can make them skeptical and more resistant to positive views shared by others.

Self-efficacy

The results indicated that self-efficacy can only influence perceptions of ease of use, which is in line with past research showing a positive relationship between technology self-efficacy and perceived ease of use (Holden & Rada, 2011). This is logical because more confidence in one's ability to use GenAI will lead to perceived mastery and ease of use. However, results also indicated that this confidence alone is insufficient to generate positive attitudes or behavioral intentions to use GenAI, suggesting that the issue may not lie in the ability to use the technology but rather in the ongoing concerns and controversies surrounding its use. This finding aligns with past research that the relationship between self-efficacy and behavioral intentions is often mixed and not always significant (Holden & Rada, 2011; Motshegwe & Batane, 2015). Attitudes and behavioral intentions are shaped by a broader set of cognitive, social, and contextual factors such as values, beliefs, institutional support, trust, and peer influence, which may overshadow the influence of self-efficacy alone. According to Bandura (1997), four factors impact self-efficacy in different ways: mastery of experiences, social modeling, verbal persuasion, and emotional responses. These factors highlight the complexity of self-efficacy, with social reinforcement and trust playing significant roles in shaping it. This suggests that self-efficacy, while important, is not the sole driver of attitudes or behavioral intentions, which are instead shaped by a much wider range of considerations.

Another possible explanation for the limited significance of self-efficacy, despite faculty feeling capable of using AI technology (i.e., high self-efficacy), they may question its relevance or effectiveness. This skepticism can undermine their intentions to use the technology, which helps explain why perceived usefulness had a stronger impact on attitudes and behavioral intentions than ease of use. Additionally, resistance may also arise from faculty being accustomed to traditional teaching methods, concerns about increased workload or time commitments to use the AI technology, or perceived threats to autonomy. Therefore, while faculty may have the self-efficacy to use AI, they may still hold negative attitudes or fail to integrate it into their work.

Conclusion

This study integrated the TAM model and SCT theory to explore higher education faculty's perceptions, attitudes, motivations, and concerns and examines the potential benefits, drawbacks, and factors behind adopting or rejecting GenAI tools. Results found theoretical support for the proposed model to evaluate GenAI adoption. Specifically, findings show that communicating the practical benefits of GenAI is necessary for GenAI adoption. However, perceived ease alone is insufficient to encourage adoption, but when coupled with positive attitudes and social circles, it becomes influential in encouraging adoption. Furthermore, trust and social reinforcement are major and critical players in influencing GenAI adoption decisions. There is a social dynamic involved in the GenAI adoption process that can shape professors' perceptions, attitudes, and decisions. Positive social interactions can enhance trust by acting as a validation or reinforcement of one's views, as well as can reduce uncertainty or alleviate doubts, which increases the likelihood of technology adoption.

Implications, future studies, and limitations

This study explores the perspective of higher education faculty regarding the utilization and adoption of GenAI. A deeper understanding of educators' perspectives can shape higher education policies and guide university leaders, policymakers and educators in enhancing the educational experience for college students in an AI-driven workforce. As trust plays a pivotal role in the adoption of GenAI, educational institutions need to provide transparent information and address misinformation to reduce fear and skepticism surrounding the technology, while effectively communicating its practical benefits and functionalities to build credibility. Given the significant role of social dynamics in shaping faculty attitudes toward GenAI, constructive social dialogue and shared experiences within departments, colleges, and universities can greatly influence perceptions of new technologies. Thus, fostering a supportive social environment can deepen our understanding of the potential impacts of GenAI in educational settings, contributing to a more informed and equitable approach to improving educational practices and outcomes.

Future studies could further explore the role of institutional support and messaging regarding the use of AI. Although self-efficacy had a minimal impact on faculty adoption decisions, further investigation into the underlying reasons is necessary, as it can influence the effective utilization of this technology and provide a better understanding of faculty behaviors. Given the substantive ethical issues surrounding GenAI, it is a technology that will likely follow a less typical adoption path, particularly in higher education. For example, uncertainty regarding the faculty's use of AI for writing that does not 'cross the line' will cause many to pause. Therefore, it is crucial to address concerns related to the responsible and ethical use of GenAI. Institutions also face ongoing decisions regarding the availability of AI tools that are often embedded in existing software. Additionally, using qualitative methods offers a deeper understanding of how faculty members perceive GenAI technology, its ethical considerations, and its potential impact on their teaching practices. Incorporating open-ended questions within the different areas of use could further elucidate the findings. Research should examine how the adoption of GenAI varies across academic disciplines and cultural contexts, identifying unique challenges and opportunities within each field. Given the rapid developments in GenAI, longitudinal research is necessary to assess how perceptions and uses of GenAI evolve over time.

The targeted sampling strategy of non-STEM fields partially limits the generalizability of this study. There is little doubt that educators beyond the scope of this population will differ in their views of the role of GenAI in their work. Furthermore, the study was conducted with two mid-sized research-intensive public universities in the U.S that may have limited generalizability to other educational contexts compared to smaller institutions, private universities, teaching-intensive and international settings, potentially leading to different outcomes. The reliance on self-report data regarding potentially controversial topics may result in responses that might be viewed as more favorable at the expense of accuracy. Additionally, the study's focus on a specific point in time may not capture evolving attitudes or changes in behaviors, especially as GenAI technology rapidly advances. Another potential limitation is self-selection bias can influence the findings and limit the generalizability of the results. Consequently, the results may not fully reflect the diversity of perspectives, behaviors, or experiences within the broader population. Finally, while we studied the role of trust and social reinforcement, several factors can affect faculty AI adoption such as institutional support and culture, training and professional development, and discipline or areas of specialization.

Appendix

See Tables 4, 5, 6, 7, 8, 9 and 10

Table 4 List of abbreviations

Abbreviation	Term
GenAI	Generative artificial intelligence
PU	Perceived usefulness
PEU	Perceived ease of use
TAM	Technology acceptance model
UTAUT	Unified theory of acceptance and use of technology
SCT	Social cognitive theory
BI	Behavioral intention
Att	Attitude
SR	Social Reinforcement
SE	Self-efficacy

Table 5 TAM and attitude

Model	Unstandardized coefficients		Standardized coefficients	t	Sig
	B	Std. error	Beta		
(Constant)	0.226	0.268		0.844	0.400
PU	0.749	0.061	0.655	12.221	0.000
PEU	0.235	0.077	0.163	3.040	0.003

a. Dependent variable: attitude

Table 6 TAM and behavioral intentions

Model	Unstandardized coefficients		Standardized coefficients	t	Sig
	B	Std. error	Beta		
(Constant)	1.139	0.258		4.424	0.000
PEU	0.035	0.076	0.024	0.462	0.645
PU	0.399	0.079	0.347	5.065	0.000
Attitude	0.464	0.070	0.462	6.633	0.000

a. Dependent variable: Behavioral_Intention

Table 7 PU and PEU

Model		Unstandardized coefficients		Standardized coefficients	t	Sig
		B	Std. error	Beta		
1	(Constant)	1.613	0.298		5.414	0.000
	PEU	0.471	0.086	0.367	5.487	0.000

a. Dependent variable: PU

Table 8 Self-efficacy

Dependent variable	Parameter	B	Std. Error	t	Sig	95% Confidence interval	
						Lower bound	Upper bound
PU	Intercept	3.116	0.199	15.639	0.000	2.723	3.509
	Self_Efficacy	0.017	0.029	0.597	0.551	− 0.040	0.074
PEU	Intercept	2.538	0.143	17.710	0.000	2.255	2.820
	Self_Efficacy	0.131	0.021	6.334	0.000	0.090	0.172
Att	Intercept	3.102	0.226	13.700	0.000	2.655	3.548
	Self_Efficacy	0.052	0.033	1.593	0.113	− 0.012	0.117
BI	Intercept	4.020	0.229	17.569	0.000	3.569	4.471
	Self_Efficacy	0.019	0.033	0.568	0.571	− 0.046	0.084
SR	Intercept	2.221	0.205	10.816	0.000	1.816	2.626
	Self_Efficacy	0.061	0.030	2.046	0.042	0.002	0.119
Trust	Intercept	2.330	0.195	11.944	0.000	1.945	2.715
	Self_Efficacy	0.072	0.028	2.564	0.011	0.017	0.128

a. Computed using alpha = 0.05

Table 9 Social reinforcement

Dependent variable	Parameter	B	Std. error	t	Sig	95% Confidence interval	
						Lower bound	Upper bound
PU	Intercept	2.317	0.181	12.797	0.000	1.960	2.674
	Social_Reinforcement	0.348	0.065	5.345	0.000	0.220	0.477
PEU	Intercept	2.973	0.150	19.797	0.000	2.677	3.269
	Social_Reinforcement	0.161	0.054	2.984	0.003	0.055	0.268
Att	Intercept	2.566	0.211	12.136	0.000	2.149	2.983
	Social_Reinforcement	0.335	0.076	4.400	0.000	0.185	0.485
BI	Intercept	3.520	0.218	16.158	0.000	3.090	3.949
	Social_Reinforcement	0.238	0.078	3.037	0.003	0.083	0.393
Trust	Intercept	2.194	0.187	11.701	0.000	1.824	2.564
	Social_Reinforcement	0.232	0.067	3.447	0.001	0.099	0.366
SE	Intercept	5.610	0.486	11.553	0.000	4.652	6.568
	Social_Reinforcement	0.357	0.175	2.046	0.042	0.013	0.702

Table 10 Trust

Dependent variable	Parameter	B	Std. error	t	Sig	95% Confidence interval	
						Lower bound	Upper bound
PU	Intercept	1.756	0.183	9.580	0.000	1.395	2.118
	Trust	0.525	0.062	8.428	0.000	0.402	0.648
PEU	Intercept	2.509	0.156	16.074	0.000	2.201	2.817
	Trust	0.316	0.053	5.961	0.000	0.212	0.421
Att	Intercept	1.676	0.205	8.158	0.000	1.271	2.081
	Trust	0.630	0.070	9.024	0.000	0.493	0.768
BI	Intercept	2.732	0.222	12.294	0.000	2.294	3.170
	Trust	0.503	0.076	6.664	0.000	0.354	0.652
SR	Intercept	1.905	0.217	8.773	0.000	1.477	2.333
	Trust	0.254	0.074	3.447	0.001	0.109	0.400
SE	Intercept	5.241	0.534	9.810	0.000	4.187	6.295
	Trust	0.466	0.182	2.564	0.011	0.107	0.824

a. Computed using alpha = 0.05

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Author contributions
AS: conception, design of the work, acquisition, analysis, interpretation of data, drafted the work, Approved the submitted version (and any substantially modified version that involves the author's contribution to the study); Agreed both to be personally accountable for the author's own contributions and to ensure that questions related to the accuracy or integrity of any part of the work, even ones in which the author was not personally involved, are appropriately investigated, resolved, and the resolution documented in the literature. KH: design of the work, acquisition, interpretation of data, drafted the work, Approved the submitted version (and any substantially modified version that involves the author's contribution to the study); Agreed both to be personally accountable for the author's own contributions and to ensure that questions related to the accuracy or integrity of any part of the work, even ones in which the author was not personally involved, are appropriately investigated, resolved, and the resolution documented in the literature.

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Availability of data and material
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Declarations

Ethics approval and consent to participate
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Competing interests
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Enhancing sustainable academic course delivery using AI in technical universities: An empirical analysis using adaptive learning theory

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ABSTRACT

The educational landscape is undergoing a significant transformation driven by the rapid advancements in Artificial Intelligence (AI) that hold immense potential for enhancing sustainable academic course delivery, fostering deeper understanding, and improving student-learning outcomes. However, while AI applications promise individualized learning experiences and more efficient instructional methods, their integration into Technical Universities, particularly in developing countries, remains limited. Few studies address the unique challenges and opportunities of deploying AI in this context, leaving educators and policymakers without clear, empirically-backed strategies for implementation. This study seeks to bridge this gap by analyzing the impact of AI integration on academic course delivery in Technical Universities, guided by Adaptive Learning Theory. A mixed-method approach was adopted, combining qualitative interviews with 8 students and 8 lecturers and structured surveys from 124 randomly selected students and lecturers, achieving an 81 % response rate. Structural equation modeling was employed to examine the relationships between AI-driven parameters and academic course delivery. It was found that personalized learning, natural language processing, intelligent tutoring systems, and data-driven insights significantly enhance course delivery, while virtual and augmented reality showed limited impact in this setting. The results highlight AI's potential to transform course design and delivery in Technical Universities, leading to improved learning outcomes. The study presents exciting possibilities that AI presents for educators and policymakers.

1. Introduction

The application of Artificial Intelligence (AI) across various industries has significantly enhanced operational processes and improved outcomes. In manufacturing, for instance, AI has been instrumental in improving decision-making and process efficiency [1], while also enabling predictive maintenance and autonomous operations [2]. Similarly, the rapid adoption of AI is reshaping the workforce landscape, creating both opportunities and challenges that demand urgent upskilling and reskilling initiatives to future-proof sectors such as education and technical training [3]. These industry-wide transformations underscore the growing relevance of AI in enabling adaptive and sustainable systems, making its application in academic course delivery, especially within Technical Universities, both timely and critical. In education, AI-driven tools such as natural language processing (NLP), intelligent tutoring systems (ITS), data-driven insights (DDI), and virtual/augmented reality (VR/AR) have demonstrated their potential to improve learning experiences and instructional delivery [4–7]. However, concerns persist among educators regarding data privacy, algorithmic bias, and the potential for AI to undermine students' critical and analytical thinking skills [8,9]. Despite these concerns, research has highlighted AI's capacity to enhance learner-instructor interactions, underscoring the need for further investigation into its role in academic course delivery, particularly in Technical Universities [5,10,11]

A thorough analysis of AI in Education (AIED) revealed that AI has the potential to transform hybrid education by improving the independence of both students and instructors, while creating a more dynamic and participatory learning atmosphere [12]. AIEd has been extensively adopted and used in the educational settings of many universities in developed countries [5,13–16]. However, these studies do not cover specialized applications to Technical Universities (TUs) and other intrinsic challenges that such institutions of developing countries ought to overcome for complete adoption and integration in academic course delivery.

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As Technical Universities in developing countries strive to improve educational quality and accessibility, the integration of Artificial Intelligence (AI) offers transformative potential for academic course delivery. AI applications in personalized learning, natural language processing, intelligent tutoring systems, and data-driven insights hold the promise of individualized learning experiences, enhanced instructional methods, and more efficient resource allocation. Despite the growing potential of AI-driven tools in education, the adoption of Virtual and Augmented Reality (VR/AR) remains a challenge, particularly in resource-limited settings. The integration of VR/AR requires specialized hardware, high-bandwidth internet, and significant institutional investment, which can be prohibitive for many Technical Universities. For instance, institutions often struggle with the high costs of headsets and other equipment, as well as limited budgets to support such investments [17]. Additionally, factors such as accessibility, cost, and technical expertise hinder widespread implementation. Faculty members frequently lack sufficient training to effectively integrate VR/AR into curricula, while students face challenges in mastering the required digital literacy skills [18]. These barriers make VR/AR less immediately impactful compared to other AI-driven tools such as Natural Language Processing (NLP) and Intelligent Tutoring Systems (ITS), which are more scalable and accessible in constrained environments. Understanding these limitations is crucial for designing more inclusive AI adoption strategies in education. Further, the adoption of AI in education has been limited, particularly in the technical higher education sector of developing nations. Existing studies focus predominantly on AI's general benefits in broader educational contexts, with little attention to how these technologies can be harnessed specifically within Technical Universities, where practical and hands-on learning are crucial.

The lack of empirical studies on AI's impact in this setting creates a significant knowledge gap, leaving educators, policymakers, and administrators without clear evidence or frameworks for implementing AI effectively. Additionally, the unique needs, constraints, and opportunities presented by Technical Universities in developing countries (such as resource limitations, specific skill requirements, and diverse student demographics) necessitate tailored approaches to AI integration.

This study seeks to address these gaps by examining the impact of AI tools on academic course delivery within Technical Universities, using Adaptive Learning Theory (ALT) as a guiding framework. The ALT is a methodology for teaching and learning that attempts to personalize lessons, readings, practice activities, and assessments for individual students based on their current skills and performance [19]. The justification for choosing this theory is founded evidence that it is useful for providing immediate and specific problem-solving techniques, and adopting learning contents specific to student skill proficiency [14,20, 21]. Through a mixed-method approach, this study integrates qualitative insights from interviews and quantitative survey data to provide a comprehensive understanding of AI's role in academic course delivery. This directly addresses the study's research questions:

1. How do students and lecturers perceive the role of AI in enhancing course delivery?
2. Which AI-driven tools significantly influence academic course delivery in Technical Universities?
3. What are the key barriers to adopting AI technologies, particularly Virtual and Augmented Reality (VR/AR), in Technical Universities?

Moreover, this the study fills the gap in literature characterised by the a noticeable lack of studies that use factor analysis and partial least squares structural equation model in examining the enhanced academic course delivery using AI as a tool. The study provides empirical evidence for informed decisions by stakeholders, ultimately contributing to improved learning outcomes and educational quality in the technical higher education sector.

2. Literature review

2.1. Theoretical foundation: adaptive learning theory

The theoretical foundation of this study is based on the adaptive learning theory. The adaptive learning theory in the educational space provides a flexible learning environment for learners and facilitators [22]. The idea of learning within the adaptive learning module creates an alleyway for the development of learning content as part of the learning support tool [23]. It is widely acknowledged that adaptive learning is a type of learning that offers a suitable environment for learning, ultimately, through the discovery and summarization of learners themselves during learning, creates theories, and is able to work out issues on their own. Adaptive learning is predicated on individual differences in learners' knowledge background, learning attitude, learning style, and learning ability. From the educators' perspectives, adaptive learning has been defined as the use of adaptive learning systems as instructional tools to gather and evaluate data, plan lessons, comprehend the learning state, assess, and promptly modify the curriculum to match students' evolving needs.

In the context of TUs, adaptive learning could provide an intelligent and dynamic modification of learning materials, activities, and content to match the particular requirements and preferences of individual students using AI. Adaptive learning theory was used for this study because it provides tailored learning experiences, raises students' engagement, maximising and allowing flexibility in course content delivery by tutors and facilitators [22,24–26]. It allowed the researchers to explore the effect of AI capabilities for optimising learners and educators' outcomes for enhanced academic course delivery.

2.2. Technical universities and artificial intelligence

Technical Universities (TUs) were established in Ghana per the Technical Universities Act 2016 (Act 922) to train students in the technical, vocational, professional, research and innovation fields. Therefore, transformations in the development of curriculum and course content delivery using AI are crucial for the TUs considering the changing academic environment. AI in education provides new opportunities, potentials and challenges for educational innovations. Change to personalized learning, stimulating the instructor's role and the development of complex educational system have been enhanced [27, 28]. AI techniques such as natural language processing, artificial neural networks, machine learning, deep learning, and genetic algorithm have been implemented to create intelligent learning environments for behaviour detection, model building, learning recommendation, among others [29,30]. Wang and coworkers [15] have considered the relevance of AI applications such as ChatGPT and Large Language models (LLM) by teachers in the school settings. On the hindsight, AI adoption can be associated with academic integrity, infrastructure and a potential for job displacement [31,32]. Ethical AI policies, transformative frameworks, PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis), six thinking hats framework and ABCD listing frameworks have been developed as theoretical frameworks for AI [15, 33–35].

While this study focuses on Technical Universities (TUs) in Ghana, it is important to place the discussion within a broader global context. Various TUs and applied sciences universities worldwide have successfully integrated AI with a sustainability lens, offering valuable insights. For instance, Germany's universities of applied sciences have leveraged AI in smart manufacturing and green technology education, optimizing energy use and resource efficiency [36]. Similarly, Finland's technical institutions employ AI-driven adaptive learning systems to enhance sustainability in education [37]. However, the adoption of AI in TUs across different regions presents unique challenges, particularly in resource-constrained settings like Ghana. Limited access to high-performance computing, unreliable internet connectivity, and the high costs of AI adoption can hinder full-scale implementation. Therefore, AI solutions in these contexts must be designed to optimize energy efficiency, leverage cost-effective cloud-based technologies, and align with institutional sustainability goals. Integrating these global perspectives highlights the potential for AI-driven educational models tailored to different socio-economic and infrastructural realities.

2.3. Barriers to AI integration in technical universities in developing countries

While the integration of Artificial Intelligence (AI) into education holds immense potential, its adoption in Technical Universities (TUs) within developing countries is often met with significant challenges. One major barrier is the high implementation cost associated with AI technologies [38]. The financial investment required for acquiring, implementing, and maintaining AI systems often exceeds the budgets of many Technical Universities (TUs) in developing countries. These institutions frequently prioritize other critical needs, leaving minimal funding for advanced technologies [38]. Furthermore, the ongoing expenses for updates, maintenance, and scaling exacerbate the financial burden.

Another significant challenge is the lack of adequate training and technical expertise. Effective use of AI tools requires instructors and administrative staff to have sufficient knowledge and skills [39]. However, training programs tailored to the specific needs of AI in education are often unavailable or insufficient in developing countries. As a result, many educators feel unprepared to adopt AI, and the steep learning curve further discourages widespread usage [40].

Ethical and privacy concerns pose significant barriers to AI adoption in education [18]. The use of AI involves collecting and processing personal data, raising critical issues related to data security and privacy [18]. In developing countries, where data protection laws are often weak or poorly enforced, there is a heightened risk of data misuse and potential algorithmic discrimination.

Infrastructure limitations present another substantial hurdle. Many Technical Universities in developing countries, particularly in low-bandwidth and rural settings, lack the necessary technological infrastructure, such as reliable internet connectivity, modern hardware, and adequate IT support. These deficiencies make it challenging to implement and sustain AI-driven adaptive learning tools, significantly hindering their effectiveness and accessibility [41].

Finally, resistance to change within educational institutions slows down AI adoption. Traditional teaching methods are deeply rooted in the culture and practices of many Technical Universities (TUs). Educators and administrators may be skeptical about the benefits of AI, leading to reluctance in embracing these advancements [40]. This resistance often stems from skill gaps and a lack of understanding of AI's potential. In developing countries, the challenges are compounded by infrastructural limitations and the need for strategic navigation between technological potential and effective implementation [40].

Addressing these barriers requires a comprehensive approach that includes increasing investments in infrastructure, making AI tools more affordable, providing capacity-building initiatives for faculty and students, and establishing ethical guidelines to ensure fair and secure use of AI. Besides, institutions can explore lightweight AI models that function offline or in hybrid learning environments. Additionally, partnerships with industry stakeholders can facilitate access to cost-effective AI solutions tailored to low-resource settings. By overcoming these challenges, Technical Universities in developing countries can unlock the full potential of AI to enhance sustainable education and improve learning outcomes.

2.4. Conceptual framework and research scope

The conceptual framework for this study is grounded in constructs from Adaptive Learning Theory (ALT) and focuses on specific AI-driven technologies that enhance academic course delivery in Technical Universities (TUs). As illustrated in Fig. 1, the framework identifies five core AI components: Personalized Learning (PL), Natural Language Processing (NLP), Intelligent Tutoring Systems (ITS), Data-Driven Insights (DDI), and Virtual and Augmented Reality (VR/AR). These components represent the operational definition of AI in this study. Each componeny is conceptualized as follows:

- **PL** refers to AI systems that adapt content to individual learning styles and progress.
- **NLP** involves AI tools that support language understanding, communication, and academic writing.
- **ITS** are systems that offer automated, interactive learning support and feedback.
- **DDI** encompasses the use of AI analytics to inform teaching and learning decisions.
- **VR/AR** refers to immersive technologies that simulate real-world scenarios to enhance engagement and comprehension.

Together, these components form the technological configuration of AI under investigation, establishing clear boundaries for the study's focus and ensuring alignment with ALT. This framework guides both the data collection and analysis phases and supports the examination of AI's pedagogical, practical, and sustainability-related impacts.

3. Methodology and data collections

3.1. Research approach

This study adopted a mixed-method approach to leverage the strengths of both qualitative and quantitative research. Data collection and analysis integrated qualitative insights and statistical examination to provide a comprehensive understanding of AI-driven course delivery in Technical Universities. A technical route design diagram for this study, outlining the sequential steps followed through the study is presented in Fig. 2. Considering the complex nature of the adaptive learning system and AI, a qualitative inductive approach was employed in the first phase of the study.

3.2. Qualitative phase

Qualitative interviews of eight (8) students and eight (8) lecturers, two focus group discussion (FDGs) and cross-sectional survey were employed for the study. The manual coding strategy was employed, following an inductive approach in which data from participants was categorized without fitting it into a predetermined coding frame. This ensured that analysis was driven by the collected data rather than imposed structures. Thematic analysis was conducted in two stages: descriptive (summarizing participant responses) and interpretative (identifying deeper patterns and meanings).

Transcription of the data initially yielded 51 distinct issues from students and lecturers. Further analysis consolidated these into 33 categories, which were further refined into 20 thematic categories such as Real-Time Feedback, Learning Style Adaptation, Predictive Student Success Modeling, and AI-Based Course Content Optimization. A final review of the transcripts and highlighted quotations led to further thematic consolidation into five overarching themes: Personalized Learning Paths, Natural Language Processing, Intelligent Tutorial Systems, Data-Driven Insights, and Virtual and Augmented Reality. To ensure reliability and consistency, a rigorous iterative review process was conducted, where the authors revisited the data multiple times to refine categories and validate emerging themes. While no automated thematic analysis software was used, intercoder agreement was established through discussion and consensus among researchers to enhance validity. Specifically, two researchers independently coded the data and then met to compare their initial codes. Differences were discussed

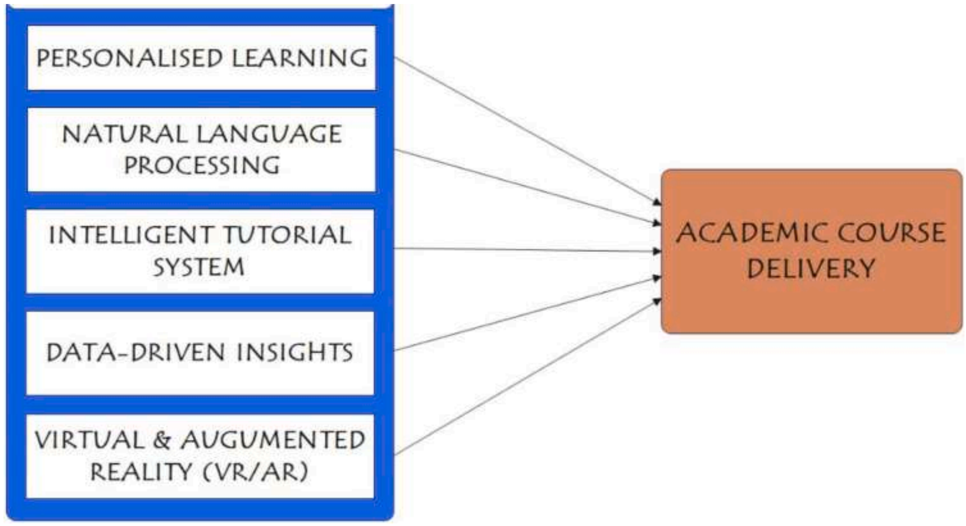

Fig. 1. Conceptual framework.
Source(s) Authors' Construct (June 2024)

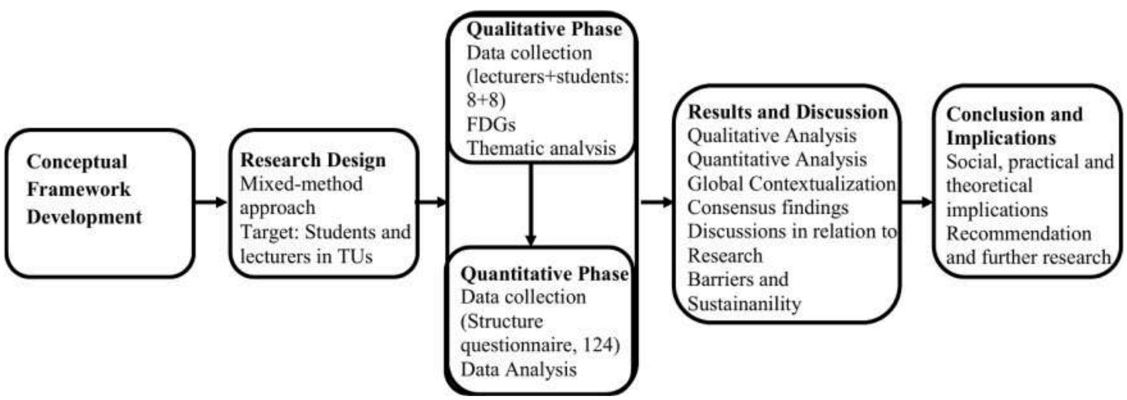

Fig. 2. Technical route design diagram for the study.

systematically until consensus was reached for each theme. This iterative process ensured that the themes were grounded in the data and reflected a shared interpretation. This consensus approach provided methodological rigor consistent with qualitative research standards. Microsoft Excel was used to support data organization. Particularly, Excel functions such as sorting, filtering, and grouping were employed to organize and review code frequencies and patterns. This facilitated the aggregation of codes into broader categories and the refinement of themes into the thematic areas.

Insights from the qualitative interviews played a fundamental role in shaping the questionnaire used to measure the constructs in the Adaptive Learning Theory (ALT). The interview data were analyzed inductively to identify key themes related to students' experiences and lecturers' usage of AI in science, engineering, and humanities course delivery. These themes were systematically mapped onto the survey constructs. For instance, discussions on AI-driven personalized learning experiences led to the development of scale items measuring Personalized Learning (PL), while feedback on AI-powered content optimization and analytics informed items related to Data-Driven Insights (DDI). Similarly, lecturers' perceptions of AI-facilitated student engagement and real-time assistance contributed to the development of items assessing Intelligent Tutoring Systems (ITS). Moreover, concerns about VR/AR accessibility and cost, which emerged as major discussion points, guided the inclusion of items assessing the challenges of AI adoption in Technical Universities. This approach ensured that the questionnaire was directly grounded in empirical qualitative insights, enhancing its validity and relevance to the study context.

The quantitative survey surveyed the students and lecturers' perceptions. The analysis identified potential impact of AI in enhancing course delivery and balanced perspective that considers both the benefits and impacts of AI integration in course delivery in TUs.

Accordingly, purposive sampling was used to select final-year students from the science, engineering, and humanities disciplines, as well as lecturers, for data collection for the qualitative analysis. This approach was appropriate because it enabled the selection of individuals with relevant experience and exposure to AI tools in academic settings, ensuring rich and targeted insights. As affirmed by Creswell [42] and Yin [43], purposive sampling is suitable when information is required from individuals with expertise and contextual knowledge of the phenomenon under study.

An interview guide was used for the interviews, which lasted between 30 min and 60 min. The triangulation methods to coding of the qualitative data and cross section analyses in the various disciplines were employed for the study.

3.3. Quantitative phase

On the other hand, the sample for the quantitative study was randomly sampled to ensure a fair representation of both students and lecturers. In the quantitative phase, the ALT was used to develop the questionnaires involving the impact of using AI on course delivery.

A total of 124 questionnaires were distributed, targeting final-year students and lecturers across different disciplines. The response rate of 81 % (100 responses) reflects the combined feedback from both groups. Additionally, the 10-times rule [44], which suggests that the minimum sample size should be at least 10 times the largest number of indicators in any construct or the largest number of structural paths directed at any latent variable, a criterion that our sample meets. The questionnaires were distributed in a hybrid form through Google Form link created and shared with students randomly and in-person in the universities between April and June 2024.

To ensure representativeness, the random sampling process involved stratification by role, where the population was divided into two distinct groups: students and lecturers. This approach ensured that both categories were proportionally represented in the study. Within each stratum, respondents were randomly selected to avoid selection bias and to provide a balanced dataset for analysis. In order to mitigate other potential biases that could arise because of AI exposure and adoption across disciplines, efforts were made to engage participants from all targeted disciplines and ensure balanced representation across roles

Additionally, the distribution of questionnaires was carried out across multiple disciplines to capture diverse perspectives on AI-driven course delivery. This method allowed for a more comprehensive understanding of the varying experiences and insights from both students and lecturers regarding the integration of AI tools in education.

The questionnaire used the five-point Likert Scale, ranging from 1, strongly disagree to 5, strongly agree. The use of the Likert scale enabled accurate ordinal measurements of variables considered in this study. The questionnaire was pre-tested on six students in the three disciplines and two lecturers before actual distribution. This paved the way for assessing the validity of the questions, and correcting errors to improve the collection of appropriate data for analysis. A sample questionnaire is provided as Supplementary Material.

3.4. Data analysis

Quantitative data analysis was performed using partial least squares structural equation modelling (PLS-SEM) version 4. This enabled assessments of validity and reliability of the study. PLS-SEM was chosen for this study due to its suitability for analyzing complex models with relatively small sample sizes and its prediction-oriented approach [45]. PLS-SEM focuses on maximizing explained variance in endogenous constructs, making it particularly effective for exploratory and applied research settings. One key reason for adopting PLS-SEM is the study's sample size, which aligns with best practices recommending PLS-SEM for studies with smaller datasets, especially when assessing complex relationships among latent variables [46]. Given our sample size, we employed bootstrapping (5000 resamples) to improve statistical reliability and mitigate over-fitting concerns

Additionally, PLS-SEM does not assume normal data distributions, making it a robust choice for datasets where normality cannot be assumed [45]. To ensure the robustness of the model estimation, key model fit indices were assessed. The Standardized Root Mean Square Residual (SRMR) of 0.079 obtained for the model falls within acceptable thresholds ($\leq$ 0.08), indicating a good model fit. Other metric values squared Euclidean distance (3.254) and geodesic distance (3.1) values further confirm model adequacy, as they are within acceptable bounds for assessing model discrepancy.

Focusing on AI's impact on academic course delivery in Technical Universities, PLS-SEM was the most appropriate choice as it allows for evaluating complex relationships between AI-driven parameters and academic outcomes, even with a relatively small sample [47]. This approach ensures that the model effectively captures relevant relationships and practical implications, making it highly relevant to this study.

3.5. Statement of informed consent

All participants were informed about the purpose and scope of this study, including the collection and usage of their data to evaluate the impact of AI tools on academic course delivery in Technical Universities. Participants were notified that their involvement was voluntary and that they could withdraw from the study at any time without penalty. They were assured of the confidentiality and anonymity of their responses, with all identifying information removed or anonymized in the reporting process. Consent was obtained from each participant prior to data collection, with an understanding that the results would be used strictly for academic research and publication purposes.

4. Results

4.1. Results of qualitative analysis

The results were corroborated with qualitative interviews and FGDs and participants revealed their familiarity with some AI tools which they mostly use daily and a few weekly for academic learning using the ALT. They indicated their familiarity with tools such as quillbot, perplexity ai, reo, lamda, chatGPT, gemini, grammarly, consensus apps, plaito and jupiter among others for academic learning. Participants in the FGDs 1 confirmed that some AI tools have been used as:

> We are in a global world and we are aware that AI is the way to go for our academic work. It is very important we familiarise ourselves with the use of AI tools in this digital technology era. The digital devices such as laptops and smart phones with access to internet enable us to access and explore the AI tools. It enables us to compete intellectually with our counterparts in the intellectual global space (Focus Group Discussion 1).

The implication of these results revealed that the participants made a conscious and deliberate effort to use the AI tools to enhance their academic work, and these had consequences on the academic course delivery. While many indicate that AI has been introduced in some of their courses of study such as software development with python, programming, project work and java script, web programming, data structures and algorithms for the science and engineering participants, little awareness existed among participants in the humanities.

Several participants indicated that the AI usage was very beneficial to them and had a significant positive impact on their academic work and learning. It was alarming for first time users of AI. They initially used it for their private studies and social activities before they explored the AI tools to assist them to understand some of their courses. Many of the participants use the AI for personalised learning and most of the time refers to the AI tools to solve some of their assignments and course work for them.

One participant stated:

> I find it sometimes difficult to comprehend some of the courses our lecturers teach us. We have seen the potential of the AI to assist us understand our courses better from different perspectives and make useful contribution during the course delivery. Though it is fast and reliable tool for academic course delivery, it requires that students become cautious in its usage since it could make one lazy (Student 5)

However, some participants raised concerns about academic integrity, particularly regarding students relying on AI to generate assignments rather than engaging in critical thinking. There were also discussions about data privacy risks, as many AI tools require personal data input, raising fears about how this information is stored and used. These concerns are particularly relevant in the context of Ghana's Data Protection Act, 2012 (Act 843), which regulates the collection, use, and disclosure of personal data. Although many AI tools operate outside local jurisdiction, participants' apprehensions reflect a growing awareness of the need for stronger safeguards and digital literacy in line with national data protection policies. Another key concern was the potential over-reliance on AI, which, according to some lecturers, might hinder students from developing independent problem-solving skills. One participant noted that while AI provides quick answers, it does not always encourage deep learning, making it essential for students to use AI responsibly.

Apart from personalised learning, it was observed from the interviews and FGDS that participants used the AI tools to facilitate their language learning and understanding of course content and delivery. It also increases their accessibility in the language processing and minimizes the language barriers in the course content. Different explanations and perspectives are demonstrated using the AI tools.

One FGDs 2 member reiterated that:

> Some of the courses delivered by our lecturers are very technical and difficult to comprehend. However, with the use of the AI, I have been able to understand many of the courses I had challenges. Technical languages are no more a barrier as explanations and different perspectives are available through AI. (Focus Group Discussion 2).

Beyond academic support, participants acknowledged AI's potential in sustainable resource management, such as optimizing learning materials and reducing reliance on printed textbooks through digital tools. Some also noted how AI-driven language translation and accessibility features promote inclusivity, enabling students from diverse linguistic backgrounds to engage with course content more effectively. Additionally, participants expressed optimism about AI enhancing future employability, as exposure to AI tools prepares them for technology-driven job markets and fosters essential digital skills.

The qualitative data disclosed that many of the participants have experienced adaptive learning to enhance their academic progress. Critical thinking skills, intellectual discourse and quality of content and relevant courses have been improved. Again, data driven insights have been acquired using the AI tools.

One participant interviewed stated:

I do acknowledge the potential benefits of the AI tools in sharpening my thinking skills and helping to be innovative and thinking outside the box. I have observed that since I started using the AI my academic performance has improved and I am able to follow the course being taught in class (Student 8).

The AI concept is catching up with the TUs because programmes and courses in AI are being introduced and the AI tools are being used for academic learning. The virtual reality and augmented reality do exist for the TUs to take advantage of it. It was noticed that though the AI concepts are being adopted in the TUs context, a policy guideline of its usage is required to obtain the maximum benefits and impact in the course delivery. It can be adopted and applied to all courses for a better understanding of students' academic work and provide a robust course content and delivery.

A lecturer interviewed claimed this:

> As a University, we cannot assume that AI tool usage is the prerogative of students to explore. We want to see our lecturers embedding this AI concept and tools usage in every aspect of our academic course and delivery. This will enhance our thinking and innovative skills. Our curriculum design and instructional strategies should be practically guided by current AI tools for more self-innovative teaching and learning as it is done in developed countries. We are far behind and must catch up quickly. It seems to me that more lecturers are becoming aware that we should develop the curriculum for our students to adopt modern technological trends (Lecturer 1).

In order to systematically present the qualitative insights, Table 1 categorizes participants' responses into key themes, highlighting their perspectives on AI integration in academic course delivery.

Table 1
Qualitative Findings on AI integration on Academic Course Delivery.

Theme	Key findings	Representative quotes
AI familiarity and usage	Most students and lecturers are familiar with AI tools such as ChatGPT, Quillbot, Gemini, and Grammarly.	"We are in a global world, and we are aware that AI is the way to go for our academic work." (FGD 1)
Benefits of AI in Learning	AI enhances personalized learning, aids in understanding complex topics, and provides multiple perspectives.	"I find it sometimes difficult to comprehend some courses. We have seen the potential of the AI to assist us understand our courses better" (Student 5)
Language Processing and Accessibility	AI tools help students overcome language barriers, improving comprehension.	"Technical languages are no more a barrier as explanations and perspectives are available through AI." (FGD 2)
Impact on Critical Thinking	AI supports intellectual discourse, improves reasoning, and enhances content quality.	"Since I started using AI, my academic performance has improved." (Student 8)
Challenges in AI Adoption	Limited awareness in humanities, lack of institutional policy guidelines, and concerns over-reliance.	"A policy guideline on AI usage is required to maximize its impact." (Lecturer 1)
Need for Curriculum Integration	AI should be embedded in all courses for better academic delivery.	"Our curriculum design and 362instructional strategies should be practically guided by current AI tools for more self-innovative teaching and learning as it is done in developed countries." (Lecturer 1)

4.2. Results of quantitative analysis

4.2.1. Demographic characteristics

The cross-section demographic composition of the study is in Table 2, which displays the ages, sex, programme and field of study for students and lecturers' respondents. The highest ages of respondents ranged from 19–29 years, representing 53 % and the least of 40 years and above represented 10 %. The respondents were predominantly males, making up to 69 % (69) of the sample according to the demographic parameters used in the study. The level of programmes of study and teaching the respondents were mainly Bachelor of Technology (B. Tech) 52 % (52). This is followed by the Higher National Diploma (HND) programmes 30 (30 %) in the Technical Universities. Only a small percentage 14 % and 4 % of the respondents respectively were studying and teaching non-tertiary and masters' students. The field of study and teaching of respondents were predominantly science and engineering representing 43 % and 42 respectively.

Table 2
Demographic Characteristics of Respondents.

Variables	Frequencies	Percentages
	$n = 100$	100 %
Age		
19–29	53	53.2
30–39	37	36.7
40–49	9	8.9
50+	1	1.2
Sex		
Male	69	69.4
Female	31	30.6
Programme		
Non-Tertiary	14	14.1
HND	30	30.2
BTech	52	52.1
Masters	4	3.6
Field of Study/Teaching		
Sciences	43	43.2
Engineering	42	41.5
Humanities	15	15.3

Source (s) Field Survey, June 2024.

4.2.2. Impact of AI on academic course delivery

Analysing the data using structural equation modelling enabled the assessment of the load of item on every factor considered for the study. We found satisfactory loadings on each of the factors personalized learning, natural language processing, intelligence tutorial system, data driven insights, virtual and augmented reality, and the measures of academic course delivery. The satisfaction of these loadings emanates from the high loading values that ranged between 0.7 and 1.0. Besides, the constructs presented in this study were assessed to empirically establish our assertion that by integrating AI into design and delivery of courses, educators would enhance course delivery in Technical Universities. It was found that AI measures such as natural language processing, intelligent tutorial system, data driven insights, and AI aids in personalized learning enhanced academic course delivery (Table 3). These were shown by the positive and statistically significant parameter or regression coefficients of the AI variables (Table 3). These findings are consistent with the findings of the qualitative analysis where respondents' consensus responses suggested that adopting AI enhanced course delivery. However, virtual and augmented reality was not statistically significant although it had a positive coefficient to suggest it could enhance academic course delivery (Table 3).

The statistically significant AI measures, natural language processing, intelligent tutoring systems, data-driven insights, and personalized learning, underscore the transformative potential of AI-driven education in Technical Universities. These findings suggest that AI integration not only enhances course delivery but also fosters sustainable educational development by improving learning efficiency, accessibility, and adaptability. In the context of sustainable development, these AI-driven improvements align with SDG 4 by ensuring inclusive and equitable learning experiences, particularly in resource-constrained environments. Moreover, the positive but non-significant effect of virtual and augmented reality highlights the need for further investment in infrastructure and digital capacity building within Technical Universities, ensuring that emerging AI technologies are both accessible and impactful in fostering long-term sustainability in education.

These results are further supported in the structural model (Fig. 3). All the factor loadings connecting every item to each variable were found to be statistical ($p = 0.000$). The model was deemed fit as 89 per cent of the variation in academic course delivery is explained by the model of the AI measures (R-square = 0.89, Adjusted R-square = 0.88). Intelligent tutorial system had 4 factor loadings and the greatest impact on academic course delivery compared to data driven insights, personalized learning, and natural language processing (Table 3). Among the variables that were statistically significant, Natural language processing had the least impact on academic course delivery (17.8 per cent). This was to be expected since natural language required more technical skills for its usage. We further assess the statistical adequacy of the study.

Further confirmation of validity of study instruments and quality of study using measures such as Cronbach alpha, composite reliability, and average variance extracted (AVE). Besides the natural language processing that could lead to a Cronbach's alpha of 77 per cent, the other variables related higher values ranging between 83 per cent and 95 per cent (Table 4). These higher values support acceptable internal consistency, demonstrating strong reliability of our measurements supporting the results for the study [48]. Furthermore, validity of our construct's reliability and validity instruments are supported with >50 per cent values for composite reliability and average variance extracted (Table 4).

Table 3
Statistical significance of AI parameters on course delivery.

AI Parameter	Coefficient	P-value
Personalized learning	0.203	0.001
Natural language processing	0.178	0.006
Intelligent tutorial system	0.376	0.000
Data driven insights	0.258	0.001
Virtual and augmented reality	0.084	0.330

The strong reliability and validity of the study instruments, as evidenced by high Cronbach's alpha (77 %–95 %), composite reliability, and average variance extracted (above 50 %), reinforce the robustness of the findings. In the context of sustainable development, these results ensure that AI-driven educational interventions are measured with precision and consistency, contributing to data-driven policy and decision-making in Technical Universities. Reliable measurement tools support the development of scalable and replicable AI-enhanced learning models, which are essential for achieving SDG 4 by promoting evidence-based improvements in teaching and learning. Furthermore, strong construct validity enhances confidence in AI's role in fostering innovation, skill development, and long-term sustainability in education.

Further, it must be mentioned clarified that the R-squared value of 0.89 indicates a strong explanatory power of the model, demonstrating that AI-driven tools significantly impact academic course delivery in Technical Universities. However, we acknowledge the potential concerns regarding overfitting, particularly given the relatively small sample size. Overfitting occurs when a model captures noise or specific patterns in the training data that may not generalize well to broader populations. Measures mitigate these risks including bootstrapping and the use of PLS-SEM, a method well-suited for predictive modeling in small sample sizes due to its ability to handle complex relationships while maintaining robustness, were employed. Additionally, model complexity was carefully managed to prevent excessive parameterization. Nonetheless, the constraints of data availability remain a limitation. Future studies with larger and more diverse datasets across multiple institutions would provide further validation and enhance the generalizability of our findings.

4.3. Contextualizing findings within the global trends in AI and education

The findings of this study aligns with global trends in Artificial Intelligence in Education. This emphasizes the transformative role of AI tools in enhancing personalized and adaptive learning experiences. The results show a significant trend of AI adoption among students for academic learning, aligning with global shifts in education. Students are actively using a variety of AI tools like QuillBot, Perplexity AI, and ChatGPT to enhance their understanding of course content, overcome language barriers, and personalize their learning experiences is consistent with global observations [49,50]. This reflects a broader move towards integrating AI to support learning and improve accessibility. The increased use of AI for personalized learning is also observed in the use of AI for assignments and coursework, which has resulted in improved academic performance and engagement among students.

However, the findings also underscore specific contextual challenges and opportunities for Technical Universities in developing countries. The conscious efforts of participants to use AI tools, despite limited institutional support, highlight a growing awareness of AI's educational value. Yet, the lack of structured curriculum integration and institutional policies for AI usage creates a gap compared to global benchmarks, where AI tools are deeply embedded in educational strategies.

Prior studies suggest that the integration of AI in educational curricula is still in its infancy, particularly in developing regions. For instance, it has been emphasized that the effectiveness of AI technology in learning is significantly influenced by infrastructure and organizational support, indicating that many institutions struggle with these foundational elements [51]. This gap in curriculum design reflects a broader trend where educational institutions fail to keep pace with technological advancements, resulting in a disconnect between students' learning experiences and the skills required in the global job market [52].

The call for policy guidelines, training, and curriculum redesign to incorporate AI tools reflects a pressing need to align universities with

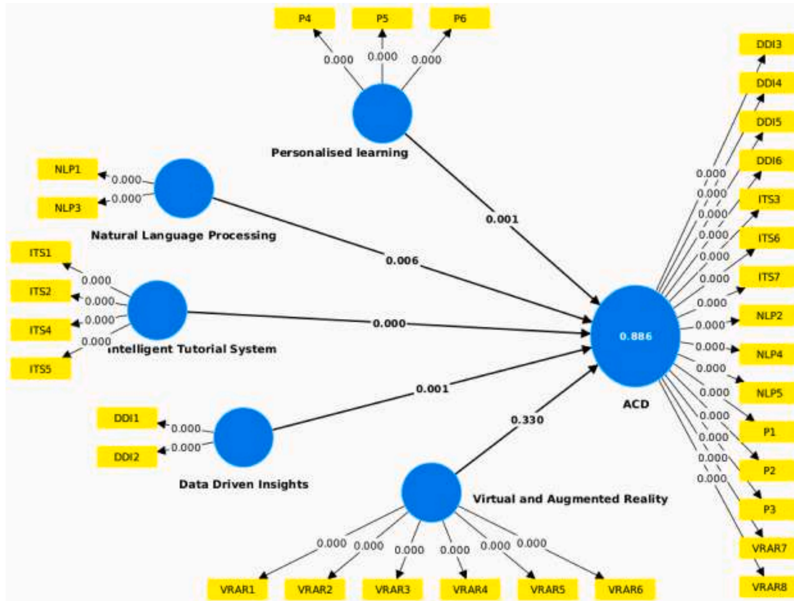

Fig. 3. Structural model of AI enhances academic course delivery (ACD). The significance of relationships is indicated by p-values on the arrows.

Table 4
Construct reliability and validity.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Academic Course Delivery	0.953	0.954	0.958	0.604
Data Driven Insights	0.832	0.84	0.922	0.856
Intelligent Tutorial System	0.891	0.891	0.925	0.754
Natural Language Processing	0.766	0.77	0.895	0.81
Personalised learning	0.899	0.903	0.937	0.832
Virtual and augmented reality	0.941	0.943	0.954	0.774

global trends which have been reported in other related studies [29,53]. By addressing these gaps and ensuring equitable access, Technical Universities can harness AI to not only improve academic course delivery but also position their students to compete in the global intellectual and technological space.

4.4. Consensus findings from qualitative and quantitative analysis

To enhance the linkage between qualitative and quantitative findings, we explicitly examined how themes identified from FGDs align with the statistical results obtained from PLS-SEM. The qualitative data revealed that faculty members and students widely acknowledged AI-driven tools as beneficial for academic course delivery, particularly in areas such as personalized learning and intelligent tutoring systems (ITS). These insights align with the statistically significant positive coefficients observed for AI measures such as natural language processing (NLP), intelligent tutoring systems (ITS), and data-driven insights (DDI). However, VR/AR emerged as a key point of divergence between qualitative and quantitative findings. While the statistical results showed that VR/AR had a non-significant effect, qualitative responses emphasized its potential benefits but also highlighted concerns regarding accessibility, infrastructure costs, and technical expertise required for effective adoption. This suggests that while VR/AR holds promise, its limited practical implementation and institutional readiness may have contributed to the observed statistical insignificance. These consensus findings emphasize the need for targeted institutional strategies to overcome implementation barriers and maximize AI's impact on academic course delivery. A summary of the alignment between qualitative and quantitative findings is presented in Table 5, highlighting points of convergence and divergence across the AI components examined.

5. Discussion

This study examined the impact of AI integration on academic course delivery in Technical Universities (TUs), guided by the following research questions:

1. How do students and lecturers perceive the role of AI in enhancing course delivery?

Table 5
Alignment of Qualitative Themes and Quantitative Results on AI Tools.

AI Component	Qualitative Insight	Quantitative Result	Alignment
Personalized Learning (PL)	Strongly perceived as enhancing learning flexibility and student engagement	Statistically significant positive effect ($p < 0.05$)	Aligned
Natural Language Processing (NLP)	Used to support academic writing, comprehension, and language processing	Statistically significant positive effect ($p < 0.05$)	Aligned
Intelligent Tutoring Systems (ITS)	Recognized for adaptive feedback, student support, and independent study	Statistically significant positive effect ($p < 0.05$)	Aligned
Data-Driven Insights (DDI)	Helps track student performance and inform learning strategies	Statistically significant positive effect ($p < 0.05$)	Aligned
Virtual and Augmented Reality (VR/AR)	Acknowledged potential benefits, but barriers noted: access, cost, lack of training	Statistically non-significant effect (positive coefficient)	Partial divergence

2. Which AI-driven tools significantly influence academic course delivery in TUs?
3. What are the key barriers to adopting AI technologies, particularly Virtual and Augmented Reality (VR/AR), in TUs?

Addressing Research Question 1, qualitative findings revealed that both students and lecturers recognize AI as a valuable tool in academic learning. Students highlighted AI's role in improving understanding of complex course content, while lecturers emphasized the urgency of integrating AI into curriculum development. These insights were reinforced by statistically significant relationships between AI parameters namely personalized learning (PL), natural language processing (NLP), intelligent tutoring systems (ITS), and data-driven insights (DDI), and course delivery ($P < 0.05$). This aligns with recent studies on AI in education that contextualize student learning, reduce teaching workload, and enable intelligent feedback systems [5,13,16,54,55].

In response to Research Question 2, participants reported frequent use of AI tools such as ChatGPT, Grammarly, Quillbot, Consensus AI, Gemini, and others. ChatGPT and Grammarly were most used (27 %), confirming trends in similar studies [56]. Although all respondents had access to AI tools, most used laptops (64 %) or smartphones (21 %), while inconsistent internet access remained a challenge. Our findings confirmed that PL significantly enhances academic delivery (Table 3), as AI systems tailor content to individual learner needs, consistent with Chaudhry and Kazim [57]. Likewise, NLP supported comprehension and linguistic accessibility [58,59], and ITS improved engagement through real-time feedback and adaptive learning [60–63]. DDI also enabled strategic decision-making through performance trend analysis [64,65], highlighting its relevance in resource-constrained TUs.

In relation to Research Question 3, while VR/AR showed a positive coefficient, it was not statistically significant (Table 3). Qualitative insights revealed four main barriers: lack of awareness and training, limited curricular integration, infrastructure costs, and institutional resistance. Many lecturers and students had not received adequate training on VR/AR, and the technology remained peripheral to the curriculum. Moreover, advanced hardware requirements and usability issues limited accessibility. Institutional resistance rooted in traditional teaching cultures further stalled adoption [66].

To address these barriers, TUs should implement structured training programs, develop course-specific VR/AR content in collaboration with industry, and embed VR/AR in core curricula. Cloud-based VR platforms may improve accessibility, while policies and budget allocations can incentivize adoption of immersive technologies.

Beyond academic delivery, the study emphasizes AI's role in fostering socioeconomic development. Tools like ITS and DDI nurture critical thinking and innovation skills vital for bridging workforce gaps in technology and engineering. AI-enabled education also supports entrepreneurial ecosystems by equipping students with self-directed learning capacities and creative problem-solving abilities. These outcomes align with global sustainability objectives, including SDGs on Quality Education, Decent Work and Economic Growth, and Industry, Innovation, and Infrastructure. This aligns with global best practices and ethical considerations as emphasized in UNESCO's Guidance for Generative AI in Education and Research [67].

Ultimately, by integrating AI in teaching and learning, TUs can act as catalysts for socioeconomic transformation, creating inclusive, innovation-driven ecosystems where education and technology intersect. This study thus reinforces existing AIEd research while offering local insights that inform broader implementation strategies. Overall, the findings of this study not only align with and reinforce existing research in AI and education but also offer new context-specific insights for Technical Universities in developing countries, thereby contributing to the global discourse on AI integration in sustainable and inclusive academic delivery.

5.1. Social, practical and theoretical implications

Education policymakers should unreservedly embrace the use of AI tools for enhancing education, especially in Africa. Rigorous utilisation of AI in Technical Universities (TUs) across all courses and programmes will boost the technological drive for innovation in these emerging universities [68–70]. Practically, this will encourage more applied research in this area by TUs. The use of AI could also enhance entrepreneurship education in the TUs [71–73]. Consequently, the integration of AI in course design and delivery will improve knowledge transfer through personalised learning for students and educators alike. This will enable both groups to explore and better understand Natural Language Processing (NLP), Intelligent Tutoring Systems (ITS), Data-Driven Insights (DDI), and Personalised Learning (PL), which can drive innovation and improve learning outcomes.

However, the successful integration of AI in education requires targeted policy measures and a collaborative approach involving government, institutional governance, and industry stakeholders. Governments should develop clear policy frameworks that support the integration of AI tools in education, prioritizing equitable access to the required digital infrastructure, such as internet connectivity and devices like smartphones, laptops, and desktops [74–76]. Institutional governance within TUs must adopt strategies to embed AI into curricula while promoting responsible and ethical AI use. This includes capacity-building initiatives for faculty members to integrate AI-driven teaching tools and ensuring that students are educated on the ethical implications of AI usage.

Furthermore, fostering industry collaboration is crucial to accelerate AI adoption. Partnerships with tech companies can ensure that cutting-edge AI tools are accessible and tailored to the specific educational needs of TUs. These collaborations can also provide opportunities for research, internships, and skills improvement, enabling students to contribute meaningfully to the workforce and innovation ecosystems. By leveraging such partnerships, TUs can align with global best practices in AI integration and position themselves as key players in the knowledge economy.

To ensure the systematic and sustainable integration of AI in Technical Universities, institutions can adopt best practices from established frameworks such as UNESCO's guidelines on AI in education and the IEEE's Ethically Aligned Design for AI. UNESCO's guidance emphasizes human agency, inclusion, equity, and ethical governance, providing foundational policies for responsible AI implementation in education [67]. The IEEE framework advocates embedding ethical considerations into AI systems from their inception, prioritizing transparency, human well-being, and accountability (Shahriari and [77]). Technical Universities can align their AI strategies with national digital transformation policies, leveraging governance models that emphasize inclusive education and long-term resource efficiency. For instance, Singapore's Institute of Technical Education (ITE) has implemented AI-driven educational models through collaborations like its AI Lab with Microsoft, equipping students with responsible AI skills [78]. Furthermore, Technical Universities can look to models such as India's AI for All program, which integrates AI literacy at multiple education levels and fosters industry-academia collaboration [79]. Establishing clear institutional policies, faculty training programs, and AI ethics committees can further support responsible and structured AI adoption in technical universities.

Graduates trained in AI from Technical Universities (TUs) play a critical role in addressing local and national development goals by driving technological innovation, improving productivity, and fostering digital transformation in key industries. In Ghana, AI expertise aligns with government initiatives such as the National Digital Transformation Agenda, which emphasizes the use of emerging technologies to enhance education, healthcare, and industrial processes [80]. Graduates skilled in AI can contribute by optimizing agricultural processes through predictive analytics, enhancing financial inclusion via AI-driven fintech solutions, and supporting smart city initiatives for efficient urban planning. By leveraging such frameworks, Ghanaian TUs can develop structured AI curricula that are industry-aligned, government-supported, and locally relevant, ensuring that AI adoption contributes meaningfully to sustainable development

5.2. Implications on global sustainability agenda

The integration of AI in education, particularly in Technical Universities (TUs), holds substantial potential to contribute to recognized sustainability frameworks, such as the United Nations Sustainable Development Goals (SDGs). AI-enhanced academic course delivery aligns closely with SDG 4, which emphasizes inclusive and equitable quality education and lifelong learning opportunities for all. By personalizing learning experiences, AI can bridge learning gaps, promote equity, and ensure that diverse student populations, including those in underserved and resource-constrained communities, have access to tailored, high-quality education. This fosters the development of skills needed for sustainable economic growth and innovation, as outlined in SDG 8.

Further, AI tools enable data-driven insights, which empower educators and institutions to optimize resource allocation, reduce inefficiencies, and promote sustainability within their operational structures. For instance, by leveraging intelligent tutorial systems and virtual platforms, TUs can minimize dependence on physical infrastructure and traditional methods, reducing environmental footprints. This contributes to SDG 9, which advocates for innovation, infrastructure development, and sustainable industrialization.

The broader implications of AI-enhanced education also support SDG 17, which emphasizes partnerships for sustainable development. AI integration facilitates global collaboration by enabling students and educators to access shared knowledge, collaborate across borders, and adopt best practices in technology-driven education. In this way, the study's findings on AI's role in improving academic course delivery can be positioned as a pathway toward achieving sustainability by building resilient, adaptive, and equitable educational ecosystems. By embedding AI into the core of educational delivery in TUs, institutions can foster sustainability not only in their academic outcomes but also in their contributions to societal and environmental resilience.

To embed AI in pedagogically efficient, sustainable, and ethically responsible ways, TUs should adopt a structured AI integration framework guided by key principles such as transparency, accountability, and equitable access. To begin with, policy frameworks should be developed to ensure AI applications align with institutional and national education goals while mitigating risks such as data privacy concerns and algorithmic bias. Furthermore, faculty and student training programs should be prioritized to build digital literacy and ethical awareness regarding AI's role in education. In addition, industry collaborations with AI firms and policymakers can facilitate the development of contextually relevant AI solutions tailored to the needs of TUs. It is further suggested that AI integration should be continuously monitored through impact assessments and feedback loops, ensuring that the technology remains a tool for inclusion and not exclusion. By aligning AI-driven education with global sustainability initiatives, TUs can create a transformative learning ecosystem.

6. Conclusion

A conceptual framework based on ALT was developed for the study, which established that AI enhanced academic course delivery. The study confirmed the relationships between AI-inspired tools involving PL, NLP, ITS, DDI and VRAR and improving academic course delivery. The study bridges the theoretical gap of how the interaction between PL, NLP, ITS, DDI and VRAR is pivotal in defining AI tools. The study showed that AI (parameterized by PL, NLP, ITS, DDI) positively influences academic course delivery for effective academic performance with the exception of VRAR whose effect is not statistically significant. Nevertheless, qualitative analysis of FGDs provided general support that using AI enhanced academic course delivery and learning outcomes. Therefore, the study provides an empirical support to the preposition that the integration AI in academic course delivery in TUs improve learning outcome. This sets the basis for other future works.

Future research could explore how Technical Universities (TUs) can systematically integrate AI solutions to align with sustainability goals, such as optimizing energy consumption, minimizing resource wastage, and fostering economic resilience. For instance, AI-driven systems could enhance efficiency by reducing redundant administrative processes, enabling smart resource allocation, and supporting energy-efficient digital learning environments. Additionally, AI applications in education could contribute to socio-economic development by improving workforce readiness, fostering innovation ecosystems, and promoting equitable access to learning resources. Further, a potential future study could employ longitudinal studies to assess AI's sustained impact on student performance, retention, and engagement over multiple semesters or years. Additionally, for long-term integration, Technical Universities must establish clear policies and structured training modules that equip lecturers with the skills to embed AI-driven approaches consistently across curricula, ensuring both pedagogical effectiveness and sustainability. Examining these synergies will provide valuable insights for policymakers and institutions seeking to balance technological advancement with sustainable development objectives.

7. Limitation and future research

One limitation of this study is the sample size, consisting of qualitative interviews with 8 students and 8 lecturers, along with structured responses from 124 randomly selected students, resulting in an 81 % response rate. While the sample size may appear modest, it was selected to ensure a manageable yet insightful balance of perspectives, considering the study's specific context in Technical Universities within a developing country. The qualitative component allowed for in-depth understanding of participant experiences with AI-driven course delivery, while the quantitative survey provided statistically relevant insights that reflect broader trends in student perceptions and learning outcomes. However, this sample size may limit the generalizability of the findings across diverse educational institutions or regions. Larger samples could potentially capture a wider range of experiences and further validate the findings. Future studies with expanded participant pools could build on these results, helping to confirm or refine the identified relationships between AI tools and academic course delivery outcomes.

Besides, the limited use of AI tools significantly restricts the potential benefits that AI could bring to educational practices. Future research should investigate how a more comprehensive and widespread integration of AI could enhance academic course delivery. Second, the study focused exclusively on technical education, which, while important, does not account for the variety of subjects and learning styles found in a broader educational curriculum. It would be useful to explore the application of AI tools across different educational fields to determine if the findings are consistent across a wider range of subjects. Furthermore, future studies should replicate this research in various emerging countries to provide a more comprehensive understanding of how AI can be integrated into diverse educational systems. Moreover, the focus on one geographical area and one type of education highlights the need for broader studies that consider different views and educational levels.

CRediT authorship contribution statement

Emmanuel S. Adabor: Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Elizabeth Addy:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Nana Assyne:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Emmanuel Antwi-Boasiako:** Writing – review & editing, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2025.100828.

Data availability

Data is included in submission as supplementary material

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GenAI-Infused Adult Learning in the Digital Era: A Conceptual Framework for Higher Education

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Abstract: Adult learners are a neglected species in the generative artificial intelligence (GenAI) era. The sweeping changes brought by GenAI in the educational arena have implications for adult learning. GenAI in education will usher in a world of adult learning that will be radically different from its predecessor. However, how adult learners will apply GenAI technologies to achieve their educational and professional goals remains blurred. To address this gap, it is crucial to examine essential principles for integrating GenAI into adult learning. For effective digital transformation of education, GenAI should optimize adult learning and ensure the safety of adult learners. This study proposes a "GenAI adult learning ecology" framework (GenAI-ALE) for higher education institutions in this digital era permeated by GenAI. The GenAI-ALE considers eight (8) essential principles categorized into two main themes; institutional factors (GenAI curriculum design, GenAI divide, GenAI policy, GenAI ethics) and interpersonal factors (GenAI human-centered andragogy, GenAI literacy, GenAI interest, and GenAI virtual learning). Malcolm Knowles' andragogical model is used to provide a context for integrating GenAI into adult learning. Applying the framework in a real-world context follows four iterative systematic steps; pre-perception and perception, GenAI readiness, assessment, and outcome. Reimagining new forms of adult learning in the GenAI revolution calls for higher education institutions to develop education systems where there is a synergy between humans (adult learners) and GenAI.

> "The andragogical model advocates for instructional technologists and educators to tailor GenAI tools to adult learning strategies."

Keywords: artificial intelligence, generative AI, GenAI, adult learning, higher education

Introduction

Advanced artificial intelligence (AI) technologies are rapidly disrupting the

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educational landscape like never before. Particularly, the introduction of ChatGPT by OpenAI in November 2022 has popularized the application of generative artificial intelligence (GenAI) technologies in everyday life including education. Generative AI (GenAI) pertains to "the production of entirely new creative works, such as text, pictures, music, or poetry, in response to simple prompts" (Cacicio & Riggs, 2023, p. 80). Popular examples of GenAI are ChatGPT, Midjourney, DALL-E, Synthesia, Bard, Stable Diffusion, which can all aid educators in task automation (Cacicio & Riggs, 2023; Sætra, 2023). In adult education where there is limited teacher capacity and resources, GenAI tools have the potential to expedite the rapid creation of high-quality, personalized, and engaging materials for the purposes of instruction and assessment in any given learning context (Cacicio & Riggs, 2023).

However, amid the euphoria of the transformative potential of GenAI technologies (e.g., ChatGPT, Claude, Bard, and Bing Chat) in the field of education, there have been doomsday predictions of their use by teachers and students (Rudolph et al., 2023). Educators have received mixed messages and have a great deal of uncertainty about the impact of GenAI tools in terms of teacher practice, teacher education, and student learning (Mishra et al., 2023). Hence, a cautious approach to the adoption of GenAI tools for teaching and learning is recommended due to several factors such as their accuracy, response quality, perceived usefulness, ethical issues, etc. (Adarkwah et al., 2023a; Tlili et al., 2023).

In this light, the "GenAI adult learning ecology" framework (GenAI-ALE) is proposed to guide educators in implementing GenAI as an educational tool in adult learning. It is believed that the proposed framework will promote safe and responsible use of GenAI technologies in adult learning. One of the core aims of educating adults is to enhance their competencies and provide them with foundational skills needed to address real-world challenges. In a survey, 71% of adults with higher education degrees, especially postgraduates, believe AI chatbots will impact their jobs (Hsu & Ching, 2023a). Hence, providing a framework to guide the design, development, and implementation of GenAI tools for adult learners is of immense value.

Potential of Generative AI for Adult Learners

Adult learners represent a diverse and multifaceted population, characterized by varying socio-economic backgrounds and educational trajectories (Hollander et al., 2023). The utilization of GenAI offers a unique opportunity to personalize their learning experiences, fostering independence and enhancing educational outcomes (Hsu & Ching, 2023b) (see Table 1). GenAI can provide hands-on activities and deeper conceptual understanding through interactive experiences (Salinas-Navarro et al., 2024).

The use of GenAI tools such as ChatGPT can enhance the overall learning experience of adults (Lin, 2023). In this GenAI era where adult learners are expected to gain multiliteracy skills, GenAI tools such as ChatGPT can help in adult literacy development (Ciampa et al., 2023). A survey involving 400 adult educators found that over 75% of the respondents acknowledge the potential of GenAI to support adult learning and education in content creation and as a teaching tool (Cacicio & Riggs, 2023) (see Table 2).

Despite the transformative potential of GenAI for adult learners, adult educators have to be alert of its potential dangers to educational quality to be able to fully harness its benefits. For example, Tlili et al. (2023) calls for a cautious approach to integrating GenAI technologies such as ChatGPT into education because of its ability to encourage plagiarism and cheating, foster laziness among learners, and its tendency to provide misleading or inaccurate information. GenAI tools may also lack quality responses, provide undesirable results and probabilistic outcomes, and have a risk of being biased (Dwivedi et al., 2023).

The GenAI-ALE Framework

The generative artificial intelligence adult learning ecology (GenAI-ALE) framework is

Table 1. GenAI Examples and Their Potential Application in Adult Learning.

No.	Examples	Application in adult learning	Authors
1	ChatGPT	For improving the reading, writing, critical thinking skills, and self-directed learning of adult learners	(Ciampa et al., 2023; Lin, 2023)
2	Synthesia	For generating instructional video content for adult learners	(Leiker et al., 2023)
3	Midjourney	For creating realistic images to enhance the immersive learning experience of adult learners	(Hsu & Ching, 2023b; Sætra, 2023)
4	Dall-E 2	For automating assessment and instruction and enhancing the creativity of adult learners	(Cacicio & Riggs, 2023)
5	InstructGPT	For answering questions and creating customized learning materials for adult learners	(Bhavya et al., 2022)
6	Perplexity	For providing a "knowledge hub" for seeking quick and accurate answers tailored to the needs of adult learners	(UNESCO, 2023b)

Table 2. A Comparison of Traditional Adult Learning Methods With GenAI-Infused Learning Approaches.

No.	Aspect	Traditional adult learning methods	GenAI-Infused learning approaches	Sources
1	Delivery and Facilitation approach	Face-to-face lectures, seminars, and workshops	The use of digital resources tailored to learner needs	(Dwivedi et al., 2023; OECD, 2023)
2	Assessment	Paper-based exams in many cases as a summative assessment	Multiple form of summative or formative assessment such as digital or online exams with instant analysis and visual representation	(Baidoo-Anu & Owusu Ansah, 2023; Dwivedi et al., 2023)
3	Learning activities and Feedback	Curated course materials with passive, teacher-centered learning, and manual feedback	Dynamic course materials with inquiry-based learning and personalized feedback	(Adarkwah, et al., 2023b; Lund & Wang, 2023; Salinas-Navarro et al., 2024)
4	Learning Engagement	Teacher-student or peer-to-peer classroom interactions	Immersive and simulated learning experience	(Baidoo-Anu & Owusu Ansah, 2023; Mishra et al., 2023; Salinas-Navarro et al., 2024)
5	Accessibility	Fixed time and space for learning with limited accessibility to course materials outside the classroom	Technology-enhanced learning environment with on-demand access to course materials	(Chiu, 2023; Tlili et al., 2023)

designed to guide the effective integration of generative AI technologies into adult learning environments (Figure 1). It consists of two main categories: institutional factors and interpersonal factors, each with specific components that form the backbone of the framework. Poquet and de Laat (2021) argue that the implications of technologies on lifelong learning (LLL) are both personal and institutional. Interpersonal factors refer to considerations related to individual students' personal characteristics, interactions, and relationships within the learning environment and how they engage with the learning content. Institutional factors pertain to considerations related to the educational institution as a whole involving the readiness, mechanism, and support systems for integrating GenAI into adult learning and education practices.

In the GenAI-ALE framework, both interpersonal and institutional factors have four subfactors. Interpersonal factors involve; GenAI human-centered andragogy, GenAI literacy, GenAI interest, and GenAI virtual learning. Institutional factors involve GenAI curriculum design, GenAI divide, GenAI policy, and GenAI ethics.

In constructing the framework, a systematic literature search was performed on the Web of Science (WoS) database to identify relevant and recent literature on GenAI use in education. Using the search string "Generative AI" OR "GenAI" OR "ChatGPT" OR "Chatbots," an initial 1018 were obtained. The search was limited to only research articles, the year range 2023-2024, and to the research areas "education educational research or computer science." The year range was chosen for the literature search because publications on GenAI peaked during this period. The two research areas were focused on because adult education or learning falls within education educational research and GenAI applications such as ChatGPT also fall within the computer science area. The search did not concentrate on articles specifically related to only adult education due to the scarcity of research articles on GenAI specific to adult education. The 1018 records were downloaded as an Excel file and screened for data extraction. The final records included (n = 14) in the study were color-coded while the remaining 1005 were deleted.

The final records were only highly cited journal articles on GenAI (see Table 3). The criteria for selecting highly cited papers were articles with 100 citations or more. Additionally, two reports from the United Nations Educational, Scientific and Cultural Organization (UNESCO) on GenAI used in transforming education policy and practice were included (see Table 4). A content analysis was performed to extract key themes to form the subfactors in the GenAI-ALE framework. Content analysis is defined as "a research technique for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use" (Krippendorff, 2013, p. 24). In this study, inferences were made from the 14 journal articles from the WoS database and the two reports from UNESCO (UNESCO, 2023a, UNESCO, 2023b) to construct the subfactors of the framework. Inferences were made by extracting textual data from each of the final records and organizing texts with similar meanings into themes. Keywords in each of the subfactors were searched in the abstract and main body of the included studies during data extraction. The extracted excerpts from the studies organized into themes were stored as an MS Word file. Below, the subfactors associated with both interpersonal and institutional factors are discussed.

Interpersonal Factors

GenAI Human-Centered Andragogy

This factor describes adopting teaching methods that prioritize the needs and preferences of adult learners. This includes using GenAI to provide personalized support, feedback, and learning pathways tailored to individual learner profiles. Andragogy simply points to the education of adults in contrast to pedagogy which emphasizes more on the education of children and youth education (Forrest & Peterson, 2006). Human-centered andragogy is a form of educating adults that is learner-centered (Forrest & Peterson, 2006). UNESCO's (2023b)

Table 3. Literature From WoS Used in Constructing the Framework.

No.	Author	Title	Year	Citation count
1	Stokel-Walker and Van Noorden	The promise and peril of generative AI	2023	212
2	Tlili et al.	What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education	2023	196
3	Lim et al.	Generative AI and the future of education: Ragnarok or reformation? A paradoxical perspective from management educators	2023	101
4	Stokel-Walker	CHATGPT listed as author on research papers	2023	255
5	Biswas	ChatGPT and the future of medical writing	2023	193
6	King	A conversation on artificial intelligence, chatbots, and plagiarism in higher education	2023	158
7	Cotton et al.	Chatting and cheating: Ensuring academic integrity in the era of ChatGPT	2024	211
8	Farrokhnia et al.	A SWOT analysis of ChatGPT: Implications for educational practice and research	2023	119
9	Cooper	Examining science education in ChatGPT: An exploratory study of generative artificial intelligence	2023	113
10	Dave et al.	ChatGPT in medicine: An overview of its applications, advantages, limitations, future prospects, and ethical considerations	2023	172
11	Cascella et al.	Evaluating the feasibility of ChatGPT in healthcare: An analysis of multiple clinical and research scenarios	2023	201
12	Dwivedi et al.	So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy	2023	461
13	Lund et al.	ChatGPT and a new academic reality: Artificial intelligence-written research papers and the ethics of the large language models in scholarly publishing	2023	114

(continued)

Table 3. (continued)

No.	Author	Title	Year	Citation count
14	Huh	Are ChatGPT's knowledge and interpretation ability comparable to those of medical students in Korea for taking a parasitology examination?: A descriptive study	2023	124

Table 4. UNESCO Report on GenAI Used for Constructing the Framework.

No.	Author	Title	Year
1	UNESCO	Guidance for generative AI in education and research	2023
2	UNESCO	Generative AI and the future of education	2023

recommendation for incorporating GenAI into education is to adopt a human-centered approach which focuses on the development of human capabilities and agency for effective human-machine collaboration in learning, life, and work. In a human-centered andragogy, more emphasis is laid on the adult learner than the GenAI technology.

GenAI Literacy

This factor touches on enhancing adult learners' understanding and skills using GenAI tools. GenAI literacy "include the ability to understand how LLMs are trained; to appreciate the differences between AI tools designed for specialized tasks as opposed to an all-purpose [function]; and to understand what types of problems current GenAI tools are good at solving" (Bridges et al., 2024, p. 73). With the knowledge that GenAI will revolutionize education, work, and society, there is a need to build AI-literate citizens (Adarkwah, et al., 2023; Chen et al., 2023a; Chiu, 2024; Tlili et al., 2023). For adult learners to be able to successfully use GenAI tools in work and learning, there is a need to create opportunities for learners to build an understanding of GenAI and contemplate their individual relationships with GenAI (Chen et al., 2023). For example, developing impactful prompts is a required skill to fully harness the potential of GenAI (Robertson et al., 2024).

GenAI Interest

This factor refers to cultivating interest and motivation among adult learners to engage with GenAI technologies. It includes demonstrating the practical benefits of GenAI in real-world contexts and creating engaging learning experiences that resonate with learners' intrinsic motivations. The way a learner views AI tools is crucial for sparking interest in using the tool (Albayati, 2024). Chiu (2024) adds that in the workplace setting, young adults are more inclined to use GenAI than their elders. Hence, adult educators have the duty to raise awareness among adults and cultivate their interest in utilizing GenAI tools.

GenAI Virtual Learning

This factor involves facilitating virtual learning environments integrating GenAI tools to provide flexible and accessible educational opportunities. It includes utilizing AI-enhanced platforms for virtual classrooms, discussions, and assessments to support distance and part-time learners. GenAI technologies can facilitate virtual learning practices (Leiker et al., 2023) and make education accessible to all learners resulting in a more equitable and inclusive education. Adult learners, often working professionals or part-time students, are actively involved in distance education (Pozdnyakova & Pozdnyakov, 2017). GenAI tools are currently accessible as add-ons in virtual meeting platforms for educational purposes and can be seamlessly incorporated into learning management systems.

Institutional Factors

GenAI Curriculum Design

This factor refers to developing a curriculum that incorporates GenAI tools, such as ChatGPT, to enhance personalized learning experiences and improve digital literacy. The adoption of GenAI technologies for adult learning practices calls for new instructional approaches such as making changes to curriculum and assessment practices (Tlili et al., 2023). GenAI educational tools should be integrated into curricula policies (Fullan et al., 2023). A GenAI curriculum should be underpinned by fundamental pedagogical theory, ensure teaching approaches align with learning strategies, and emphasize how GenAI can help improve digital/AI literacy. Institutions that aim to embrace GenAI for teaching and learning activities should write an explicit curriculum related to GenAI (Healy, 2023).

GenAI Divide

This factor points to addressing the digital divide by ensuring equitable access to GenAI technologies for all adult learners by overcoming barriers related to learners' socio-economic status or geographic location. The advancement in AI can amplify existing societal inequalities if only a section of individuals or groups can access advanced AI systems (e.g., GenAI technologies) and leverage their capabilities. The digital divide posed by GenAI is expected to widen over time as these services are likely to transition into paid services (Dwivedi et al., 2023). For adult learners, aside from the challenge with access, they might not possess the technical capabilities to use the tool efficiently compared to the younger generation (Chiu, 2024; Hsu & Ching, 2023b). Adult educators will need to build AI talent, strengthen AI competencies and skillsets, and create an AI-enabling environment for learners.

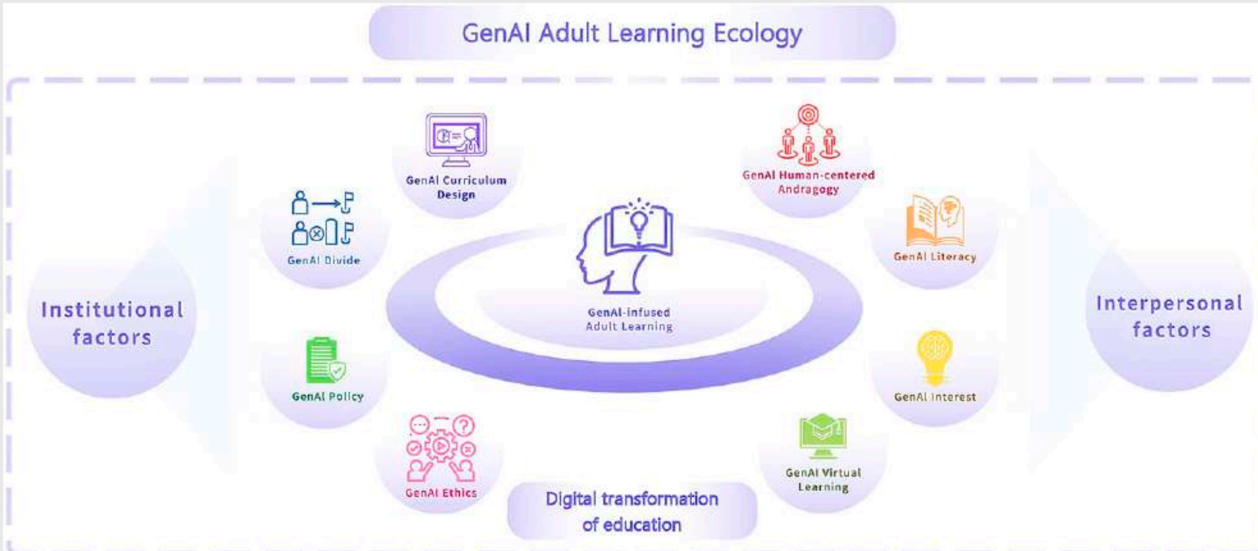
GenAI Policy

This factor involves establishing comprehensive policies and guidelines for the ethical and responsible use of GenAI in education. These policies should cover data privacy, intellectual property, academic integrity, and the regulated/appropriate use of AI-generated content. GenAI policies represent a university's preference for governing emerging technologies and deeper assumptions relating to assessment in higher education (Luo (Jess), 2024). According to UNESCO (2023b), a policy framework for the use of GenAI in education and research includes promoting inclusion, linguistic, and cultural diversity, promoting human agency, monitoring and validating GenAI systems for education, developing the AI competencies of learners, building the capacity of teachers and researchers to make good use of GenAI, etc. Adult educators will need to evaluate and redesign policies and integrate GenAI in a manner that promotes equitable learning experiences both in traditional classrooms and experiential learning settings.

GenAI Ethics

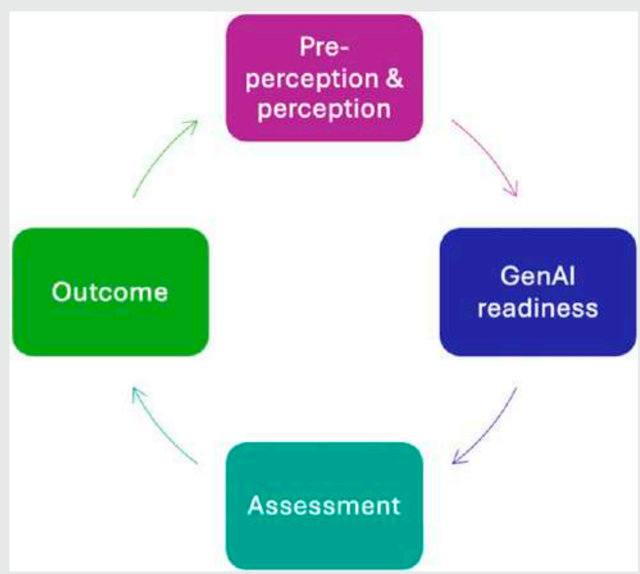
This factor is defined as implementing ethical guidelines to ensure that GenAI technologies are used in ways that promote fairness, accuracy, and transparency. Generative AI should be designed with ethical considerations in mind (Tlili et al., 2023) for it to be a trustworthy tool for researchers, teachers, and learners (UNESCO, 2023b). Human-centric ethics in institutions that increasingly make use of GenAI is important for its appropriate use (Elyoseph et al., 2024). Some of the ethical issues around GenAI revolve around prompts that can generate harmful, biased, and inappropriate content (UNESCO, 2023b), fairness, honesty, and responsibility, fake information, cheating,

Figure 1. The GenAI Adult Learning Ecology (GenAI-ALE) framework.



overreliance (Tlili et al., 2023), etc. When thinking of ethical consideration of implementing GenAI, adult educators should focus on the ethical problems of the end user and the ethical problems in the development of the technology. See As in See Figures 1 and 2.

Figure 2. Systematic steps for the application of the GenAI-ALE framework.



GenAI-ALE and the Andragogical Model

GenAI implementation in adult education and learning practices calls for the need to rethink Malcom Knowles's andragogical model in light of emerging technologies. Andragogy as defined by Knowles simply refers to a set of principles or assumptions designed to facilitate adult learning and program development (Rossman, 2000). Knowles developed an andragogical model based on his principles of andragogy with the model stating that adult educators should guide and not manage instructional content (McGrath, 2009). That is, the principles of andragogy provide a context for integrating a GenAI in adult learning.

The six (6) principles of andragogy and their implication based on the proposed GenAI adult learning ecology (GenAI-ALE) framework (see Table 5). The GenAI-ALE implication was inferred from the explanation of the six principles of andragogy derived from the work of Knowles et al. (2005).

Table 5. Principles of the Andragogical Model and Their GenAI-ALE Implication.

No.	Principle	Explanation (Knowles et al., 2005)	GenAI-ALE implication
1	The learner's need to know	Adults need to know why they need to learn something before undertaking to learn it	Adult educators have to consider conscientizing learners about the importance of GenAI literacy and its role in personalizing learning
2	Self-concept of the learner	Adults have a self-concept of being responsible for their own decisions, for their own lives	Adult educators have to consider GenAI policy and GenAI ethics as crucial factors to foster a sense of responsibility among adult learners in using GenAI technology
3	Prior experience of the learner	Adults come into an educational activity with both a greater volume and a different quality of experience from that of youths. Any group of adults will be more heterogeneous in terms of background, learning style, motivation, needs, interests, and goals than is true of a group of youths	Adult educators have to consider how to help adults forgo their presuppositions to be receptive to new approaches and alternative ways of thinking while at the same time tailoring GenAI to their specific preferences and bridging the GenAI divide between youth and adults to ensure diverse adult population are able to effectively use GenAI.
4	Readiness to learn	Adults become ready to learn those things they need to know and be able to do in order to cope effectively with their real-life situations	Adult educators have to consider GenAI virtual learning practices that promote simulation of real-life situations in experiential learning settings
5	Orientation to learning	Adults are motivated to learn to the extent that they perceive that learning will help them perform tasks or deal with problems that they confront in their life situations	Adult educators have to consider designing a GenAI curriculum to build learner competencies for problem-solving in the real world
6	Motivation to learn	Adults are responsive to some external motivators (better jobs, promotions, higher salaries, and the like), but the most potent motivators are internal pressures (the desire for increased job satisfaction, self-esteem, quality of life, and the like)	Adult educators need to build the GenAI interest of learners targeting their innate desires to use the technology for learning and work

Application of the GenAI-ALE Framework

While the GenAI-ALE framework provides promising solutions in revolutionizing adult higher education, its effective adoption follows four (4) systematic steps that need frequent iteration and contextualization. The steps are gleaned from the works of Gupta and Yang (2024) and Basgen et al. (2024) on GenAI implementation applicable in higher education. Gupta and Yang (2024) present a GenAI technology adoption model aimed at elucidating the complex process that entrepreneurs and other innovation ecosystem actors such as libraries, go through for its adoption. According to the researchers, there are three stages in the adoption process involving pre-perception & perception (awareness of GenAI technologies), assessment (evaluating the performance of GenAI for educational operations), and outcome (assessing the overall effect of GenAI adoption). As a vital step, GenAI readiness or preparedness emphasized in the work by EDUCASE (Basgen et al., 2024) is placed between the perception & perception and assessment phases in the work by Gupta and Yang (2024).

Conclusion, Implications, and Limitations

The integration of GenAI technologies in adult education represents a significant shift in the educational landscape. This study highlights the need for a structured approach to leverage GenAI effectively in adult learning environments. The conceptual framework of *GenAI adult learning ecology* (GenAI-ALE) outlines key institutional and interpersonal factors for consideration when integrating GenAI into adult education and learning practices. Malcom Knowles's andragogical model serves as a foundational theory for adopting GenAI technologies in adult learning. The andragogical model advocates for instructional technologists and educators to tailor GenAI tools to adult learning strategies.

Moreover, although the review of literature highlights that although GenAI has a transformative potential for adult education and learning practices, it poses potential threats. As a practical implication, adult educators must be aware of the dangers posed by GenAI and install mitigation structures to counteract the negative effects and challenges of using the technology. Institutions should develop comprehensive policies to guide the ethical use of GenAI in adult education.

Despite the burgeoning literature on GenAI's impact on education recently, there are still fewer studies focusing on adult education and learning. As a theoretical implication, the study calls for further investigations into implementing GenAI in adult higher education such as implementing and contextualizing the GenAI-ALE framework in different educational settings. Using the framework as a springboard, future research should investigate the impact of specific GenAI tools on adult learning outcomes, including cognitive skills, critical thinking, and creativity.

A limitation of the study is that it primarily discusses theoretical aspects of applying the GenAI-ALE framework in adult higher education. To compensate for this, a GenAI adoption model on how to systematically implement the GenAI-ALE in adult higher education is presented. Future researchers can strengthen the findings of the current study by including empirical evidence or pilot studies that apply the GenAI-ALE framework in actual adult learning settings.

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Preparing future educators for AI-enhanced classrooms: Insights into AI literacy and integration

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ABSTRACT

The rapid transformation of educational practice by artificial intelligence (AI) requires that teacher-education programmes prepare pre-service teachers to integrate AI into their teaching. This qualitative study explores pre-service teachers' perceptions of AI integration in education and identifies the support they need to develop AI literacy. We conducted semi-structured interviews with 15 pre-service teachers and used thematic analysis to interpret the data. Our findings revealed that these future educators recognised AI's potential to enhance personalised learning and increase classroom efficiency but worried about relying on AI too much and losing the human element in teaching. The participants also highlighted significant challenges in developing AI literacy, including insufficient training and a lack of institutional support in their programmes. The need to maintain data privacy and protect against algorithmic bias emerged as critical areas of concern. This study underscored the urgent need for comprehensive AI literacy curricula in teacher education that encompass both technical skills and ethical understanding. We recommend that educational institutions provide practical AI experiences, establish clear ethical guidelines and offer continuous professional development opportunities. By addressing these needs, teacher-education programmes can prepare future educators to leverage AI technologies to enhance educational outcomes.

1. Introduction

The growing reliance on artificial intelligence (AI) has significantly influenced the field of education, reshaping teaching, learning and assessment practices. It is increasingly important that educators understand how AI can support teaching and learning (Crompton et al., 2022; Zawacki-Richter et al., 2019). Generative AI (GenAI) tools such as ChatGPT, DALL-E, Gemini, and others offer new opportunities to personalise learning, enhance student engagement and improve classroom efficiency (Chiu, 2023; Kohnke, Moorhouse, & Zou, 2023a). As these technologies are integrated into the classroom and pedagogical practice, educators must become AI literate: that is, able to understand AI tools and incorporate them into their pedagogy to prepare students for a future in which AI plays a central role (Cervera & Caena, 2022; Holmes & Tuomi, 2022).

Given the critical need for AI literacy among educators, it is essential to examine how teacher preparation programmes equip future teachers not only with technological skills but also with the capacity for self-directed learning (SDL). Teacher-education programmes, particularly those offering initial teacher education (ITE), play a crucial role in preparing pre-service teachers to navigate this evolving landscape. However, these programmes have often struggled to keep pace with rapid technological advancements (Park & Son, 2022; Starkey, 2020). The gap between AI's potential in education and how pre-service teachers are trained to use it suggests an urgent need for more comprehensive AI-focused training (Moorhouse & Kohnke, 2024; Moorhouse et al., 2024). Pre-service teachers are tomorrow's educators and will play a pivotal role in determining AI's classroom applications.

To address this gap, SDL is essential for empowering pre-service teachers to acquire the knowledge and skills needed to integrate AI into education effectively. SDL fosters adaptability, problem-solving and independent exploration – qualities that are essential when working with rapidly evolving technologies like AI (Knowles, 1975; Wang et al., 2024). These capabilities empower pre-service teachers to stay current

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with technological advancements and use AI tools to enhance teaching and learning in dynamic educational environments (Moorhouse et al., 2024). By cultivating SDL, pre-service teachers can take the initiative in their learning, equipping themselves to meet the evolving demands of AI-enhanced classrooms (Ayanwale et al., 2024; Ng et al., 2023).

Many studies have explored AI applications in education (e.g. Martin et al., 2024; Zhang & Aslan, 2021). However, few have focused on how future educators perceive and prepare to implement AI in practice. Understanding pre-service teachers' experiences with AI, including their SDL strategies, is crucial for identifying gaps in teacher-education programmes and ensuring that future teachers are prepared to navigate the complexities of AI integration. The attitudes, knowledge and preparedness of pre-service teachers will directly influence how students experience AI-enhanced learning environments. Therefore, teacher-education programmes are vital in fostering AI literacy among pre-service teachers (Chiu & Sanusi, 2024; Ding et al., 2024). These programmes must provide the training, resources and support to enable future teachers to integrate AI into their pedagogy (e.g. Crompton & Burke, 2023; Moorhouse et al., 2024). AI-literate educators not only understand the technical aspects of AI but also recognise its ethical implications and limitations in an educational setting (Hockly, 2023; Sperling et al., 2024).

This qualitative study explores and analyses pre-service teachers' perceptions of the integration of AI into education. Examining their experiences, challenges and anticipated practices contributes to the knowledge of AI in education and offers insights into how teacher-education programmes can better prepare future educators for AI-enhanced classrooms. Additionally, it highlights the importance of developing SDL skills to ensure that pre-service teachers can adapt to the evolving demands of AI integration. Accordingly, this study investigates the following research questions:

RQ 1. How do pre-service teachers perceive the potential and challenges of integrating AI into their teaching practices?

RQ2. What strategies and institutional support do pre-service teachers require to develop AI literacy and integrate AI into their future classrooms?

2. Literature review

This literature review explores five key areas related to the integration of AI in teacher education. First, the concept of AI literacy is discussed, highlighting its growing importance and the challenges faced by pre-service teachers in developing AI-related skills. Second, the role of SDL in supporting pre-service teachers' professional development and AI integration is examined. Third, the review addresses the need for effective teacher preparation for AI-enhanced classrooms. Fourth, it considers the evolving role of AI in supporting and complementing teachers' practices. Finally, the review examines the role of teachers in AI-enhanced classrooms, focusing on how they can foster equitable and inclusive learning environments. Together, these sections establish the context for this study and identify gaps in the existing literature. In this paper, AI literacy is used as an inclusive term that encompasses both traditional AI and its evolvement into Generative AI (GenAI), reflecting the continuous advancements in AI technologies and their applications in education.

2.1. AI literacy

AI literacy is 'a set of competencies that enables individuals to evaluate AI technologies critically; communicate and collaborate effectively with AI; and use AI as a tool online, at home and in the workplace' (Long & Magerko, 2020, April, p. 598). Although AI is becoming increasingly important in education, efforts to integrate AI literacy into teacher-education programmes remain limited (Ng et al., 2023). Sperling et al. (2024) noted that teacher-preparation curricula often overlook AI literacy. Pre-service teachers face various challenges in becoming knowledgeable about AI, including misunderstandings, misleading information, platform limitations and ethical concerns (Akgun and Greenhow, 2022). These challenges highlight the need for comprehensive AI literacy training that prepares future educators to responsibly navigate emerging technologies. Limited research examines how teacher-education programmes support pre-service teachers in overcoming challenges related to AI literacy or how their AI literacy influences the creation of equitable and effective AI-enhanced learning environments. As Ayanwale and colleagues (2024) emphasised, AI literacy is more than just a technical issue; it also encompasses competence in AI usage, detection, ethics, and problem-solving.

Teacher education equips instructors to influence student achievement and foster broader societal and economic improvements (Miao & Shiohira, 2024). Enhancing AI literacy in pre-service teacher training will enable future educators and their students to thrive in an AI-driven landscape.

Despite its growing importance, AI literacy has been slow to gain traction in initial teacher education. Before the launch of ChatGPT, there were few references to AI in the teacher-education literature. Even within the broader context of ITE, there is a lack of research investigating how pre-service teachers and their educators engage with, experience or view AI (Celik et al., 2022). The limitations of early rule-based AI systems may have led to a lack of interest from ITE researchers. Understanding how teacher-education programmes can effectively integrate AI literacy into their curricula and prepare pre-service teachers for the challenges of using AI in educational contexts remains under-explored. Moreover, while the importance of AI literacy is widely acknowledged, empirical research on how pre-service teachers perceive, develop, and apply AI literacy skills in practice is still limited. Contributing to this research gap, ITE has been slow to adapt its curricula and instruction to advancements in digital technology (Park & Son, 2022).

GenAI is increasingly influencing all aspects of education, making AI literacy essential for pre-service teachers. Teacher-education programmes must prepare pre-service teachers with the skills and knowledge to engage with AI in their professional practice (Moorhouse & Kohnke, 2024). The successful adoption of new tools depends significantly on teachers' understanding of pedagogically sound strategies and their ability to incorporate various technologies into their lessons (Ding et al., 2024). AI requires more than technical knowledge – pre-service teachers must understand how to use AI to enhance teaching and support student learning (Celik, 2023; Moorhouse & Kohnke, 2024). However, many prospective educators are unprepared to work with AI-driven educational applications, lacking the technological skills necessary to analyse data or automate student assignments and feedback (Seo et al., 2021). As teachers who create AI-enhanced learning environments can improve educational outcomes (Almasri, 2024), developing AI literacy grounded in effective pedagogical strategies is essential for training pre-service teachers to become effective educators (Moorhouse & Kohnke, 2024).

2.2. Self-directed learning and AI

SDL is critical in fostering autonomy, particularly in language learners. Self-directed learners take the initiative to diagnose their learning needs, set learning goals, identify resources and evaluate their progress (Garrison, 1997; Knowles, 1975). For pre-service teachers, these skills are essential as they must independently learn and adapt to rapidly evolving educational technologies, including GenAI tools. SDL equips pre-service teachers to navigate the complexities of integrating AI into their teaching practises and prepares them to foster autonomy in their future students (Guan et al., 2024).

AI tools have been shown to support language learners' SDL by providing personalised feedback, adaptive learning experiences and real-time data that allow learners to engage in independent study at their own pace (Zawacki-Richter et al., 2019). For instance, AI-powered language apps (e.g. Duolingo) can tailor exercises to individual learner needs, encouraging autonomy and reducing reliance on traditional teacher-led instruction (Zawacki-Richter et al., 2019). These examples highlight AI's capacity to support SDL, which is also relevant to pre-service teachers as they explore how to implement similar tools in their professional development and teaching (Ding et al., 2024).

However, AI's potential extends beyond language education. GenAI tools enable teachers to create lesson plans, customise materials based on students' proficiency levels, deliver personalised feedback and design individualised learning pathways (Chiu, 2023; Kohnke et al., 2023a; Kohnke & Zou, 2025). Moreover, AI tools can act as tutors, collaborators and experts (Hwang & Chen, 2023), enhancing SDL opportunities. By leveraging these AI capabilities, pre-service teachers can develop their pedagogical skills, build confidence in using AI for educational purposes and prepare to create autonomous learning environments for their students (Ayanwale et al., 2024; Moorhouse et al., 2024).

SDL is essential for the professional development of pre-service teachers and their readiness for the classroom. Research has suggested that AI can significantly enhance self-directed professional development by providing pre-service teachers with tools to reflect on their practices, explore new teaching methodologies and independently seek resources tailored to their specific needs (Molefi et al., 2024; Ng et al., 2023). AI systems such as intelligent tutoring platforms and lesson-planning tools can offer pre-service teachers personalised feedback and insights to refine their instructional strategies and classroom management skills (Ding et al., 2024). These tools allow pre-service teachers to engage in self-directed exploration of GenAI, enabling them to adopt innovative teaching practices and adapt to new challenges in AI-enhanced classrooms (Chiu & Sanusi, 2024; Farjon et al., 2019).

Furthermore, AI supports pre-service teachers in developing self-regulatory strategies, which are essential to their current training and future roles as educators. SDL not only helps pre-service teachers master AI tools but also equips them with critical skills for life-long learning and professional growth, such as goal-setting, self-monitoring, and time management. These self-regulatory strategies also enable pre-service teachers to model and cultivate autonomy in their students, aligning with broader trends in education that emphasise the importance of self-regulated learning (Kramarski & Michalsky, 2010).

Despite these benefits, there is limited research on how pre-service teachers utilise SDL to explore AI professional development tools. Additionally, there is little understanding of the institutional support and resources required to facilitate SDL for the integration of AI into teaching practices. By engaging in SDL through AI, pre-service teachers can strengthen their pedagogical skills and prepare to create autonomous learning environments for their students. This dual focus – on pre-service teachers' professional growth and their ability to foster SDL in students – underscores the importance of preparing pre-service teachers to use AI effectively (Moorhouse & Kohnke, 2024). This outcome aligns with broader educational trends emphasising the cultivation of self-regulation in learners in increasingly digital and AI-enhanced classrooms (Benson, 2011; Zawacki-Richter et al., 2019).

2.3. Teacher preparation for AI integration

As AI literacy becomes more essential, preparing pre-service teachers for AI integration requires a significant shift in training. Given the growing prevalence of GenAI tools like ChatGPT and AI-driven learning systems, teacher-education programmes must move beyond traditional digital tools like Kahoot! and Mentimeter (Kohnke & Moorhouse, 2022; Moorhouse & Kohnke, 2020). These programmes must prepare future teachers to effectively use AI, understand digital pedagogy and navigate the ethical issues associated with AI use in the classroom (Sperling, 2024).

Pre-service teachers not only need to know how to use these AI tools, they must critically assess how these technologies impact teaching and learning (Farjon et al., 2019). For instance, they should be trained to incorporate AI tools into their lessons to enhance student engagement, support personalised learning and streamline grading and class management. Additionally, pre-service teachers must be cognisant of ethical challenges such as data privacy risks, potential biases in AI algorithms and how AI might affect student assessments (Nguyen et al., 2023). Unfortunately, research indicates that many teacher-preparation programmes fail to provide adequate AI skill development opportunities (Park & Son, 2022), leaving pre-service teachers unprepared to confidently navigate AI-enhanced classrooms (Moorhouse, 2024).

It remains to be seen how GenAI will impact education, and what skills and knowledge pre-service teachers will require for digital proficiency. These needs will evolve as technology advances and its effects on human behaviour, actions and beliefs become more apparent (Starkey, 2020). As technology continues to advance, teacher-education programmes must evolve accordingly to meet the evolving demands of AI integration. This involves providing hands-on experience along with clear guidelines on using AI tools, including key issues such as ethical use, safeguarding student data and AI's role in evaluating student performance. Pre-service teachers lacking this preparation may engage in inconsistent practices and achieve poor student outcomes.

2.4. The role of AIin supporting and complementing teachers

As AI is integrated into education, the role of the teacher is changing. To be effective in modern classrooms, pre-service teachers must gain a solid understanding of AI while also developing their foundational teaching skills. Many pre-service teachers struggle with interpreting learning analytics, understanding how AI can enhance their teaching and grasping the pedagogical implications of integrating AI into their practice (Salas-Pilco et al., 2022). This lack of familiarity often leads to hesitation in adopting AI as a resource (Backfisch et al., 2021).

However, the rapid development of GenAI tools has expanded their usability for teachers, from automating routine tasks to providing personalised learning experiences. AI can be particularly beneficial for new teachers still honing their teaching skills by alleviating the burden of grading and administrative duties (Holstein & Aleven, 2022). By automating these tasks, AI can allow pre-service teachers to focus on developing and delivering meaningful, student-centred instruction. AI can also provide data-driven insights, helping new teachers make informed decisions that improve student learning outcomes (Cheng & Wang, 2023).

Although AI's benefits are clear, more research is needed to explore how it can complement the practices of current and future educators (Alfoudari et al., 2021). One promising approach is the concept of human–AI complementarity, which suggests that AI should support teachers rather than replace them (Holstein & Aleven, 2022). This concept is especially relevant for pre-service teachers, who must learn to balance their instructional strengths with AI capabilities. AI integration with human teaching can maximise learning potential (Cukurova et al., 2019). For example, AI has been shown to streamline routine feedback on lower-level writing tasks in English as a foreign language instruction, freeing teachers to focus on complex aspects such as organisation and revision (Gayed et al., 2022). This provides crucial support for pre-service teachers, who may need extra help managing their time and balancing the demands of classroom instruction.

2.5. The role of teachers in AI-enhanced classrooms

AI tools open new possibilities for personalising learning experiences, transforming traditional teaching methods to help students achieve better outcomes (Seo et al., 2024). Recent advancements in GenAI models like ChatGPT help teachers boost their classroom efficiency and effectiveness (Liu et al., 2023). AI tools such as MagicSchool.ai and Alayna.us assist teachers with lesson planning (e.g. designing lesson plans and assignments, generating materials, etc.). Other tools, such as MagicSchool.ai student version help students take charge of their learning and build problem-solving, collaboration and digital literacy skills (Miao & Shiohira, 2024). Teachers play a crucial role in fostering such abilities by developing these skills and designing activities that encourage students to engage with AI meaningfully (Seo et al., 2024). To achieve this, they must feel confident and competent using AI in their classrooms.

Developing AI literacy during teacher training is crucial, as educators will be expected to integrate these technologies into everyday teaching practices (Ding et al., 2024; Sperling, 2024). Pre-service teachers lacking a solid foundation in AI literacy will have a limited ability to foster the digital skills their students need in a technology-driven world (Moorhouse, 2024). Furthermore, teachers with poor AI literacy may inadvertently reinforce inequalities in digital literacy access by failing to recognise that students from less advantaged backgrounds may lack exposure to AI outside the classroom (Karan & Angadi, 2024). Thus, ensuring that pre-service teachers receive adequate preparation to integrate AI into their future teaching practices is essential. Such educators can foster an equitable and inclusive learning environment and prepare today's students for tomorrow's workforce demands (Ng et al., 2021). Prioritising AI literacy turns future classrooms into spaces where technology enhances learning for all students rather than exacerbating existing disparities.

3. Methodology

This section outlines the research design, participants, data collection, and data analysis methods employed to explore pre-service teachers' perceptions of AI integration in teaching and their development of AI literacy. Grounded in a phenomenological approach (Creswell, 2013), this study captures the richness and complexity of participants' lived experiences, providing a robust framework for examining how emerging technologies intersect with teacher education.

3.1. Research design

In this qualitative study, we aimed to explore pre-service teachers' perceptions of integrating AI into their teaching practices and developing AI literacy. We adopted a phenomenological approach to capture the lived experiences and subjective meanings that participants ascribed to AI integration in education (Creswell, 2013). This design allowed us to delve deeply into participants' perspectives and understand the complexities surrounding AI literacy in teacher education.

3.2. Participants

We recruited 15 pre-service teachers for this study. Using stratified sampling, we selected participants from different programmes at a single university to ensure a variety of experiences with AI in educational contexts and the inclusion of individuals at various stages in their training. All participants were enrolled in a teacher-education programme at an English-medium university in Hong Kong but were pursuing diverse subject specialisations (e.g. Chinese language, mathematics, science, English language arts, and early childhood education). This provided a range of perspectives on AI integration (Table 1).

Table 1
Participant demographics.

No.	Gender	Age	Programme
1	Female	21	Bachelor of Education (Chinese Language)
2	Female	20	Bachelor of Education (General Studies)
3	Female	21	Bachelor of Science (Maths)
4	Female	26	BEd (English Language)
5	Female	21	Bachelor of Arts (English Primary Education)
6	Female	22	Bachelor of Education (English Language)
7	Female	22	Bachelor of Education (Chinese Language)
8	Female	22	Bachelor of Education (English Language)
9	Female	21	Bachelor of Education (Chinese Language)
10	Female	21	Bachelor of Science (Maths)
11	Choose not to identify	22	Bachelor of Education (English Language)
12	Male	23	Bachelor of Education (English Language)
13	Male	23	Bachelor of Science (Maths)
14	Female	22	Double Degree Bachelor of Education (English Language & English Education)
15	Female	24	Bachelor of Arts (Early Childhood Education)

3.3. Data collection

We collected data through individual semi-structured interviews conducted in the summer of 2024. Semi-structured interviews align with the phenomenological approach adopted in this study as they allow participants to articulate their lived experiences and subjective interpretation of AI integration into education in a flexible yet focused manner (Creswell, 2013). This format provides a balance between structure and openness, enabling researchers to explore predefined topics while following up on participants' unique insights and perspectives (Kvale & Brinkmann, 2009). Grounded in phenomenological philosophy, this approach emphasises understanding individuals' lived experiences and the meaning they ascribe to those experiences (van Manen, 1990). By using open-ended questions and allowing for in-depth probing, semi-structured interviews facilitate the collection of rich, descriptive data on participants' perceptions and experiences.

To structure the interviews, we developed an interview guide based on our research questions and the literature on AI in education (Appendix). Key topics included participants' perceptions of AI's potential and challenges, their experiences with AI tools, strategies for developing AI literacy and anticipated practices in their future classrooms. This ensured we covered essential areas while allowing flexibility to explore participant' unique perspectives.

Each interview lasted approximately 30–50 min and was conducted in person. With the participants' consent, we audio-recorded the interviews and transcribed them verbatim to ensure accuracy in our data analysis. We provided participants with copies of their transcripts for initial member checks (Merriam & Tisdell, 2016), permitting them to confirm or clarify their responses.

We obtained ethical approval for the study from the university's Institutional Review Board. We assured participants that we would maintain confidentiality and anonymity; pseudonyms were used when reporting the findings to protect their identities. Participation was voluntary, and we informed participants that they could withdraw from the study at any time without penalty.

3.4. Data analysis

We followed the thematic analysis procedure outlined by Braun and Clarke (2006). This method allowed us to identify, analyse and report patterns (themes) within qualitative data, providing a rich and detailed account of participants' experiences. We began our analysis by immersing ourselves in the interview transcripts, noting initial reflections. Each researcher independently generated initial codes and manually labelled relevant segments. This independent process ensured diverse perspectives were considered. Using Google Docs, we compared and refined codes through collaborative discussions, reconciling differences and merging similar codes to form a comprehensive list.

Next, we grouped similar codes and developed thematic maps to visualise relationships between themes and subthemes, identifying overarching patterns and refining our understanding. We finalised the themes through iterative review and discussion, ensuring consistency across the data. Finally, we selected representative extracts and organised the themes to address our research questions, using participant quotes to support key findings.

Throughout the analysis, we used an inductive approach, allowing themes to emerge from the data rather than imposing existing theories or assumptions. This approach was appropriate for our exploratory study as we aimed to understand how the participants interpreted their experiences (Patton, 2015). To ensure transparency and trustworthiness, we conducted a second member check (Merriam & Tisdell, 2016). We sent each participant a summary of the themes, subthemes and representative quotes. None of the participants requested additions or offered further suggestions.

4. Findings

The analysis of the interviews with the pre-service teachers revealed three interconnected themes that collectively illustrated the complex landscape of AI integration: 1) AI applications in teaching and learning, 2) challenges and support in AI literacy development and 3) preparation for the AI-enhanced classroom. The findings are presented thematically to reflect the interconnected and overlapping nature of the themes identified in this qualitative study. While the themes collectively address the two research questions (RQ1 and RQ2), they are not strictly organized by RQ because they often address multiple aspects of pre-service teachers' perceptions and needs. This thematic structure allows us to capture the complexity and interrelatedness of their experiences with the integration of AI into teaching. These themes provide insights into pre-service teachers' perceptions of the place of AI in education and how they are preparing to integrate AI into their future careers.

4.1. Applications of AI in teaching and learning

The participants recognised the potential of AI to enhance student engagement and provide personalised learning experiences. Teacher 6 highlighted the benefits of AI-powered platforms such as Google Classroom, which can provide 'individual guidance' to compensate for 'insufficient learning experiences outside the classroom.' Teacher 3 emphasised the potential of AI to make learning more interesting: 'It can increase student engagement because traditional teaching and learning can be boring … I think knowing AI can help promote a better learning environment.' Teacher 4 made similar points: 'It would significantly increase efficiency, add some liveliness and make the classroom more interesting.' Teacher 7 emphasised the potential of AI to support self-directed learning: 'For students, it might be the ability to explore independently or the self-learning skills that schools currently emphasise. If students can use AI positively and engage in self-directed learning, I think it would benefit them' This suggests that AI can enhance both learning effectiveness and the learning atmosphere.

These future educators' understanding of AI provides a foundation to explore the practices they anticipate adopting in their professional lives. While they may have limited experience, they demonstrate progressive thinking about the role of AI in education.

4.1.1. Anticipated practices in AI integration

The participants described various ways of integrating AI into teaching practices, from lesson planning to assessment. Teacher 11 envisioned using AI for brainstorming pedagogical methods: 'Sometimes when I can't come up with how to write a teaching plan, I can ask the AI tool to give me some inspiration … I can ask ChatGPT to provide some details or ideas … it gives me a direction to try.'

Teacher 12 discussed leveraging AI for interdisciplinary lesson design: 'I wanted to design a lesson that involved interdisciplinary topics … I asked ChatGPT to help me come up with some math-related questions and activities.' Teacher 4 used AI tools to plan activities: 'I ask it to recommend some in-class activities, such as grammar or listening exercises.' Teacher 2 highlighted the ability to generate examples of knowledge constructs: 'Many times, we need to explain a concept in detail, and ChatGPT can help me provide examples my students can relate to.'

Some participants, including Teacher 11, used AI to create visual aids: 'When I teach poetry … I can generate an image to help students better visualise a scene.' This approach underscores the potential of AI to enhance student engagement through multimodal learning experiences. Teacher 1 used AI for improving teaching activity designs: 'Sometimes, when I feel my activities are not good enough, I ask ChatGPT for suggestions and compare them with my ideas … I see it as a reference for comparison, and if ChatGPT's version is better, I will use it.'

These responses reveal a nuanced understanding of AI's capabilities and limitations in the context of lesson planning. They illustrate that pre-service teachers conceptualise AI as a personalised teaching assistant. However, their reliance on AI for lesson planning raises significant questions about the development of pedagogical creativity and the possibility that teaching practices could become homogenised across different contexts.

Teacher 12 highlighted the use of AI-enhanced platforms for formative assessment: 'Our teacher uses Google platforms to assign homework to students. Students can complete the assignment online and review the results, and you can clearly see who answered correctly and who didn't. It's saving time.' However, Teacher 10 observed, 'Electronic platforms can help with grading assignment, but only if it's multiple-choice questions … I don't think they can be effective with long questions.' This suggests that while AI is useful, it cannot replace human judgment in more complex evaluation tasks.

4.2. Challenges and support

4.2.1. Barriers to developing AI literacy

Interviewees identified several barriers in their teacher education programmes to developing AI literacy. For example, Teacher 7 noted, 'There is still some resistance among our teachers to using ChatGPT for our lesson plans or group assignments.' This resistance might stem from concerns about academic integrity or the appropriate use of AI in education. However, it may hinder pre-service teachers' opportunities to develop AI literacy. Teacher 10 acknowledged that pre-service teachers' knowledge of AI was incomplete: 'Whenever I think of AI, I only think about ChatGPT and DeepL, but there are many other software options. So my skills are limited.' This reflection reveals a gap in the AI literacy of pre-service teachers. The fact that they are chiefly familiar with popular applications suggests that teacher education programmes should expose them to a broader range of tools. This requires technological infrastructure as well as changes in teacher education curricula. The need for additional preparation was highlighted by Teacher 1: 'Teachers need a basic understanding of AI before they can use it effectively. It would also be a challenge for teachers to incorporate AI into their curriculum design gradually.'

Teacher 5 pointed out some practical challenges in transferring knowledge to the classroom: 'Using Kahoot during our school classes goes smoothly, but once it's implemented in the classroom, the students can't find the buttons or understand how to scan the QR code.' This further highlights the need to prepare students to use AI-enhanced learning tools.

4.2.2. Strategies for developing AI literacy

The participants also noted the importance of developing AI literacy and establishing clear guidelines for AI use in their future classrooms. Teacher 14 articulated this need: 'Schools and teachers must first define and set limits on the use of AI in education. How much AI influence can be tolerated in students' work? What level of AI usage is allowed or strictly prohibited?' This sentiment was echoed by Teacher 9, who expressed concern about unclear policies: 'Maybe I'm a little concerned about the regulations that schools have regarding AI usage … It can be confusing.' This highlights the need for clear institutional guidelines to support effective and ethical AI literacy in teacher education programmes.

The participants reported varying levels of institutional assistance for the development of AI literacy. Teacher 8 reported taking 'a course that provides a brief introduction to AI, and the teacher mentioned what we can do with ChatGPT'. Teacher 13 also recalled institutional efforts: 'It seems like the school helped us activate the ChatGPT account, but I can't remember whether version 3.5 or 4.0 was used. I tried using it, and I think it's good. I think the school is very generous.'

Although some institutions were taking proactive steps to provide AI resources to pre-service teachers, other participants, such as Teacher 2, were unaware of any: 'No. I haven't seen any support for it. Maybe there is support, and I don't know.' Many interviewees desired more comprehensive training and resources to develop their AI literacy. Teacher 3 suggested that 'it would be beneficial to organise workshops that guide us, as university students and future teachers, on how to approach AI correctly.' Teacher 14 outlined a possible approach: 'First, I would attend AI workshops or courses to understand AI skills comprehensively. Then, I would select practical AI applications for students and organise relevant courses based on their abilities and receptiveness.'

Teacher 13 believed that training about AI would not end with graduation: 'Once we become teachers, the school will also push us to attend these lectures and develop AI skills. In this process, we are constantly learning about AI, and as teachers, we need to keep up with the pace.' This perspective highlights the importance of continuous professional development relating to AI for educators. The challenges and needs identified by the participants provide crucial context for understanding how they envision their future careers.

4.3. *Preparing for the AI-enhanced classroom*

4.3.1. *Evolving teacher competencies for AI integration*

Throughout the interviews, the pre-service teachers emphasised the importance of developing AI knowledge and skills to prepare for their careers. Teacher 2 suggested that AI proficiency has become a key indicator of teacher quality: 'I believe that teachers' use of AI determines their level. Unlike in the past, where having a vast amount of knowledge was enough to become a teacher, now we need to incorporate AI as a supplement in the classroom.' Teacher 7 noted that strong AI skills can help an educator stand out from the crowd: 'If you have skills in this area, you have an advantage. Currently, most teachers still don't know how to use AI, or maybe they use it to some extent, but not at a professional level.' Teacher 5 elaborated: 'For younger student teachers like us, the school emphasises the importance of AI learning, and teachers need to learn AI technology to teach students.' This reiterates the idea that AI literacy could become a defining trait of future teachers.

4.3.2. *Fostering AI literacy in students*

The participants emphasised their future role in preparing students for a world in which AI is increasingly prevalent. Teacher 6 noted, 'I think this is very important because I feel students will need AI skills in the future … They must start learning and getting exposed to the knowledge of AI early.' Teacher 14 highlighted the importance of teaching the appropriate use of AI: 'Teachers should learn to guide children in using AI as an aid to learning, rather than replacing their brains.' This suggests the nuanced view that students should be taught to develop critical Gen-AI literacy to maintain ownership of knowledge while engaging in AI-enhanced learning (Ou et al., forthcoming).

A statement by Teacher 8, 'If a teacher has no understanding of AI, then their students miss out on the opportunity to learn about it', shows a recognition of teachers as gatekeepers of AI literacy for their students. Teacher 6 agreed that educators need to develop AI literacy to prepare their students for the future: 'As they grow up, AI will also continue to develop, and I believe it will become increasingly important.' Teacher 9 echoed this sentiment: 'Yes, it is important because AI will increasingly appear in our lives. So, a teacher should learn how to use it in their field or understand what it is.' This perspective highlights the idea that AI can support the development of crucial 21st-century skills, with teachers facilitating the process.

5. Discussion

This study addressed two key research questions: (1) How do pre-service teachers perceive the potential and challenges of integrating AI into their teaching practices? and (2) What strategies and institutional support do pre-service teachers need to develop AI literacy and integrate AI into their future classrooms? The findings reveal not only opportunities but also significant challenges in preparing pre-service teachers for AI-driven educational contexts. This discussion critically examines these findings through four interconnected areas: AI as a tool for personalised learning and efficiency, the challenges of developing AI literacy, the role of institutional support and professional development, and the need to balance AI integration with pedagogical objectives. These insights contribute to the broader conversation on teacher preparation in the age of AI and have implications for curriculum design, professional development and policy reform in teacher education.

5.1. *AI as a tool for personalised learning and efficiency*

The pre-service teachers in Hong Kong see significant potential in AI to enhance personalised learning and classroom efficiency. AI-powered platforms, such as adaptive learning systems and GenAI tools, offer tailored feedback, support differentiated instruction and enable self-learning (Chiu, 2023; Kohnke et al., 2023a). These tools can create more student-centred learning environments by allowing students to engage with content at their own pace in ways suited to their individual needs (Zawacki-Richter et al., 2019). However, the participants expressed concern about relying too heavily on AI for routine tasks, such as lesson planning and assessment. While AI can automate certain aspects of classroom management, it may limit opportunities for pedagogical creativity and critical reflection, particularly for early career teachers (Moorhouse & Kohnke, 2024). These concerns reflect broader worries, reflected in the literature, about the uncritical adoption of AI in education. AI should complement the relational and human elements of teaching rather than replace them (Holstein & Aleven, 2022); it should support student–teacher interactions rather than undermine them (Cervera & Caena, 2022).

5.2. *Challenges in developing AI literacy*

The second research question highlights the challenges pre-service teachers face in developing the AI literacy needed to integrate AI tools into their pedagogy. The findings suggest that pre-service teachers may be familiar with basic tools such as ChatGPT but often lack a deeper understanding of AI's more advanced functionalities and ethical implications (Seo et al., 2021). This aligns with the literature, which points to gaps in teacher-education programmes regarding the comprehensive training needed for AI literacy (Park & Son, 2022; Starkey, 2020).

This lack of preparedness is compounded by the fact that AI literacy is not simply about mastering technical skills. Pre-service teachers must be aware of AI's limitations and biases, as well as ethical considerations including data privacy and algorithmic fairness (Akgun and Greenhow, 2022; Holmes & Tuomi, 2022). Without a solid foundation in these areas, pre-service teachers may struggle to use AI in ways that align with pedagogical best practices and ethical standards. This finding underscores the urgent need for teacher-education programmes to integrate structured AI training into their curricula to provide pre-service teachers with theoretical knowledge and practical experience (Ng et al., 2023).

5.3. *The role of institutional support and professional development*

Institutional support plays a critical role in fostering AI literacy among pre-service teachers. Although some teacher-education programmes have begun introducing AI into their curricula, many pre-service teachers in our study reported insufficient training and support. This finding confirms previous findings that teacher-education programmes have been slow to adapt to AI-driven technological shifts (Sperling et al., 2024; Starkey, 2020).

In addition to initial training, continuous professional development is vital to refine AI competencies and stay current with emerging tools and best practices (Moorhouse et al., 2024). The literature emphasises that AI literacy is an evolving competency that requires life-long and self-directed learning as part of teachers' professional development (Long & Magerko, 2020, April; Ng et al., 2023; Ou et al., 2024). Moreover, establishing clear institutional guidelines for the ethical use of AI is essential. Pre-service teachers need frameworks that address critical issues such as data privacy, algorithmic bias and the appropriate use of AI in student assessment (Akgun and Greenhow, 2022). Without such policies, AI could be used in ways that are inconsistent or ethically problematic, potentially exacerbating educational inequalities (Sperling et al., 2024).

5.4. Balancing AI integration with pedagogical objectives

AI integration must align with broader pedagogical goals. AI should not only be viewed as a tool for automating routine tasks but also as a means of enhancing student-centred practices. This requires an approach to AI integration that prioritises creativity, critical thinking and the ethical use of technology (Cukurova et al., 2019; Holstein & Aleven, 2022; Moorhouse et al., 2023). As AI takes on more routine aspects of classroom management, teachers must focus on complex teaching elements such as fostering higher-order thinking, supporting student well-being and providing targeted interventions for individual learners (Ng et al., 2023).

6. Conclusion

This study reveals that pre-service teachers recognise the potential of AI in education but face significant challenges in developing AI literacy. They perceive AI as a powerful tool for personalising learning and increasing classroom efficiency but express concerns about over-reliance on AI and the potential loss of the human element in teaching. The findings also highlight a critical gap in AI literacy among pre-service teachers, encompassing both technical and ethical considerations.

The findings yield implications for enhancing AI literacy education in teacher training and professional development. First, there is an urgent need for teacher-education programmes to integrate comprehensive AI literacy training into their curricula, as Tan, Cheng, and Ling (2024) argue. Educational institutions and policymakers must develop clear guidelines for the ethical use of AI in classrooms, addressing data privacy, algorithmic fairness and the appropriate balance between AI-assisted and traditional teaching methods. Furthermore, the findings point to the necessity to incorporate AI limitations, bias, and relevant ethical considerations as central elements of teacher AI literacy pedagogy. Critical concerns about privacy and bias must be addressed in both pre-service training and ongoing professional development. The dynamic nature of AI technology necessitates ongoing learning and skill development for teachers, so continuous professional development is essential.

6.1. Recommendations

Based on these findings, we propose the following recommendations for teacher education in the AI era.

1 Enhance AI literacy in Teacher-Education Programmes
- Develop and implement comprehensive AI literacy curricula covering technical skills and ethical considerations.
- Regularly update these curricula to keep pace with rapidly evolving AI technologies.
- Provide ample opportunities for pre-service teachers to gain practical experience with AI tools in educational settings.

2. Develop Institutional Support and Policies for AI usage
   - Establish guidelines that address data privacy, algorithmic fairness and the appropriate use of AI in education.
   - Create education policies that support AI literacy among teachers, including funding for AI-related professional development.
   - Develop standards for AI usage in education at the policy level.
3. Implement Continuous Professional Development on AI literacy
   - Establish regular professional development programmes focused on AI literacy for pre-service and in-service teachers.
   - Foster partnerships between educational institutions, AI developers and researchers to ensure AI tools are developed with pedagogical needs in mind.
4. Address AI Ethical Considerations
   - Develop comprehensive ethical guidelines for AI use in education through collaboration between educational institutions and policymakers.
   - Integrate ethical considerations into AI literacy training, focusing on issues such as bias, privacy and the appropriate use of AI in assessment.

6.2. Future research directions

Our results support Moorhouse & Kohnke, 2024 call for comprehensive AI literacy training. Future research should focus on developing and evaluating specific AI literacy curricula for pre-service teachers. By designing and implementing such curricula, we can address significant gaps in teacher-education programmes and equip future educators with the skills they need to integrate AI into their teaching practices. Additionally, researchers should explore the long-term impact of AI integration on teaching practices and student outcomes. Longitudinal studies that track pre-service teachers as they enter the profession could provide valuable insights into how AI literacy training translates into classroom practice and affects student learning over time (Ng et al., 2023). By developing evidence-based strategies for AI integration, we can enhance teaching effectiveness and student outcomes in our increasingly AI-driven educational landscape. Implementing these recommendations will better prepare future educators to harness the benefits of AI while navigating its complexities.

6.3. Limitations

While our study provides valuable insights, it has several limitations. First, our sample size was limited to 15 pre-service teachers, who may not have fully represented the diverse perspectives of all future educators; this limits the generalisability of our findings. Second, our participants' experiences and perceptions of AI integration may have been influenced by their educational context and not be applicable elsewhere. Third, relying on self-reported data through interviews introduces the possibility of response bias, including social desirability bias. Finally, the rapid evolution of AI technologies means that the challenges and perceptions we identified could become outdated quickly. This emphasises the need for continual research in this dynamic field.

CRediT authorship contribution statement

Lucas Kohnke: Writing – original draft, Methodology, Conceptualisation, Visualization, Formal analysis. **Di Zou:** Writing – review & editing, Validation, Methodology. **Amy Wanyu Ou:** Writing – review & editing, Validation. **Michelle Mingyue Gu:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Data availability

The dataset generated and/or analyzed during the current study are not publicly available due to privacy policy.

Code availability

All code included in this study is available from the first author upon reasonable request.

Ethics declaration

Informed consent was obtained from all participants, and their privacy rights were strictly observed. The data can be obtained by sending request e-mails to the corresponding author.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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ChatGPT has been used for proofreading the language in this article. However, it should be noted that ChatGPT was not involved in generating any ideas. Any errors, if present, are solely mine.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.caeai.2025.100398.

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ARTICLES FOR UTM SENATE MEMBERS

"AI and the transformation of education"

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RESEARCH ARTICLE

The future of learning or the future of dividing? Exploring the impact of generative artificial intelligence on higher education*

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Abstract

This article examines the impact of generative artificial intelligence (GAI) on higher education, emphasizing its effects in the broader educational contexts. As AI continues to reshape the landscape of teaching and learning, it is imperative for higher education institutions to adapt rapidly to equip graduates for the challenges of a progressively automated global workforce. However, a critical question emerges: will GAI lead to a more inclusive future of learning, or will it deepen existing divides and create a future where educational access and success are increasingly unequal? This study employs both theoretical and empirical approaches to explore the transformative potential of GAI. Drawing upon the literature on AI and education, we establish a framework that categorizes the essential knowledge and skills needed by graduates in the GAI era. This framework includes four key capability sets: AI ethics, AI literacy (focusing on human-replacement technologies), human–AI collaboration (emphasizing human augmentation), and human-distinctive capacities (highlighting unique human intelligence). Our empirical analysis involves scrutinizing GAI policy documents and the core curricula mandated for all graduates across leading Asian universities. Contrary to expectations of a uniform AI-driven educational transformation, our findings expose significant disparities in AI readiness and implementation among these institutions. These disparities, shaped by national and institutional specifics, are likely to exacerbate existing inequalities in educational outcomes, leading to divergent futures for individuals and universities alike in the age of GAI. Thus, this article not only maps the current landscape but also forecasts the widening educational gaps that GAI might engender.

Policy Significance Statement

This study underscores the critical need for policy and education leaders to adopt and implement comprehensive and inclusive policies in higher education to effectively leverage the capabilities of generative artificial intelligence (GAI). Our analysis shows sharp disparities in GAI readiness across top universities, which implies an impending widening of educational inequalities in the absence of effective policy measures. Policymakers must prioritize the development of robust GAI integration strategies that not only enhance curricula with essential AI skills and ethics but also ensure equitable access for all individuals and institutions. By systematically aligning educational frameworks with the evolving demands of the AI era, we can equip graduates with the necessary tools to thrive in a digitally driven future under transformative technological advancement.

*The article has been updated since original publication. A notice detailing the change has also been published.

1. Introduction

Generative artificial intelligence (GAI), including transformative technologies such as ChatGPT, is rapidly changing the contours of various sectors of human life (Zawacki-Richter et al., 2019; Galindo et al., 2021). One domain standing at the center of this monumental transformation is higher education (Hannan and Liu, 2023). As policymakers and leaders navigate the threshold of an era where AI technologies possess the power to redefine traditional learning and teaching methodologies (Novak and Gowin, 1984; Jung, 2018; Li, 2023; Welsh, 2023), some critical questions arise: What capacities should be offered to university students in the era of GAI, and what curriculum reforms are needed accordingly? How prepared are our higher education institutions to embrace this transformation? More crucially, will the future of GAI-enhanced education be a future of expanded opportunity or a future of deepening divides, where only the privileged few benefit while the majority are left behind?

The advent of GAI presents a dual challenge for higher education worldwide (OECD, 2023). The first challenge is awareness and comprehension: educational institutions must comprehend the meanings and implications of the rise of GAI for the future of work and the teaching and learning of higher education. This understanding will help them identify the essential knowledge and skills in the AI era. The second, and conceivably more significant challenge, is reconfiguration and transformation. Major changes, including curriculum reforms and institutional restructuring, are often necessary to incorporate or strengthen the capacities essential for the AI era in university education, preparing them for a future increasingly intertwined with AI automation. Addressing these challenges requires an analysis from both theoretical and empirical perspectives, which constitutes the essence of this study.

While GAI adoption is gaining traction worldwide, the strategies, priorities, and challenges differ remarkably across cultural contexts (Wong and Hinnant, 2023). In the Global North, particularly across North America, Europe, and Oceania, many universities initially took a cautious, fragmented approach to GAI adoption, centered around concerns for academic integrity, ethical use, and the development of advisory mechanisms (Moorhouse et al., 2023). Despite growing interest, these institutions often lack cohesive, curriculum-wide frameworks and struggle with comprehensive stakeholder engagement and equitable access (Mollick and Mollick, 2023). Furthermore, much of the existing literature on GAI in education has focused disproportionately on these Western contexts, leaving a gap in understanding how GAI is being integrated into other global regions (Jin et al., 2025).

This study argues that Asia provides a particularly compelling and underexplored region for testing and analyzing the integration of GAI in higher education. It is home to both highly Westernized institutions and traditionally influenced universities (Capano et al., 2025), making it a unique region for comparative analysis. This coexistence is reflected in the contrast between highly modernized and Westernized universities, such as those in Hong Kong, Singapore, and South Korea, and institutions that remain deeply influenced by traditional pedagogical norms and sociocultural values, as seen in parts of Japan, China, and Southeast Asia. Moreover, given their openness to technological innovation and proactive stance in educational reform (Jin et al., 2025), Asian universities are particularly well positioned to showcase the early and more structured forms of GAI adoption. If such transformations are to be observed at scale, they are likely to emerge first in this region.

This study embarks on an examination of this pressing issue, with a concentrated focus on the role and readiness of top Asian universities in the current rising tide of GAI. First, Asian universities would be more likely to become the pioneers in adopting GAI in their teaching and learning. Asia is often the forerunner in blending technology and higher education to promote its national competitiveness and global soft power (Nye, 2004; Wojciuk et al., 2015). With the legacy of the developmental state, heavy investment in higher education and human capital is one of the main aspects of advanced Asian countries and regions for sustaining their economic miracle and enhancing their competitiveness in the global marketplace (Cummings, 1996; Marginson, 2011; Woo, 2018). They will serve as the standard of global education under the norms and pressures of enhancement and progress in institutional development (DiMaggio and Powell, 1983; Karens et al., 2015; Fay and Zavattaro, 2016). At the same time, Asia is a region with good variations, such as cultural norms and pedagogical modes shaped by national and institutional contexts (Deem et al., 2008; Knight, 2008; Mok, 2015). Focusing on Asian universities provides a unique vantage point for the analysis to understand if there will be divergence in paths and paces in GAI adoption and application due to contextual and institutional differences.

In essence, this study aims to address the research questions of how GAI can transform university education and learning and to what extent universities are prepared to equip their graduates with the necessary knowledge, capacities, and skills for the GAI era from both theoretical and empirical perspectives. In the theoretical section, based on a critical review of the literature concerning AI and the future of work, this study will construct a theoretical framework that identifies essential capacities needed to prepare university students for the AI era. In the empirical analysis, by examining AI policy documents related to teaching and learning, as well as core curricula for all graduates, this study assesses how ready top Asian universities are to embrace GAI by implementing the proposed framework.

2. GAI and the future of work

AI has begun to redefine job roles and functions, automate repetitive tasks, and transform various industries (Taeihagh, 2021; Heaven, 2023; Noy and Zhang, 2023). One of the most prominent impacts of AI, and particularly GAI, on the future of work is automation (Frey and Osborne, 2017; Wong, 2020). The ability of AI systems to learn from data and make decisions can automate a wide range of tasks, from mundane, repetitive tasks to complex, cognitive tasks (Brynjolfsson et al., 2023). For GAI, it can generate human-like text, design websites, or even compose music, demonstrating its potential to disrupt fields of knowledge workers once thought to be the exclusive domain of human cognition (Choi et al., 2023).

AI automation does not necessarily mean a replacement of human jobs (Kane et al., 2022). Instead, it often results in job transformation. AI is likely to automate specific tasks within jobs rather than eliminate entire jobs. Therefore, workers may need to shift their focus to tasks that require human strengths, such as emotional intelligence, critical thinking, creativity, and complex problem solving—skills that AI currently cannot replicate (Wirtz and Müller, 2019).

AI is not only automating and transforming existing jobs but also creating new ones. As the AI industry grows, there is a rising demand for AI specialists, data scientists, and machine learning engineers (Muller, 2018). Besides, industries are recognizing the need for AI ethicists to navigate the ethical complexities of AI deployment (Heimans et al., 2023). In the educational sector, for instance, the introduction of AI tutors and AI-driven learning management systems has created roles for AI education specialists who can bridge the gap between AI technology and educational needs (Molesworth et al., 2009; Hashmi and Bal, 2024).

The rise of AI has implications for the skills that will be in demand in the future of work. While technical skills related to AI and data analysis are gaining importance, soft skills such as emotional intelligence, adaptability, and complex problem solving are becoming increasingly valuable. These "human skills" complement AI systems and enable workers to perform tasks where humans have the edge over machines (Acemoglu and Autor, 2011). As argued by Lee (2018) (see Figure 1), the degree of automation of a job is determined by the elements of creativity and social intelligence; both are the strengths of humans. Jobs involving routine tasks are more susceptible to automation, while those involving complex problem solving and human interaction are less likely to be automated. Out of the four quadrants, AI would only replace jobs in the danger zone, which emphasizes optimization in the absence of social skills.

The impact of AI, however, is not unidirectional, nor is it uniformly distributed across sectors and geographies (Kuh, 2019). GAI presents a complex array of opportunities and challenges as economies step into a future intimately intertwined with these digital technologies. Workers in routine jobs, often with lower wages, face a higher risk of job displacement due to automation. Similarly, regions with a high concentration of such jobs may face significant economic challenges (Johansen, 2019). The rise of AI is automating tasks, transforming jobs, creating new roles, shifting skill demands, and potentially exacerbating inequalities. Policymakers, educators, and industry leaders must work together to mitigate the challenges and harness the opportunities that AI brings to the future of work. For higher education, this necessitates a rethinking of curricula to ensure that students are equipped with the skills needed for the

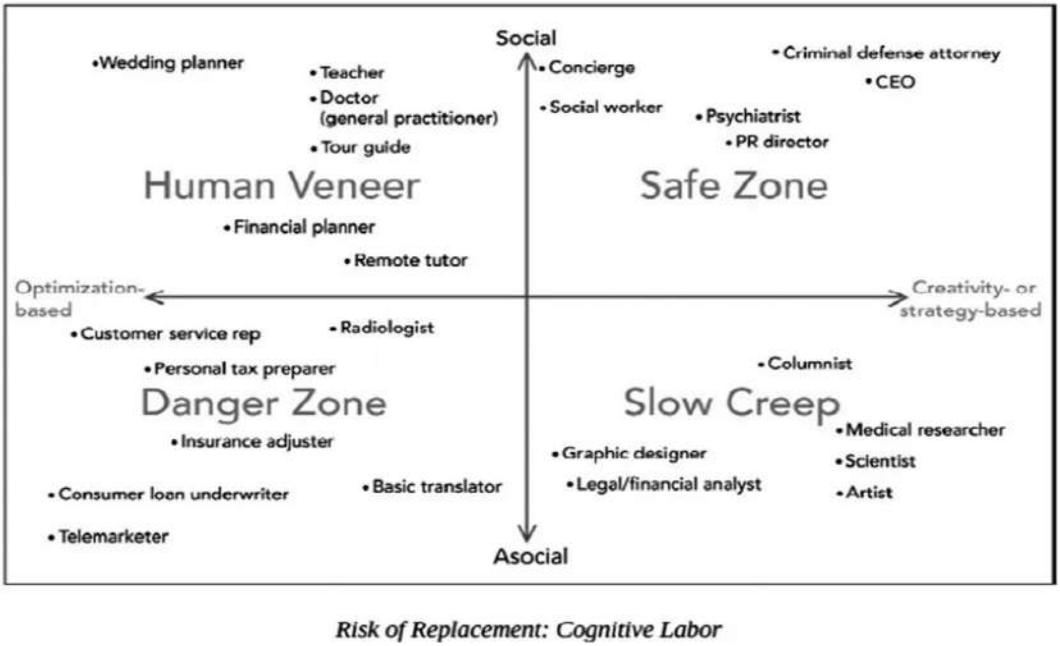

Figure 1. *AI and replacement of the human workforce.*
Source*: Lee (2018).*

AI-infused future of work. It also calls for a commitment to lifelong learning, acknowledging that education is a continuous process in the face of rapid technological change (Chan and Hu, 2023; Bowen and Watson, 2024).

Asian universities have the potential to lead the way in redefining and revolutionizing higher education for the future of work. By integrating GAI into their teaching and learning processes and reshaping their curricula, they can prepare their students for a future where AI is an integral part of work, fostering a workforce that can thrive in the age of GAI. From a broader perspective, this transformation also has implications for national competitiveness.

Countries that can successfully navigate the AI-driven shift in the future of work stand to gain in terms of economic growth and global influence (Johnson and Acemoglu, 2023).

3. Effects on higher education

GAI is a transformative force in higher education to reshape its contours (Yilmaz and Yilmaz, 2023). Its potential to radically enhance teaching, learning, and research is only just starting to be realized. Nevertheless, the integration of GAI in educational contexts also gives rise to concerns and challenges, including ethical considerations, infrastructure upgrades, and the necessity of identifying new capacities and transforming curricula to equip students for the future of work.

One of the most profound impacts of GAI on higher education lies in its capacity to transform pedagogical strategies (Dill and Soo, 2005). It can tailor study materials according to an individual student's learning needs, thereby optimizing learning outcomes. For example, GAI systems can create personalized quizzes or suggest additional reading materials based on a student's comprehension level. They can even generate illustrative examples to elucidate complex concepts, making learning more interactive and engaging (Downing et al., 2023). Moreover, GAI can foster a more dynamic learning environment. GAI-powered chatbots can provide instant responses to student queries, thereby freeing up instructor time for more complex discussions. These systems can also provide real-time feedback to students, enhancing their learning experience and boosting academic engagement.

GAI is also a potent tool for academic research and training. In data-intensive disciplines like bioinformatics or climate science, GAI can generate hypotheses or identify patterns that would be nearly impossible for humans to discern alone. This capability can fast-track scientific discovery and enable researchers to tackle more complex and nuanced problems (Rudolph et al., 2023). For instance, Google's DeepMind used GAI to predict protein structures, a scientific problem that has eluded researchers for decades and could revolutionize drug discovery. In the humanities and social sciences, GAI can analyze large text corpora to unearth cultural trends, linguistic patterns, or social dynamics. This automation allows researchers to focus on interpretation and theory development. The Literary Lab at Stanford University, for example, uses GAI to analyze vast volumes of literature, revealing patterns and trends in literary history.

However, one significant concern is the ethical use of AI. Universities must ensure that GAI systems are used responsibly, respecting privacy and avoiding bias (Guenduez and Mettler, 2023; Moorhouse et al., 2023). In the process, university management needs to champion the ethical use of GAI and foster collaboration among faculty, IT staff, and administrators to ensure the successful integration of GAI into teaching, learning, and research (Harding, 2023). Furthermore, they need to advocate for equity in the adoption of GAI. They should ensure that all students, regardless of socioeconomic background, have access to GAI tools and receive the necessary training to use them effectively.

In resource and infrastructure management of universities, GAI offers significant benefits. It can predict student enrollment numbers, optimize course scheduling, manage library resources, and even monitor energy use on campus. These applications not only save resources but also enhance the overall student and staff experience within higher education institutions (Crompton and Burke, 2023; Labadze et al., 2023). Nevertheless, the successful implementation of GAI in higher education requires significant investment in infrastructure upgrades. This might entail scholarship programs for tech-based courses, free on-campus digital literacy workshops, or partnerships with tech companies to provide resources for students.

Importantly, higher education institutions have a responsibility to prepare students for a future where GAI is prevalent. This involves integrating GAI into the curriculum, not only within computer science and data science courses but also across all disciplines. Regardless of their major, students need a technological literacy of GAI, its applications, and its ethical implications. In addition, universities must foster the development of "human capacities and skills" that complement technical abilities. These skills, which GAI cannot replicate, will allow students to thrive in the future of work (Mindell and Reynolds, 2022). Higher education leaders play a crucial role in navigating this transformation. As universities launch this transformation, they have the opportunity not just to adapt to the GAI era but to shape it, influencing how GAI is used and understood in society at large (Lynch, 2006). Ultimately, the goal is to create a synergistic and collaborative relationship between humans and AI, where both can learn from and enhance each other, fostering an enriched educational environment that is truly responsive to the needs and potential of all students.

4. New capacities for the GAI era

GAI demands a new set of capacities that can broadly be categorized into technical capacities and human intelligence, such as soft skills and ethical understanding (Lewis, 2007). The in-between capacity of fostering human–AI collaboration under the concept of human-centered AI is also highly relevant (Bates et al., 2020). With a focus on AI-specific capabilities, technical skills form the cornerstone of new capacities but go beyond simply writing code to include a foundational understanding of how AI algorithms function and can be improved. As data are the fuel that drives AI systems, data analysis skills are also paramount (Laato et al., 2023). These include the ability to extract, clean, and transform data into actionable insights and visualize data to summarize and present evidence and stories in a way that is accessible and meaningful.

In this connection, computational thinking is one of the essential skills that involve various techniques, such as abstraction (remove details and extract relevant information), decomposition (break down data and problems into smaller parts), pattern recognition (observe patterns and trends in data), and algorithmic thinking (determine what steps are needed to solve a problem) (Welsh, 2023). It encapsulates a mindset that enables people to use logical and analytical thinking to break down complex problems, examine them systematically, and come up with effective solutions with the support of computers. As AI technologies become more integrated into our daily lives and the workplace, computational thinking skills can enable individuals to better comprehend and utilize AI technologies, making them more effective in their interactions with these tools.

While computer and technology literacy is a crucial skill, it is insufficient for the job skills and capacities needed in the AI era (Acar, 2023). The ability to collaborate with AI and human intelligence is also critical (Lee, 2018). These capabilities are about creating a balance between utilizing technology and enhancing human capabilities that set us apart from machines (Shneiderman, 2022). There is an increasing demand for skills that AI systems cannot easily replicate—capacities and skills that are distinctively human. These include creative thinking, critical thinking, emotional intelligence, and complex problem solving. For instance, while AI can analyze data patterns, it may lack the creative thinking required to develop innovative solutions or the emotional intelligence needed to understand human needs and responses (Tlili et al., 2023). Furthermore, ethical considerations around AI use are becoming increasingly important, from issues of data privacy to algorithmic bias. Understanding these issues requires not just computational thinking but also ethical and critical reasoning under social and cultural contexts.

Despite the technical nature of AI, human strengths and intelligence remain an indispensable aspect of new capacities in the AI era. As shown in Figure 2, technical skills are not ranked at the top by the World Economic Forum as the most critical skills at present and in the future (World Economic Forum, 2023). Critical thinking skills, such as creative thinking and capacities unique to humans, including resilience, motivation, self-awareness, empathy, and leadership, are integral in the AI era. The ability to not only consume information but also to analyze, evaluate, and synthesize it is key (Jandrić, 2023). These skills enable mankind to make informed decisions, solve complex problems, and generate innovative ideas. They also provide a framework for understanding and questioning the assumptions and biases that underpin AI systems.

While AI can outperform humans in many tasks, it does not possess the capacity for genuine creativity. The ability to generate new ideas, think outside the box, and approach problems from novel angles is uniquely human (Madan and Ashok, 2023). Creativity is not limited to artistic endeavors; it is equally vital in scientific and technical fields, where it drives innovation and progress (Spector and Ma, 2019). Emotional intelligence—the ability to perceive, understand, manage, and use emotions—is another unique human trait (Mollick and Mollick, 2023). As AI systems take over more routine tasks, emotional intelligence becomes even more important. It enables effective collaboration, leadership, and customer service, and it underpins the empathy and ethical understanding that are critical in the AI era.

Given the rapid pace of GAI development, the ability and willingness to continually learn and adapt are crucial. Lifelong learning involves not only keeping up-to-date with the latest AI developments but also seeking out new skills and knowledge areas and being open to new ideas and perspectives. The rise of GAI

Top Skills of 2023	Top Skills on the Rise
1. Analytical thinking	1. Creative thinking
2. Creative thinking	2. Analytical thinking
3. Resilience, flexibility and agility	3. Technological literacy
4. Motivation and self-awareness	4. Curiosity and lifelong learning
5. Curiosity and lifelong learning	5. Resilience, flexibility and agility
6. Technological literacy	6. System thinking
7. Dependability and attention to detail	7. AI and big data
8. Empathy and active learning	8. Motivation and self-awareness
9. Leadership and social influence	9. Talent management
10. Quality control	10. Service orientation and customer service

Figure 2. *Top skills in work jobs.*
Source*: World Economic Forum (2023).*

brings with it a host of ethical considerations. This includes understanding the implications of AI for privacy, bias, accountability, and the broader societal and economic impacts.

To equip students with these capacities, universities need to adapt and transform their teaching methods and curricula. AI should be integrated into the curriculum across a range of disciplines. This could involve offering new courses on GAI, data science, and machine learning, as well as incorporating AI-related content into existing courses. Universities should also place greater emphasis on developing soft and human skills. This could be achieved through pedagogical strategies, such as group projects, case studies, and debates, which foster teamwork, communication, creativity, and critical thinking. Universities could provide resources and support for emotional intelligence development, such as workshops, counseling services, and self-assessment tools. They need to ensure that students understand the ethical implications of AI by encouraging students to contemplate and debate ethical dilemmas related to AI, such as privacy concerns, algorithmic bias, and the impact of AI on jobs and inequality.

5. Research design, methods, and data

This study conducts a content analysis to evaluate GAI policy documents and the core curricula required for all graduates from top Asian universities, using data collected between September and November 2024. Core curriculum is defined as the set of courses or academic requirements mandated for all students regardless of major. It focuses specifically on undergraduate curricula rather than graduate programs because most universities have a more uniform and standardized curriculum structure at the undergraduate level, particularly in core or general education requirements that all students must complete regardless of major. In contrast, graduate programs tend to be more specialized, diverse, and decentralized, often varying significantly across departments, faculties, and research tracks, which make cross-institutional comparisons more complex. Moreover, this focus aligns with one of the main objectives of this study to examine how foundational skills and capacities related to GAI are being integrated into the foundation and core mission of higher education, preparing the younger generation for the AI-driven future.

"Top Asian universities" in this study refer to universities located in Asia that are ranked among the top in either the Quacquarelli Symonds (QS) or Times Higher Education (THE) rankings. They include all Asian universities that are ranked in the Top 100 in either of the two rankings in 2024. The decision to focus on these top-ranking universities is guided by the assumption that these institutions are more likely to have the resources and capacity to implement GAI strategies and reforms. Asia is a major hub of technological development and innovation, and policies from top Asian universities can provide valuable insights into the region's approach to GAI in higher education. These top universities often set the benchmark for educational standards and are frequently the early adopters of new educational trends and technology. Their policies can thus offer a glimpse into the future directions of higher education reform in response to GAI.

Content analysis is a major research method for interpreting and understanding the context of textual data (Radu, 2021). It involves systematically coding and identifying themes or patterns within the data through a systematic classification process. Specifically, qualitative content analysis is applied to GAI policy documents and the core curricula required for all graduates, regardless of their majors, as issued by the selected universities and made available in English on their publicly accessible websites. Similar to the research on national AI strategies (Ulnicane et al., 2021; Papyshev and Yarime, 2023), these documents will be collected and then coded based on the theoretical framework developed in previous sections, particularly the dimensions of GAI integration and the four core capacities needed for the AI era: AI ethics, AI literacy, human–AI collaboration, and human-distinctive capacities.

For the GAI policy documents, this coding process will categorize their content into major themes related to GAI and education, such as curriculum reforms, access rights, decision-making, defined areas of use, academic honesty, and institutional strategies. By coding and analyzing these documents, the research aims to identify the extent to which the GAI strategies and core curricula of these universities align with the recommended reforms and new capacities under GAI. Through the analysis, the research will shed light on the current state of adaptation and transformation with GAI in higher education and the potential gaps that may exist. Initially, coders identified relevant keywords and phrases related to the major themes of the study, such as "curriculum reforms," "access rights," "academic honesty," "curriculum redesign," "prompt engineering," "ethical use," "AI literacy," "AI ethics," "human–AI collaboration," and "GAI tools." These keywords were guided by the framework's categories and the core capacities needed for the AI era.

After identifying keywords and phrases, each document was read in full by all coders to ensure contextual understanding beyond surface-level mentions. The coding was conducted manually by a team of three coders. The coding process followed an iterative and collaborative approach to ensure intersubjective reliability. Coding disagreements were discussed collectively until a consensus was reached, thereby enhancing the interobjectivity and consistency of the analysis. This collaborative process ensured that the coding was both conceptually grounded and responsive to the nuances of institutional language and framing.

6. Analysis and findings

The analysis of AI policy documents from the Top 25 Asian universities revealed several key findings. As shown in Table 1, out of the 25 top-ranking Asian universities, only 11 had policies explicitly related to GAI. It can be seen in Table 2 that, notably, none of the Chinese universities within the sample had a policy on GAI. This disparity underscores the varying degrees of GAI adoption across different countries and areas in Asia and suggests that the integration of GAI into higher education is not yet widespread, even among top universities.

The analysis identified several issues addressed in the GAI policies of the universities under study. These policies typically encompassed a wide range of areas, each with its unique implications:

6.1. Access rights

Policies often detail who has the right to access and use GAI technologies. For instance, some universities allowed only faculty members and certain students enrolled in specific programs to access GAI resources, thus ensuring that these powerful tools are used responsibly.

6.2. Academic honesty

Policies highlighted the importance of maintaining academic integrity when using GAI. This included guidelines on plagiarism and the misuse of AI-generated content, emphasizing that students should use GAI as a tool for learning and not as a means to bypass academic work.

6.3. Prompt engineering

Policies emphasized the need for timely implementation and integration of GAI in curricula. This might include directives for faculty to adopt GAI tools in their teaching practices or initiatives to introduce GAI-related courses.

6.4. Awareness of its importance

Policies underscored the significance of GAI in the future of education and the workforce. They stressed the need for awareness campaigns or educational programs to inform students and staff about the transformative potential of GAI.

6.5. Balancing the risks and benefits of GAI

Policies acknowledged the potential risks and benefits associated with GAI. These might include discussions on how GAI can enhance learning but also the potential for misuse or overreliance on technology.

Table 1. *Top Asian universities and generative AI policies: the full list*

Universities	Country/region	QS ranking	THE ranking	Generative AI policies
National University of Singapore	Singapore	8	19	Yes
Peking University	China	17	14	No
Tsinghua University	China	25	12	No
Nanyang Technological University	Singapore	26	32	No
The University of Hong Kong	Hong Kong SAR	26	35	Yes
The University of Tokyo	Japan	28	29	Yes
Seoul National University	South Korea	41	62	No
Zhejiang University	China	44	55	No
Kyoto University	Japan	46	55	No
The Chinese University of Hong Kong	Hong Kong SAR	47	53	Yes
Fudan University	China	50	44	No
Shanghai Jiao Tong University	China	51	43	No
KAIST—Korea Advanced Institute of Science & Technology	South Korea	56	83	No
The Hong Kong University of Science and Technology	Hong Kong SAR	60	64	Yes
The Hong Kong Polytechnic University	Hong Kong SAR	65	87	Yes
Universiti Malaya	Malaysia	65	N/A	Yes
National Taiwan University	Taiwan	69	N/A	Yes
City University of Hong Kong	Hong Kong SAR	70	82	Yes
Yonsei University	South Korea	76	76	No
Korea University	South Korea	79	N/A	Yes
Osaka University	Japan	80	N/A	Yes
Tokyo Institute of Technology	Japan	91	N/A	Yes
Pohang University of Science and Technology	South Korea	100	N/A	No
University of Science and Technology of China	China	N/A	57	No
Nanjing University	China	N/A	73	No
Total: 25				Yes: 12 (48%); No: 13 (52%)

6.6. Future of work

Policies reflected on how GAI could influence the future job landscape. This might involve outlining the types of jobs that could be affected by AI and the skills that students would need to acquire to stay competitive.

6.7. Availability and manual of practices

Policies provided guidelines on how to use GAI and where to access it. This could involve creating user manuals or online resources to help students and faculty navigate GAI tools.

6.8. Ethics and student accountability

Policies stressed the ethical aspects of using GAI and students' responsibility. This could include sections on data privacy, informed consent, and the ethical use of AI technologies.

Table 2. *Generative AI policies and Asian top universities by country*

Country	Number of top universities	Number (%) with GAI policies	Number (%) without GAI policies
China	7	0 (0%)	7 (100%)
Hong Kong SAR	5	5 (100%)	0 (0%)
South Korea	5	1 (20%)	4 (80%)
Japan	4	3 (75%)	1 (25%)
Singapore	2	1 (50%)	1 (50%)
Malaysia	1	1 (100%)	0 (0%)
Taiwan	1	1 (100%)	0 (0%)

6.9. Value and potential in teaching and learning

Policies recognized the potential of GAI to enhance teaching and learning. They might highlight examples of how GAI can be used to personalize learning or assist in complex research tasks.

6.10. Defined areas of use

Policies specify the areas of teaching, learning, and research in which GAI should be employed.

6.11. Importance of traditional learning and human interaction

While acknowledging the benefits of GAI, policies also emphasized that technology should not replace traditional learning methods and normal human interactions. They might stress the continued importance of classroom discussions, one-on-one tutoring, and other traditional forms of pedagogy.

6.12. Target users

Policies identified both students and teachers as the primary users of GAI. They might outline specific ways in which these different groups can benefit from GAI, such as students using GAI for learning and teachers using it to enhance their teaching strategies.

6.13. Decision-making

Policies clarified who is responsible for determining when and how GAI should be used. This could range from individual teachers making decisions for their classes to university-wide committees setting guidelines.

6.14. Contextual and situational approach

Policies advocated for the adoption of a contextual and situational approach in the use of GAI. This suggests that the use of GAI should be adapted based on the specific learning context and situation, rather than applying a one-size-fits-all approach.

Despite the wide range of issues addressed in the GAI policies, few universities mentioned full-scale curriculum reforms, a key area identified in the literature review as necessary for preparing students for the AI era. This observation is further confirmed by the second stage of analysis, in which we examined the core curriculum required for all graduates in some of the top Asian universities. Table 3 shows the Top 10 Asian universities based on their average ranking in THE and QS that have their core curriculum available in English online. Among them, only one university has courses in all categories (computer and digital literacy, AI, human intelligence and capacities such as creativity and innovation, and human–AI collaboration) to equip their graduates well for the future of work under GAI. Although many universities

Table 3. Core curricula required for all graduates in top Asian universities in the GAI era

Universities	Computer and digital literacy	AI	Human intelligence and capacities	**Human–AI collaboration**
1. National University of Singapore	Yes	No	No	No
2. University of Tokyo	No	No	No	No
3. Nanyang Technological University	Yes	No	No	No
4. University of Hong Kong	No	No	No	No
5. The Chinese University of Hong Kong	Yes	No	No	No
6. Kyoto University	Yes	No	No	No
7. Seoul National University	Yes	No	No	No
8. Hong Kong University of Science and Technology	No	No	No	No
9. KAIST—Korea Advanced Institute of Science & Technology	No	No	No	No
10. Hong Kong Polytechnic University	Yes	Yes	Yes	Yes
Total	6	1	1	1

examined do offer those courses, they are elective courses, meaning that students can graduate from those universities without completing them.

These findings indicate a notable discrepancy between the theoretical recommendations and actual practices in these top Asian universities. The lack of mention of comprehensive curriculum reforms in the GAI policies suggests a need for greater alignment between university policies and the evolving demands of the AI era. These findings highlight the current state of GAI integration in top Asian universities and reveal a critical gap in addressing the need for full-scale curriculum reforms.

7. Discussion: selective adoption, equity, and divergence

With a focus on Asia, this study initiated an exploration into how top universities are preparing for the GAI era and the implications of these policies and measures on higher education. We aim to understand the GAI policies within higher education institutions, the areas they cover, and how they align with the evolving needs of the AI era, particularly in relation to comprehensive curriculum reforms.

GAI is adopted selectively rather than universally by universities. Our findings indicated that only 11 out of the top 25 Asian universities had explicit policies on GAI, with none from Chinese universities. These policies encompassed a broad range of areas, from access rights and academic honesty to the roles of students and teachers in GAI usage. However, a significant gap was identified in the absence of full-scale curriculum reforms in the GAI policies, which are affirmed by the examination of the core curricula of some of the top Asian universities. These findings carry significant implications for equity and quality of higher education at both the student and institutional levels. They underscore the urgent need for universities to develop comprehensive GAI policies that cover all relevant areas and align with the demands of new capacities of the AI era. These policies should be rooted in a clear understanding of the potential benefits and risks of GAI, guiding students and faculty toward ethical and effective use of this technology. The results point toward a need for education policies that foster the integration of GAI into the curriculum and promote the development of crucial skills for the AI era, such as creative thinking, social intelligence, and ethical reasoning.

In addition, the variations observed in GAI policies and reforms across the seven countries/regions in the study reflect broader national characteristics, including differing education policies, technological priorities, and levels of digital infrastructure. For instance, universities in Hong Kong tend to show more explicit integration of GAI into their education, matching its agendas for digital innovation and AI ambition. In contrast, institutions in South Korea and China demonstrate strong research orientation but more limited curricular reform at the undergraduate level, possibly due to centralized curriculum standards or slower institutional adaptation. These cross-country differences underscore how national education strategies and governance models shape the pace and form of GAI adoption in higher education.

From an equity perspective, these variations carry particularly significant implications. The divergence in GAI policies among top Asian universities suggests varying levels of readiness for this new era. This divergence could lead to disparities at the individual, university, and country levels, as different entities adopt GAI at various rates and in multiple ways. For instance, as education and training on AI and new capacities remain optional in many prestigious institutions, the impact of AI on personal performance and achievement depends on individual discretion and choice.

Looking ahead, the impact of GAI on higher education is expected to grow. As GAI technologies become more advanced and accessible, they have the potential to significantly transform teaching and learning practices, enabling more personalized and efficient education. However, they may also exacerbate existing inequalities if access to and use of these technologies are unevenly distributed (Luo, 2024). Therefore, universities need to carefully navigate these challenges, balancing the pursuit of innovation with the commitment to equity and inclusivity.

Based on the current state of GAI integration in top Asian universities, there is a need for more comprehensive and aligned GAI policies. They should emphasize the importance of a nuanced understanding of GAI's implications and a balanced approach to harnessing its benefits while mitigating its risks. As we venture deeper into the AI era, such an approach will be crucial to shaping a future of higher education that is innovative, equitable, and beneficial for all—a future that will, in turn, play a pivotal role in national development and competitiveness.

To a considerable extent, the ability of GAI to generate "social good for all" depends on how effectively it is integrated into higher education. If GAI is used to enhance personalized learning, facilitate research, and equip students with vital AI skills, it could significantly boost national competitiveness by creating an AI-savvy workforce and fostering AI-driven innovation (Miller, 2023). However, if GAI is not well integrated or if its potential risks and challenges are not adequately addressed, it could exacerbate educational inequalities and lead to a workforce that is ill prepared for the AI era.

8. Policy recommendations and future research agenda

Policymakers and educators need to carefully consider how to best integrate GAI into higher education. This includes developing comprehensive GAI policies, investing in faculty training, and ensuring equitable access to AI resources (Bradford, 2023). By doing so, they can ensure that higher education serves as a powerful driver of both personal development and national competitiveness for ensuring that students and educators rise with AI.

Furthermore, to support a more cohesive and equitable adoption of GAI in higher education, the following specific policy recommendations are proposed. First, universities should develop comprehensive institutional frameworks that guide the integration of GAI across teaching, learning, and research. These frameworks must address ethical concerns, pedagogical opportunities, and infrastructure needs, ensuring that GAI is deployed responsibly and effectively. Regular reviews and updates of these frameworks are essential to keep pace with the rapid evolution of AI technologies.

Second, there is a pressing need for core curriculum reforms that embed GAI-related competencies across all disciplines. These reforms should include AI literacy, ethical reasoning, human–AI collaboration, and the cultivation of human-distinctive capacities, such as creativity, empathy, and critical thinking. Making these components mandatory for all students, and not just for those in Science, Technology, Engineering, and Mathematics (STEM) fields, will ensure that graduates across the board are equipped for the AI-driven future of work.

Third, policymakers and university leaders must ensure equitable access to GAI tools, platforms, and training. This includes investing in infrastructure, offering inclusive digital literacy programs, and providing targeted support for students from disadvantaged or underrepresented backgrounds. Without such measures, the benefits of GAI could inadvertently deepen existing educational and social inequalities.

Fourth, faculty development should be a central focus of GAI policy. Institutions should implement continuous professional development programs that enable educators to effectively incorporate GAI into their pedagogy and research. Moreover, fostering interdisciplinary collaborations can help universities explore the full potential of GAI across diverse academic domains.

Last, but not least, regional cooperation is imperative. Establishing cross-country networks or consortia among universities across countries and regions can facilitate the sharing of best practices, policy innovations, and research related to GAI in higher education. Such collaborative platforms could play a pivotal role in reducing disparities in GAI readiness and promoting a more unified, strategic response to the opportunities and challenges posed by this transformative technology.

Due to the scope and methodological limitations of this study, institutional heterogeneity could not be explored in depth. It is important to recognize that universities differ significantly in terms of national contexts, enrollment sizes, faculty composition, undergraduate-to-graduate student ratios, disciplinary emphases (including the prominence of engineering and AI-related programs), and available resources or budgets. Moreover, distinguishing between public and private universities could shed light on how differing levels of government oversight, funding structures, and policy mandates shape the pathways through which GAI is adopted and implemented. These variations may influence the adoption and implementation of GAI policies and curricula in ways not fully captured in this analysis. Future research should adopt a more granular, comparative case study approach to investigate how different institutional attributes mediate the integration of GAI in higher education.

Future studies could further refine the analysis by employing advanced qualitative content analysis techniques, such as grouping institutional policies into higher-order thematic categories. This would allow for a more systematic comparison across universities and help reveal broader patterns in how GAI is being conceptualized and operationalized in higher education. Universities from other regions and graduate-level curricula could also be included in future studies. In particular, incorporating leading non-Asian institutions, such as those in the United States, one of the global AI powers where much of the development and early adoption of GAI technologies has taken place, would provide valuable international benchmarks and highlight global contrasts in policy, pedagogy, and institutional strategy.

9. Conclusion

This article aims to explore whether GAI will lead to a more inclusive educational future or deepen existing divides. In the exploration of the impact of GAI on higher education, this paper reveals a critical juncture for the future of learning in universities. The essential knowledge and skills framework established, which encompasses AI ethics, AI literacy, human–AI collaboration, and human-distinctive capacities, identifies the crucial areas where curricula must evolve to prepare graduates effectively for the future of work in the AI era. Despite the transformative potential of GAI, without strategic intervention and comprehensive policy adaptations, there is a real risk that GAI could also become a divisive force, exacerbating disparities across educational institutions and among individual learners. Our research underscores a significant variance in GAI readiness and implementation. This variance, influenced by distinct national and institutional contexts, risks widening the educational gap rather than closing it.

Our findings indicate that the adoption of GAI in higher education is not yet comprehensive or universal. The disparities in GAI policy adoption and curriculum integration could lead to divergent futures, where some institutions advance rapidly while others lag behind. This potential divergence brings into sharp relief the dual possibilities posed by GAI: it can either foster unprecedented educational advancements or contribute to increasing educational inequity. Universities, policymakers, and educational leaders must collaborate to implement robust GAI policies that are inclusive and comprehensive. These policies should not only address technological integration but also ensure equitable access to GAI resources, fostering an environment where all students can benefit from AI advancements. By achieving "AI for All," higher education can harness the benefits of GAI to enhance learning and innovation while safeguarding against deepening educational divides, thus steering the future towards greater equity and inclusion in the GAI era.

While this study focuses on the current state of GAI adoption in higher education, it is likely that adoption will continue to increase, driven by rapid technological advancement, growing student familiarity, and institutional pressure to remain competitive. However, this adoption will not be uniform. Institutional and contextual factors, such as technological capacity, national culture, organizational values, regulatory environments, and resource availability, will shape the pace and nature of integration. As a result, we are likely to see greater divergence rather than convergence across institutions and regions, further exacerbating existing inequalities in educational outcomes and institutional innovation.

Data availability statement. The data that support the findings of this study are openly available on the official websites of the universities included in the study.

Author contribution. All authors have contributed to the major tasks and stages of the research, including conceptualisation, methodology, data curation, formal analysis, project administration, and writing.

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ARTICLES FOR UTM SENATE MEMBERS

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6. University teachers' digital competence and AI literacy: moderating role of gender, age, experience, and discipline (2025	Education Sciences (Article from : Multidisciplinary Digital Publishing Institute (MDPI))

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Article

University Teachers' Digital Competence and AI Literacy: Moderating Role of Gender, Age, Experience, and Discipline

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Abstract

The present research aims to contribute to the effective development of AI literacy and thus to its proper educational integration by investigating (i) the relationship between teachers' AI literacy and digital competence and (ii) whether this relationship varies by gender, discipline, age, and teaching experience. This is the first large-sample study in Hungary to comprehensively analyze such relationships, based on a representative sample of 1103 teachers from 13 fields of education. After a theoretical grounding and literature review, the study describes the research methodology, analyzes the empirical results, and concludes. The research contributes to the AI literacy literature by providing empirical evidence from a previously understudied population—Hungarian university teachers—and by refining the understanding of the role of digital competence in the context of technological transformation. The findings highlight that the development of AI literacy does not require a one-size-fits-all approach but rather strategies tailored to the specific needs of target groups (e.g., gender, scientific fields, and experience levels).

Keywords: AI literacy; digital competence; higher education

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1. Introduction

Artificial intelligence (AI), particularly generative AI tools, has emerged as a transformative force in 21st-century education, reshaping teaching methodologies, administrative processes, and learning experiences. Educators play a key role in the integration of technology into education—the successful application of AI tools in classrooms primarily depends on whether teachers are willing to adopt and integrate them into their teaching and learning strategies (Bozkurt, 2023; Mujiono, 2023). However, the effective and ethical use of AI tools requires specific competences, referred to in the literature as AI literacy (Long & Magerko, 2020; Hornberger et al., 2023; Ng et al., 2021). Long and Magerko (2020) define it as "a set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace".

Its relevance and complexity are illustrated by the successive additions to the various frameworks summarizing digital competences for educators, which are related to AI activities and competencies (for more details, see later sections). In addition, new pedagogical competency frameworks focusing specifically on AI literacy are also emerging. The AI Competency Framework for Teachers developed by UNESCO defines the knowledge, skills, and values educators should master in the age of AI. The framework is divided into five key dimensions: human-centered mindset, ethics of AI, AI foundations and applications, AI pedagogy, and AI for professional development. Within these, it outlines 15 competencies that can be achieved at 3 levels: acquire, deepen, and create. The framework aims to serve as a global reference for developing national AI competency frameworks, informing teacher training programs, and designing assessment parameters. Additionally, it provides strategies for teachers to enhance their AI knowledge, apply ethical principles, and support their professional growth (UNESCO, 2024).

The importance of AI literacy in higher education is, therefore, undeniable, but there are a number of challenges in developing it. The lack of clear guidelines for integration can hinder educators' ability to effectively utilize AI tools, which leads to uncertainty and reluctance in adoption (Michel-Villarreal et al., 2023). In addition, Kizilcec (2023) pointed out the psychological barriers to adoption of AI technologies, creating barriers to the effective implementation. Another challenge is the varying levels of digital competence among educators, which can affect their ability to engage with AI technologies: educators with limited digital skills may find it difficult to grasp AI concepts and applications, thereby impeding their overall AI literacy (Walter, 2024). Furthermore, the need for continuous professional development is critical, as the fast-paced evolution of AI technologies requires educators to stay updated with the latest advancements (Walter, 2024).

The present research aims to contribute to the effective development of AI literacy and thus to its proper educational integration by investigating (i) the relationship between teachers' AI literacy and digital competence and (ii) whether this relationship varies by gender, discipline, age, and teaching experience. This is the first large-sample study in Hungary to comprehensively analyze such relationships, based on a representative sample of 1103 teachers from 13 fields of education. After a theoretical grounding and literature review, the study describes the research methodology, analyzes the empirical results, and concludes, contributing to the global discourse on AI literacy.

2. Theoretical Background

2.1. AI Literacy and Digital Competence

The relationship between AI literacy and digital competence is interconnected yet distinct, as AI literacy can be viewed as a specialized subset within the broader framework of digital competence. With AI becoming an integral part of the digital learning environment and tools, existing digital competence frameworks for education are expanding to include AI-related skills.

The supplement to the DigCompEDU Framework (Bekiaridis & Attwell, 2024) expands the EU's DigCompEdu framework by integrating AI-related competencies in education, recognizing AI's impact on teaching and learning and the need for educators to use it effectively. It explores AI both as a learning tool and subject, aligning competencies with DigCompEdu's six key areas, providing guidance on applications, skill development, competency progression, challenges, and solutions. A further supplementary proposal (Georgopoulou et al., 2024) focuses on strengthening critical thinking, which, combined with AI features, can enable educators to empower students to become responsible and informed digital citizens in the era of generative AI. The AI-TPACK, as an extension of the well-known Technological Pedagogical Content Knowledge framework, emphasizes human–AI collaboration in education, integrating AI not just as a tool but as a fundamental component that reshapes teaching, learning, and content delivery in the AI era (Mishra et al., 2023; Ning et al., 2024).

The relationship between university teachers' AI literacy and their digital competence is an increasingly pertinent topic in the context of higher education. This literature review synthesizes existing research to explore this relationship and examines how factors such as gender, discipline, age, and teaching experience may moderate it. Kizilcec argues that understanding educators' perspectives on emerging technologies is essential for maximizing their benefits, suggesting that digital competence is closely tied to educators' readiness to adopt AI tools (Kizilcec, 2023). The interplay between AI literacy and digital competence is further supported by the Common Framework for Artificial Intelligence in Higher Education (AAI-HE Model) proposed by Jantakun et al., which illustrates how these competencies can enhance educational outcomes (Jantakun et al., 2021).

2.2. AI Literacy and Demographic Factors

The UNESCO AI Competency Framework for Teachers (UNESCO, 2024) emphasizes that the development of AI literacy must be inclusive and equitable, taking into account different social and demographic groups. The DigCompEdu framework highlights the importance of personalized, differentiated approaches, and according to Venkatesh et al. (2003), gender, age, and experience significantly influence technology acceptance, so we can conclude that they are also key factors in the development of AI literacy. For women, older people, and those with less experience, ease of use and social support increase the acceptance of AI tools, while for men and younger people, emphasizing usefulness increases acceptance. Targeted training and a supportive environment tailored to these demographic groups are necessary.

Moreover, the moderating effects of demographic factors, such as age, gender, teaching experience, and field of study, are critical to understanding the nuances of this relationship. Møgelvang's research indicates that gender differences persist in technology acceptance and usage, which may extend to AI tools in educational contexts (Møgelvang et al., 2024). This suggests that male and female educators might exhibit different levels of AI literacy and digital competence, potentially influencing their engagement with AI technologies. Research suggests that gender differences in attitudes toward AI among educators are partly due to differences in perceptions of the technology, partly due to differences in participation in professional settings, and partly due to the social embeddedness of the technology. According to a meta-analysis by Cai et al. (2017), women tended to have fewer positive attitudes toward the use of technology than men, which may be reflected in educational applications of AI, although the difference was small. Gibert and Valls (2022) emphasized that women's underrepresentation in the field of AI stems from structural inequalities, which may affect their participation and attitudes toward AI. Research by Møgelvang et al. (2024) showed that women in higher education were less likely and more narrowly focused on using generative AI chatbots, more likely to focus on text tasks, with greater concern for critical thinking, while men used them more frequently and more widely (see also McGrath et al., 2023, for similar gender differences in AI knowledge among Swedish university teachers). Venkatesh et al. (2003), in their model of information technology adoption, found that women tended to evaluate technology use more in terms of effort and social norms, while men tended to prioritize utility.

Empirical studies provide further insight into these gender dynamics. For instance, Al-Riyami et al. (2023) found in their research of Omani educators that gender significantly moderated the acceptance of Fourth Industrial Revolution (4IR) technologies, including AI. Specifically, women were more influenced by social factors, while men placed greater emphasis on facilitating conditions, such as infrastructure and technical support (Al-Riyami et al., 2023). However, the overall impact of gender was limited, suggesting that other contextual factors like training and infrastructure may overshadow gender differences in this context (Al-Riyami et al., 2023). Similarly, Zhang and Villanueva (2023) observed significant gender differences among Chinese university teachers regarding generative AI preparedness and digital competence. Female educators scored higher in digital competence areas, such as subject matter knowledge and pedagogical strategies, while men rated themselves higher in creativity and problem-solving related to AI. These findings indicate that women may excel in integrating AI into teaching practices, while men focused more on its creative applications, potentially reflecting differing priorities or training experiences.

In contrast, several studies reported no significant gender effects. Berber et al. (2023) found that among Turkish academics, gender did not significantly influence digital competence, suggesting that other factors like age or experience may be more determinative. Similarly, Xu et al. (2024) concluded that among Chinese university educators, gender did not moderate the acceptance or intention to use AI tools under the UTAUT2 model, with no significant impact on constructs like facilitating conditions or behavioral intention (Xu et al., 2024). Lérias et al. (2024) also found no correlation between gender and AI literacy levels among Portuguese polytechnic educators, indicating that individual skills and training opportunities may outweigh gender differences (Lérias et al., 2024).

These mixed findings align with broader theoretical frameworks. Venkatesh et al.'s (2003) observation that women prioritize effort and social influence while men focus on utility may explain some of the differences seen in Al-Riyami et al. (2023)'s study, where social factors were more critical for women. Conversely, the lack of gender effects in the works of Xu et al. (2024) and Lérias et al. (2024) could reflect contexts where professional training or institutional support minimize gender-based disparities, as suggested by Gibert and Valls (2022). Møgelvang et al.'s (2024) findings on women's narrower use of AI chatbots and greater concern for critical thinking might resonate with Zhang and Villanueva's (2023) results, where women showed higher digital competence, potentially indicating a more cautious or purpose-driven approach to AI. Meanwhile, the lower GAI-preparedness observed by Zhang and Villanueva (2023) among female teachers could potentially indicate a latent barrier for female educators, although this requires further investigation.

Research examining the relationship between educators' teaching experience and their AI or digital competence yielded varied results. According to Ghimire et al. (2024), at a research university in the United States, the length of teaching experience did not significantly influence familiarity with or acceptance of generative AI tools, regardless of whether the educators were novices or had been teaching for a longer period. In contrast, Berber et al. (2023) determined in Turkey that academics with shorter teaching experience (1 month to 2 years) exhibited higher digital competence than those with over 15 years, suggesting that recent technological knowledge may provide an advantage. Xu et al. (2024) found in China that experience with AI tool usage (1 to 7+ years) did not moderate acceptance. Regarding educators teaching at different educational levels, specific observations about the relationship between teaching experience and AI literacy are scarce. Lérias et al. (2024) reported from the Portalegre Polytechnic University in Portugal that educators' teaching cycles did not affect their AI literacy levels, indicating that experience across educational levels is not a decisive factor in AI literacy.

The studies known to us regarding the age-related findings of university educators present a mixed picture concerning the technological acceptance and competence of higher education instructors. Several studies suggested that younger educators are more open to technology and exhibit greater competence: Al-Riyami et al. (2023) found that for faculty members under 46 years old, social influence significantly affected their behavioral intention to use 4IR-related technologies, as evidenced by the path analysis, while this effect was not significant for those aged 46 and above. Zhang and Villanueva (2023) noted that 21–30-year-old teachers demonstrated higher digital competence. Similarly, Berber et al. (2023) reported outstanding competence among 21–27-year-olds, and Mah and Groß (2024) identified age-related differences in the positive perception of AI, with those under 30 rating it lower compared to older groups. In contrast, several studies found no significant correlation between age and technological attitudes or literacy. Ghimire et al. (2024) concluded that age did not influence awareness or attitudes toward generative AI. Xu et al. (2024) showed that age did not moderate the acceptance of AI tools among Chinese educators. Likewise, Lérias et al. (2024) determined that age was not a predictor of AI literacy. These findings suggest that the impact of age may be context dependent, and other factors, such as professional background or training, might play a more dominant role in technological acceptance.

Furthermore, the field of study could also moderate this relationship, as university teachers' attitudes toward AI tools are fundamentally shaped by their field of training or profession, which shapes their attitudes through a unique combination of digital competences, pedagogical paradigms, and ethical contexts. In the humanities and social sciences, the emphasis on creativity and critical thinking requires applications other than AI, such as text analysis or ethical reflection, as opposed to the natural sciences, where data analysis and simulations dominate (Marciniak & Baksa, 2024). Ghimire et al. (2024) found that in the United States, instructors from the College of Science and the School of Business exhibited greater awareness and more positive attitudes toward generative AI tools, while those from the College of Arts scored lower, particularly in technical understanding. Similarly, Al-Riyami et al. (2023) in Oman observed that instructors with IT and engineering backgrounds showed stronger acceptance of 4IR technologies compared to those from non-technological fields. Zhang and Villanueva (2023) in China highlighted the high generative AI preparedness of instructors from the Faculty of Physics and Information Science, while those from the Physical Education Faculty demonstrated lower levels. In contrast, Lérias et al. (2024) in Portugal found no significant correlation between training area and AI literacy, suggesting that the impact of departmental affiliation may be context dependent. Overall, instructors from technological and scientific faculties generally hold an advantage in AI-related competencies.

Ethical considerations further widen the gap between disciplines. In healthcare, data security and algorithm bias are prominent issues, warranting comprehensive AI education for ethical application (Busch et al., 2023). This context-dependent ethical sensitivity shapes the cautious attitude of educators, especially in areas under social scrutiny, such as medicine or law. At the same time, uncertainty about the effectiveness and reliability of AI is pervasive: many instructors feel unprepared to critically evaluate the technology, which increases mistrust, especially in dental or other practice training (Uribe et al., 2024).

In conclusion, the literature suggests a relationship between university teachers' AI literacy and their digital competence, with moderating effects of factors such as age, gender, teaching experience, and field of study varying by context. While the field of study consistently influences AI-related competencies, the impact of gender, age, and experience is less uniform, highlighting the importance of training and institutional support in shaping educators' engagement with AI technologies.

The aim of the study is to answer the following research questions:

RQ1: Is the Hungarian university teachers' AI literacy related to their digital competence?

RQ2: If it is related, is this relationship moderated by the teacher's age, gender, teaching experience, and field of education?

As AI continues to evolve and permeate educational practices, understanding these dynamics will be crucial for developing effective training programs and policies aimed at enhancing educators' competencies in this area.

3. Materials and Methods

3.1. Design

During the research, we used a survey research design with a quantitative approach. The data collection was conducted using a questionnaire (MS Forms). The sampling took place between 30 January 2024 and 27 March 2024, using an online, self-administered method, in higher education institutions in Hungary selected based on expert selection. Our expert group, consisting of professionals with in-depth knowledge of the Hungarian higher education system and the integration possibilities of artificial intelligence, defined the selection criteria: geographical location, size, type, profile of the institutions, and their experience with artificial intelligence. After that, the higher education institutions were selected, taking into account diversity and the likelihood of adopting artificial intelligence. In the selected institutions, a contact person was sought to distribute the questionnaire within the institution. Participation in the study was voluntary, and respondents provided online informed consent. The study received ethical approval from the Research Ethics Committee of the University Institute of Psychology (BTK/8779/2023), and the data complied with ethical principles. The data were stored in a secure database accessible only to the research team. After the analysis, a summary report was shared with those interested.

3.2. Sample

In total, 1103 Hungarian university teachers participated in the study, with an average age of 48.9 years (SD = 10.9). These teachers had varying levels of higher education teaching experience, averaging 16.3 years (SD = 10.8). Among the participants, 564 were women and 539 were men. Regarding the field of education, the participants came from 13 different fields.

To ensure representativeness across the dimensions of the field of education, age, and gender, post-weighting was applied. The target population of the research was the population of individuals currently teaching in Hungarian higher education institutions. For the field of education, data from the OH/FIR Institutional Staff Statistics for the spring of 2022/2023 (available at https://firstat.oh.gov.hu/intezmenyi-letszamstatisztika (accessed on 23 November 2024)) were used. For age, data from the OECD (Indicator D8: What is the profile of academic staff?) for 2021 were utilized. For gender, data from the OH/FIR Higher Education Statistical Data for 2022/2023 (Section 3.2; available at https://kir.oktatas.hu/firstat.index?fir_stat_ev=2022 (accessed on 23 November 2024)) were employed.

The case-preserving weighting was conducted using an iterative method based on marginal distributions (RIM), with 5 iterations performed. A total of 1103 completed questionnaires were included in the study; due to rounding, the weighted sample size was 1128. The full range of the sample weights was 0.18–2.44. No data imputation was applied.

The sociodemographic composition of the weighted teacher sample—based on the four variables included in this study: gender, age, field of education, and higher education experience—as well as the frequency of refusals to answer, are summarized in Table 1.

Table 1. Sociodemographic characteristics of the weighted study sample (N = 1128).

Variable Name	Variable Values	Missing Values, N (%)	N (%) or Mean (SD)
Gender		0 (0)	
	Male		645 (57.2%)
	Female		483 (42.8%)
Age (years)		2 (0.2%)	47.5 (11.20)
Higher education experience (years)		0 (0)	15.6 (10.9)
Field of education		0 (0)	
	Political Science		32 (2.9%)
	Humanities		151 (13.4%)
	Economics		146 (12.9%)
	Theology		29 (2.6%)
	Information Technology		69 (6.1%)
	Law		39 (3.5%)
	Engineering, Agricultural Sciences		206 (18.2%)
	Arts, Art Mediation		76 (6.6%)
	Medical and Health Sciences		208 (18.5%)
	Teacher Training		76 (6.7%)
	Sport Sciences		10 (0.9%)
	Social Sciences		25 (2.2%)
	Natural Sciences		60 (5.4%)

3.3. Measures

In addition to the personal variables (gender, age, field of science, and higher education experience) collected from the participants, we employed two measurement tools. We interpreted AI literacy as "a set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace" according to Long and Magerko's (2020) definition and used the AI literacy scale developed by Hornberger et al. (2023) to measure it. Within the framework of the present study, we examined the following dimensions and scales of the questionnaire: (I) understanding intelligence (2 items), (II) AI's strengths and weaknesses (2 items), (III) recognizing AI (2 items), (IV) human role in AI (2 items), and (V) learning from data (2 items). For each of these, respondents were required to select the correct answer from four different response options.

We defined digital competence as "the skills related to the use of information and communication technologies in teaching and learning, as well as in other activities related to education (educational management, related individual and organizational communication, research activities)" (Dringó-Horváth et al., 2022) and measured it using the higher-education-specific version of DigCompEdu (Redecker & Punie, 2017) adapted by Dringó-Horváth et al. (2020) and Horváth et al. (2020). Using this framework, the digital competence level of teachers can be assessed with 22 items across 6 different competence areas: (1) teachers' professional engagement (4 items), (2) searching for and using digital resources (3 items), (3) the learning–teaching process supported by digital solutions (3 items), (4) assessment practices (4 items), (5) supporting students (3 items), and (6) developing their digital competence (5 items) (Redecker & Punie, 2017). Each multiple-choice question within these areas was scored from 0 to 4 points. The respondents' digital competence level was determined based on the total score (ranging from 0 to 88 points), which was obtained by summing the scores from each area.

3.4. Procedure

The descriptive analyses for DigCompEdu, the reliability assessment (Cronbach's alpha), and the calculation of descriptive statistics for the AI literacy items (difficulty index and discrimination index) were conducted using SPSS 30.0 (SPSS Inc., Chicago, IL, USA) and MS Excel.

Further analyses were performed using the R program (R Core Team, 2022), utilizing, in addition to the base packages, the following packages: lavaan (Rosseel, 2012), survey (Lumley, 2020), mirt (Chalmers, 2012), haven (Wickham et al., 2023b), dplyr (Wickham et al., 2023a), and psych (Makowski, 2018).

To test for unidimensionality, we fitted a unidimensional model using confirmatory factor analysis, and its fit was evaluated using the following commonly used indices and thresholds, which indicate a unidimensional structure of the response patterns: RMSEA < 0.08 (Awang, 2012) and SRMR < 0.08 (Byrne, 1994). The AI literacy of the test-takers was estimated using Item Response Theory (IRT), as described in the article publishing the original measurement tool. We selected among the Rasch, 2-PL, and 3-PL models using multiple model-fit and item-fit indices: we applied the M2/df statistic (Backhaus et al., 2015; Brown, 2015) with a cutoff value of 0.3, the RMSEA and SRMR statistics with a cutoff value of ≤ 0.05 (Maydeu-Olivares, 2013), and the TLI and CFI indices with a threshold of ≥ 0.95. The fit of the items was examined using the signed chi-square ($S - X^2$) index (Orl&ø& Thissen, 2003). The independence of the item residuals was assessed using the Q3 statistic, based on the criterion $Q3 \leq 0.2$ (Chen & Thissen, 1997).

Additionally, in SPSS 30.0 (SPSS Inc., Chicago, IL, USA), to achieve objective O1, we used regression analysis, considering teachers' digital competence as the independent variable and AI literacy as the dependent variable. Then, to achieve objective O2, we conducted moderation analyses using the blockwise method, incorporating the variables of gender, field of education, age, and higher education experience.

To answer research question RQ1, we used regression analysis, considering teachers' digital competence as the independent variable and AI literacy as the dependent variable. Then, to answer research question RQ2, we conducted moderation analyses using the blockwise method, incorporating the variables of gender, field of education, age, and higher education experience. These analyses were performed with SPSS 30.0 (SPSS Inc., Chicago, IL, USA).

4. Results

4.1. The DigCompEdu Test

In the current study sample, the average DigCompEdu score was M = 50.478 (SD = 18.076), which, considering the maximum achievable score of 88 points, represents a 57.35% result. For the DigCompEdu questionnaire, the data analysis showed an excellent internal consistency for the whole instrument, with a Cronbach's alpha of 0.936.

4.2. Descriptive Statistics of AI Literacy Items

Participants correctly answered an average of M = 5.29 (SD = 2.04) out of the 10 AI literacy items. Due to the multiple-choice format, it can be expected that, on average, they would have guessed correctly on 2.25 items. Table A1 presents the descriptive statistics for all examined AI literacy items. The difficulty index (corrected for guessing) was 0.035 for one item—recognizing AI 1—and ranged between 0.104 and 0.811 for the other items, which is ideal (between 0.05 and 0.95). The recognizing AI 1 item proved to be too difficult compared to the others, but its discrimination ability was acceptable (discrimination index of 0.297), so we continued with the analysis. The discrimination indices for all items were at least 0.2 (ranging between 0.267 and 0.429), indicating that the items had at least acceptable discrimination ability. Figure 1 shows the average raw scores (difficulty indices) for the domains (competencies).

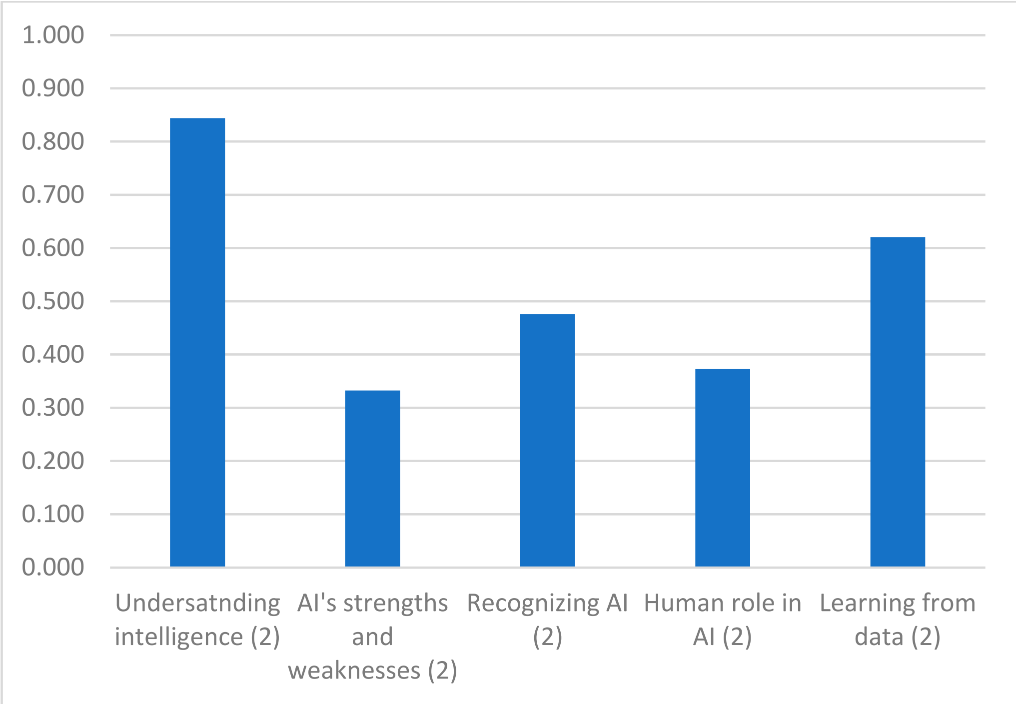


Figure 1. Mean score for each competency. Numbers in brackets indicate the number of items per competency.

4.3. Checking for Unidimensionality

The assumption of unidimensionality was tested using a confirmatory factor analysis (CFA) with a single-factor model. The results indicated that the model fit the data well ($\chi2$ = 217.750, df = 35, $p < 0.001$, RMSEA = 0.0688, and SRMR = 0.0549). Therefore, we can say that the assumption of unidimensionality was not entirely clear-cut, but the results were acceptable.

4.4. Fitting the IRT Models

After fitting the three classical IRT models (Rasch, 2-PL, and 3-PL), we examined the model fits. As shown in Table A2, the 3-PL model fit well, only disregarding the TLI criterion, while the Rasch model and the 2-PL model showed acceptable fits based on the RMSEA and SRMR indices, but poor fits based on the M2/df, TLI, and CFI indices.

When comparing the three models using AIC and BIC, the 3-PL model proved to be the weakest; however, since AIC and BIC penalize model complexity, and given that all model fit indices supported the 3-PL model, we used this model for estimating the personal AI literacy abilities in our further analyses. The distribution of our sample according to the AI literacy estimated by IRT scores is presented in Figure A1. The assumption of local independence was verified using the Q3 statistic based on the 3-PL model (Yen, 1984). We examined the correlations between the residuals of all items, and every correlation was less than 0.2, indicating that local independence was not violated.

4.5. Relationship Between AI Literacy and Digital Competence

The results of a simple linear regression analysis, with digital competence as the independent variable and AI literacy as the dependent variable, showed that digital competence was positively related to AI literacy (R^2 = 0.110; B = 0.005; $p < 0.001$). The subsequent moderation analyses were conducted in three steps. In each analysis, AI literacy was the dependent variable, and digital competence was the independent variable. The moderator variables were as follows:

- First step: Gender and field of education.
- Second step: Age and field of education.
- Third step: Higher education experience and field of education.

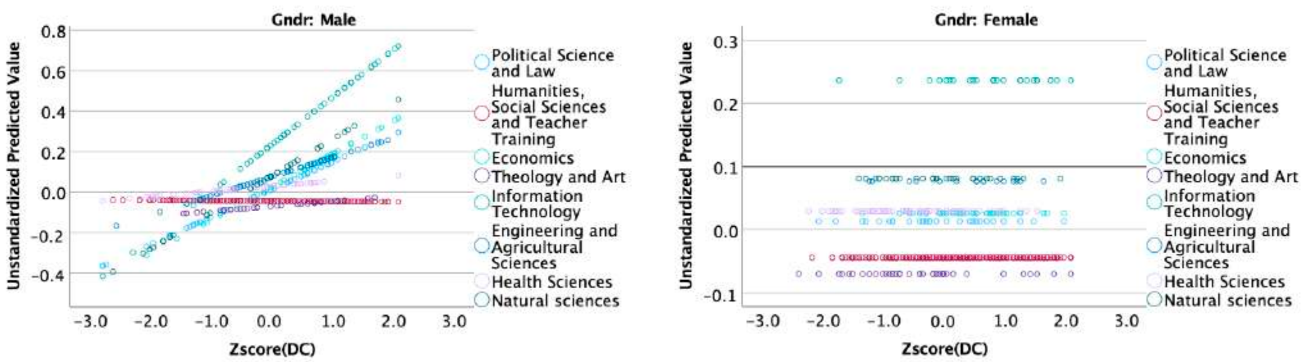
4.5.1. First Step: Moderating Effects of Gender and the Field of Education

The field of education variable was transformed into eight categories by combining fields (see Table A3), and the information technology field (ID = 6) was chosen as the reference category. Our results indicate that the relationship between digital competence (DC) and AI literacy significantly differed by gender and certain fields of education. The DC $\times$ Gender interaction remained significant in all models, suggesting that digital competence was more strongly correlated with AI literacy scores among men, while among women, AI literacy was less dependent on the level of digital competence.

From Model 2, it can be concluded that the fields of education alone did not have a moderating effect, meaning that the correlation between digital competence and AI literacy did not differ significantly across fields of education.

However, Model 3 showed that by considering both fields of education and gender, the differences between genders can be nuanced. As seen in Figure 2, the difference between genders—in terms of the relationship between digital competence and AI literacy—varied by field of education. In the sample:

- The strongest relationship between DC and AI literacy was observed among men in information technology education, along with the most significant difference compared to women.
- Similar relationships were observed in the fields of political and legal sciences, economics, engineering and agricultural sciences, and natural sciences. Based on the regression, these fields did not show significant differences from the information technology field (see Table 2).
- However, the fields of humanities, social sciences, and teacher training, theology and arts, and health sciences differed from this pattern. Here, the gender differences were weaker than in information technology education (see Table 2).



(**a**) (**b**)

Figure 2. Variation in the relationship between digital competence and AI literacy by gender and fields of education: (**a**) male and (**b**) female.

Table 2. The relationship between digital competence and AI literacy, with gender and field of education as moderators *.

		B	SE	*p*	LLCI	ULCI
Model1 (R^2 = 0.011)						
DCxGndr → AI_Lit		0.104	0.030	<0.001	0.045	0.162
Model2 (R^2 = 0.012)						
DCxGndr → AI_Lit		0.093	0.046	0.043	0.003	0.183
DCxField → AI_Lit	DCxField1	0.011	0.085	0.897	−0.156	0.179
	DCxField2	−0.012	0.053	0.818	−0.116	0.190
	DCxField3	0.064	0.077	0.409	−0.088	0.216
	DCxField4	0.021	0.079	0.793	−0.134	0.175
	DCxField8	−0.026	0.072	0.722	−0.166	0.115
	DCxField11	0.035	0.059	0.548	−0.080	0.151
	DCxField15	0.055	0.103	0.591	−0.147	0.257
Model3 (R^2 = 0.025)						
DCxGndr → AI_Lit		0.318	0.096	<0.001	0.131	0.506
DCxField → AI_Lit	DCxField1	−0.147	0.180	0.413	−0.500	0.205
	DCxField2	0.058	0.066	0.381	−0.072	0.188
	DCxField3	0.064	0.114	0.576	−0.160	0.287
	DCxField4	0.082	0.102	0.421	−0.118	0.281
	DCxField8	−0.187	0.0156	0.230	−0.492	0.119
	DCxField11	0.122	0.075	0.103	−0.025	0.268
	DCxField15	−0.006	0.181	0.972	−0.362	0.349
DCxFieldxGndr → AI_Lit	DCxField1xGndr	−0.002	0.012	0.881	−0.026	0.022
	DCxField2xGndr	−0.021	0.008	0.006	−0.035	−0.006
	DCxField3xGndr	−0.012	0.010	0.206	−0.031	0.007
	DCxField4xGndr	−0.020	0.010	0.041	−0.040	−0.001
	DCxField8xGndr	−0.002	0.011	0.855	−0.023	0.019
	DCxField11xGndr	−0.023	0.008	0.004	−0.038	−0.007
	DCxField15xGndr	−0.008	0.013	0.551	−0.033	0.018

* DC: teachers' digital competence (standardized); Gndr: gender (reference: female); AI_Lit: AI-literacy (based on IRT scores); Field: field of education; Field6 (reference): information technology; Field1: political and legal sciences; Field2: humanities, social sciences, and teacher training; Field3: economics; Field4: theology and arts; Field8: engineering and agricultural sciences; Field11: health sciences; Field15: natural sciences.

4.5.2. Second Step: Moderating Effects of Age and the Field of Education

Our second moderation analysis—in which the moderator variables were age and field of education—is presented in Table 3. According to Model 1, the DC × Age interaction was not significant (B = −0.008, p = 0.740), indicating that teachers' age alone did not influence the relationship between digital competence and AI literacy. Model 2 shows that the DC × Age interaction remained non-significant (B = −0.012, p = 0.610), confirming that age alone did not moderate the effect of DC, nor did the DC × Field interactions ($p > 0.05$). Furthermore, as seen in Model 3, the DC × Field × Age interactions were also not significant ($p > 0.05$). Thus, teachers' age, either alone or in combination with the field of education, did not influence the relationship between digital competence and AI literacy. This suggests that the relationship between digital competence and AI literacy did not differ significantly between younger and older teachers, and no significant differences were observed across fields of education as a function of age.

Table 3. The relationship between digital competence and AI literacy, with age and field of education as moderators *.

		B	SE	p	LLCI	ULCI
Model1 ($R^2 < 0.001$)						
DCxAge → AI_Lit		−0.008	0.023	0.740	−0.053	0.037
Model2 ($R^2 = 0.009$)						
DCxAge → AI_Lit		−0.012	0.024	0.610	−0.058	0.034
DCxField → AI_Lit	DCxField1	0.086	0.077	0.262	−0.065	0.237
	DCxField2	0.035	0.049	0.475	−0.061	0.130
	DCxField3	0.122	0.072	0.092	−0.020	0.264
	DCxField4	0.064	0.076	0.402	−0.086	0.214
	DCxField8	0.053	0.060	0.377	−0.065	0.171
	DCxField11	0.076	0.055	0.171	−0.033	0.184
	DCxField15	0.128	0.099	0.195	−0.066	0.322
Model3 ($R^2 = 0.015$)						
DCxAge → AI_Lit		−0.104	0.080	0.195	−0.261	0.050
DCxField → AI_Lit	DCxField1	0.086	0.077	0.264	−0.065	0.237
	DCxField2	0.016	0.050	0.752	−0.082	0.114
	DCxField3	0.120	0.073	0.100	−0.023	0.262
	DCxField4	0.048	0.080	550	−0.109	0.205
	DCxField8	0.051	0.006	0.394	−0.067	0.170
	DCxField11	0.080	0.056	0.153	−0.030	0.190
	DCxField15	0.217	0.114	0.058	−0.007	0.441
DCxFieldxAge → AI_Lit	DCxField1xAge	0.087	0.119	0.465	−0.147	0.321
	DCxField2xAge	0.174	0.097	0.073	−0.016	0.364
	DCxField3xAge	0.104	0.101	0.303	−0.094	0.302
	DCxField4xAge	0.067	0.135	0.214	−0.097	0.432
	DCxField8xAge	0.048	0.098	0.623	−0.144	0.241
	DCxField11xAge	0.105	0.094	0.261	−0.078	0.289
	DCxField15xAge	−0.063	0.131	0.631	−0.319	0.194

* DC: teachers' digital competence (standardized); Age: age of teachers in years (standardized); AI_Lit: AI-literacy; Field: field of education; Field6 (reference): information technology; Field1: political and legal sciences; Field2: humanities, social sciences, and teacher training; Field3: economics; Field4: theology and arts; Field8: engineering and agricultural sciences; Field11: health sciences; Field15: natural sciences.

4.5.3. Third Step: Moderating Effects of Higher Education Experience and the Field of Education

Our third moderation analysis—in which the moderator variables were teaching experience in years and field of education—is presented in Table 4. Model 1 showed that the DC × Texp interaction was not significant ($p = 0.914$). Similarly, in Model 2, the DC × Texp interaction remained non-significant (B = −0.001, $p = 0.955$), and the DC × Field interactions were also not significant ($p > 0.05$). However, in Model 3, when additional variables were included, the effects of the interactions became clearer: the DC × Texp interaction became significant with a negative coefficient (B = −0.144, $p = 0.043$), indicating that for those with more teaching experience, the relationship between DC and AI literacy was weaker. Additionally, in Model 3, the DC × Field8 × Texp interaction was significant (B = 0.278, $p = 0.005$), suggesting that for teachers in the engineering and agricultural fields, compared to those in information technology, teaching experience strengthened the relationship between DC and AI literacy more significantly.

Table 4. The relationship between digital competence and AI Literacy, with teaching experience and field of education as moderators *.

		B	SE	*p*	LLCI	ULCI
Model1 ($R^2 < 0.001$)						
DCxTexp → AI_Lit		0.002	0.023	0.914	−0.042	0.047
Model2 ($R^2 = 0.009$)						
DCxTexp → AI_Lit		−0.001	0.023	0.147	−0.047	0.042
DCxField → AI_Lit	DCxField1	0.087	0.077	0.257	−0.064	0.238
	DCxField2	0.032	0.048	0.507	−0.063	0.127
	DCxField3	0.120	0.072	0.096	−0.021	0.262
	DCxField4	0.054	0.076	0.423	−0.089	0.211
	DCxField8	0.054	0.060	0.374	−0.065	0.172
	DCxField11	0.079	0.055	0.152	−0.029	0.187
	DCxField15	0.122	0.099	0.218	−0.073	0.317
Model3 ($R^2 = 0.017$)						
DCxTexp → AI_Lit		−0.144	0.071	0.043	−0.284	−0.004
DCxField → AI_Lit	DCxField1	0.083	0.078	0.287	−0.070	0.236
	DCxField2	0.029	0.049	0.554	−0.067	0.125
	DCxField3	0.119	0.072	0.098	−0.022	0.261
	DCxField4	0.060	0.079	451	−0.096	0.215
	DCxField8	0.058	0.060	0.331	−0.060	0.177
	DCxField11	0.079	0.055	0.155	−0.030	0.187
	DCxField15	0.212	0.125	0.090	−0.033	0.457
DCxFieldxTexp → AI_Lit	DCxField1xTexp	0.170	0.113	0.133	−0.052	0.391
	DCxField2xTexp	0.163	0.088	0.065	−0.010	0.335
	DCxField3xTexp	0.153	0.097	0.118	0.039	0.344
	DCxField4xTexp	0.136	0.111	0.220	−0.081	0.352
	DCxField8xTexp	0.278	0.098	0.005	0.085	0.471
	DCxField11xTexp	0.137	0.085	0.108	−0.030	0.303
	DCxField15xTexp	0.019	0.129	0.883	−0.234	0.272

* DC: teachers' digital competence (standardized); Texp: teaching experience in years (standardized); AI_Lit: AI-literacy; Field: field of education; Field6 (reference): information technology; Field1: political and legal sciences; Field2: humanities, social sciences, and teacher training; Field3: economics; Field4: theology and arts; Field8: engineering and agricultural sciences; Field11: health sciences; Field15: natural science.

5. Discussion

The results showed that digital competence positively correlated with AI literacy ($R^2 = 0.110$, $p < 0.001$), which is consistent with the literature's findings that digital skills play a fundamental role in understanding and applying AI technologies (e.g., Long & Magerko, 2020; Kizilcec, 2023). This relationship suggests that teachers' ability to effectively use digital tools in education promotes the development of their AI-related knowledge and skills.

The analysis of gender differences yielded particularly noteworthy results. Digital competence correlated more strongly with AI literacy among male teachers, while this relationship was weaker among females. This difference was particularly pronounced in the fields of information technology, political and legal sciences, economics, engineering, agricultural sciences, and natural sciences, while in the humanities, social sciences, teacher training, theology, arts, and health sciences, the gender difference was less significant. These results partially align with the research by Møgelvang et al. (2024), which found that men were more likely to use generative AI tools and approach technology application with different motivations, and McGrath et al. (2023) reported higher AI knowledge among male Swedish university teachers. Similarly, Mah et al. (2025) found that female German and Austrian university teachers placed greater emphasis on the ethical implications of AI in education compared to their male counterparts, and reported disciplinary differences, with arts faculty perceiving domain-specific AI applications as highly relevant and engineering faculty placing less emphasis on ethical considerations. Furthermore, Kallunki et al. (2024) noted that Finnish university faculty across diverse disciplines, such as arts and engineering, perceived AI as both an opportunity and challenge for teaching, with young teachers and educational technology experts adopting AI more readily.

The phenomenon may be explained by differing levels of technological self-confidence (Zhang et al., 2023), as well as sociocultural norms that may steer men toward more technology-oriented roles. However, some studies reported no significant gender effects (e.g., Berber et al., 2023), suggesting these differences may vary by context. In contrast, Salhab (2024) found that female instructors in a Palestinian university exhibited significantly more positive attitudes toward AI literacy integration into the curriculum, highlighting the role of cultural and contextual factors in shaping gender differences in AI-related perceptions.

Interestingly, age was not a significant moderator in the relationship between digital competence and AI literacy, neither on its own nor when examined in conjunction with the fields of study. This finding aligns with research indicating that age does not consistently influence technology acceptance (e.g., Ghimire et al., 2024; Xu et al., 2024; Galindo-Domínguez et al., 2024), though it contrasts with studies suggesting younger teachers exhibit greater openness or competence with new technologies (e.g., Al-Riyami et al., 2023; Zhang & Villanueva, 2023). The result suggests that in the Hungarian higher education context, the presence of digital competence may support the development of AI literacy to a similar extent across all age groups.

However, the moderating effect of higher education experience presented a more nuanced picture. For teachers with more experience, the relationship between digital competence and AI literacy was weaker (B = -0.144, $p = 0.043$), suggesting that more experienced teachers rely less on their digital skills in understanding or applying AI tools. This aligns with findings that less experienced teachers exhibit higher digital competence (Berber et al., 2023) and contrasts with McGrath et al. (2023), who found that Swedish university teachers with over 30 years of experience reported higher AI knowledge and greater willingness to adopt AI-based tools compared to those with less experience. These differences may reflect a reliance on established pedagogical methods over new technologies, though some studies found no such effect of experience on technology acceptance (e.g., Ghimire et al., 2024; Al-Riyami et al., 2023).

The fields of study themselves did not significantly moderate the relationship between digital competence and AI literacy, suggesting that the relationship was relatively general across higher education disciplines. This finding was unexpected given prior evidence of field-specific differences (e.g., Ghimire et al., 2024) but may reflect Hungary's unified digitalization efforts (Hungary's Artificial Intelligence Strategy, 2020). This aligns with broader efforts to integrate AI literacy into higher education teaching and learning, emphasizing the need for educators to develop AI competencies across disciplines (Chan, 2023).

The research contributes to the AI literacy literature by supporting the role of digital competence with large-scale, Hungarian-specific data and offering a new perspective on the moderating effects of gender and higher education experience. The context-dependent nature of the results underscores that the development of AI literacy does not require a uniform approach but rather a strategy that takes into account the specificities of the target groups (e.g., gender and scientific fields). The findings suggest that while the relationship between digital competence and AI literacy was broadly consistent across disciplines, context-specific factors like gender and experience played significant roles.

The results have several practical and theoretical implications. Firstly, the positive relationship between digital competence and AI literacy suggests that developing teachers' digital skills is crucial for integrating AI technologies into higher education. This is in line with the recommendations of the UNESCO AI Competency Framework (UNESCO, 2024), which advocates for the joint development of teachers' digital and AI-based competencies. Educational strategies that combine foundational digital pedagogy with targeted, hands-on AI activities—such as prompt-engineering tasks, workshops using AI-tools, or scenario-based ethical discussions—proves especially effective. To support long-term development and quality assurance, we recommend tracking AI literacy progression using a combination of standardized assessments—such as the AI/digital competency instruments employed in this study—and authentic artefacts like lesson plans or student work samples that demonstrate meaningful AI integration.

Secondly, the gender differences suggest that training programs aimed at increasing AI literacy should consider gender-specific needs. For example, programs focusing on increasing technological self-confidence for female teachers, while for men, deepening technical skills may be more effective. This suggests that when developing AI literacy, gender differences should be prioritized, while field-specific effects may be less critical given the consistent relationship observed across disciplines. This is particularly relevant in information technology and other technology-oriented fields, where gender differences were more pronounced.

Thirdly, the negative moderating effect of higher education experience warns that special support strategies are needed for experienced teachers. For example, targeted workshops or mentoring programs can help them keep up with the rapid development of AI technologies and integrate them into their pedagogical practice.

6. Conclusions

Our results indicated that digital competence was significantly and positively related to AI literacy, supporting the assumption found in international literature that digital skills play a fundamental role in understanding and integrating AI technologies into education (Long & Magerko, 2020; Kizilcec, 2023; Jantakun et al., 2021). Gender differences were particularly pronounced: the correlation between digital competence and AI literacy was stronger among male teachers, especially in information technology and other technology-oriented fields, while among female teachers, this relationship was weaker, particularly in the humanities, social sciences, and health sciences disciplines. However, some studies reported no significant gender effects (e.g., Berber et al., 2023; Xu et al., 2024), suggesting context-specific influences. Higher education experience also played a significant moderating role, with the relationship being weaker among more experienced teachers. Interestingly, age was not a determining factor, suggesting that in Hungarian higher education, the presence of digital competence supports the development of AI literacy to a similar extent across all age groups, despite mixed international findings where younger educators often show greater digital competence (e.g., Al-Riyami et al., 2023; Zhang & Villanueva, 2023).

The research contributes to the AI literacy literature by providing empirical evidence from a previously understudied population—Hungarian university teachers—and by refining the understanding of the role of digital competence in the context of technological transformation. The findings highlighted that the development of AI literacy does not require a one-size-fits-all approach but rather strategies tailored to the specific needs of target groups (e.g., gender and experience levels, with less emphasis on scientific fields given their consistent relationship). This aligns with the recommendations of the UNESCO

AI Competency Framework for teachers (UNESCO, 2024), which advocates for the joint development of teachers' digital and AI-based competencies.

Finally, the limitations of the research also provide guidance for future studies. The use of self-administered questionnaires may introduce bias, and due to the Hungarian context, the generalizability of the results may be limited to other cultural or educational systems. Further longitudinal research is needed to explore how AI literacy evolves, especially in a rapidly changing technological environment. Additionally, international comparative analyses could help contextualize the Hungarian-specific findings and compare them with global trends. Finally, to deepen the understanding of the relationship between AI literacy and digital competence, qualitative research—such as interviews or case studies—may also be warranted to uncover individual motivations and the role of contextual factors.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Károli Gáspár University of the Reformed Church in Hungary Institute of Psychology (BTK/8779/2023, 22 December 2023).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original data presented in the study are openly available in KREPOZIT (the digital commons of Károli Gáspár University of the Reformed Church in Hungary) at https://krepozit.kre.hu/handle/123456789/1641 (accessed on 23 November 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
TPACK	Technological Pedagogical Content Knowledge
UTAUT	Unified Theory of Acceptance and Use of Technology
RIM	Random Iterative Method
IRT	Item Response Theory
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Squared Residual
TLI	Tucker–Lewis Index
CFI	Comparative Fit Index
CFA	Confirmatory Factor Analysis
AIC	Akaike Information Criterion
BIC	Bayes Information Criterion
SD	Standard Deviation
SE	Standard Error
LLCI	Lower Limit of Confidence Interval
ULCI	Upper Limit of Confidence Interval
DC	Teachers' Digital Competence

Texp	Teaching Experience in Years
AI-Lit	AI-Literacy
Field	Field of Education
Gndr	Gender
Age	Age of Teachers in Years

Appendix A

Table A1. Descriptive item statistics for the AI literacy items.

Item	Item Label	Difficulty index	Difficulty Index Corrected for Guessing	Discrimination Index
01	Understanding intelligence 1	0.830	0.773	0.310
02	Understanding intelligence 2	0.858	0.811	0.267
03	AI's strengths and weaknesses 1	0.337	0.116	0.292
04	AI's strengths and weaknesses 2	0.328	0.104	0.300
05	Recognizing AI 1	0.277	0.035	0.297
06	Recognizing AI 2	0.675	0.566	0.420
07	Human influence 1	0.346	0.128	0.297
08	Human influence 2	0.401	0.201	0.351
09	Learning from data 1	0.801	0.735	0.429
10	Learning from data 2	0.440	0.253	0.406

Table A2. Model fit indices.

Model	M2/df	RMSEA	SRMR	TLI	CFI	AIC	BIC
Rasch	4.629	0.057	0.064	0.821	0.825	12,444.79	12,490.04
2-PL	4.923	0.060	0.054	0.807	0.850	12,440.17	12,525.65
3-PL	2.060	0.030	0.047	0.948	0.971	12,451.42	12,577.12

Table A3. Merging of educational fields.

Field Before Merging	Field After Merging	Field ID
Political science Law	Political and Legal Sciences	1
Humanities Social Sciences Teacher Training	Humanities, Social Sciences, and Teacher Training	2
Economics	Economics	3
Theology Arts, Art Mediation	Theology and Arts	4
Information Technology	Information Technology	6
Engineering, Agricultural Sciences	Engineering, Agricultural Sciences	8
Medical and Health Sciences Sports Science	Health Sciences	11
Natural Sciences	Natural Sciences	15

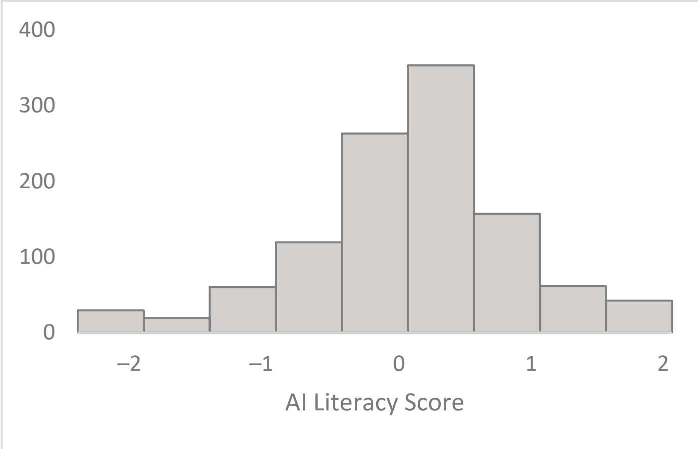

Figure A1. The distribution of IRT-estimated AI literacy in the sample.

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ARTICLES FOR UTM SENATE MEMBERS

“AI and the transformation of education”

TITLE	SOURCE TITLE
7. AI-driven educational transformation in ICT: Improving adaptability, sentiment, and academic performance with advanced machine learning (2025)	PLoS ONE (Article from : Public Library of Science)

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RESEARCH ARTICLE

AI-driven educational transformation in ICT: Improving adaptability, sentiment, and academic performance with advanced machine learning

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Abstract

This study significantly contributes to the sphere of educational technology by deploying state-of-the-art machine learning and deep learning strategies for meaningful changes in education. The hybrid stacking approach did an excellent implementation using Decision Trees, Random Forest, and XGBoost as base learners with Gradient Boosting as a meta-learner, which managed to record an accuracy of 90%. That indeed puts into great perspective the huge potential it possesses for accuracy measures while predicting in educational setups. The CNN model, which predicted with an accuracy of 89%, showed quite impressive capability in sentiment analysis to acquire further insight into the emotional status of the students. RCNN, Random Forests, and Decision Trees contribute to the possibility of educational data complexity with valuable insight into the complex interrelationships within ML models and educational contexts. The application of the bagging XGBoost algorithm, which attained a high accuracy of 88%, further stamps its utility toward enhancement of academic performance through strong robust techniques of model aggregation. The dataset that was used in this study was sourced from Kaggle, with 1205 entries of 14 attributes concerning adaptability, sentiment, and academic performance; the reliability and richness of the analytical basis are high. The dataset allows rigorous modeling and validation to be done to ensure the findings are considered robust. This study has several implications for education and develops on the key dimensions: teacher effectiveness, educational leadership, and well-being of the students. From the obtained information about student adaptability and sentiment, the developed system helps educators to make modifications in instructional strategy more efficiently for a particular student to enhance effectiveness in teaching. All these aspects could provide critical insights for the educational leadership to devise data-driven strategies that would enhance the overall school-wide academic performance, as well as create a caring learning atmosphere. The integration of sentiment analysis within the structure of education brings an inclusive, responsive attitude toward ensuring students' well-being and, thus, a caring educational environment. The study is closely aligned with sustainable ICT in education objectives and offers a transformative approach to integrating AI-driven insights with practice in this field. By integrating notorious ML and DL methodologies with educational challenges, the research puts the basis for future innovations and technology in this area. Ultimately, it contributes to sustainable improvement in the educational system.

Introduction

In an era defined by rapid technological advancements, one of the most promising innovations is the application of machine learning (ML) in various fields [1]. learning, a subset of AI, empowers computers to learn from information and make decisions without being expressly programmed. Its potential to revolutionize industries is evident in sectors like healthcare, finance, and marketing. However, despite the increasing adoption of ML analytics, further research is needed to understand the specific application of the different methods and how they can be used to solve multifaceted problems facing education systems, learning personalisation, performance prediction and adaptive learning environments. Also, most solutions are limited to normal or local scenarios. In addition, few studies delve into global adoptions of ML solutions or the legal requirements that must enforce the implementation of such solutions. These predispositions have not gained sufficient attention in the existing literature, even though they remain critical in cross-cultural and cross-institutional settings, including those that involve international online learning, such as the COIL program, given the different educational and emotional issues likely to emerge.. The amalgamation of machine learning techniques and educational practices holds the promise of reshaping the landscape of learning and pedagogy, offering personalized experiences, refined assessments, and improved outcomes. Machine learning algorithms, driven by patterns and insights extracted from data, are designed to recognise complex relationships and adapt over time. They analyze large datasets to uncover trends, identify correlations, and predict future outcomes. In the context of education, ML algorithms can be trained on enormous student data, encompassing factors such as learning styles, performance history, and engagement metrics. This data-driven approach provides educators and institutions with actionable insights that can be used to tailor instructional methods to individual student needs and preferences. Traditional education systems have often struggled to address the diverse learning profiles of students within a single classroom. This is where machine learning steps in, offering adaptability as a core advantage [2]. Adaptability entails the ability to customize learning experiences to suit each student's pace and comprehension level. Machine learning algorithms can evaluate a student's progress and learning trajectory, identifying areas of difficulty and adjusting the curriculum accordingly [3]. This customized approach improves understudy commitment as well as advances a more profound comprehension of the topic.

Sentiment analysis is a potent branch of machine learning entailing the deciphering of human emotions and opinions from written text [4]. Having sentiment analysis integrated within the education system can immensely help to determine what students are doing, engaging in, and understanding about the study matter [5]. By analyzing written assignments, forum posts, and feedback from students, sentiment trends can be analyzed for potential problems, and from there it becomes very easy to intervene with the right support quite early enough to save the situation. This proactive approach contributes to a holistic learning environment that would cater to not only academic growth but also emotional and psychological needs [6]. Another aspect of machine learning, predictive analytics, can have a pivotal role in promoting better academic achievement [7]. Predictive analytics algorithms, through historical data and performance indicators, can predict student outcomes and those who are likely to underperform. An educator can intervene at the early stage, giving extra guidance and resources to the student who needs it. Institutions can also use this information to help develop and give improved tailored curricula, techniques of teaching, and placement of resources [8]. The integration of machine learning into education is an evolutionary process that will revolutionize how both students learn and educators teach. Flexibility in the customization of every student's learning needs is provided through machine learning, coupled with sentiment analysis to enable a holistic understanding of the state of emotions. Predictive analytics empowers institutions to provide proactive support for students and further fine-tune their educational strategies. It showcases the great potential to create a more inclusive, effective, and student-centred education system where adaptability, sentiment analysis, and academic excellence come into view from the eyes of machine learning [9]. As we delve into the realms of this technological revolution in education, it becomes clear that the journey is only beginning. The cited references shed light on the evolving landscape of education infused with machine learning techniques. By studying these pioneering works, educators, researchers, and policymakers can collectively harness the potential of machine learning to foster a new era of learning that prioritizes personalization, emotional well-being, and academic success. The notation guide of each algorithm and additional abbreviations is shown in "Table 1".

The rest of the paper is ordered as follows: Related Work Section mentions the literature review. The proposed methodology is discussed in the Research Methodology Section. Machine Learning Model Development explains the various ML models details followed by Model Training and Evaluation Section to describe the details of models training and evaluation. Finally, the results and discussion are elaborate in Results and Discussion Sections, respectively.

Motivation

The motivation behind this study stems from the pressing need to advance educational practices through innovative technologies. As education systems increasingly integrate technology, there is a growing demand for methods that not only enhance academic performance but also address the evolving needs of students and educators. The following key motivations guided this research:

Table 1. Notation guide.

S/N	Notations	Description
1	ML	Machine Learning
2	EDA	Exploratory Data Analysis
3	KNN	k-Nearest Neighbors
4	RF	Random Forest
5	DT	Decision Tree
6	NB	Naïve Bayes
7	XGB	XGBoost
8	NN	Neural Network
9	ANN	Artificial Neural Network
10	SVM	Support Vector Machine
11	EVF	Evimp Functions
12	CART	Classification and Regression
13	PEM	Proposed Ensemble Model

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- **Improving Educational Outcomes**: Traditional educational methods often struggle to keep pace with the diverse and dynamic needs of students [59]. By harnessing advanced machine learning and deep learning techniques, this study aims to provide more accurate, data-driven insights that can significantly improve academic outcomes and personalize learning experiences.
- **Enhancing Teacher Effectiveness:** Educators face the challenge of adapting their teaching strategies to cater to the varied needs of students [60]. This research seeks to support teachers by providing tools that enable more precise assessments of student adaptability and performance, thereby enhancing instructional effectiveness and enabling more targeted interventions.
- **Supporting Educational Leadership**: Educational leaders require data-driven strategies to make informed decisions that impact school-wide academic performance and the overall learning environment [61]. This study provides insights that can help leaders implement effective, evidence-based strategies to improve educational outcomes and foster a supportive learning atmosphere.
- **Focusing on Student Well-Being**: Recognizing the importance of student well-being, this research incorporates sentiment analysis to better understand and address students' emotional and psychological needs. By doing so, it aims to create a more responsive and supportive educational experience that contributes to students' overall well-being and engagement.
- **Advancing Sustainable ICT in Education**: As the integration of ICT in education grows, there is a need for sustainable and impactful applications of technology [62]. This study aligns with the goals of sustainable ICT by exploring innovative AI-driven approaches that offer long-term benefits for educational improvement and adaptation.

These motivations collectively drive the research, aiming to leverage machine learning and deep learning to transform education into a more effective, personalized, and supportive experience for all stakeholders involved.

Related work

ML is a powerful tool that has the potential to transform and revolutionize almost all industries, and education is no exception. This paper tries to draw a roadmap of various ways in which machine learning techniques have been used to transform and enhance education [10]. Bringing ML to education has increased its personalization of learning [11], intelligent tutoring systems [12], analysis of educational data [13], and prediction of student performance [14].

In [15], the author presents ten compelling use cases that demonstrate how machine learning can be employed in a practical setting in education. From personalized learning paths and adaptive assessments to systems that recommend intelligent content for students and even systems for early predictions of student performance, examples are demonstrated to illustrate how machine learning can change traditional educational methodologies. With the help of machine learning algorithms, the learning experience can now be individualized to each student's needs, which is bound to make the experience more engaging and, therefore, the learning performance better. Personalized learning, one of the key concepts in contemporary education, has been enhanced to a great extent by the ML models described by the author in [16]. Learning examples and tendencies from each enable ML models to personalize content and delivery approaches within special care for the learning style of every student, increasing engagement and understanding and leading to improved learning outcomes. Intelligent tutoring systems apply ML to deliver real-time, personalized guidance to help students understand complicated concepts and consolidate weak areas [7]. The data generated through online platforms, assessments, and interactions are huge. The ML techniques analyze this data to obtain insights into student behavior, preferences, and progress. It is this data-driven approach that drives educators to make necessary data-informed adjustments in curriculum and teaching methodologies.

In [14], the author talks about how ML also plays a pivotal role in predicting student performance. By analyzing historical data, demographic factors, and academic indicators, ML models can forecast students at risk of underperforming. Early intervention strategies can then be employed to provide timely support, reducing dropout rates and fostering academic success. Moreover, ML techniques are facilitating the development of smart content recommendation systems [13]. These systems suggest supplementary materials such as articles, videos, and exercises that align with the student's current topics of study. This encourages self-directed learning and broadens students' understanding of subjects. The Author in [17], delves into the current state of utilizing machine learning techniques within the context of educational metaverses, and investigates the extent to which machine learning has been integrated into educational metaverse platforms. Educational metaverses encompass virtual and augmented reality environments designed for educational purposes. The authors likely examine the challenges, advancements, and potentials of employing machine learning algorithms to enhance the interactivity, personalization, and overall effectiveness of educational experiences within these immersive virtual environments. However, the integration of ML into education is not without challenges. Issues such as data privacy, algorithmic bias mentioned in [18], and the digital divide must be carefully addressed to ensure equitable and ethical use of ML in education. ML is reshaping the educational landscape. While challenges exist, the benefits of enhanced learning outcomes and tailored educational experiences make the incorporation of ML an essential avenue for the future of education. The idea of versatility has arisen as a critical power driving the change in training, particularly with regard to computerized time. Lately, the worldwide instructive scene has gone through exceptional changes because of the Coronavirus pandemic. Institutes, teachers, and students had to quickly embrace new advancements and educational ways to deal with guarantee continuity in learning [19,20]. The pandemic highlighted the significance of adaptability in education, with institutions and individuals embracing remote learning platforms such as Zoom and Microsoft Teams as quoted by the author in [21].

This sudden move required adjustments in teaching approaches to make them compatible with the online setting without compromising learning outcomes this view is supported by [22]. Also illustrating the difficulty and triumphs of both educators and learners is [23] and [24]. The point being made was that adaptability was key. Education adaptability It goes beyond the pandemic and includes changes such as modernizing lessons in brick-and-mortar schools to include technology [25]. These investigations focus on important characteristics of technological support for learning. In[63], the authors investigate the effects of technostress on learning environments and performance in order to point out the problems observed among learners. In [64], the authors examine the trend towards development of policy for AI use in higher education, to describe policy requirements for AI regulation. In International online learning, [65] posited self-regulation as a mediator between emotional intelligence and student performance in learning from Latin American universities. Together, these works underscore the need to grasp the psychological, regulating, and technical substrates of the contemporary educational process and, in particular, distance and blended learning.

Adaptive learning systems, for example, as presented in [26], personalize the delivery of content regarding the progress and learning style of individual students. Such systems serve as an example of how adaptability optimizes the learning process itself, based on what every pupil may need for enhanced engagement and comprehension. This concept embraces lifelong learning, evidenced by [27], highlighting the importance of preparing students to fit into an ever-changing job market. This new paradigm requires that educational institutions impart to learners the skills of adaptability—how to acquire new knowledge and competencies during their careers. The transformative potential of adaptability also aligns with competency-based education, as detailed in [28]. This approach emphasizes skill acquisition over traditional course completion, empowering learners to progress at their own pace and demonstrating mastery before advancing Adaptability has emerged as a hallmark of transforming education in the digital age. Having been realized through adaptation to remote learning during COVID, it has shown the need for pedagogical flexibility and technology infusion [19,20].

Various studies state that adaptability allows us to survive not only in difficult situations but also to improve the quality and effectiveness of education in both traditional and virtual environments. The education evolution will continually be sculpted by the ability of institutions, educators, and learners to embrace change to lend adaptability for better learning outcomes. Sentiment analysis in educational applications is an emerging sub-field of natural language processing that has the potential to help redefine learning. This paper sets out to provide an exhaustive review of how sentiment analysis techniques are applied in the revolution of education toward the capturing and analyzing of emotions, attitudes, and opinions by learners, educators, and stakeholders [29]. Sentiment analysis technology has opened novel avenues to understand the emotional states of learners, as elaborated in references [30,31]. Gauging students' reactions towards learning materials is done by sentiment analysis algorithms of written or verbal expressions to be aware of the engagement level and confused topics. This real-time feedback mechanism allows educators to tweak their teaching strategies to better fit the needs of the students, both emotionally and cognitively. Also, from [32] and [22], this sentiment analysis changes methodologies of assessments. In trying to find out how students feel or perceive certain learning engagements, there has always been a loophole in traditional assessments [33]. For instance, sentiment analysis provides non-intrusive ways of understanding students' feelings towards exams, assignments, and coursework, helping educators design more inclusive and effective evaluation methods. Institutions are using sentiment analysis to enhance student well-being [34]. Works such as [35] and [36] exemplify that sentiment analysis through social media monitoring can be used in detecting students' emotional struggles, enabling the support units to take action promptly. Such proactivity helps in creating a better learning environment for the students. Sentiment analysis has also been shown to be effective during personalized learning journeys, such as in the cases presented by [37] and [38]. Sentiment analysis through algorithms could assist by suggesting appropriate learning resources for students based on their emotional states and learning preferences, thereby helping learners stay motivated and engaged in their educational journey.

Institutions are using sentiment analysis to enhance student well-being [34]. Works such as [35] and [36] exemplify that sentiment analysis through social media monitoring can be used in detecting students' emotional struggles, enabling the support units to take action promptly. Such proactivity helps in creating a better learning environment for the students. Sentiment analysis has also been shown to be effective during personalized learning journeys, such as in the cases presented by and [38]. Sentiment analysis through algorithms could assist by suggesting appropriate learning resources for students based on their emotional states and learning preferences, thereby helping learners stay motivated and engaged in their educational journey. Institutions are using sentiment analysis to enhance student well-being [34]. Works such as [35] and [36] exemplify that sentiment analysis through social media monitoring can be used in detecting students' emotional struggles, enabling the support units to take action promptly. Such proactivity helps in creating a better learning environment for the students. Sentiment analysis has also been shown to be effective during personalized learning journeys, such as in the cases presented by [37] and [38]. Sentiment analysis through algorithms could assist by suggesting appropriate learning resources for students based on their emotional states and learning preferences, thereby helping learners stay motivated and engaged in their educational journey.

However, sentiment analysis in education faces challenges from the contextual sensitivity of linguistic nuances [29]. The validation of truthfulness and fairness of sentiment analysis models, which is discussed in [29] and [32], is important to avoid algorithmic bias and hence ensure fair outcomes. This has therefore brought ML into convergence with a framework of education, which offers adaptive systems on how to infer sentiment analysis for good academic performance. This is an all-encompassing review describing this symbiotic relationship, which demonstrates how on a cumulative basis it reshapes the landscape of education [39]. Machine learning has brought adaptive learning models [40] for personalized education, where learning pathways can be variant and adapted according to the pace, preference, and strength of the learners. It is done through real-time sentiment analysis [41], which models the emotional status of learners [42]. Sentiment analysis, in turn, further boosts adaptability through tracking students' engagement, confusion, and motivation [43], [44]. By gauging the students' sentiments, the educators can timely intervene and customize the learning experience for maximum efficacy [45]. This transformative power is in the area of academic excellence as well [46], in which the synergy of adaptability, sentiment analysis, and machine learning sparks pre-emptive measures. Analytic predictive algorithms forecast the performance of students, identifying at-risk underperforming students [47]. Through sentiment analysis, references [48] and [36] demonstrate how affective data inform the design of interventions aimed at improving academic support strategies and thereby increasing student success. As further evidence of this connection between academic success and adaptability, competency-based education has entered the learning environment [49]. Sentiment analysis can be used to detect whether a flexible approach to learning is working for students so that refinements may be made accordingly to achieve optimum success. Further, sentiment analyses will allow institutions to make adjustments in content, pacing, and support systems to achieve higher engagement and attainment [50]. However, there are still some challenges: It thus becomes very important that the sentiment analysis model learns context and nuances [41], as biases may influence the accuracy of emotional assessments [51]. These ethical considerations highlighted in reference [52] point to responsible machine learning integration, mitigating privacy issues and algorithmic biases. Sentiment analysis is, according to Vasilis Bourikas (2023), the most considerable factor in increasing student engagement and building resilience in higher education. It can act as a good tool for identifying those students who are struggling and providing help custom-made to their needs, building good coping methods [53]. In "Machine Learning in Education: How to Boost Efficiency," Fayrix (2022) deals with the application of machine learning for online education efficiency. The essay goes in-depth about how machine learning can potentially improve personalization in material and the ability for larger and further reach, speed up processes, and lift ROI [54,55]. Itransition (2022) explores the various implementations of machine learning in education in an article titled "ML in Education: 10 Use Cases, Technologies, Benefits, and Barriers." The latter discusses ten different applications, among which are personalized learning, new assessment methodologies, and recommendation systems. In "The Impact of Artificial Intelligence on Learning, Teaching, and Education," the European Commission of 2021 has deeply explored the potential effects of the application of AI on education. The present paper explores how AI can support teaching and learning, also by tackling the challenges on the way toward the full realization of its benefits [56].

Another study focuses on sentiment analysis to further advance student learning [57]. Therefore, the current paper checks for the use of sentiment analysis in identifying underperforming students, providing targeted support, and tracking the academic progress of those students. Another paper [58] underscores the transformational potential of machine learning in education. It emphasizes AI that provides personalized growth opportunities designed to articulate the needs and weaknesses of students individually. In conclusion, it is this combination of machine learning, adaptivity, sentiment analysis, and academic brilliance that makes possible an educational ecosystem pulsating with dynamism. These elements will enrich personal learning journeys, harness emotional insights to predict outcomes, and further better the quality, inclusivity, and efficacy of education using this transformational framework. The future is in harmonizing these elements into a holistic learning environment that takes care of diverse needs and aspirations.

Research methodology

The research method of our study is a step-by-step process that follows the achievement of our research objectives. It starts with the data exploration stage, in which an education dataset that meets the criteria of our research is identified. Subsequently, this research merged various sources of data into an enriched dataset. The preprocessing of data involved data cleansing, handling missing values, and standardization of the format. After performing this preprocessing step, we train Deep Learning classifiers, followed by their assessment of whether or not they have produced predictive accuracy. In parallel, feature engineering was performed to increase the importance of dataset variables. A partitioning resulted in a 75-25 train-test split that allowed the following application of Machine Learning classifiers. The models have been very trained and closely measured for their accuracy and effectiveness. This methodology reflects a comprehensive approach, spanning dataset exploration, aggregation, preprocessing, DL, and ML techniques, culminating in a robust evaluation within the educational context as also shown in Fig 1.

Data collection and preprocessing

The dataset employed in this study comprises information concerning students' adaptability, sentiment analysis, and academic excellence. The dataset encompasses a total of 1205 entries, each characterized by 14 attributes, including gender, age, education, organization type, IT pupil status, area, load-shedding, monetary condition, web type, network type, class term, self-learning the executive framework utilization, gadget utilized, and adaptivity level. Before starting examinations, data preprocessing methods were executed to deliver the dataset appropriate for ML algorithms. Missing values were examined, revealing no instances of missing data within the features. Categorical attributes were numerically encoded, while the "Adaptivity Level" feature was transformed into numerical values, with categorical labels "Low," "Moderate", and "High" replaced by 0, 1, and 2, and for the sentiment analysis, positive and negative sentiments respectively.

Continuous variables are those that can take on any value in a specified range and are measured on a scale. In this study, we included the age which is actually a numerical value that can vary continuously. Another continuous variable is the class duration, which measures the length of online classes usually in minutes or hours. Another continuous variable is financial condition, as it represents the condition of the financial status of the student and also

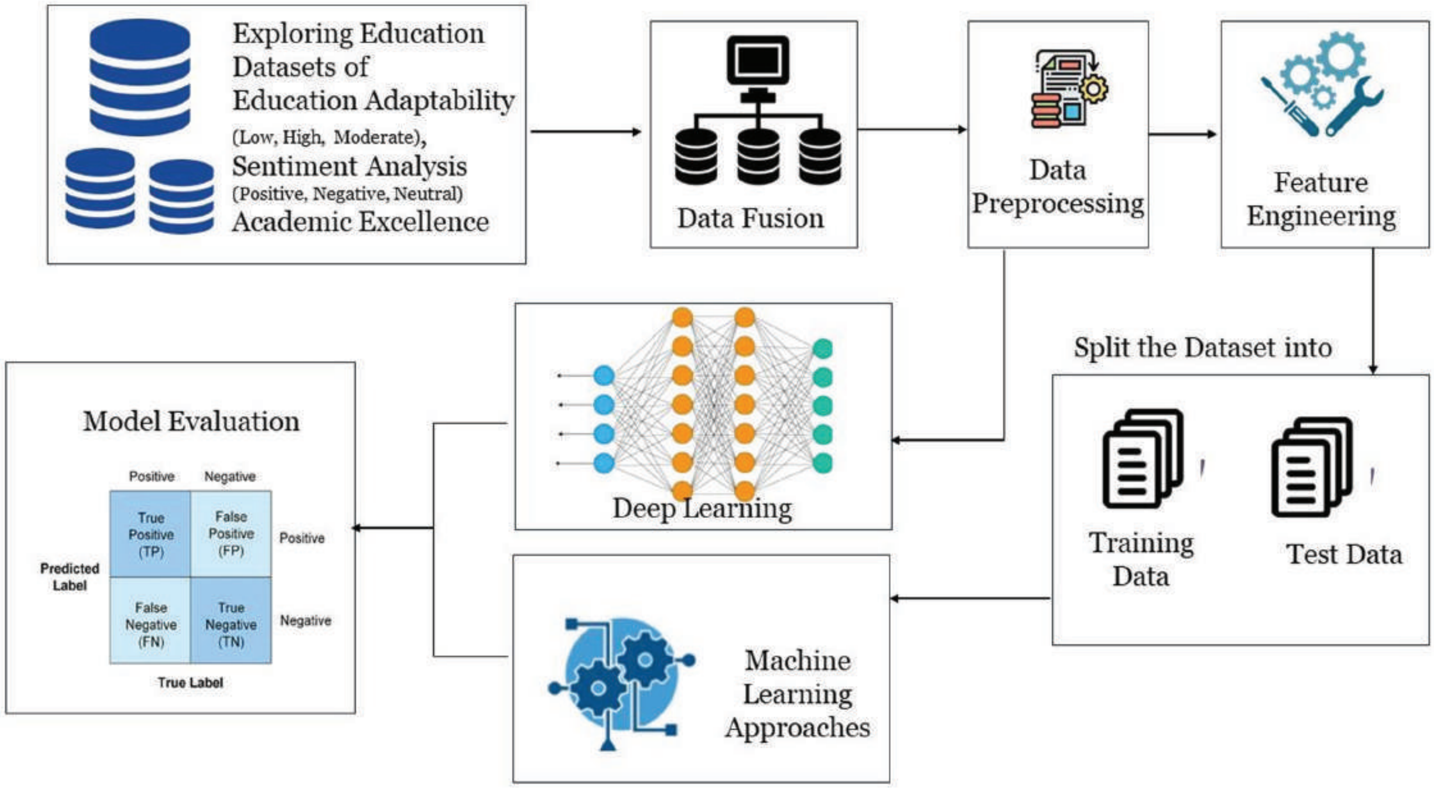

Fig 1. Exploring education through artificial intelligence proposed methodology.

https://doi.org/10.1371/journal.pone.0317519.g001

can be quantified through an income level or score of financial stability. Self-LMS usage represents another continuous variable because it tracks the number of hours a student uses self-learning management systems every week. There is yet another continuous variable: internet speed, measured in megabits per second (Mbps), which might change from student to student. On the contrary, **categorical variables** are those that represent distinct groups or categories that cannot be measured on a numerical scale. Such variables help to classify the students into various groups for the analysis. For example, gender forms a categorical variable that categorizes the students into different groups such as Male, Female, or Other. Another categorical variable is the education level of the student, indicating whether the student is in school, college, or university. Institution type, on the other hand, distinguishes between public and private institutions of educational institutions. The variable IT student determines whether a student is pursuing an IT-related course of study, categorized as yes or no. Location refers to whether the student lives in an urban or rural area, whereas load shedding reports whether the student suffers from power cuts frequently, which is referred to as Yes or No. The Network type variable, differentiates between internet connections like Mobile Data or Broadband, whereas the Devices used category differentiates the types of devices that the student utilizes for online learning including Smartphones, Laptops, or tablets. Adaptability level is a categorical variable; that is, it classifies the group of students into Low, Medium, and High categories according to their adaptability to online education. With regards to the explicit and explicit description of continuous and categorical variables, the research study lays out the different categories of data to be analyzed and how they contribute to understanding factors that influence the adaptability of the students and their academic achievement.

Exploratory data analysis (EDA)

Before model development, an exploratory data analysis (EDA) was performed. Descriptive statistics, including means, standard deviations, and quantiles, were computed to glean insights into attribute distributions. Various visualizations, such as bar plots, histograms, and scatter plots, were generated to visualize the characteristics of categorical and continuous variables. As shown in Fig 2(a) and Fig 2(b) most of the students either it's a boy or a girl prefer the Mobile platform for online education instead of Laptops/computers and they use cellular data. This thing clearly illustrates that they are not attaining the education attentionally. They go through it like an ordinary process, using the cell phone along travel anywhere, would be helpful but the alarming situation is that their number (Students who are using the cellphone for online classes and using cellular data) is increasing rapidly instead of other students who are taking the classes form laptops/computer. Additionally, potential correlations between attributes were investigated through visual exploration.

Data splitting and standardization

The dataset was split into a training subset and a testing subset in a ratio of 75% for training and 25% for testing. The attributes were separated: input variable, X, from the target variable, "Adaptivity Level," y. To make the model converge and improve in performance, the input variables were standardized using the StandardAero from the scikit-learn library.

Correlation matrix

A correlation matrix is a statistical tool that computes the relationship between every variable in a dataset. These coefficients, demonstrate the direction and strength of linear association. It helps in identifying patterns and dependencies between variables, hence helping in feature selection or data exploration. Looking into the correlation matrix will dictate most aspects of data-driven decision-making in finance, scientific study, etc (Fig 3).

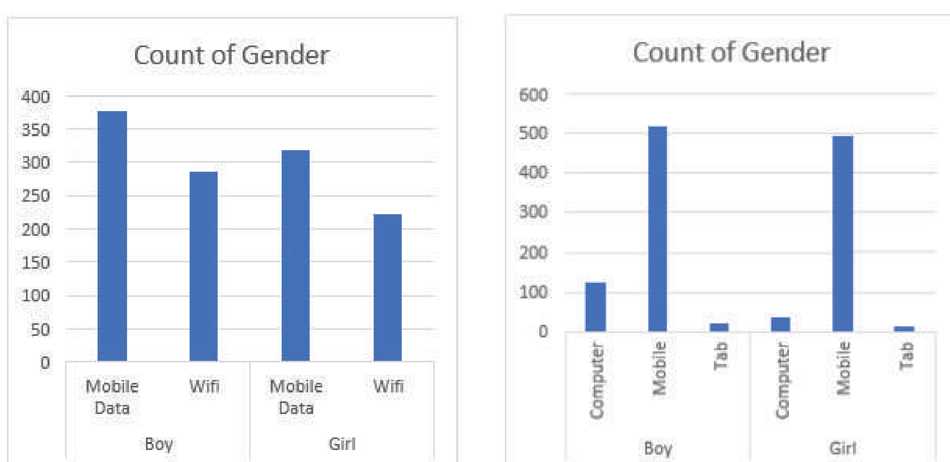

Fig 2. Visualizations comparing gender and Internet types.

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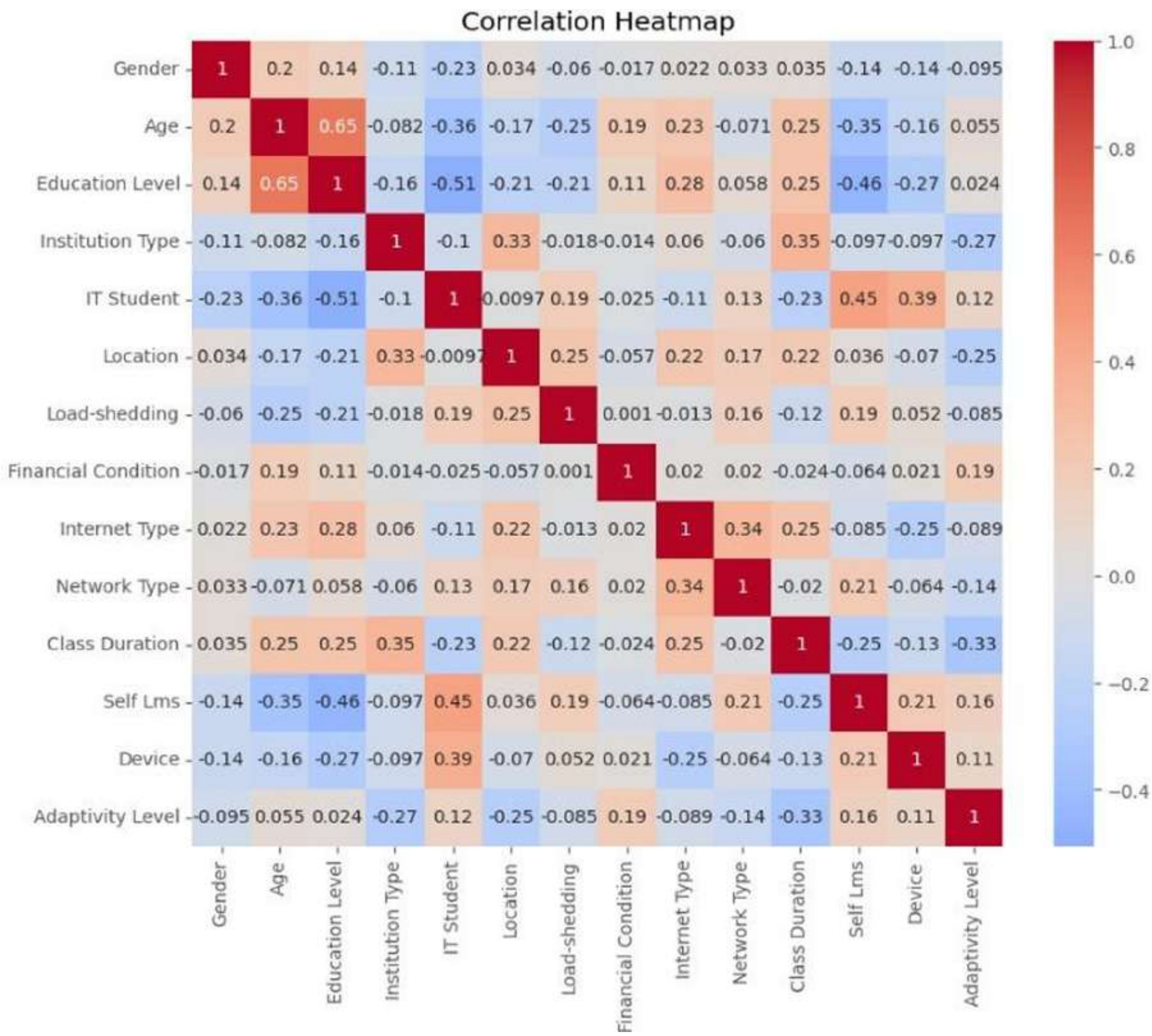

Fig 3. Correlation matrix.

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Machine learning model development

Diverse machine learning algorithms were employed for model development:

Convolutional neural network (CNN)

The present study employed the Convolutional Neural Network (CNN) to identify the influence of image-based attributes on change in education. Built purposely to discard complex spatial components in images, the CNN was suitable for uncovering visual factors associated with adaptability, sentiment analysis, and academic excellence in learners. In general, the basic architecture of the CNN is built upon convolutional layers, pooling layers, and fully connected layers that enable the presented architecture to extract important patterns and relationships within the visual data. The model was trained on the training dataset with an emphasis on minimizing a pre-assigned loss function as displayed in equation (1). Evaluation metrics, including precision and loss, were utilized to survey CNN's presentation. Fundamental outcomes showed an accuracy of 89%.

$$y = \text{argmax}_j \left(f(x;\theta)_j + \gamma g(x;\theta) \right) \tag{1}$$

Where:

The terms are the same as for CNN, with the addition of the g(x;θ) term, which controls the interaction between the CNN and the bounding boxes.

Recurrent convolutional neural network (RCNN)

Apart from this, the study used a recurrent convolutional neural network to detect temporal dependencies concerning spatial characteristics. In general, RCNN architecture incorporated the power of CNN and recurrent layers to give a complete scenario about students' adaptability, sentiment analysis, and academic excellence. It captured temporal dependencies along with the spatial characteristics of the sequences of images, considering their spatial characteristics through an RCNN, as shown in equation (2). A model was trained with a particular loss function used to minimize training. The evaluation metrics measured accuracy and loss to identify the RCNN's performance. The first observation was an accuracy of around 74%.

$$y = \text{argmax}_j f(x;\theta)_j \tag{2}$$

XGBoost

For this purpose, the XGBoost algorithm has been adopted. XGBoost is considered one of the best algorithms for the prediction of complex relationships in tabular data because it uses boosting. The sequential construction of decision trees exposes patterns responsible for the adaptability, sentiment analysis, and academic excellence of students as shown in equation (3). Trained over the training data, the XGBoost model has been evaluated using accuracy, precision, recall, F1-score, and others. The calculation shows around 88%.

$$h(x) = f(x) + \sum_{i=1}^{m} \beta_i \left[g(x;\theta_i) + \gamma_i h(x) \right] \tag{3}$$

Where:

The terms are the same as for gradient boosting, with the addition of the i term, which controls the interaction between the weak learners

Decision tree

The Decision Tree algorithm was applied to all the non-image attributes to make them interpretable. Decision Trees provide clear attribute relations from the straightforward decision paths, which influence the adaptability, sentiment analysis, and academic excellence of students. Equation (5) denotes how: Decision Trees were trained on a training dataset and then evaluated through accuracy metrics to get a clear understanding of their ability to make informed educational predictions based on interpretable rules. Preliminary results show a performance level of about 75%.

$$y = \text{argmax}_j \, p(y = j \mid x) \tag{4}$$

Random forest

Working from the Decision Trees concept, the Random Forest algorithm leveraged the collective intelligence of several trees in its extension. That is to say, it generated several decision trees with slight variations and captured different perspectives on the influences that shape adaptability, sentiment analysis, and excellence in academics for the students. The ensemble nature of the algorithm ensures that the predictions are robust because it mitigates overfitting and accounts for a variety of attribute interactions, as in equation (6). Random Forests were applied to the training and testing datasets, respectively, and an accuracy of about 73% was recorded.

$$y = \frac{1}{n}\sum_{i=1}^{n} h_i(x) \tag{5}$$

Stacking approach

In analyzing non-image attributes, by applying the stacking hybrid approach DT, RF, XGBoost as a base model and the Gradient Boosting algorithm as a meta-model was employed as shown in Fig 4.

This stacking approach sequentially builds using the base models DT, RF, and XGBoost to enhance predictions, as illustrated in equation (4). This allows an in-depth review of the intricate relationships impacting students' adaptability, sentiment analysis, and academic performance. The meta-model Gradient Boosting was trained and evaluated on the training dataset using indicative metrics to provide insights into its ability to capture complex attribute interactions. The accuracy of the first results was around 90%.

$$h(x) = f(x) + \sum_{i=1}^{m} \beta_i \left[g(x; \theta_i) \right] \tag{6}$$

Analysis

We experienced several algorithms concerning the proposed platform for their accuracy. We want to evaluate thoroughly to find out the most efficient algorithm that gives precise results and reliable outcomes. This would, in turn, help in fine-tuning the performance and reliability of the entire system.

Analyzing CNN

The confusion matrix in Fig 5 summarizes our model's performance across Low, Moderate, and High classes. It accurately predicted Low instances (113), Moderate instances (134), and

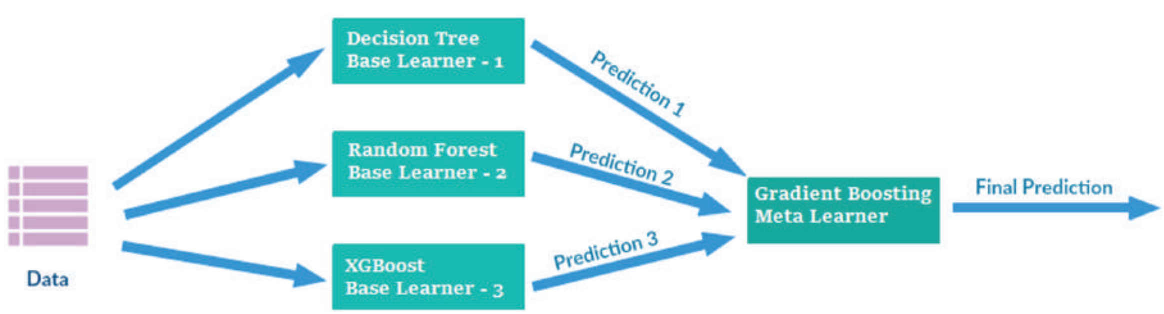

Fig 4. Architecture of the proposed stacked ensemble learning model, illustrating the use of three base learners (decision tree, random forest, and XGBoost) to generate predictions (Prediction 1, Prediction 2, and Prediction 3), which are then combined by a gradient boosting meta-learner to produce the final prediction. This approach leverages the strengths of individual models to enhance overall predictive accuracy.

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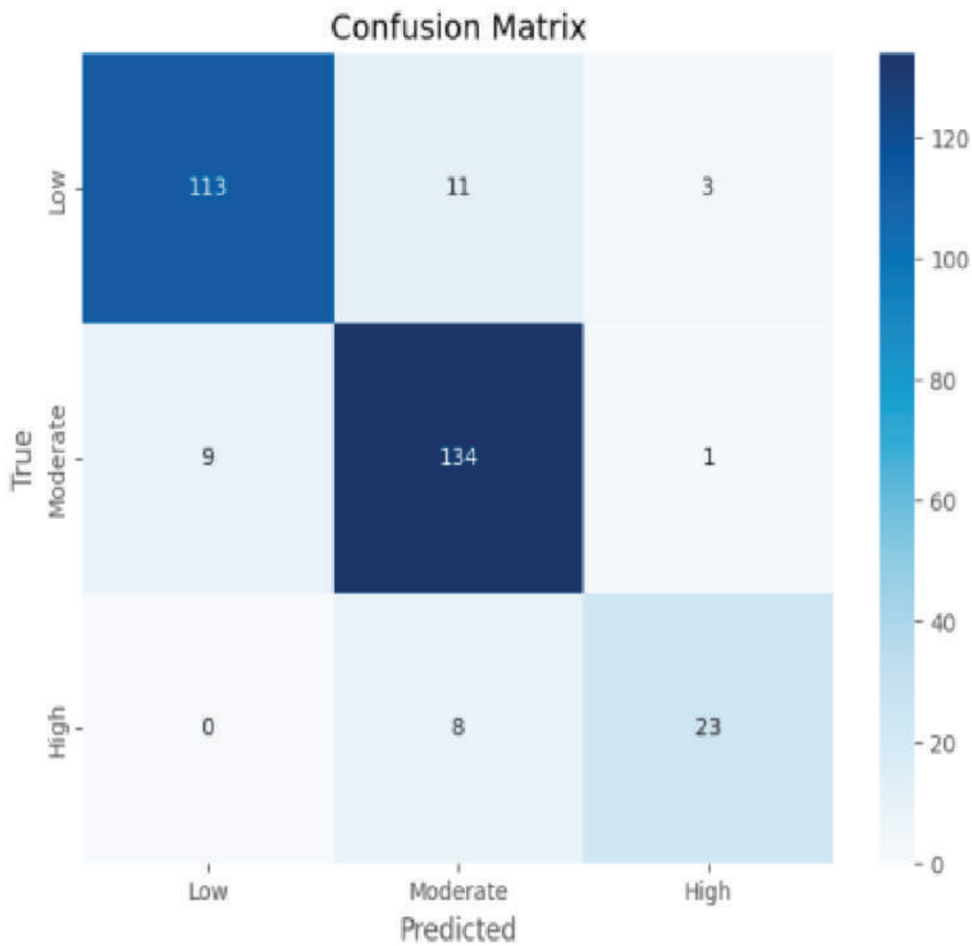

Fig 5. CNN model evaluation.

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High instances (23). However, misclassifications were observed: predicting Moderate as High (8), Low (11); predicting High as Moderate (1), Low (3); and predicting Low as Moderate (9).

Analyzing RCNN

Fig 6 demonstrates precision in predicting Low instances (117), Moderate instances (88), and High instances (24). However, some misclassifications emerged: predicting Moderate as Low (66), High as Moderate (5), and High as Low (2). These results provide insight into the model's.

Analyzing decision trees

Fig 7 demonstrates accuracy in predicting High instances (15), Moderate instances (107), and Low instances (105). However, a degree of misclassification emerged: predicting Moderate as High (13) and Low (20), and predicting High as Moderate (4) and Low (2). These findings accentuate the model's proficiency within each class, while also revealing areas where misclassifications occurred, particularly between Moderate and High classes, and in the Low class. This matrix serves as a comprehensive snapshot of the model's performance, illuminating its predictive prowess and areas warranting further scrutiny.

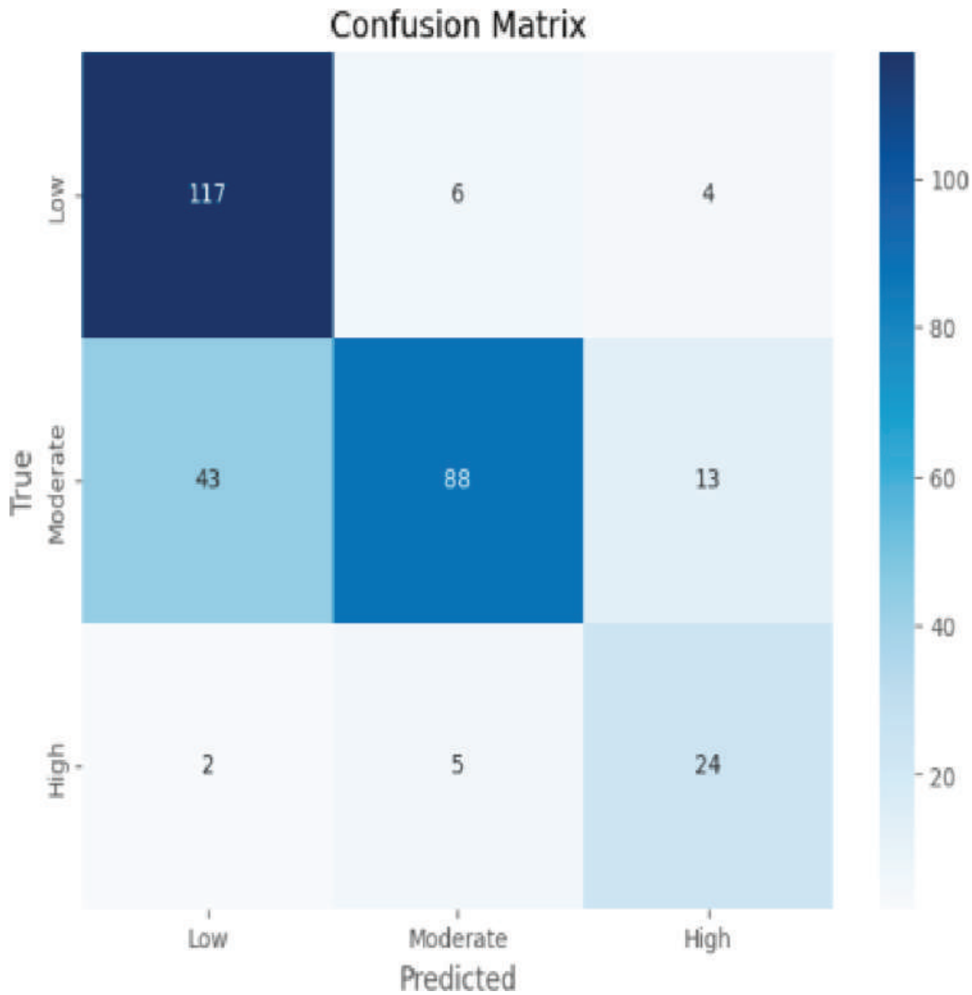

Fig 6. RCNN model evaluation.

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Analyzing stacking approach

Fig 8 demonstrates Predictions of "Low" were largely aligned with the true class (115 instances), although some instances were misclassified as "Moderate" (7 instances). For "Moderate" predictions, accuracy was evident within the class (137 instances), though misclassifications arose into "High" (10 instances) and "Low" (9 instances). Instances predicted as "High" demonstrated precision within the class (21 instances), while misclassifications were observed as efficacy within each class and shed light on instances where misclassifications occurred, particularly between Moderate and Low and High and Moderate classes "Low" (3 instances). This matrix encapsulates the model's performance trends across classes, shedding light on its strengths and misclassification patterns.

Analyzing XG boosting

Fig 9 Predictions of "Low" displayed alignment with the true class (113 instances), except for instances misclassified as "Moderate" (9 instances). For "Moderate" predictions, concordance within the class (135 instances) was prevalent, alongside misclassifications into "High"

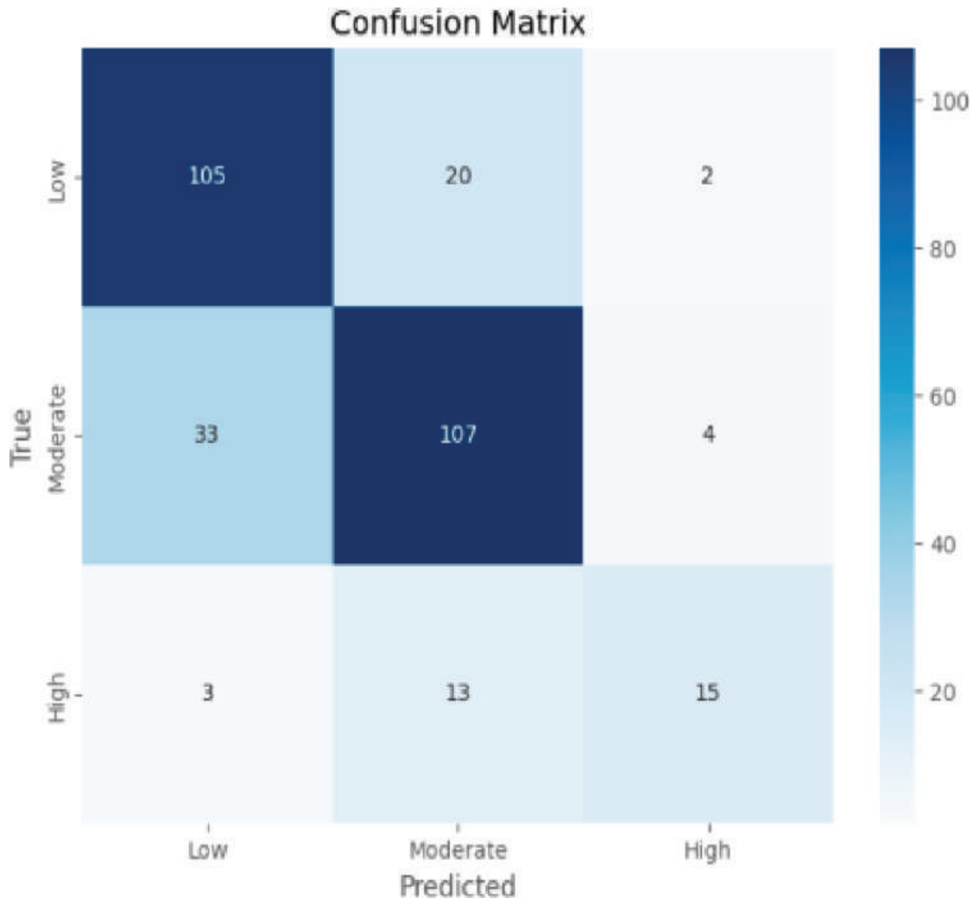

Fig 7. Decision tree evaluation.

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(12 instances) and “Low” (11 instances). Instances classified as “High” exhibited precision within the class (19 instances), but misclassifications emerged as “Low” (3 instances). This matrix encapsulates the model’s proficiency within these classes, spotlighting both its accurate predictions and areas warranting further attention.

Analyzing random forest

The confusion matrix in Fig 10 outlines our model’s predictions within the High, Moderate, and Low classes. Instances predicted as “Low” aligned with the true class (73 instances), though misclassifications arose as “Moderate” (5 instances). For “Moderate” predictions, precision within the class (139 instances) was evident, alongside misclassifications as “High” (21 instances) and “Low” (54 instances). Instances classified as “High” displayed precision (10 instances), with no misclassifications, yet this class was not predicted for “Moderate” or “Low.” This matrix encapsulates the model’s effectiveness across classes, emphasizing accurate predictions and areas warranting investigation.

Image and non-image attributes

For image-based attributes, convolutional neural networks (CNN) and recurrent convolutional neural networks (RCNN) were designed. CNN focused on extracting spatial features

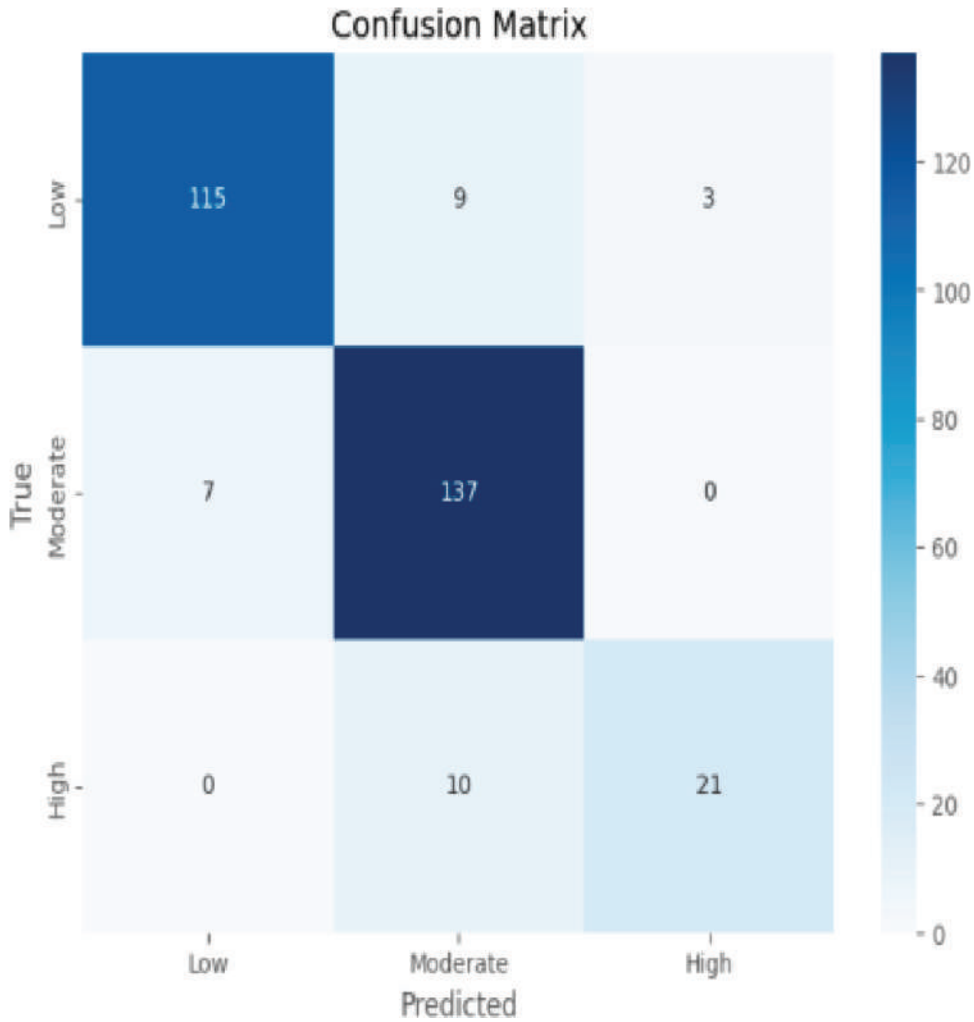

Fig 8. Stacking approach evaluation.

https://doi.org/10.1371/journal.pone.0317519.g008

from images, while RCNNs considered both spatial and temporal features. Ensemble techniques, including XGBoost, stacking Gradient Boosting meta-model, Decision Tree, and Random Forest, were employed for non-image attributes. These algorithms are renowned for their capability to capture complex relationships within data.

Model training and evaluation

Models were trained using the training dataset. CNN and RCNN models were trained on image-based attributes, while ensemble models were trained on non-image attributes. The training involved the optimization of respective algorithm-specific objective functions. Model evaluation encompassed diverse metrics appropriate to each algorithm: For CNN and RCNN: Evaluation metrics included accuracy and loss on the testing dataset. For ensemble models: Metrics such as accuracy, precision, recall, and F1-score were employed to gauge model performance.

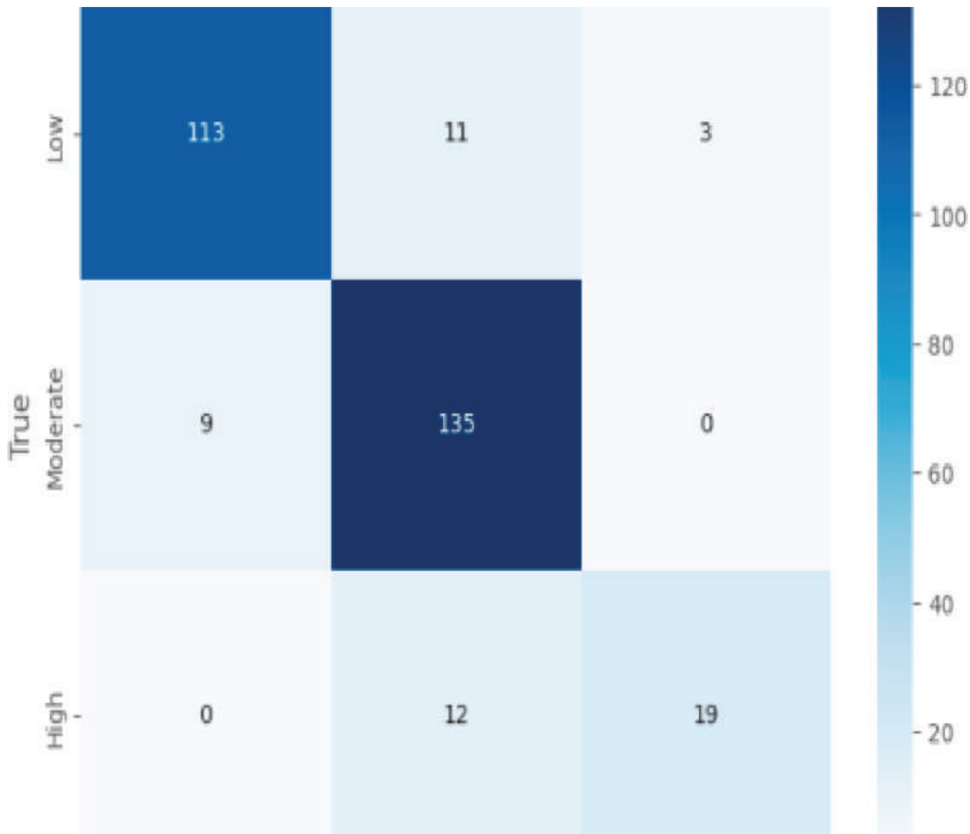

Fig 9. XG boosting evaluation.

https://doi.org/10.1371/journal.pone.0317519.g009

Results

In this section, we present the results of the machine learning (ML) and deep learning (DL) classifiers on various assessment parameters, including accuracy, recall, and F-measure. The performance of these classifiers is evaluated based on the precision of AI models in investigating instructional versatility, academic excellence, and sentiment analysis data. Among the classifiers evaluated, the Gradient Boosting Tree (GBT) outperformed others in terms of accuracy.

Parameters to be evaluated

Precision, accuracy, recall, and F-measure are the key evaluation metrics considered in this study to assess the performance of the ML classifiers, as shown in Table 2. The evaluation involves calculating the specificity (accuracy) and sensitivity (recall) for each classifier to analyze the predicted precision. The accuracy, precision, recall, and F-measure are derived using the following standard formulas:

Accuracy: The ratio of the number of correctly identified instances to the total number of instances in the dataset, as shown in Eq (7). The confusion matrix evaluation scores for CNN, RCNN, XGB, Decision Tree, Stacking approach, and Random Forest are shown in Figs 11-15.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \quad (7)$$

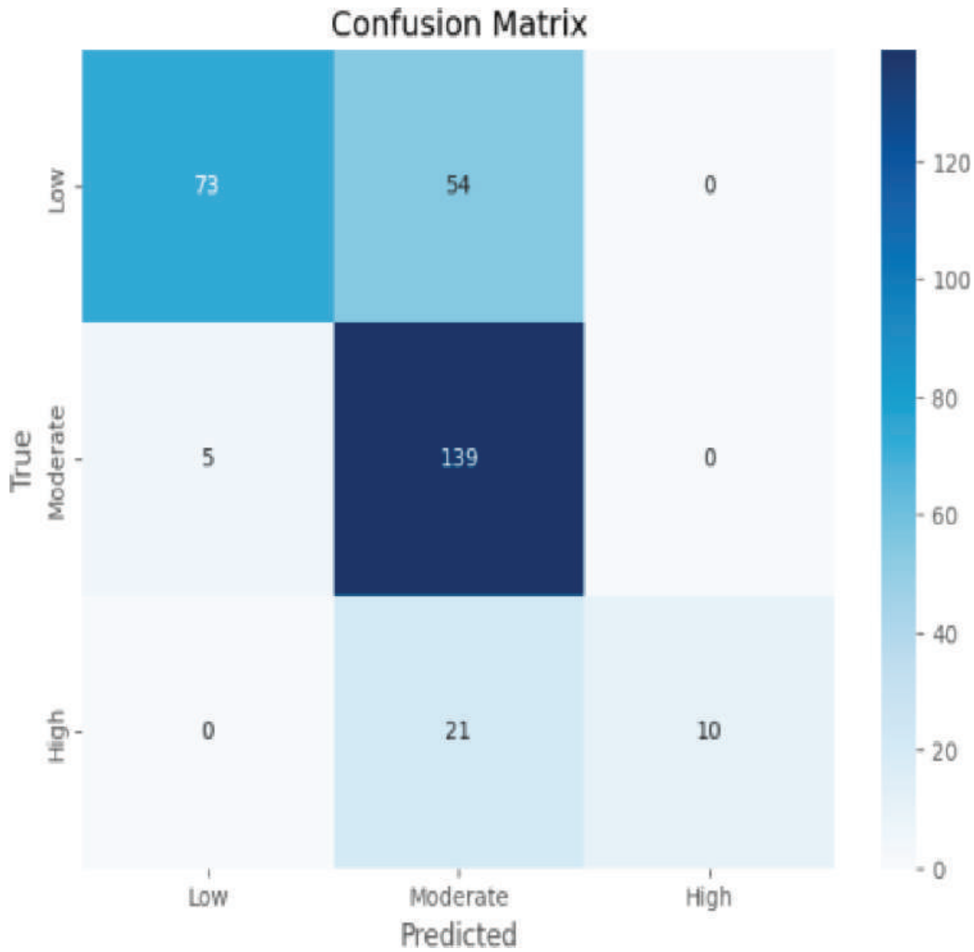

Fig 10. Random forest evaluation.

https://doi.org/10.1371/journal.pone.0317519.g010

Table 2. Accuracy of ML classifiers.

Classifiers	Accuracy	Precision	Recall	F-Measure
RF	73%	0.94	0.57	0.71
XGBoost	88%	0.93	0.89	0.91
Decision Tree	75%	0.74	0.83	0.78
Gradient Boosting	90%	0.94	0.91	0.92
RCNN	74%	0.72	0.92	0.81
CNN	89%	0.93	0.89	0.91

https://doi.org/10.1371/journal.pone.0317519.t002

Precision: The average probability of retrieving relevant information, as shown in Eq (8).

$$\text{Precision} = \frac{TP}{TP + FP} \quad (8)$$

Recall: The average probability of full retrieval, as shown in Eq (9).

Low		Moderate		High	
Recall	0.89	Recall	0.93	Recall	0.74
Precision	0.93	Precision	0.86	Precision	0.85
F1-Score	0.91	F1-Score	0.90	F1-Score	0.79

Fig 11. Confusion matrix evaluation of CNN.

https://doi.org/10.1371/journal.pone.0317519.g011

Low		Moderate		High	
Recall	0.92	Recall	0.61	Recall	0.77
Precision	0.72	Precision	0.89	Precision	0.59
F1-Score	0.81	F1-Score	0.72	F1-Score	0.67

Fig 12. Confusion matrix evaluation of RCNN.

https://doi.org/10.1371/journal.pone.0317519.g012

Low		Moderate		High	
Recall	0.83	Recall	0.74	Recall	0.48
Precision	0.74	Precision	0.76	Precision	0.71
F1-Score	0.78	F1-Score	0.75	F1-Score	0.58

Fig 13. Confusion matrix evaluation of XGB.

https://doi.org/10.1371/journal.pone.0317519.g013

Low		Moderate		High	
Recall	0.89	Recall	0.94	Recall	0.61
Precision	0.93	Precision	0.85	Precision	0.86
F1-Score	0.91	F1-Score	0.89	F1-Score	0.72

Fig 14. Confusion matrix evaluation of decision trees.

https://doi.org/10.1371/journal.pone.0317519.g014

Low		Moderate		High	
Recall	0.57	Recall	0.97	Recall	0.32
Precision	0.94	Precision	0.65	Precision	0.99
F1-Score	0.71	F1-Score	0.78	F1-Score	0.49

Fig 15. Confusion matrix evaluation of stacking approach.

https://doi.org/10.1371/journal.pone.0317519.g015

$$\text{Recall} = \frac{TP}{TP + FN} \quad (9)$$

F-Measure: After calculating the precision and recall, the F-measure combines these two scores. The traditional F-measure is calculated using the following equation:

$$\text{F-Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

The recall, precision, and F1-scores of CNN, RCNN, Decision Trees, Gradient Boosting, XGB, and Random Forest are shown in Table 2.

ROC curves

The ROC curve is used to visually represent the trade-off between the True Positive Rate (sensitivity) and the False Positive Rate (specificity) as the classification threshold varies. The ROC curves for CNN, RCNN, XGB, Decision Tree, Stacking approach, and Random Forest are shown in Figs 16–21.

ML and DL classifiers accuracy

Table 2 shows the accuracies of various classifiers used in transforming education through machine learning and deep learning techniques for exploring adaptability, sentiment analysis, and academic excellence. The Stacking model achieved the highest performance, while the Random Forest (RF) classifier performed the least. The Gradient Boosting classifier achieved an accuracy of 90%, as shown in Figure 22.

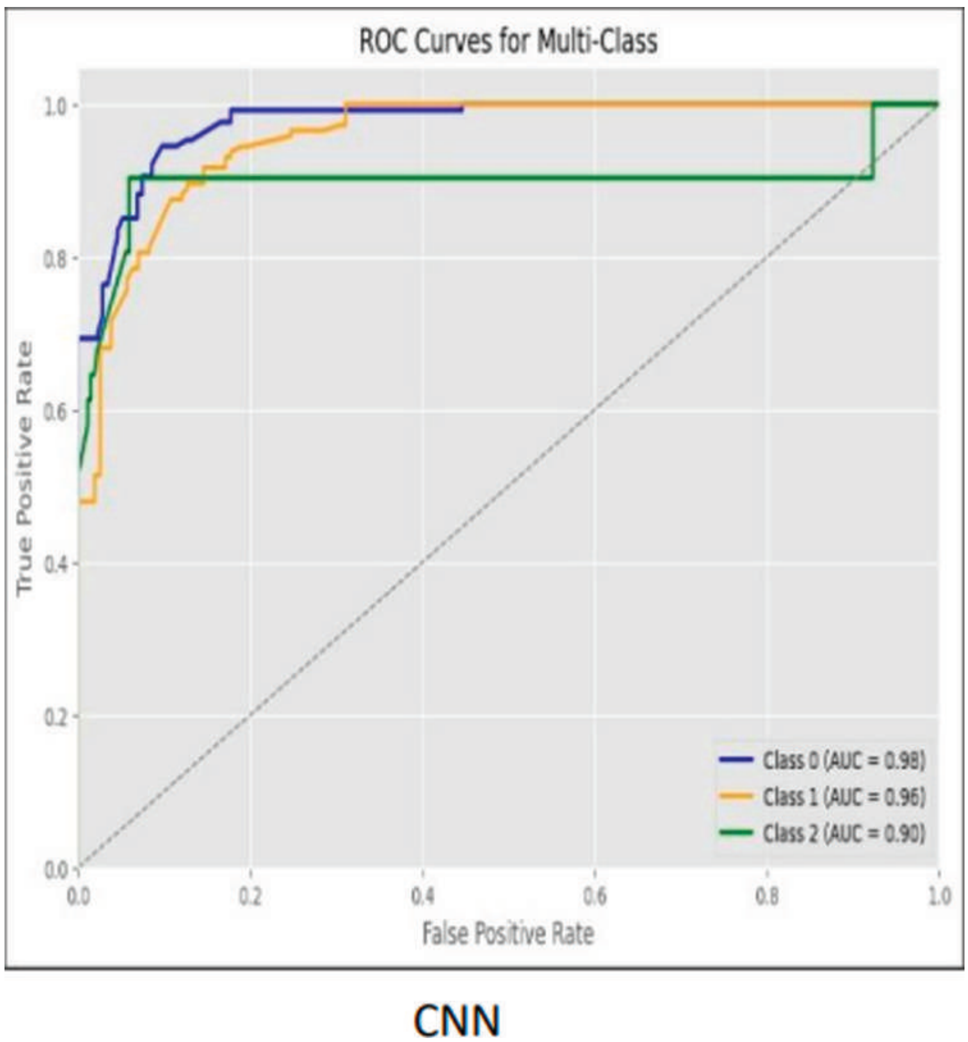

Fig 16. ROC curve CNN.

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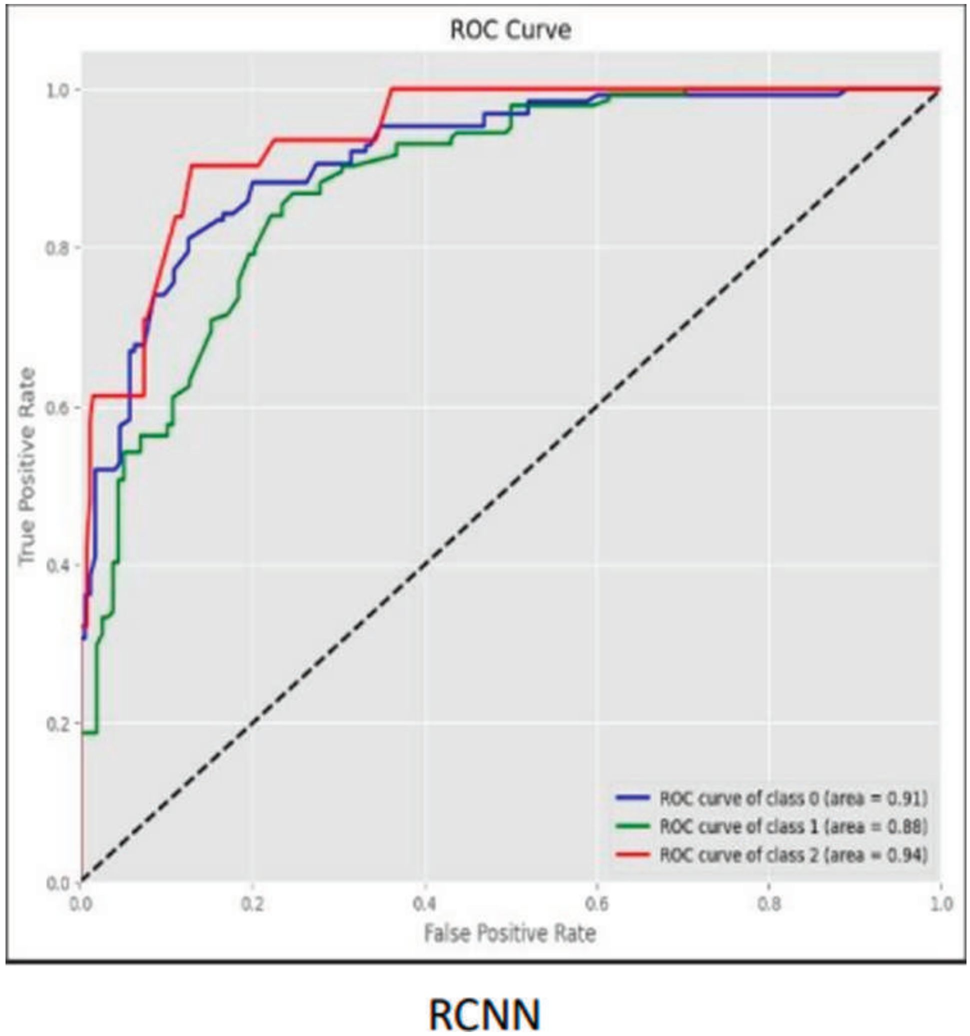

Fig 17. ROC curve RCNN.

https://doi.org/10.1371/journal.pone.0317519.g017

Discussion

In this section, we provide a thorough interpretation of the results presented in the previous section. The findings indicate that the Gradient Boosting Tree (GBT) classifier, with its 90% accuracy, outperformed other models like Random Forest (RF), which had the least accuracy at 73%. The performance of the classifiers was evaluated using several key metrics, such as accuracy, precision, recall, and F-measure. The stacking model exhibited superior results, showcasing its potential in accurately transforming educational data.

This study's findings align with previous research in the field of educational technology and machine learning, particularly in the areas of adaptability and sentiment analysis. Recent advancements in deep learning, such as the use of Convolutional Neural Networks (CNN) and Recurrent Convolutional Neural Networks (RCNN), have demonstrated significant promise in extracting relevant patterns from educational data. Our results corroborate these findings, with CNN and RCNN models achieving strong recall and precision values.

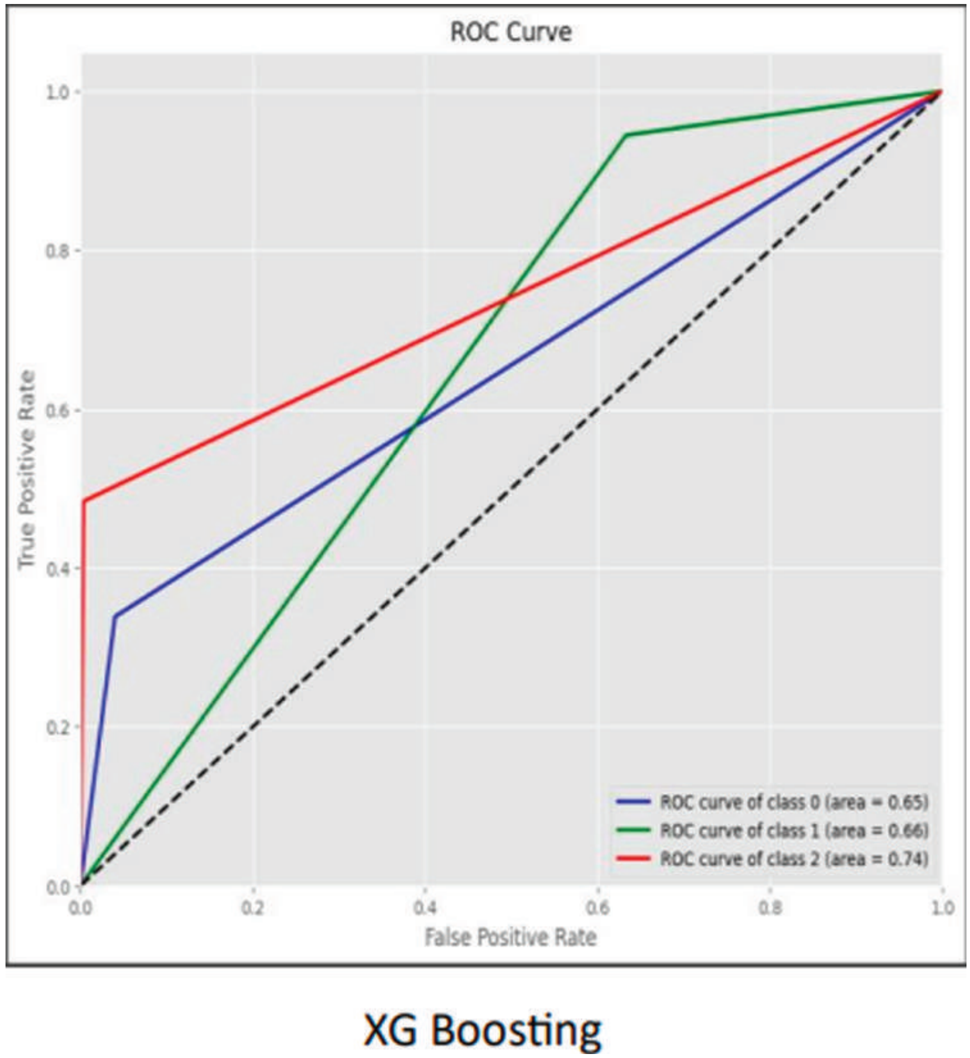

Fig 18. ROC curve stacking meta model gradient boosting.

https://doi.org/10.1371/journal.pone.0317519.g018

Moreover, the ROC curve analysis revealed a strong relationship between the True Positive Rate and False Positive Rate for most classifiers, further supporting the efficacy of the proposed models. As shown in the ROC curves, the Stacking approach with Gradient Boosting demonstrated the most favorable trade-offs between sensitivity and specificity.

The study contributes to the growing body of research on using machine learning and deep learning techniques in educational technology. By leveraging AI models like Gradient Boosting and Stacking, educational institutions can better understand and enhance various aspects of the learning environment, such as adaptability, academic excellence, and sentiment analysis.

We believe that the implications of this study are significant, providing valuable insights for researchers and educators alike. Future research should focus on refining these models and exploring their practical applications in real-world educational settings.

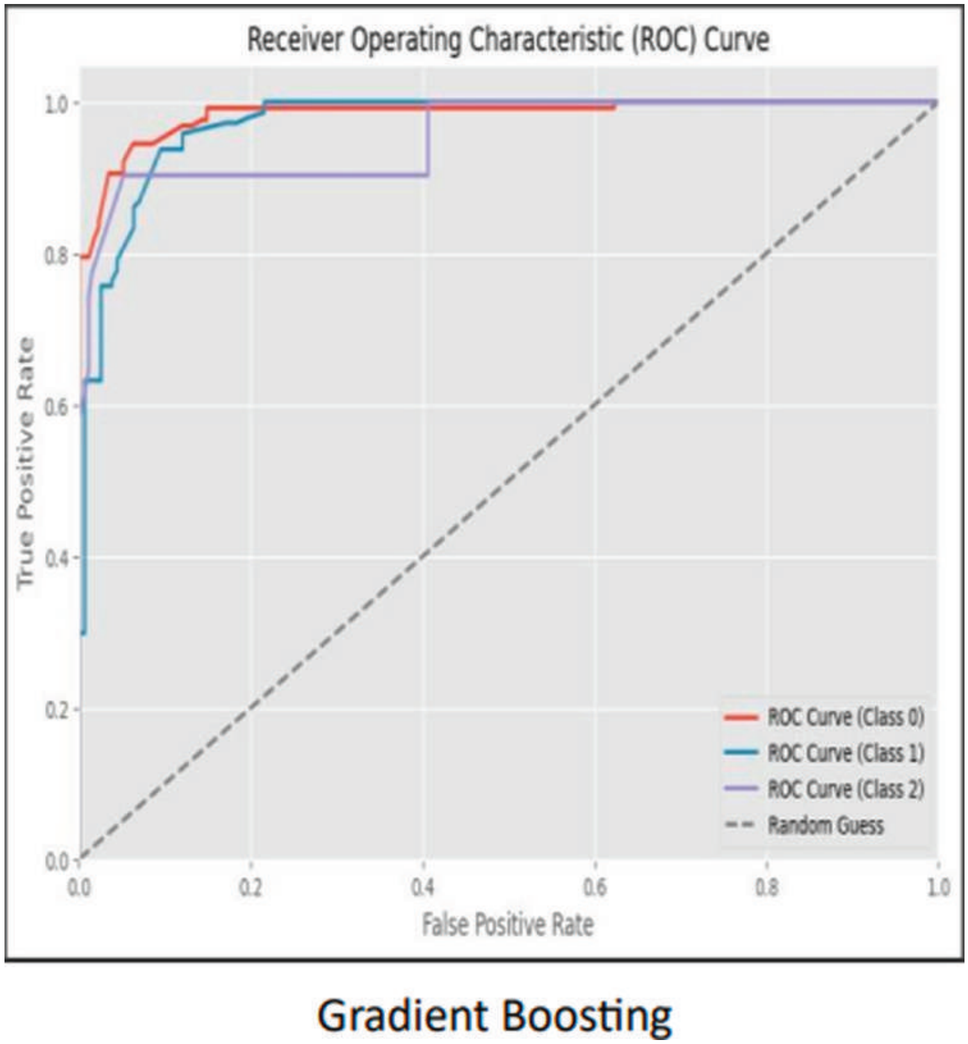

Fig 19. ROC curve XG boosting.

https://doi.org/10.1371/journal.pone.0317519.g019

Theoretical contribution and practical implication

This study presents several significant contributions in the field of educational technology by leveraging the applications of advanced machine learning and deep learning techniques. The key contributions include:

- **Development of a Comprehensive AI Framework**: The research introduces a robust AI framework that integrates a diverse array of algorithms—XGBoost, CNN, RCNN, RF, DT, and a hybrid stacking approach. This framework demonstrates superior performance, with the stacking approach achieving a 90% accuracy, thus providing a highly effective tool for analyzing and improving educational outcomes.
- **Enhanced Sentiment Analysis Capabilities:** By employing CNNs and RCNNs, the study advances sentiment analysis in educational contexts. The CNN approach achieved an accuracy of 89%, showcasing its effectiveness in understanding and interpreting students' emotional and psychological states. This capability allows for more nuanced insights into student well-being, contributing to a more empathetic and responsive educational environment.

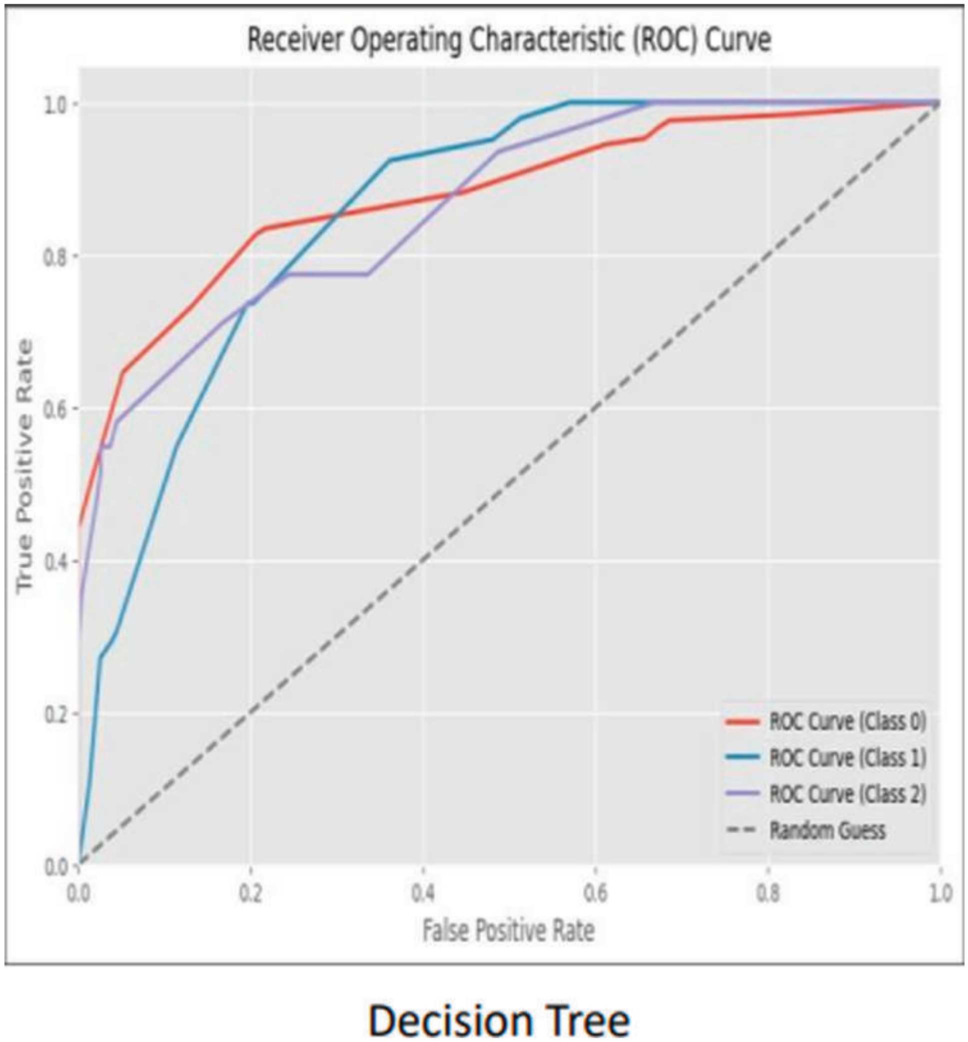

Fig 20. ROC curve decision trees.

https://doi.org/10.1371/journal.pone.0317519.g020

- **Insights into Teacher Effectiveness and Instructional Strategies:** The study's findings offer valuable insights into how AI can support teachers in refining their instructional methods. The ability to analyze student adaptability and performance data helps educators tailor their teaching strategies to better meet individual student needs, thereby enhancing instructional effectiveness and overall educational quality.
- **Data-Driven Strategies for Educational Leadership:** The research provides educational leaders with actionable insights that can be used to develop and implement data-driven strategies. These strategies are designed to improve school-wide academic outcomes and foster a supportive and efficient learning environment, aligning with contemporary goals for educational leadership.
- **Focus on Student Well-Being**: The incorporation of sentiment analysis into the framework emphasizes the importance of addressing students' emotional and psychological needs. By offering a more comprehensive understanding of student well-being, the study contributes to creating a more holistic and supportive educational experience.

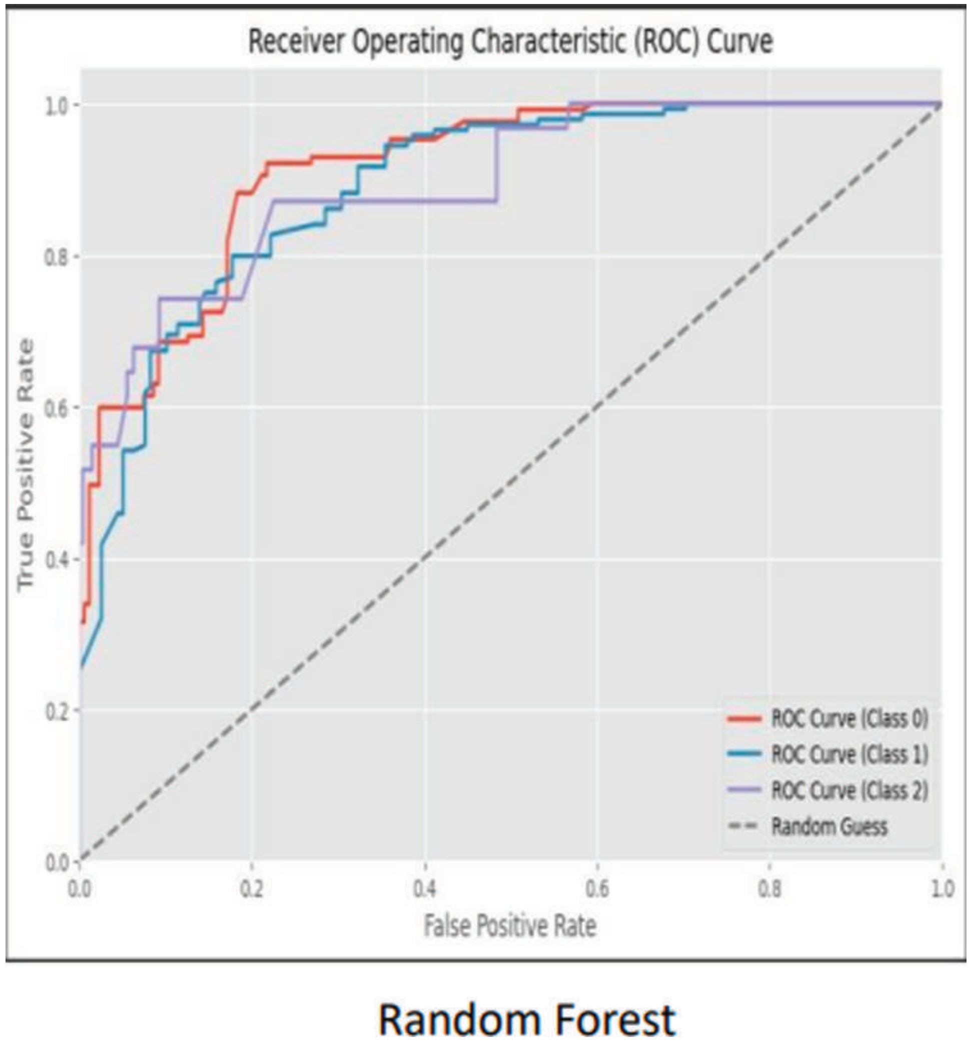

Fig 21. ROC curve random forest.

https://doi.org/10.1371/journal.pone.0317519.g021

- **Alignment with Sustainable ICT Goals**: The study aligns with the goals of sustainable ICT in education by providing innovative, AI-driven solutions that promote long-term educational improvement. The application of advanced technologies not only enhances educational outcomes, but also supports the sustainable development of ICT in educational settings.

These contributions collectively advance the application of AI in education, providing a transformative approach that benefits students, educators, and educational institutions alike.

Limitations

While this study provides valuable insights into the performance of various machine learning and deep learning classifiers in transforming education through adaptability, sentiment analysis, and academic excellence, it is important to acknowledge the following limitations:

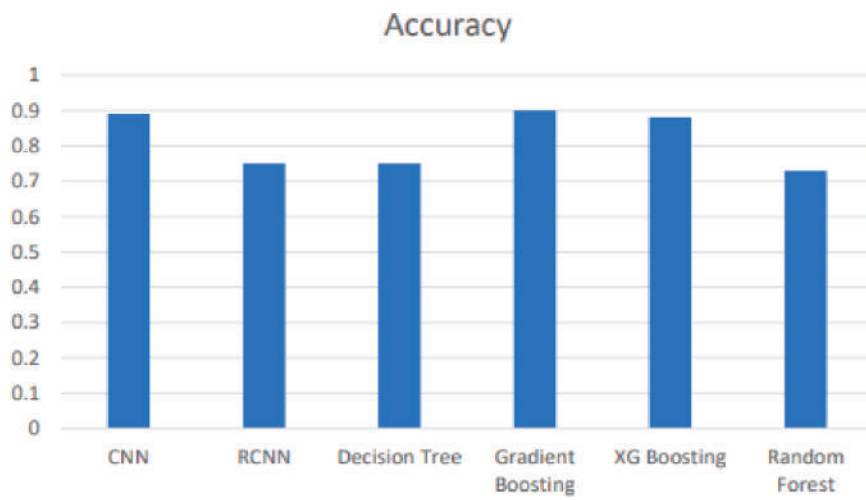

Fig 22. Accuracy chart of ML and DL classifiers.

https://doi.org/10.1371/journal.pone.0317519.g022

- **Data Dependency:** The findings of this study are significantly dependent on the set of datasets employed for the training and testing purposes. Concerning the external validity of the results, we would like to point to the fact that the nature of these datasets may limit the ways in which the system can learn about the educational environment and all its possible variations.
- **Model Interpretability:** Even though other sophisticated deep learning models such as CNN and RCNN presented high overall performance, they are black box types, making it difficult to analyze the results. Different models deal with this aspect differently, and how these models make decisions remains a topic of debate and central to their use in real life.
- **Computational Complexity:** Certain classifiers, including most deep learning models, are computationally intensive and take longer to train. Such a limitation could hamper their viability to solve problems in real-life settings, especially in large-scale education systems in developing nations.
- **Class Imbalance:** Class imbalance in the classifiers' input dataset may have affected performance. Despite using oversampling and undersampling, more extensive research into enhanced methods to tackle this problem could further improve classifier performance.
- **Scope of Features:** The range of features employed in this work does not exhaust all possible factors affecting the quality of education and educational performance. Future research could extend the involvement of more attributes, including demographic information, institutional resources, and interactions between teachers and students.
- **Limitations in Evaluation Metrics:** Unlike accuracy, precision, recall, and F-measure, other evaluation metrics do not capture all aspects of model performance, especially in scenarios where the dataset is imbalanced. Alternative evaluation methods, such as AUROC or MCC, could potentially provide a better understanding of how well the model truly performs.

Conclusion and future work

This study makes a substantial contribution to the field of educational technology by applying advanced machine learning and deep learning techniques to transform education. By employing a range of algorithms, including XGBoost, Convolutional Neural Networks (CNN), Region-based Convolutional Neural Networks (RCNN), Random Forest, Decision Trees, and a hybrid stacking approach (integrating Decision Tree, Random Forest, and XGBoost as base models with Gradient Boosting as the meta-model), the research achieved a notable accuracy of 90% with the stacking method. The CNN approach, demonstrating an accuracy of 89%, proved effective in sentiment analysis, while the RCNN, Random Forest, and Decision Trees provided valuable insights into the complex interactions between machine learning and educational contexts. The bagging XGBoost algorithm, with an accuracy of 88%, underscored its potential for enhancing academic performance. Utilizing a robust dataset from Kaggle, which includes 1205 entries and 14 attributes related to adaptability, sentiment, and academic excellence, this study has achieved significant outcomes. The developed system enhances teacher effectiveness by enabling educators to tailor teaching strategies to individual student needs, thereby improving instructional effectiveness. Educational leaders can leverage these insights to implement data-driven strategies that enhance school-wide academic outcomes and create a more supportive learning environment. Moreover, the focus on student well-being through sentiment analysis contributes to a more holistic and responsive educational experience. This research aligns with the goals of sustainable ICT in education, providing a transformative approach to educational improvement through AI-driven insights.

Author contributions

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Investigation: Ahmad Alshammari.

Methodology: Azhar Imran.

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Validation: Jianqiang Li.

Visualization: Ahmad Alshammari.

Writing – original draft: Azhar Imran.

Writing – review & editing: Jianqiang Li.

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Article

AI-Driven Smart Transformation in Physical Education: Current Trends and Future Research Directions

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Abstract: Although the rapid development of Artificial Intelligence (AI) in recent years has brought increasing academic attention to the intelligent transformation of physical education, the core knowledge structure of this field, such as its primary research topics, has yet to be systematically explored. The LDA (latent Dirichlet allocation) topic model can identify latent themes in large-scale textual data, helping researchers extract key research directions and development trends from extensive literature. This study is based on data from the Web of Science Core Collection and employs a systematic literature screening process, utilizing the LDA topic model for in-depth analysis of relevant literature to reveal the current status and trends of AI technology in physical education. The findings indicate that AI applications in this field primarily focus on three areas: "AI and data-driven optimization of physical education and training", "computer vision and AI-based movement behavior recognition and training optimization", and "AI and virtual technology-driven innovation and assessment in physical education". An in-depth analysis of existing research shows that the intelligentization of physical education, particularly in school and athletic training contexts, not only promotes sustainable development in the field but also significantly enhances teaching quality and safety, allowing educators to utilize data more precisely to optimize teaching strategies. However, current research remains relatively broad and lacks more precise and robust data support. Therefore, this study critically examines the limitations of current research in the field and proposes key research directions for further advancing the intelligent transformation of physical education, providing a solid theoretical framework and guidance for future research.

Keywords: physical education and training; latent Dirichlet allocation; physical development; artificial intelligence

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1. Introduction

With the continuous advancement of technology, artificial intelligence (AI) has found increasingly deep applications across various fields, particularly in education, where it demonstrates tremendous potential. As a tool capable of optimizing resource allocation, improving teaching quality, and promoting personalized learning, AI equips educators with new resources and offers students a more efficient learning experience. In the field of physical education, traditional teaching methods often overlook individual differences among students, resulting in standardized training methods with limited personalized feedback [1]. To address this issue, it is essential to recognize the importance of a pedagogical approach that prioritizes the holistic development of students. Physical education should not merely focus on performance metrics but also foster cognitive, personal, and social skills, ensuring that all aspects of student growth are considered [2]. By designing personalized learning paths and conducting targeted training data analysis, AI can better address individual needs, enhancing the overall effectiveness of physical education. Through data-driven decision-making, AI provides teachers with precise insights to optimize their teaching strategies, allowing them to create more personalized plans based on each student's abilities and performance, thereby improving the specificity and effectiveness of instruction [3].

With the rapid advancement of artificial intelligence technology, its application in the field of education, especially in physical education, is increasingly expanding and deepening [4]. This study focuses on the intersection of physical education and AI, using the LDA topic model to systematically identify the main research directions in AI applications within physical education. By revealing the primary themes and trends in current research, this study aims to provide educators and researchers with structured insights that promote the intelligent development of physical education.

The remainder of this study is structured as follows: Section 2 reviews relevant research on AI in the field of physical education, providing a theoretical foundation for subsequent analysis. Section 3 describes the process, methods, and results of determining the research themes. Section 4 discusses the current status of the research themes and summarizes various aspects. Section 5 outlines the contributions of this study and provides an outlook on the future development of AI integration in physical education.

2. Literature Review

2.1. Applications of AI in Physical Education

As an essential part of education, physical education not only aims to improve students' physical fitness but also emphasizes their comprehensive development in cognitive, social, and psychological aspects [5]. Physical education is divided into four sub-disciplines: physical education training, sports humanities, exercise biology, and traditional ethnic sports [2]. Unlike sports training, which is oriented towards skill enhancement and competitive performance, physical education focuses on students' holistic growth and lifelong participation in physical activities [6]. Therefore, the application of AI in physical education should be based on multidimensional educational goals to meet students' diverse needs.

The application of Artificial Intelligence (AI) in physical education has become a significant research topic in the field of education. AI improves and innovates physical education methods through technical means to enhance teaching effectiveness and personalization [1]. It can improve educational quality through personalized feedback, optimization of teaching resources, and enhancing the overall learning experience, thereby compensating for the limitations of standardized teaching models in accommodating individual student differences [4]. The application of AI in personalized learning is particularly effective, as it provides targeted feedback and learning pathways to meet the needs of different students, thereby enhancing teaching effectiveness. The widespread use of wearable devices has deepened AI applications in physical education, as these devices can monitor students' physical conditions, enhance teacher–student interactions, and develop personalized learning plans based on real-time data, ultimately improving overall teaching quality [7].

In the dynamic and unpredictable environment of physical education, the application of AI technology greatly alleviates spatial and temporal limitations, making intelligent and flexible physical education possible. For example, AI assists students in scientifically training during fragmented times and spaces, thereby enhancing training efficiency and effectiveness [1]. Additionally, the application of advanced technologies like Augmented Reality (AR) in physical education significantly improves educational quality, particularly in the acquisition and understanding of motor skills. By using 3D models to demonstrate complex movement details, students can understand learning steps from multiple perspectives [8]. The integration of AI with AR and Virtual Reality (VR) holds promise for providing more immersive and interactive experiences in physical education, enabling students to receive guidance within real movement contexts. Research shows that AR-assisted instruction has notable advantages in skill acquisition and motivation enhancement [9]. Through AR and VR technologies, students can simulate and practice physical skills in a virtual environment, receive real-time feedback, and experience personalized training, which increases their learning interest and improves their athletic skills [10].

The application of AI in physical education not only demonstrates unique advantages in improving teaching efficiency and personalization but also plays an active role in ensuring safety and teaching quality. In the future, the integration of AR and VR with AI is expected to continuously enhance the immersive and interactive aspects of physical education, supporting comprehensive and scientific physical training. Machine vision and 3D motion teaching positioning technologies will further improve the precision and effectiveness of athletic training, providing scientific support for physical education and training [11].

In recent years, there has been a growing academic interest in the field of intelligent physical education, resulting in a large body of related research. However, issues such as scattered research directions and content have also emerged in this field. Existing studies have attempted to analyze literature on the integration of Artificial Intelligence (AI) and physical education using traditional bibliometric methods. Although the study by Lee and Lee [12] offers valuable insights into this field, it primarily relies on quantitative statistical data and lacks in-depth thematic exploration of text content, potentially overlooking certain research themes. This approach has limitations in revealing the breadth and evolution of topics and may not fully reflect the application trends and complexities of AI in physical education. To address these limitations, this study employs the LDA topic model to systematically analyze the relevant literature, aiming to explore the primary research directions in the integration of AI and physical education through a broader data pool. This approach not only captures the thematic distribution within the existing literature but also better illustrates the current applications and future potential of AI in physical education, providing a more comprehensive theoretical framework for subsequent research.

2.2. Applications and Advantages of LDA Topic Modeling

In recent years, with the development of big data technologies and text mining tools, researchers have increasingly adopted data-driven methods to analyze large-scale text data, aiming to reveal key themes and development trends within specific research fields. This data-driven approach has been widely applied in academia, especially in the natural sciences, technical sciences, and health sciences, where methods like keyword network analysis are used to understand the structure and evolution of scientific knowledge. This approach not only reveals research topics across different disciplines but also helps researchers identify potential research hotspots and future trends, enhancing the understanding of disciplinary development [13,14]. However, keyword network analysis has certain limitations: many articles may lack keywords, or the keywords provided may be selected from a predefined list, making it difficult to accurately reflect the actual content and research focus of the articles [15]. With the rapid advancement of artificial intelligence in recent years, traditional literature analysis methods such as keyword networks have gradually struggled to handle high-dimensional data and address complex problems. Consequently, researchers have turned to natural language processing (NLP) methods to study scientific documents in greater depth, providing more comprehensive support for scientific research. Among these techniques, the LDA topic model, a prominent text mining tool, has garnered significant attention in academia [16,17]. The LDA topic model can identify latent topics within large-scale text data, aiding researchers in extracting key research directions and development trends from extensive literature [18]. Compared to traditional qualitative literature reviews, the LDA model provides higher systematization and objectivity in a data-driven manner, capable of revealing hidden thematic structures.

The advantages of LDA topic modeling have been widely applied across various disciplines, especially in research that requires the analysis of large text datasets, such as sociology and education [19,20]. Hamed Jelodar et al. [17] have also demonstrated that the LDA model can effectively identify hidden topics within large-scale documents by analyzing word frequency and distribution patterns. It has been extensively applied in complex fields such as software engineering, political science, healthcare, and linguistics and is suitable for a variety of contexts, including social media and academic research.

In this study, we apply the LDA topic model to analyze research directions on AI in physical education, providing a more systematic perspective for research and practice in the field. Compared to traditional methods, the LDA model reveals latent thematic structures, helping to capture AI application trends and its future potential comprehensively. This study aims to provide theoretical support for the intelligent development of physical education and to encourage further research in this area.

3. Methods and Materials

3.1. Data Sources and Research Methods

This study aims to analyze the current achievements, future development directions, and potential challenges in the integration of "artificial intelligence and physical education". We selected journal articles from the Social Sciences Citation Index (SSCI) and Science Citation Index (SCI) in the Web of Science (WOS) Core Collection as the data sources, reflecting a focus on rigor and credibility [21,22]. Our search query was constructed as TS = (("Artificial intelligence" OR "Artificial neural network" OR "case-based reasoning" OR "cognitive computing" OR "cognitive science" OR "computer vision" OR "data mining" OR "data science" OR "deep learning" OR "expert system" OR "fuzzy linguistic modelling" OR "fuzzy logic" OR "genetic algorithm" OR "image recognition" OR "k-means" OR "knowledge-based system" OR "logic programming" OR "machine learning" OR "machine vision" OR "natural language processing" OR "neural network" OR "pattern recognition" OR "recommendation system" OR "recommender system" OR "semantic network" OR "speech recognition" OR "support vector machine" OR "SVM" OR "text mining") AND ("physical education" OR "sports education" OR "fitness education" OR "sports training")). Although the search strategy includes various interdisciplinary keywords, this study has rigorously screened the data to ensure that all selected literature is directly related to the application of artificial intelligence in physical education. The keywords "cognitive computing" and "communication codes" have practical applications in personalized feedback and learning analytics within physical education. By incorporating these keywords, we are able to comprehensively capture the diverse application scenarios and technological needs in the intelligent transformation of physical education [17]. This search covered the period from 1 January 2003 to 1 August 2024. We chose this timeframe because, since 2003, the field of AI integration with physical education has seen a significant increase in attention. This period allows us to observe the development of technology, policy support, and emerging trends and challenges in practice. The cutoff date for the search was 1 August 2024, when we conducted the final literature search and data collection. The search strategy was designed to cover all potentially relevant literature on the research topic. However, despite the broad scope, the search may include some articles that are less relevant to the topic. The framework of Data sources and research methods is shown in Figure 1.

We implemented a multi-round filtering process to ensure the quality of the selected literature. The initial search resulted in 652 articles. In the first round of screening, the primary author reviewed the titles, abstracts, and relevance to the research topic, eliminating approximately 381 irrelevant or off-topic articles, reducing the pool to 271 articles. In the second round, three members of the research team systematically evaluated the remaining articles, focusing on thematic alignment and relevance to the research objectives, removing 124 articles that, despite appearing relevant, did not meet the content requirements of the study [23]. In the third round, a cross-review of the remaining 147 articles was conducted, with several experts reviewing to eliminate articles with high redundancy or insufficient connection to the core topic, leading to the exclusion of 51 more articles. After multiple rounds of rigorous filtering and review, a final set of 96 eligible journal articles was selected for analysis.

After constructing the dataset, we performed text preprocessing, including stemming and thematic summarization. Next, we applied the LDA topic model to identify key themes in the text and used the perplexity metric to determine the optimal number of topics in the model. By analyzing the probability distribution of topic words, we explored the research hotspot of "AI integration with physical education" through visualization analysis. The framework of the study is shown in Figure 2.

Project	Description
Research Objectives	Analysis of the Current Achievements, Future Development Directions, and Potential Challenges of the Integration of "Artificial Intelligence and Physical Education"
Data Sources	Articles selected from the Social Sciences Citation Index (SSCI) and the Science Citation Index (SCI) within the Web of Science (WoS) Core Collection represent the pinnacle of academic research in their respective fields
Search Strategy	Innovation and Evaluation of Physical Education Driven by Artificial Intelligence and Virtual Technology
Search Strategy Design	TS=(("Artificial intelligence" OR "Artificial neural network" OR "case-based reasoning" OR "cognitive computing" OR "cognitive science" OR "computer vision" OR "data mining" OR "data science" OR "deep learning" OR "expert system" OR "fuzzy linguistic modelling" OR "fuzzy logic" OR "genetic algorithm" OR "image recognition" OR "k-means" OR "knowledge-based system" OR "logic programming" OR "machine learning" OR "machine vision" OR "natural language processing" OR "neural network" OR "pattern recognition" OR "recommendation system" OR "recommender system" OR "semantic network" OR "speech recognition" OR "support vector machine" OR "SVM" OR "text mining") AND ("physical education" OR "sports education" OR "fitness education" OR "sports training")).
time frame	The field of integrating artificial intelligence with physical education has received significant attention during the period from January 1, 2003, to August 1, 2024.The cutoff date for the search was August 1, 2024, when we conducted the final literature search and data collection.

Figure 1. Data Sources and Retrieval Strategies.

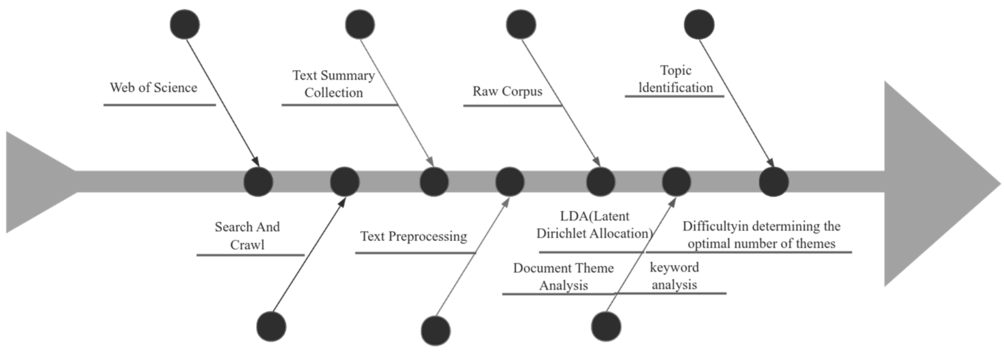

Figure 2. Research approach for topic analysis based on the LDA model.

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3.2. LDA Topic Model

Latent Dirichlet allocation (LDA) is a probabilistic Bayesian model for analyzing discrete data and is one of the most effective techniques in text mining. This widely used data mining technique is adept at uncovering latent data and identifying relationships between data and documents [17]. The core feature of the traditional LDA model is its unsupervised nature, which enables it to autonomously execute multiple analysis steps with minimal human intervention, even achieving automatic labeling functionality [24].

The LDA topic model is one of the most effective techniques in text mining and has been applied in numerous disciplines and industries. For instance, significant results related to LDA have been achieved in fields such as biomedical research, communication studies, and maritime target detection [17,25].

In this study, we employed the LDA topic model based on Dirichlet distributio
cause of its superior performance in handling large volumes of documents and inter
ing identified latent themes, compared to several other algorithms [26]. This approa
fectively addresses the challenges posed by co-occurrence and keyword analysis in

In this study, we employed the LDA topic model based on Dirichlet distribution because of its superior performance in handling large volumes of documents and interpreting identified latent themes, compared to several other algorithms [26]. This approach effectively addresses the challenges posed by co-occurrence and keyword analysis in traditional bibliometric studies. In many cases, documents may not explicitly list keywords or the keywords are merely selected from a predefined list, which significantly limits their accuracy and affects the true and comprehensive representation of the document's content [15].

Topic modeling infers latent themes from textual data and automatically identifies topics within articles, showing their distribution across different documents. This method does not rely on predefined keywords or co-citation relationships but instead extracts information directly from the text, enabling a more accurate capture of the document's meaning [27].

Figure 3 illustrates the generative process of the latent Dirichlet allocation (LDA) model [27], which assumes that each document is a mixture of several topics and that each topic is a distribution over multiple words. In this model, α and β control two Dirichlet distributions. The parameter α randomly generates the topic multinomial distribution θ for each document, θ then randomly generates a topic z, and β randomly generates the word multinomial distribution φ for the corresponding topic. Combining the topic z and the corresponding word distribution φ generates a word w. This process continues until a document with m words is generated, ultimately leading to n documents under k topics [28]. Through this model, we obtain the document-topic and topic-word distributions related to the integration of artificial intelligence and physical education.

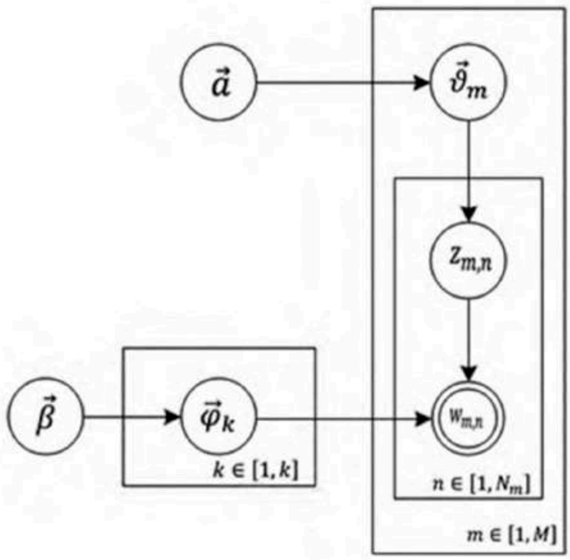

Figure 3. Graphical representation and document generation process of the LDA model.

The document–topic distribution helps analyze the directions and focus areas of AI integration with physical education. By comparing the topic distributions of different documents, we can identify which topics are frequently associated with integrating AI and physical education. Analyzing the document–topic distribution also helps uncover new research directions and unexplored area [17]. Researchers can determine new research avenues and propose recommendations by identifying topics that appear less frequently in existing documents.

Similarly, the topic–word distribution provides a deeper understanding of the research content in the AI and physical education domain. By comparing the word distributions within different topics, we can identify φk and recognize which words are frequently associated with AI and physical education integration [28]. This analysis not only helps determine future research directions but also provides new suggestions for policymakers, highlighting their crucial role in shaping the future of AI in physical education [17].

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The above analysis highlights the core themes and discussion points of AI integration with physical education. This approach provides a deeper understanding of current research and guides future research directions and policy-making, ultimately promoting the realization of AI integration in physical education.

3.3. Paradoxical Leadership

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The LDA algorithm begins with setting parameters, including the prior parameters α and β from the Dirichlet distribution, as well as the number of topics, k. In this study, the values of α and β were set to 0.1 and 0.01, respectively, which are common settings in the literature [29].

Since the number of topics k significantly affects the estimated topics, selecting the appropriate number of topics is crucial. We used topic perplexity to determine the optimal number of topics.

(1) Topic Perplexity: When the cosine similarity between topics decreases as the number of topics increases, there may be an issue of over-clustering. Therefore, we introduced perplexity as a measure to reduce such problems. Perplexity is a standard method for measuring the predictive power of the LDA model [30]. It is expressed by the following Formula (1).

$$Perplexity = exp\left\{-\frac{\sum_{d=1}^{M} log_P(w_d)}{\sum_{d=1}^{m} N_d}\right\} \quad (1)$$

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The LDA topic model requires the number of topics to be predefined. A widely recognized method for determining this is by using perplexity, a key indicator for selecting the optimal number of topics. As illustrated in Figure 4, the model achieves its lowest perplexity when the number of topics is set to 3. This finding is further supported by the pyLDAvis visualization results (pyLDAvis version 3.3.1) presented on the left side of Figure 5. We observe that when the number of topics is set to 3, there is minimal overlap between topics, indicating better classification performance. Therefore, the number of topics in this study was finalized as 3. The right side of Figure 5 shows the top 30 words most closely associated with Topic 1. By entering different queries in the "Selected Topic" text box in the upper left corner of Figure 5, the top 30 words with the highest correlation for each topic can be displayed.

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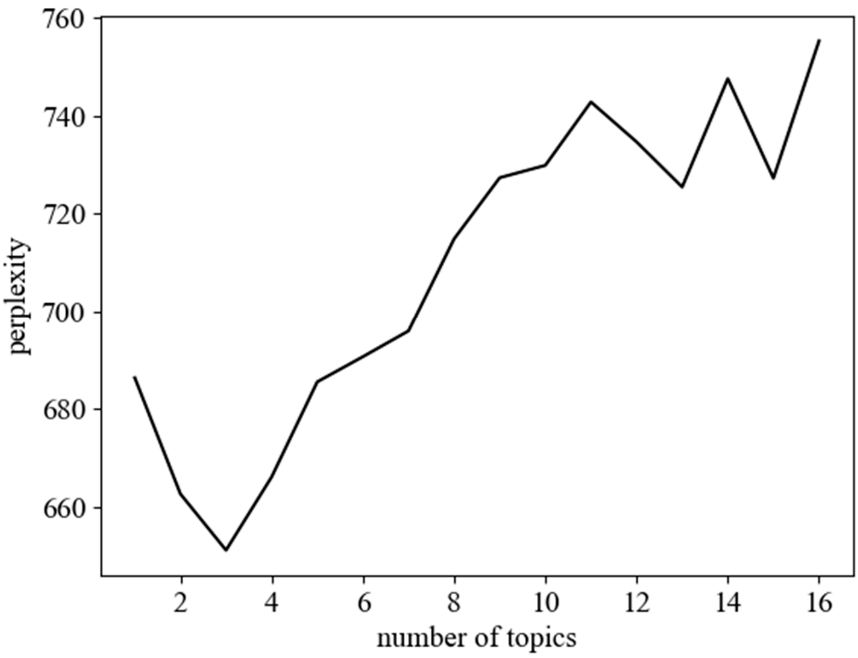

Figure 4. Topic perplexity.

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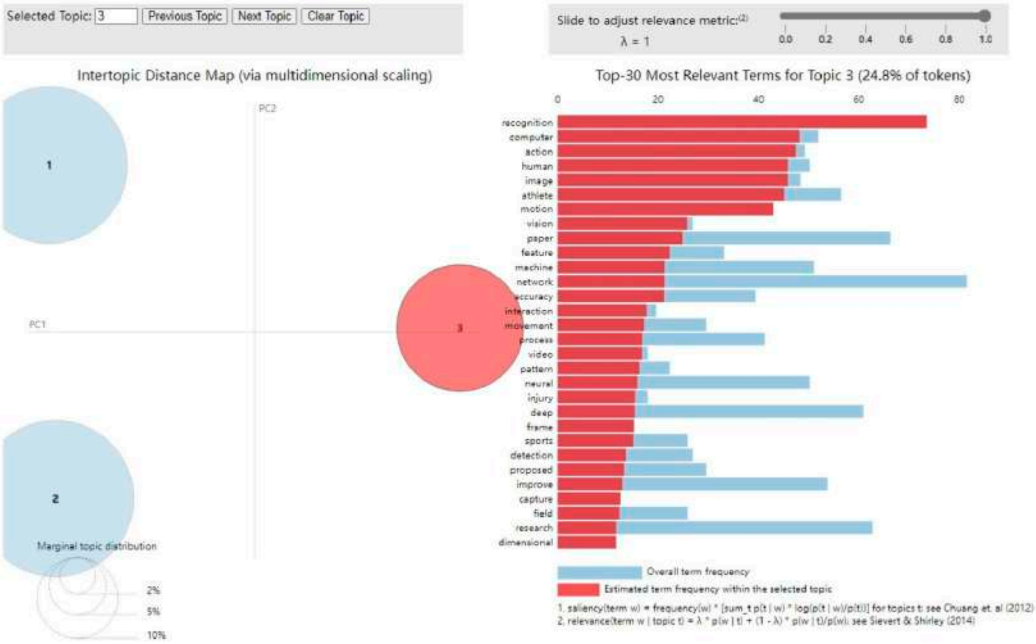

Figure 5. Visualization of pyLDA results [31,32].

4. Data Results and Analysis

4.1. Data Results

After completing the LDA model training, we obtained two important output files: the "document-topic" distribution and the "topic-word" distribution. To identify and label each topic effectively, we first analyzed the top-ranking words under each topic in the "topic-word" distribution. We prioritized the top 15 high-probability words in each topic and used these keywords to determine the core content of the topic [19]. However, certain words, despite appearing at the top, may not truly represent the core content of the topic. For example, common or stop words (such as "the", "is", "in", etc.) may appear in high-probability positions but have weak distinguishing power for the topic. In such cases, considering words further down the list of high-probability terms can provide more detail and insight into the topic, helping to accurately interpret and label it. By selecting the top 15 high-probability words, we can capture the core essence of the topic while maintaining flexibility in addressing the influence of stop words.

During this process, we excluded vague or repetitive topics to ensure each identified topic is unique and clearly defined. By organizing and analyzing these high-probability words, we assigned appropriate labels to each topic. Table 1 presents the three main topics identified through the LDA topic model related to integrating artificial intelligence and physical education and the distribution of their corresponding high-probability words. This provides a basis for further understanding each topic's core content and characteristics.

For example, in Topic 1 from Table 1, high-probability words include "algorithm", "network", "system", "BP", "mining", and "intelligent". These terms suggest that this topic focuses on the development of neural network algorithms and data mining technologies in artificial intelligence, as well as their application in physical education. Therefore, we have labeled this topic as "AI and Data-Driven Optimization of Physical Education and Training". In Topic 2, high-probability words such as "students", "learning", "AI", "college", "quality", and "improve" indicate that the topic explores the role of artificial intelligence in enhancing the learning quality of college students, particularly in connection with physical education. Hence, this topic has been labeled "Motion Behavior Recognition and Sports Training Optimization Based on Computer Vision and AI". Topic 3 includes high-probability words like "recognition", "learning", "deep", "motion", "system", and "human", highlighting the application of recognition systems and deep learning technologies in sports training.

Based on these keywords, this topic has been named "AI and Virtual Technology-Driven Innovation and Evaluation in Physical Education".

Table 1. Distribution of topics and high-probability feature words.

Number	Topic Identification Categories	Top 15 High-Probability Feature Words of the Topic
Topic1	AI and Data-Driven Optimization of Physical Education and Training	Network, student, college, mining, neural, design, deep, classroom, development, research, PE, analysis, BP, time, paper
Topic2	Sports behavior recognition and sports training optimization based on computer vision and AI	Recognition, computer, action, human, image, athlete, motion, vision, paper, feature, machine, network, accuracy, interaction, movement
Topic3	Innovation and Evaluation of Physical Education Driven by Artificial Intelligence and Virtual Technology	Student, AI, evaluation, analysis, information, improve, machine, virtual, quality, college, research, activity, PE, performance, teacher

Explanatory note: PE = physical education; BP = Back Propagation.

4.2. Analysis of Hot Topics in the Integration of Artificial Intelligence and Physical Education

4.2.1. AI and Data-Driven Optimization of Physical Education and Training

With the rapid development of artificial intelligence (AI), various industries are actively seeking ways to integrate AI technologies and the field of physical education is no exception [33]. Increasingly, research is focusing on the application of AI in physical education, making exploring how AI can enhance teaching and training outcomes a prominent research area [7]. The advancement of AI technologies, particularly the application of neural networks, deep learning, and data mining, has profoundly impacted physical education and training [34,35]. In the simulation training results, high-probability keywords such as "network", "student", "college", and "mining" indicate that scholars in this research area tend to explore the integration of neural networks, deep learning, and data mining technologies within physical education and training. These studies go beyond a superficial understanding of the broad concept of AI, delving into the application and future development of data mining ("mining", "system") and deep learning ("deep") technologies in physical education and training. This research plays a critical role in unlocking the potential of current physical education and enhancing its sustainability. Data mining ("mining", "system") and deep learning technologies ("deep") provide better technical support for physical education, making them crucial for optimizing both teaching and training processes [33]. Hence, Topic 1 has been labeled "AI and Data-Driven Optimization of Physical Education and Training".

In recent years, many scholars have explored how AI technology can optimize physical education classes, analyze training data, and improve teaching outcomes through the application of neural network technologies. The studies by Li et al. [36] and Liu et al. [37] indicate that the integration of network technology ("network") with higher education physical education not only enhances teaching effectiveness, promotes the smartification of physical education, optimizes resource allocation and boosts student participation but also offers new perspectives and methods for research in the field of physical education. This integration not only helps improve the current state of physical education but also has a profound impact on its future development. Their study shows that AI can not only compensate for the limitations of traditional education but also enhance students' overall competencies, allowing them to grasp key concepts in real-world settings. Wan [5] specifically highlighted the promising application of BP neural networks in sports training, demonstrating that BP neural networks can enhance students' physical functions, enabling them to perform at their best while showcasing the multiple benefits of physical exercise. Yang et al. [1] predicted that the integration of AI technology will lead to revolutionary changes in future physical education. The application of AI holds great potential, as it can provide precise, data-driven support for curriculum design and training evaluation in physical education. These studies provide a solid foundation for the integration of AI with physical education and clearly highlight the significant value of AI in this field.

These studies summarize the multiple advantages of artificial intelligence and data-driven technologies in physical education, which not only have a positive impact on students and teachers but also promote the intelligent transformation of the entire education system, enhancing the efficiency and engagement of teaching. As algorithms continue to improve and the trend toward smartification accelerates, the education system can leverage a variety of technologies and methods to promote sustainable development. These studies provide a theoretical foundation for the intelligent transformation of physical education and offer guidance for future educational reforms, particularly in improving the efficiency and effectiveness of physical education [33].

4.2.2. Motion Behavior Recognition and Sports Training Optimization Based on Computer Vision and AI

Driven by globalization and technological innovation, advancements in computer vision and artificial intelligence have profoundly impacted sports training and education. By analyzing high-probability keywords such as "recognition", "computer", "action", "human", and "vision", it is evident that this topic focuses on the significant influence of AI and motion recognition technologies on student education and athlete training, particularly in areas such as athlete motion recognition, sports analysis, and training process optimization. In recent years, combining motion recognition technologies with AI has become a research hotspot as researchers explore how these technologies can enhance effectiveness and accuracy in sports training and education. Therefore, Topic 2 has been labeled as "Motion Behavior Recognition and Sports Training Optimization Based on Computer Vision and AI".

Scholars within this topic examine the contributions of motion behavior recognition, enhanced by computer vision and AI technologies, to the optimization of sports training. Regarding the application of computer vision technology in motion behavior recognition, Liu et al. [38] pointed out that compared to manual methods, AI-powered motion behavior recognition not only improves accuracy and objectivity but also provides real-time feedback, helping reduce subjective bias. This enables students to adjust their posture and performance in a timely manner, improving teaching efficiency and promoting personalized instruction to some extent. Research by Lin and Song [39] showed that athlete motion recognition can enhance individual athletic performance and improve students' overall abilities. When combined with human–computer interaction technologies, real-time communication between athletes and training equipment can be achieved, significantly increasing the precision and efficiency of training feedback. Lin and Song [39] emphasized that machine learning and motion recognition can improve training outcomes and efficiency, but integrating motion recognition results with machine learning technologies remains a challenge. Lv et al. [40] focused on using deep learning algorithms to enhance the accuracy and efficiency of motion recognition in sports training. The study noted that as deep learning technology advances, motion recognition will be applied more broadly across various real-world scenarios. Future research may further explore more efficient network architectures and training strategies, as well as cross-scenario and cross-perspective motion recognition techniques. Yang et al. [1] demonstrated that human–computer interaction technologies, when introduced into sports education and training, can assess students' learning attitudes and interests, thereby boosting their enthusiasm for learning.

This topic highlights how motion behavior recognition technology, based on computer vision and artificial intelligence, is driving revolutionary advancements in sports training and education. It improves the efficiency and accuracy of motion recognition and provides technical support for creating personalized training programs, demonstrating broad application prospects. Additionally, AI technology has significantly enhanced the fairness of physical education. Intelligent evaluation systems offer precise, unbiased feedback to each student, increasing transparency in teaching, reducing the impact of human bias, and ensuring the fair allocation of educational resources. This, in turn, promotes the comprehensive development of students, making physical education more equitable and inclusive [41,42].

4.2.3. AI and Virtual Technology-Driven Innovation and Evaluation in Physical Education

The development of artificial intelligence has brought profound changes to the field of physical education. In particular, the combination of generative AI and virtual reality (VR) technologies has not only transformed traditional teaching models but also revolutionized aspects such as teaching quality, efficiency, and the evaluation of student performance. Generative AI can generate personalized training plans based on individual student data, simulate various sports scenarios in real-time, and provide dynamic feedback to students and teachers, optimizing physical education programs. This technology helps teachers create innovative teaching methods tailored to individual student needs and enables more accurate evaluations. By analyzing high-probability keywords such as "student", "AI", "evaluation", "analysis", "information", and "improve", it is clear that this topic focuses on the impact of AI and VR technologies on physical education, particularly regarding the formulation of teaching plans and the innovation of teaching methods. Therefore, Topic 3 has been labeled as "AI and Virtual Technology-Driven Innovation and Evaluation in Physical Education".

Regarding the application of artificial intelligence in physical education, Wang [35] pointed out that by introducing data mining technologies, universities can more effectively manage and analyze students' physical performance data. Additionally, data visualization transforms complex data into simple and easily understandable charts, helping students better understand their own performance. The visualized information also provides comprehensive data analysis and decision support, aiding teachers in delivering more precise guidance. Zhou et al. [4] explored the application of generative AI in physical education, demonstrating how it can optimize and adapt to the current educational structure, streamline classroom processes, and provide strong technical support for teachers by generating various plans to enhance teaching strategies. Similarly, Lee and Lee [12] found that generative AI can provide educators with real-time classroom insights and offer different strategies to address the varying states of learners, effectively assisting educators in decision-making and optimizing educational plans, ultimately improving teaching efficiency and quality. This technology enables more accurate data analysis and feedback, helping teachers better understand and master skills. It improves training quality and boosts student engagement in sports training. Regarding information management in physical education, Deng et al. [43] emphasized that the development of information technology has had a revolutionary impact on schools. Technologies such as big data analysis, cloud computing, and the Internet of Things (IoT) present unprecedented opportunities for school sports. By leveraging these advanced technologies, educators can more accurately understand students' physical conditions, exercise habits, and interests, allowing them to provide personalized physical education and training plans tailored to individual needs.

Their research explores the positive impact of integrating artificial intelligence and virtual reality technologies into physical education from different perspectives, revealing the promising development potential of this field. Furthermore, these technologies provide continuous technical support for the sustainable development of this area.

In the intelligent transformation of physical education, artificial intelligence and virtual reality technologies significantly enhance teaching quality. They provide a more personalized and effective learning experience in systematic physical education while also increasing student engagement in physical activities through innovative technological means [2]. Furthermore, these technologies offer technical support for teachers in implementing intelligent teaching. AI enhances the accuracy of monitoring and evaluating students' learning processes and offers real-time performance monitoring, enabling teachers to provide personalized guidance and optimize teaching strategies. Virtual reality technology helps immerse students in the learning environment, offering an unprecedented learning experience. In virtual classrooms, students can engage in sports training as if they were physically present, significantly reducing the reliance on physical spaces and equipment. This innovation not only addresses practical challenges such as venue and equipment constraints but also reduces environmental pressure, aligning with the principles of sustainable development [7]. In the future, as AI and virtual reality technologies continue to evolve, they will play an even more significant role in physical education, driving the development of more innovative and more personalized sports education.

5. Research Conclusions and Future Prospects

5.1. Research Contributions

This study systematically identifies three main application directions of artificial intelligence in physical education through LDA topic analysis. This thematic classification not only provides a structured framework for the field but also offers a clear direction for future research. Secondly, the study delves into the groundbreaking contributions of AI technology in automated movement behavior recognition and personalized feedback, highlighting the important role of AI in enhancing the scientific nature of sports training and the accuracy of feedback. Thirdly, the study presents the practical application value of integrating AI with virtual reality technology in physical education classrooms, providing data support for improving student engagement and the precision of teaching assessments. Finally, the research proposes future research directions from the perspectives of sustainability and personalization, emphasizing the potential of intelligent physical education in resource utilization, educational equity, and social benefits. Through these contributions, this study provides theoretical support and practical guidance for academic exploration and practical development in intelligent physical education.

5.2. The Current State and Trends of Intelligent Physical Education

The current research on the integration of artificial intelligence (AI) and physical education primarily focuses on three key thematic dimensions: "AI and Data-Driven Optimization of Physical Education and Training", "Motion Behavior Recognition and Sports Training Optimization Based on Computer Vision and AI", and "AI and Virtual Technology-Driven Innovation and Evaluation in Physical Education". These themes highlight AI's broad application and diversity in physical education, covering the positive impact of computer vision, data analysis, virtual simulation technologies, and deep learning on sports education [11,44,45].

The research reveals that the application of AI in physical education involves multiple complex technological layers, raising the bar for the technological proficiency of sports educators. Through an in-depth analysis of these three major themes, it becomes evident that physical education is rapidly advancing toward a more intelligent, personalized, and data-driven future.

Moreover, integrating computer vision and AI has led to revolutionary breakthroughs in motion behavior recognition and sports training optimization. By leveraging machine learning and image processing technologies, sports training can overcome the limitations of traditional manual assessments, enabling automated motion recognition and feedback. This transformation improves training accuracy and enhances scientific rigor, injecting new vitality into sports training [34,35].

At the same time, integrating artificial intelligence and virtual technologies is setting a new trend in the innovation and evaluation of physical education. In sports classrooms, the innovative application of AI and virtual reality (VR) technologies has not only significantly enhanced student engagement and learning experiences but also provided teachers with more precise tools for teaching evaluation and management through data analysis platforms. This transformation is driving the deeper development of intelligent physical education, injecting new energy into the field [46].

The fusion of AI and virtual technologies is leading a new wave of innovation in physical education evaluation. The application of AI and VR technologies in sports classrooms not only greatly increases student participation and enriches their learning experiences but also equips teachers with more accurate tools for teaching evaluation and management through data analysis platforms. This shift is deepening the progress of intelligent physical education, bringing new vitality to the field [10].

Although existing research on the integration of artificial intelligence and physical education has demonstrated the diversity and complexity of AI applications in this field and yielded significant results [13], much of the research remains focused on theoretical models and case studies, with limited exploration of practical implementation and feasibility. In particular, there is still a lack of theoretical foundation and practical cases regarding the application of core AI technologies, especially in combination with other technologies [46]. Furthermore, many studies are confined to specific sports or aspects of sports management, which, while enhancing relevance, lack comprehensive applications across different sports or even disciplines. Additionally, most research focuses on short-term outcomes, with little attention paid to long-term sustainability.

In conclusion, AI technology has become a significant driving force in the advancement of intelligent physical education. From training optimization and motion recognition to the construction of virtual teaching platforms, AI applications are comprehensively pushing physical education from traditional models toward intelligent systems. This trend not only reflects the urgent demand for technology-driven innovation in the field of physical education but also offers new pathways and opportunities for the sustainable development of physical education.

5.3. Future Research Outlook

Physical education has its unique characteristics, with each sport requiring specific skills, rules, and underlying values, which place particular demands on educational methods and approaches. While technological advancements have driven the smartification of physical education, this evolution presents both opportunities and challenges. Future research can focus on addressing these challenges.

The personalized application of AI in physical education still holds significant potential for development [12]. Future studies should focus on developing more refined personalized teaching plans, utilizing deep learning technologies to optimize and tailor content based on multidimensional data, such as students' physical fitness and athletic performance [34]. This approach aims to significantly enhance teaching quality and guide the evolution of physical education toward a more advanced level of intelligence and personalization.

The deeper integration of virtual reality (VR) and AI is a key research direction for the future. Although VR technology has been preliminarily applied in physical education, its close integration with AI remains to be further explored. A critical research question is how to combine virtual training environments with AI-driven data analysis to enable real-time adjustments to teaching content, offering students an immersive and personalized training experience.

The sustainability of smart physical education also warrants more attention. It is essential to explore how the widespread application of AI in physical education can promote long-term educational equity and efficiency while minimizing environmental resource consumption. The application prospects of AI technology in physical education are vast, extending beyond just improving training outcomes to enhancing students' learning experiences and educational equity. Future research directions should focus on how to effectively integrate AI technology into the educational system to promote the holistic development of students.

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Conflicts of Interest: The authors declare no conflict of interest.

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Article

Artificial Intelligence and the Transformation of Higher Education Institutions: A Systems Approach

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Abstract: Artificial intelligence (AI) advances and the rapid adoption of generative AI tools, like ChatGPT, present new opportunities and challenges for higher education. While substantial literature discusses AI in higher education, there is a lack of a systems approach that captures a holistic view of the structure and dynamics of the AI transformation of higher education institutions (HEIs). To fill this gap, this article develops a causal loop diagram (CLD) to map the causal feedback mechanisms of AI transformation in a typical HEI. We identify important variables and their relationships and map multiple reinforcing and balancing feedback loops accounting for the forces that drive the AI transformation and its impact on value creation in a typical HEI. The model shows how, motivated by AI technology advances, the HEI can invest in AI to improve student learning, research, and administration while dealing with academic integrity problems and adapting to job market changes by emphasizing AI-complementary student skills. We explore model insights, scenarios, and policy interventions and recommend that HEI leaders become systems thinkers to manage the complexity of the AI transformation and benefit from the AI feedback loops while avoiding policy traps that may lead to decline. We also discuss the notion of HEIs influencing the direction of AI and directions for future research on AI transformation and the sustainability of HEIs.

Keywords: higher education; artificial intelligence; AI transformation; generative AI (GenAI); ChatGPT; future of work; CLD; feedback loop; systems thinking; system dynamics; complex system; digital transformation; sustainability

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1. Introduction

The spectacular growth of generative artificial intelligence (AI) tools, like ChatGPT, since late 2022 has brought AI to the forefront of all debates about technology and its impact on the economy and society [1]. While companies explore how to benefit from generative AI investment [2], there are concerns about the future of work and the adverse social consequences of automation that may lead to a jobless future [3–5].

In higher education, the rapid adoption of ChatGPT brings excitement about opportunities for learning as well as concerns about challenges, such as students cheating on their assignments [6], for instance, by asking ChatGPT to write an essay about any topic [7]. While the initial reaction was banning generative AI, several organizations have developed guidelines about the beneficial use of such tools in higher education institutions (HEIs), such as colleges or universities. The Russell Group of universities in the UK developed five principles, emphasizing the need for "students and staff to become AI-literate", adapting "teaching and assessment to incorporate the ethical use of generative AI", upholding academic integrity and rigor, and working collaboratively to share best practices [8]. The intense interest in developing guidelines around AI in higher education underscores the topic's significance.

AI brings several opportunities and challenges for teaching, learning, student support, scholarship, and administration in HEIs. AI is not a new phenomenon in education, and it has been studied for more than 30 years, as captured in several review articles [9–14] that provide a background to inform our research. Still, less understood is how AI will transform education [15,16] and what HEIs could do about it, especially about generative AI, due to its novelty [17–20].

This article aims to study the AI transformation of higher education by deploying a systems approach [21]. It develops a causal loop diagram (CLD) model that captures the major factors that affect AI transformation in an HEI. The CLD shows the feedback loop structure that defines how an HEI creates value and how AI restructures value creation in an HEI. That allows us to understand the causal mechanism underlying several AI effects relevant to HEI, such as effects on learning, academic integrity, and jobs. Visualizing the university as a complex system helps to derive novel insights into the complex dynamics of higher education and practical implications for higher education leaders. The study underscores the significance and value of a systems approach in developing theory and understanding, designing, and managing AI transformation to create value in higher education.

The article makes several research contributions. First, it contributes to our understanding of the AI transformation of HEIs by providing a holistic view of the driving forces and the consequences of the AI transformation. Integrating systems thinking with economic concepts and incentives, we show that investment in AI can have strategic value because AI can transform the structure of value creation in an HEI. The CLD allows us to see the strategic significance of AI within a HEI from a whole-system viewpoint, contributing to higher education economics and strategy. A key concept is the AI feedback loop [22], which captures novel reinforcing value-creation processes due to AI.

Additionally, this article contributes to sustainability through the study of HEIs. Goal four of the United Nations Sustainable Development Goals (SDGs) concerns access to quality education [23]. We show that AI can support the advancement of goal four by demonstrating that AI can help HEIs improve their quality of learning, deal with associated challenges, and better their reputation. Moreover, the model provides insights into the AI-enabled sustainability of HEIs. Therefore, our work connects with two interrelated aspects of sustainability.

Moreover, the article provides practical insights for HEI leaders seeking to understand and leverage AI in higher education. We argue that HEI leaders need to become systems thinkers to manage the complexity of the AI transformation, benefiting from AI feedback loops while avoiding the associated pitfalls. We also aim to clarify what is new about generative AI in the broader historical context of AI use in higher education.

Section 2 develops the theoretical framework and Section 3 explains the research methods. Section 4 presents the CLD model and feedback analysis. Sections 5 and 6 are the discussion and conclusions, respectively.

2. Theoretical Framework

The theoretical framework provides the foundation for the development of our CLD. We study AI transformation in a typical HEI, focusing on the processes that create value in the HEI and the impact of AI on those processes while emphasizing novel opportunities and challenges due to generative AI. Therefore, we decided to organize our theoretical framework into three parts: advances in AI technology that enable the AI transformation, dimensions of AI transformation in the HEI, and AI's impact on jobs for graduating students. These three parts are aligned with the three main processes mapped in the CLD model presented in Section 4, following the methodological choices and steps explained in Section 3.

2.1. Advances in Artificial Intelligence (AI) Technology

With its continuous advances, AI has many promising business applications, and it is expected to transform our lives, businesses, and society [1,24–28]. Artificial intelligence as a field has a 70-year history, with multiple waves of progress followed by periods of challenges called AI winters. It is a diverse field of research and practice related to creating and evaluating intelligent systems [29] with various problems (e.g., reasoning, prediction, planning, vision, language understanding), approaches, technologies, and applications. One popular approach has been creating rule-based systems that encode the knowledge of experts, e.g., rules about making a medical diagnosis, but these systems have substantial limitations. Instead of capturing knowledge in software, the approach that proved most fruitful is designing algorithms that learn from data and training them with large quantities of data on powerful computers—this is the machine learning approach. Various approaches to learning are used depending on the problem: supervised learning, unsupervised learning, reinforcement learning, and others.

Most recent AI advances rely on machine learning using large-scale neural networks, called deep learning, due to the multiple layers of neurons. One example is large-scale neural networks for language, called large language models (LLMs), that can generate text, including code, following a user prompt or a sequence of user prompts (dialogue with the user), hence generative AI. LLMs are trained using large datasets [30], and because they deal with language, they also belong to the area of AI called natural language processing (NLP). OpenAI's ChatGPT, using generalized pre-trained transformer architecture with billions of parameters (weights), is the most well-known example, amongst many, of a conversational generative AI application built on an LLM. Other generative AI applications produce images, music, videos, or multiple types of media (multimodal models), so the general term 'foundation model' is sometimes used for generative AI models. The art of writing prompts to obtain the best results from the system is called prompt engineering. The systems typically incorporate filters called guardrails to ensure they do not produce offensive or otherwise undesirable content. Other significant challenges and risks are discussed in Section 2.2.5. Overall, AI advances create opportunities for benefiting from AI within an HEI, as we explain next.

2.2. Dimensions of AI Transformation in HEIs

We identify and discuss five dimensions of AI transformation in an HEI: student learning, academic integrity problems, faculty research productivity, administration and operations, and AI-related risks.

2.2.1. Student Learning

AI can support student learning by empowering instructors and students [31]. In particular, AI has the potential to transform teaching by supporting instructors. Instructors could use AI as a support to design programs or courses, create new education material and assignments, deliver better instruction that increases student engagement and motivation for learning, and to assess learning more creatively and authentically. Faculty can also use AI to automate time-consuming administrative tasks so that they can focus on creativity and innovation in teaching and research. AI and other Industry 4.0 technologies, such as the Internet of Things, can enable smart classrooms and the digital transformation of education management, teaching, and learning [32]. Other examples include learning analytics, educational data mining, intelligent web-based education [9], and cobots (collaborative robots) that assist teachers in the classroom [33]. A large-scale review of more than 4500 articles published between 2000–2019 [34] found that the main research topics include intelligent tutoring systems for special education, natural language processing for language education, educational data mining for performance prediction, discourse analysis in computer-supported collaborative learning, neural networks for teaching evaluation, affective computing for learner emotion detection, and recommender systems for personalized learning. Another review of 138 articles from 2016 to 2022 [10] found 5 five topics: assessment/evaluation, predicting, AI assistant, intelligent tutoring system, and managing student learning.

Students can use AI as a support tool to meet their learning goals via personalized adaptive learning. Applications come in various forms, such as personalized learning [35], AI teaching assistants, teacherbots [36,37], intelligent tutoring systems [38], and others. An experimental study in India found that personalized technology-aided after-school instruction improves student scores in math and language [39]. Gains attributed to the tutoring effect can be expected to be larger using more recent AI technologies, such as GPT-4. Generative AI can empower students and enhance their educational resources and experiences [40]. There are several ways that generative AI can be used in the classroom, such as a tutor, coach, or teammate [41]. Alternatively, AI can be used as a tutor or coach outside the classroom, while classroom time is used for activities that apply knowledge.

While publicly available general-purpose tools, like ChatGPT, receive most of the attention, the greatest value may come from specialized tools created with specific education objectives and trained with appropriate data or using retrieval augmented generation (RAG). An example is Khanmigo by Khan Academy (https://www.khanacademy.org/khan-labs, accessed on 14 January 2024), which aims to bring one-to-one tutoring to all students and an assistant to teachers using AI. It runs on top of the OpenAI platform and is used widely as a pilot phase, but research on its efficacy is expected in 2024 [42].

2.2.2. Academic Integrity Problems

There is significant concern that generative AI tools will facilitate high levels of cheating in higher education, undermining learning and academic honesty [43,44]. Although cheating existed before ChatGPT [45,46], just two months after ChatGPT's release, an estimated one-fifth to over one-third of students reported using it, with the vast majority believing they cheated using it [47]. Furthermore, as students become more familiar with the technology, they also become more effective at using it.

Moreover, academic integrity problems may relate to employers seeing higher education as a signaling device [48]. For instance, employers will only consider applicants who graduated college and screen candidates by grade point average (GPA) [49]. As a result, students could perceive that graduating with a degree and GPA that employers will desire is more important than learning. This creates an incentive for students to cheat using AI.

HEIs can respond by reducing incentives to cheat, increasing the value of learning, making it harder to cheat, or increasing the risk and consequences of getting caught. A systematic review of cheating in online exams from 2010 to 2021 found several approaches to reduce academic dishonesty before testing [50], such as strengthening student ethics, bringing the learning goal of the exams to mind, and moving away from summative assessments towards formative assessments. Instructors have modified their teaching and assessment in response to technologies that make cheating easier, such as the calculator [45] and Wikipedia [51]. However, with widespread AI usage, randomizing questions or shifting toward essays becomes less effective. However, anti-cheating measures have tradeoffs. For example, using online proctoring software may reduce cheating, but it also costs money, causes technological difficulties, has false positives, and reduces student's privacy. The most common initial approach by schools was using AI detection software. Unfortunately, AI detection software has an extremely high false positive and false negative rate and flags the work of non-native speakers significantly more than their peers [52]. There is a need for clear policies to deal with academic integrity and plagiarism detection challenges [53]. Therefore, HEIs must update their academic integrity policies, and faculty must update their course syllabi to account for generative AI. For instance, some courses could allow the creative use of generative AI and adjust assignments and assessments accordingly, while others prohibit it. Overall, as AI advances, students may discover new ways to cheat, and HEIs must take measures to deal with those challenges.

2.2.3. Faculty Research and Accelerated Scientific Discovery

AI, such as machine learning techniques, is increasingly used in science research, and researchers are excited about its potential [54]. However, they are also concerned about the quality of work and reproducibility of results [55]. Generative AI can support scholarly work and faculty research productivity [56]. Such tools can support problem formulation, data collection, analysis, and writing [57], including research brainstorming, identifying research questions, hypothesis generation [58–60], summarizing or conducting a literature review, creating graphs from data, and drafting parts of manuscripts.

However, all those uses come with challenges, such as AI hallucinations (making things up), accuracy, completeness, quality, and others. Moreover, the ease of creating content using generative AI tools may increase academic misconduct or result in the mass production of low-quality papers flooding journals and the established peer-review process. Both would have significant negative consequences for scholarly publishing and research, and journals are updating their editorial policies. For instance, science journals do not accept text written by AI tools [61]. Ultimately, the authors are responsible for all aspects of the research output, and they also need to be transparent about whether and how they use AI tools. While conversational generative AI tools have the potential to play a significant role in the research workflow, the details of the practical application of those tools need to be clarified (Table 6 in [57]), and guidelines must be defined [58]. Overall, AI can positively impact faculty research productivity, accelerating research and scientific discovery [59,60,62].

2.2.4. Administration and Operations: Institutional Learning

Although our review of the literature on AI in higher education finds that the main focus is student learning and teaching, other HEI areas can benefit from AI [63,64]. AI can support the HEI administration at multiple levels, including departments and schools. Moreover, admissions can use AI and data to target the right students and manage the admission process to improve enrollments. Academic advisors can use AI to guide students, improving student educational experience, satisfaction, and retention. AI can also support career advising [65], internships, and job placements for students. Managing alumni relations can be important for many HEIs, and AI helps manage the relationship. AI can support IT, human resources, athletics, facilities, and operations [66]. For instance, the IT department can use AI to automate tasks and workflows and lower the cost of managing the IT infrastructure. Facilities can use AI to make infrastructure more intelligent, allowing for efficiencies, remote management, and maintenance.

In summary, AI and data can help improve effectiveness and lower the operating costs of all university areas. Many of those opportunities for improvement can be seen as institutional learning. Therefore, an HEI can use AI to become a learning organization and pursue continuous improvement while adapting to changes in its environment.

2.2.5. AI Risks and Ethics in HEIs

Generative AI has a long history [67], and while recent generative AI signifies progress, we should be aware of its limitations [68–70] and discount the hype. For instance, LLMs are probabilistic language modelers predicting how to continue the text based on patterns learned from training data. They lack causal models of understanding the world, and their outputs need critical evaluation. ChatGPT and related tools are designed to create persuasive and authoritative output, even when they make things up, a well-known problem called hallucination. This is a severe problem for education because the only thing worse than not learning anything is learning the wrong things very well. AI-created fake media, such as images and videos (deep fakes), will exacerbate learning and social cohesion challenges.

In addition to clearly damaging misinformation, large quantities of poor-quality content are a problem for student learning. Humans have limited time and attention (cognitive capacity), and those resources can be easily wasted in an environment where multiple services compete for user attention (attention economy) using algorithms optimized for user engagement. Moreover, poor-quality content from GenAI tools may pollute the Web, affecting all users, including GenAI tools that use that content for training.

Algorithmic bias is another significant concern [71]. Algorithms may reinforce decision biases when evaluating student work, admissions, job placements, etc. In a reinforcing feedback loop, bias in historical data drives algorithmic bias, which drives decision bias, which leads to even more human bias and bias in the data.

In addition, AI in higher education also has a dark side related to data [72]. Data is an essential resource for AI. The need for large quantities of data creates privacy, security, and copyright risks. For instance, sensitive student data must be well protected. Confidential data may leak if it is used to interact with publicly available AI chatbots. Malicious actors can use AI for cyberattacks. Ignoring copyrights in model training is another issue, and ongoing lawsuits may affect how future generative AI systems work [73].

Multiple ethical issues arise. The process of training AI models often utilizes cheap global labor to label data, moderate content, or provide feedback, creating ethical concerns about labor practices [74]. Increased complexity due to fast change, loss of control, manipulation of behavior, dependence on tech firms, like OpenAI, controlling the AI platform, and lack of transparency and accountability are other issues due to AI that may negatively affect multiple areas of an HEI. Constant surveillance by AI [75] damages trust and meaningful education [76]. Automation itself is a risk, if not well designed, because it could cause an organization to do the wrong things faster and in an automated way while no one pays attention. Accountability in AI-mediated education practices is an issue that needs to be studied more [77]. The environmental impacts, carbon and water footprints, and energy consumption of AI data centers are also concerning [78].

Organizations need to take measures to manage all these AI-related risks. The explainability, transparency, and fairness [79] of AI decisions should be priorities in the design of AI systems. Human oversight, critical thinking [80], and education on the responsible and ethical use of new tools [81,82] are vital. Learning analytic systems must be thoroughly audited to ensure they are fair, transparent, and robust [83]. Generative AI tools, such as ChatGPT, raise even more ethical challenges and call for stakeholder engagement and a systemic view of the benefits and risks when applications are developed [81]. The UNESCO guidance proposes the regulation of generative AI tools by government agencies and validation of the ethical and pedagogical aspects of those tools by education institutions [82].

2.3. Jobs for Graduating Students

HEIs educate students who seek jobs after graduation. Therefore, the state of the job (labor) market and the workforce needs of companies are crucial determinants of the value of an HEI degree.

AI can be a tool that makes a worker more productive (AI augmentation) or an automation engine that eliminates the worker's job (AI substitution). Therefore, what jobs and how will be most impacted by AI is a complex question [84–87]. A way to approach that question is to think of a job as a set of tasks and consider how AI affects tasks. Then, a job with many tasks automated or augmented by AI will be affected the most [88,89]. Our study aims to connect job market changes due to AI with the value created by HEIs considering AI substitution and augmentation.

Generative AI can make knowledge workers more productive. Software developers randomly assigned to use GitHub copilot, an AI coding assistant, completed their task 55% faster than the control group [90]. Moreover, using GitHub Copilot improves other metrics, such as developer job satisfaction [91]. College-educated professionals randomly assigned to use ChatGPT in a writing task took 40% less time and produced 18% higher output quality, and participants with weaker skills benefited the most [92]. Customer support workers using generative AI achieve higher productivity but with significant heterogeneity across workers, as novice and low-skilled workers benefit the most [93]. While AI can help improve the effectiveness of consultants in many tasks, there are tasks in which AI fails, implying that overreliance on AI can lower performance [94]; for instance, LLMs hallucinate and sometimes do poorly in basic math.

Companies care about the optimal mix of humans and AI that maximizes the company's performance. The interaction of companies' needs and workers' skills and preferences will determine the effect of AI on employment outcomes. For instance, a recent study using data from a large online platform found that generative AI negatively affects freelancers' employment and earnings [95].

3. Methods

We introduce the systems approach, describe the typical CLD development process, and explain the steps we followed to develop our CLD model.

3.1. Systems Approach and CLD

A systems approach calls for a holistic view of systems with multiple interacting parts because the behavior of a complex system can only be understood by studying the whole system [21,96]. A systems approach using a CLD is called systems thinking or qualitative system dynamics [21,97,98]. The CLD is a causal system mapping tool [99] used to map the structure of a system. It shows the causal feedback processes, or feedback loops, that drive the dynamic behavior of a system. The process helps to visualize the interconnectedness of different system parts, externalize and explore mental models, and identify leverage points for system change. In addition, building a CLD with the participation of multiple stakeholders aids in visualizing the whole system and building consensus for action [100]. From a practical standpoint, a CLD can help a manager anticipate and manage dynamic complexity.

Developing a CLD to gain insight into a system has been widely used in multiple applications across multiple fields [21,101]. Examples include understanding complexity in organizations [102], business strategy [103], health systems [104–106], sustainability [107], digital technologies and business models [108,109], pandemics [110], diffusion of innovations, such as car-sharing [111], and many others. The systems approach has been used for the study of several issues in higher education, such as university management and planning [112–114], quality management [115], the enrollment crisis due to demographics [116], university funding [117], tuition inflation [118], program development [119], and others.

3.2. Development of a CLD

We built the CLD following the relevant literature on systems approach and qualitative system dynamics methodology [21,98,120–123]. We defined the problem, identified key variables (factors), and defined the system boundary. Then, we identified the rest of the variables, the causal links between variables, and the feedback loops that emerged from connecting the causal links. Making those feedback loops visible is a significant value of the CLD modeling process. A feedback loop is reinforcing (a change in a factor amplifies via the loop) or balancing (a change is dampened via the loop). The structure and interaction of the feedback loops determine the system behavior through time. A CLD is, in essence, a dynamic theory of the problem under study, and we want as many variables as possible to be endogenous.

3.3. Steps We Followed to Develop Our CLD

Our study follows the standard process for developing a CLD described above, and here we provide more study-specific methodological details. Our study relies on an extensive literature review of our topic and our exploration of current AI-related developments leveraging our domain expertise. Our domain expertise is more than 50 years of cumulative experience in higher education.

Our objective is to create a high-level, holistic map of AI transformation in a typical HEI, focusing on the processes that create value in the HEI and the impact of AI on those processes. Therefore, the key variables we want to focus on are student learning (because the primary mission of an HEI is to teach students), AI investment (because this determines whether the HEI adopts and uses AI), and HEI reputation (because HEIs compete on reputation [124,125]). Therefore, explaining how those key variables behave over time is crucial.

The definition of the system boundary is also driven by the problem we want to solve. We decided to focus on the processes within the HEI and the primary interaction of the HEI with its environment. This suggests three main processes: the AI industry that drives AI advances that affect the HEI, the focal HEI that uses AI for transformation, and the companies that offer jobs to students graduating from the HEI. These three overlapping processes were identified after an initial review of the literature on AI and education, and as a result of our study of current developments in the area. They define the boundary of the system we will explore using our CLD.

After we defined our system boundary, we went back to expand and refine the literature review and organize the theoretical framework of our research (Section 2) according to the three main processes we decided to focus on. That way, the organization of the theoretical framework is aligned with the main model components. The theoretical framework and the CLD constitute an integrated whole.

Like all models, a CLD is an abstraction of reality, and the theoretical framework section is a crucial step toward building the CLD model. In addition to the key variables mentioned above, all the CLD variables and their relationships were identified following the three main overlapping processes in the theoretical framework. A complete list of variables is presented in Table 1, and the relevant theoretical framework sections for each variable are listed in parentheses.

Table 1. Model variables and their brief description (the relevant theoretical framework section is listed in parenthesis).

#	Variable	Brief Description
1	AI R&D	Total AI R&D leading to AI advances (2.1)
2	AI capabilities	Capabilities of AI resulting from AI advances (2.1)
3	Business investment in AI	Business sector investment in AI applications (2.1 and 2.3)
4	Total AI demand	Total demand for AI in the economy (2.3)
5	Automation in business	Level of business automation using AI (2.3)
6	Business benefit from automation	The value businesses gain from AI (2.3)
7	HEI investment in education	Level of HEI's education investment (2.2)
8	HEI student learning	Student knowledge acquisition in HEI (2.2.1)
9	HEI student job placement	Successful HEI graduate employment (2.3)
10	HEI relative reputation	Overall HEI reputation (perceived quality) (2.2)
11	Enrollment in HEI	Total student enrollment in HEI (standard HEI metric)
12	HEI net revenues	HEI revenue minus the costs (standard HEI metric)
13	HEI investment in AI	HEI's AI funding (2.2)
14	Learning analytics, tools, and data	Level of learning analytics use in HEI (2.2.1)
15	Self-learning	Independent learning by students (2.2.1)
16	HEI alumni network	Size of HEI's alumni network (2.2.4)
17	Alumni giving	Level of alumni giving to HEI (2.2.4)
18	Total AI demand from HEIs	Total AI needs by colleges and universities (2.2)
19	Academic integrity problems (student cheating)	Violations of academic standards in HEI (2.2.2)
20	Measures to deal with AIPs	HEI efforts against academic misconduct (2.2.2)
21	Data about AIPs	Data about academic misconduct (2.2.2)
22	Research productivity	Scholarly output by HEI faculty (2.2.3)
23	HEI operating costs	HEI's operational expenses (standard HEI metric)
24	Personalized recruitment and advising	AI supported student recruitment and help (2.2.4)
25	Alumni engagement	HEI engagement with alumni network (2.2.4)
26	Demand for AI-skilled workforce	Business need for AI-skilled employees (2.3)
27	HEI teaching AI skills	Quality of AI-related education in HEI (2.2.1)
28	Competitor reputation	Reputation of HEI competitors (2.2)
29	AI investment by other HEIs	AI funding by other colleges and universities (2.2)
30	AI risks	Bias, security, and other AI risks (2.2.5)

After several iterations of adding, refining, and building confidence that the CLD maps what we know about the system, the validity of the resulting CLD model was further established by feedback from three domain experts—a student, a faculty member, and a university administrator—following [126]. This concludes the development of the CLD.

In the next section, we explain all the relationships between variables and present the CLD model. We emphasize the important feedback loops and derive insights from the feedback loops and their interactions. In addition, we evaluate policy interventions (leverage points) qualitatively. This can be carried out because the CLD allows us to assess how a change in one part of the system ripples through the whole system. The CLD is an essential output of this research; other researchers and practitioners can use it as a starting point for more exploration. Like all methods, the systems approach we use has limitations, discussed in Section 4.2, alongside recommendations for future research that could address those limitations.

4. CLD Model and Insights

The CLD model maps the causal mechanisms of AI transformation in a typical HEI (Figure 1). A positive arrow signifies that the cause-and-effect variables move in the same direction, while a negative causal relationship between variables is shown as a negative arrow. Letters R and B denote reinforcing and balancing feedback loops, respectively. Our model captures three interconnected processes: the AI industry that drives AI advances that the HEI adopts, the focal HEI that uses AI for transformation, and the companies that offer jobs to students graduating from the HEI.

We identified and analyzed 15 reinforcing (R) and 4 balancing (B) feedback loops that define the structure of value creation in the HEI and its interaction with the business sector and the AI industry. The CLD defines the system structure, which determines the system behavior through time. The feedback loops are summarized in Table 2 and discussed below.

Table 2. Feedback loops and their brief description. Names of reinforcing loops begin with the letter R. The letter B is for balancing loops.

Name	Variables	Brief Description
R1	1, 2, 3, 4	Business investment drives AI R&D and AI advances
R2	3, 5, 6	Benefits from automation drive business investment in AI
R3	7, 8, 9, 10, 11, 12	HEI creates value (and revenues) through quality education
R4	13, 14, 8, 9, 10, 11, 12	HEI invests in AI to improve learning
R5	2, 15, 8, 9, 10, 11, 12, 13, 18, 4, 1	AI facilitates students' self-learning
R6	22, 10, 11, 12, 13	AI can support research productivity and HEI reputation
R7	22, 8, 9, 10, 11, 12, 13	AI supports research that contributes to student learning
R8	2, 13, 18, 4, 1	Advances in AI motivate the HEI to invest more in AI
R9	23, 12, 13	HEI uses AI to lower operating costs
R10	24, 11, 12, 13	AI supports admissions and student advising
R11	13, 25, 17, 12	HEI uses AI to support alumni engagement and giving
R12	26, 27, 9, 10, 11, 12, 13, 18, 4, 1, 2, 3, 5	HEI teaches AI skills as a response to business demand for an AI-skilled workforce
R13	9, 10	HEI's reputation and job placement reinforce each other
R14	9, 16	The size of the alumni network helps job placement, which grows the alumni network
R15	20, 19, 8, 9, 10, 11, 12, 13	HEI benefits from measures to deal with academic integrity problems (AIPs)
B1	2, 19, 8, 9, 10, 11, 12, 13, 18, 4, 1	AI advances lead to more AIPs which hurts HEI
B2	19, 21, 20	HEI's efforts to deal with AIPs
B3	5, 9, 10, 11, 12, 13, 18, 4, 1, 2, 3	The job-substitution effect of AI hurts HEI job placement
B4	30, 10, 11, 12, 13	AI risks can harm the HEI's reputation

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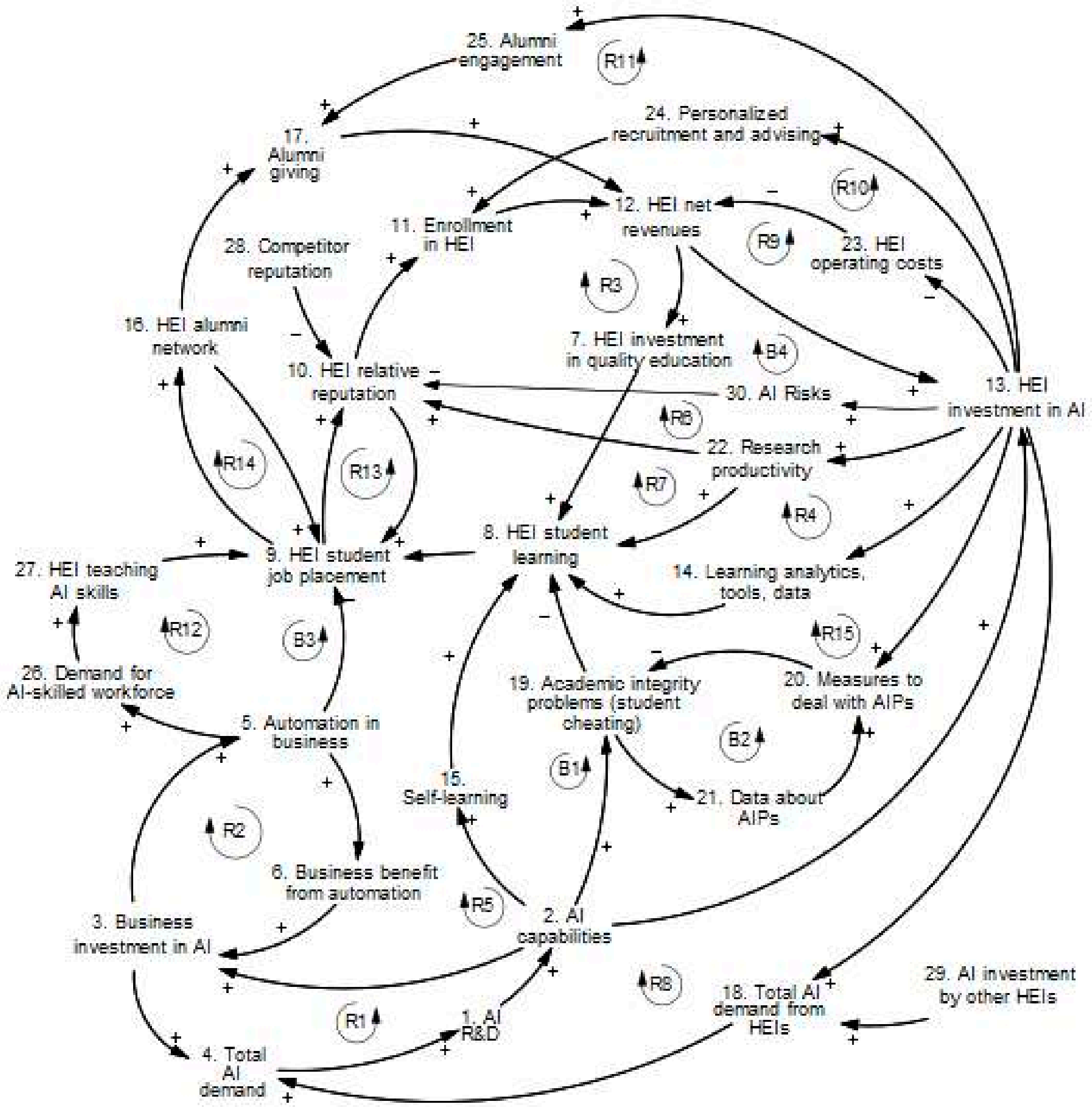

Figure 1. AI and the transformation of a higher education institution (HEI). *HEI investment in AI* aggregates investment for teaching, learning, research, admissions, student advising, and alumni relations. *HEI investment in quality education* aggregates all other investments in faculty, facilities, methods, advising, etc.

4.1. Advances in AI Technology

We start with feedback loops related to AI advances (improved AI capabilities) in the AI industry following Section 2.1. AI advances, such as generative AI and LLMs, create opportunities for AI transformation in HEIs. The following two feedback loops capture the main mechanism of AI advances.

R1: Due to AI research (R&D), AI capabilities improve and encourage more business investment in AI, motivating the AI industry to invest even more in AI R&D.

R2: As AI capabilities improve, businesses invest more in AI, thus increasing business automation. More automation benefits businesses and encourages even more investment in AI.

Loops R1 and R2, supported by R5 and R8 discussed below, are the primary economic forces driving AI advances. We focus on the AI transformation within the HEI next.

Figure 1. AI and the transformation of a higher education institution (HEI). *HEI investment in AI* aggregates investment for teaching, learning, research, admissions, student advising, and alumni relations. *HEI investment in quality education* aggregates all other investments in faculty, facilities, methods, advising, etc.

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R5	2, 15, 8, 9, 10, 11, 12, 13, 18, 4, 1	AI facilitates students' self-learning
R6	22, 10, 11, 12, 13	AI can support research productivity and HEI reputation
R7	22, 8, 9, 10, 11, 12, 13	AI supports research that contributes to student learning
R8	2, 13, 18, 4, 1	Advances in AI motivate the HEI to invest more in AI

4.2. Student Learning

We now focus on mechanisms within the HEI, starting with student learning following Section 2.2.1.

The following loop, R3, is the most fundamental feedback process that creates value for students and financially sustains a typical college or university.

R3: The HEI invests in quality education because it improves student learning and job placement and positively affects the HEI reputation, ensuring enrollment and revenue.

The following feedback loop shows how AI investment by the HEI contributes to student learning.

R4: The AI investment leads to better learning analytics, AI tools, and data, which improve student learning, allow students to find good jobs, and build the HEI's reputation. A strong reputation contributes to healthy enrollments and revenues, enabling more investment.

Another loop that affects student learning is R5, as described below.

R5: Advances in AI capabilities facilitate students' self-learning, which improves student learning.

A trade-off between formal learning (R4) and self-learning (R5) is apparent here. Suppose students undertake an increasing amount of their learning through self-learning. In that case, the position of the HEI is weakened over time because fewer students will be interested in enrolling, or those enrolled will be asking for tuition discounts.

4.3. Student Academic Integrity Problems

The AI-assisted academic integrity problems might undermine the HEI's business model, as captured by loop B1, following Section 2.2.2.

B1: Better AI leads to more academic integrity problems (AIPs), such as student cheating, which negatively affects student learning, job placement, and the HEI's reputation.

The HEI can use data about AIPs and AI to fight academic integrity problems, as shown in loop B2.

B2: As AIPs increase, the HEI will increase its efforts to deal with AIPs, aided by collecting more data about the problems.

It is in the HEI's interests to invest in measures to deal with AIPs, as shown in R15.

R15: AI investment can support dealing with AIPs, and this improves student learning, HEI reputation, and enrollments, enabling more AI investment.

4.4. Faculty Research

AI can support faculty research and contribute to further value-creation in the university, as captured by feedback loops R6 and R7, following Section 2.2.3.

R6: AI investment supporting the research productivity of the HEI faculty has a positive effect on the reputation of the HEI and leads to more robust enrollment numbers and positive net revenue.

R7: AI investment supporting the research productivity of the HEI faculty adds value to student learning due to research–teaching complementarity.

In summary, two mechanisms add value when AI investment supports faculty research. Improved research productivity is positive for the HEI's reputation (direct mechanism), and better research can support innovative teaching (indirect mechanism).

4.5. HEI Administration and Operations

Following Section 2.2.4, AI can support HEI administration and operations in multiple ways. The following feedback loops capture important mechanisms that add value to HEIs.

R8: Advances in AI motivate the HEI to invest more in AI.

R9: The HEI uses AI to lower operating costs, so there is a higher net revenue for investments in quality education and AI supporting it.

R10: The HEI uses AI to support admissions and improve new enrollment numbers, student support, student retention, and graduation rates, thus increasing total enrollment in HEI.

R11: The HEI uses AI to support alumni engagement and improve alumni giving.

4.6. AI Risks

Following Section 2.2.5, multiple AI-related risks (biased decisions, privacy, security, and misinformation) can harm the reputation of HEI. This mechanism is captured by feedback loop B4.

B4: Increased AI investment and adoption increase the risks of AI, which could harm HEI's reputation, hence harming enrollment and revenues.

The HEI must manage this feedback loop with risk prevention and mitigation measures.

4.7. Job Placement

We now focus on the interaction between HEI students looking for jobs and businesses offering jobs (Section 2.3). The following three feedback loops capture the main mechanisms.

R12: Business adoption of AI is an opportunity for job placement of students who acquire AI-complementary skills. These skills are discussed in more detail later.

The job-substitution effect of AI manifests itself as a balancing loop (B3): Business automation is a challenge for job placement because it lowers the number of available jobs.

R13: The HEI relative reputation and the student job placement reinforce each other.

R14: When the HEI does well in terms of student job placement, it enlarges its alumni network, which is an opportunity for more extensive alumni giving (which helps all the other investments), and also improves the job placements of new graduates.

4.8. AI Transformation and HEI Success

The model sheds light on the dynamic complexity of value-creation in an HEI and the impact of AI. It identifies the precise mechanism through which an HEI creates value and explains its success.

Job placement of students is a vital factor for HEI's success. Students who graduate from HEIs expect to find jobs, so job placement is a crucial factor in the system under study. The CLD shows the pivotal role of an HEI's student job placement because it affects enrollments and revenues through several pathways (e.g., R3, R4, R7). Job placement depends on student learning, an HEI's relative reputation, and job availability. AI impacts all three factors through several pathways, as shown in Figure 1. Therefore, the HEI needs to make the best use of AI to prepare its students for a job market shaped by AI, while other HEIs are likely to do the same, creating new AI opportunities and challenges over time.

AI helps the HEI improve the quality of its offered services (R4, R6, R10, R11) and lower the cost of operations for a given level of service (R9). AI can help an HEI improve learning and increase its reputation, student enrollment, and revenue through multiple reinforcing loops (e.g., R3, R4, R7). The reinforcing feedback loops together work for the benefit of a well-managed HEI. As long as AI keeps advancing, driven primarily by business demand, the reinforcing feedback loops create a virtuous cycle for an HEI that invests in AI and improves its reputation relative to its competitors. However, those same loops will hinder any HEI that falls behind in the competitive higher education market because HEIs compete on reputation. In that context, AI investments can help an HEI differentiate itself and soften competition.

In addition, AI advances intensify academic integrity problems, a balancing loop (B1), and if not adequately addressed, they may undermine learning and the associated benefits for HEIs. A potential danger is education turning into a 'market for lemons' in the eyes of employers, as employers cannot easily discern which students learned and which used AI to cheat. In extreme cases, the employment market could collapse. Measures to fight AIPs can differentiate an HEI from others if AIPs become a significant problem in the higher education sector.

In summary, AI rewires the feedback loop structure that defines how an HEI creates value. Therefore, our study underscores the crucial role of AI feedback loops [22,108,127] in the success of HEIs. Depending on AI investment and policies, an HEI can prosper or decline.

4.9. Job Market Scenarios and HEI

In the business world, AI automation lowers the demand for labor (B3) but increases the demand for new skills (R12). Successful HEIs adapt to these changes by teaching AI complementary skills. In the long-term scenario where AI automates all or most of the jobs, the current model of HEI collapses (see feedback loops R3, R4). HEIs, as we know them today, may disappear if there is no demand for degrees, perhaps except for a small number of elite HEIs educating the government and business leaders. Those HEIs that survive and thrive will need models disconnected from degrees for jobs. They will need to create value in other ways, perhaps teaching humans leisure skills, providing lifelong learning training to humans (instead of intensive higher education degrees as we know them today), or training and tuning AI systems in partnership with companies. If humans are supported by a universal basic income (UBI) [3] due to the lack of jobs, then part of that income could be support for lifelong learning, i.e., a universal basic lifelong learning income (UBLI). Under this scenario, government support will be a source of revenue for future HEIs.

An alternative long-term scenario is that AI will become a new platform for new types of jobs, and there will be an enormous demand for people to fill those jobs (similar to jobs in factories after the Industrial Revolution or office jobs with the adoption of computing). In that case, the future of HEIs is bright, especially if the job market is very fluid and people need multiple degrees over their lifetime.

4.10. Interventions

The model lets us see why and how an intervention propagates through the system. For instance, increasing AI investment will be reinforced through multiple feedback loops (R4, R6, R9, R10, R11, R15). An intervention that increases research productivity will be reinforced in R6 and R7 and then in additional feedback loops, interacting with those.

A policy focused on cost-cutting at the expense of education quality risks placing the HEI at a reinforcing decline trajectory due to R3 and other reinforcing feedback loops. If AI is used to support such a policy, then AI will speed up the decline, whereby revenues keep getting lower, and the HEI keeps cost-cutting until both approach zero.

Data is a valuable resource for the effective use of AI in HEIs (see, for instance, R4 and B2). Indeed, the more data the HEI collects about all areas (learning effectiveness, job placement, alumni, reputation, admissions, student retention, etc.), the more effective its AI can become. For an HEI, value comes from AI plus data. Therefore, interventions targeting the accumulation of high-quality data can be powerful.

Interventions targeting one variable are not a system's most potent leverage points. More powerful leverage points include creating new desirable feedback loops and changing the system's rules or goals in a desirable direction [96].

In addition to the interventions explored here, other scholars can use our CLD as a map for exploring additional policy interventions or scenarios.

5. Discussion

This article takes a novel complex systems approach to how an HEI creates value and how AI affects those value-creation processes. The article explores the effects of AI in higher education using a CLD, and it identifies multiple feedback loops and their interactions. Next, we discuss implications for academic leadership and policymakers, research limitations, and future research directions.

5.1. Lessons for Academic Leadership

AI advances in the form of generative AI create several opportunities for AI transformation, including the promise to bring HEIs closer to the vision of personalized AI assistants that support students, faculty, and administrators. In that context, our research provides a first map of AI causal mechanisms to help HEI leaders navigate an uncharted landscape of opportunities and pitfalls.

Leaders can use the CLD to build intuition and evaluate the benefits and risks of various scenarios and HEI policies. Our discussion of feedback loops in Section 4.10 is a starting point in that direction, but many other policies can be evaluated.

A crucial question for academic leaders is what competencies and skills students will need to find a job. Following our earlier exploration, students should avoid competing head-to-head with AI. Instead, they need foundational human skills that AI lacks, such as critical thinking, planning, complex problem-solving, creativity, lifelong learning, communication, management, and collaboration. Students need to learn and think in ways that differentiate them from machine learning. If AI becomes ubiquitous in firms, humans will need skills that complement what AI can do well. That includes skills to build, train, deploy, use, and manage AI systems, identify valuable use cases, devise AI strategies, lead teams or companies, etc. Moreover, students need to acquire those AI complementary skills in a way (quality, breadth, and depth) that allows them to compete effectively against other humans seeking similar jobs. For instance, managers that use AI effectively may replace those that do not.

HEIs need to monitor changes in the job market [4] and remain adaptive. For instance, a recent study argues that LLMs can transform the role of a data scientist from coding and data-wrangling to assessing and managing analyses performed by AI tools [128]. In that case, skills related to strategic planning, coordinating resources, and overseeing the product life cycle become more critical, and those teaching data scientists must adapt accordingly, perhaps gradually over time.

The effects of AI on productivity and automation are also relevant to what happens to jobs within HEIs. Will AI make instructors, administrators, and staff more productive and their jobs more fulfilling? Will AI replace instructors, administrators, and staff in the longer term? Multiple effects play a role simultaneously, and the specified time horizon matters. However, a crucial framing question is as follows: What does the HEI want to achieve with AI? The university's policy and mission matters. For instance, a university that does not grow and does not aspire to the highest learning standards may manage with a few instructors, administrators, and staff, provided all those roles become more productive, and many tasks are automated. However, a student-centered and human-centered university that appreciates its people may be successful by providing a superior education, differentiating itself from competitors focusing on cost-cutting.

A related issue is the future direction of AI. Our exploration suggests that the direction of AI advances is not predefined [129], and the social responsibility of a university lies in prioritizing how AI can empower humans by augmenting jobs rather than eliminating them [130]. As a starting point, HEIs could focus on designing and adopting personalized AI assistants for higher education, such as for faculty, students, staff, administrators (including department chairs and deans), advising, and more. At the same time, there is a need for careful integration of generative AI tools into education [131]; during the COVID-19 pandemic, students suffered both academically and socially, and we re-learned that education is a "deeply human act rooted in social interaction" (p. 7). Beyond the boundaries of the education sector, HEIs could promote AI assistants for various roles (e.g., financial analyst, CEO) across all industries and teach students accordingly.

In that direction, our CLD suggests that a single HEI has very little influence over the direction of AI, but multiple HEIs working together can have a meaningful influence. Moreover, similar to the proposals in the healthcare industry [132], there is value in open-source LLMs developed by a community of HEIs. Those insights suggest a trade-off for an HEI: Investment in AI is a tool for getting ahead of its competition, but if it wants to influence the direction of AI meaningfully, the HEI needs to collaborate with other HEIs. Along those lines, AI advances could support educational research that provides novel, rigorously validated insights into teaching and learning methods that could benefit all HEIs.

AI's promise to accelerate research and scientific discovery is aligned with the knowledge-creation mission of HEIs. However, in the longer term, only large tech companies may have the computing and data resources for complex, large-scale, and high-impact science research, such as Google DeepMind's AlphaFold for protein folding in biology [133] and discovering thousands of new materials in material science [134,135]. As a result, HEIs may be sidelined unless they partner with big tech companies, the research divide in higher education may get bigger, and big tech firms may become the gatekeepers of consequential research agendas.

Overall, AI promises several benefits but entails challenges, and ultimately, it depends on what policy the HEI wants to follow and how it intends to position itself by leveraging AI-enabled transformation while protecting itself from the associated pitfalls. Regarding generative AI, HEIs deal with fast-changing technology and applications. Therefore, HEIs need to be adaptive. It is advised to start with small-scale experiments by faculty, students, and staff, then learn from that, aggregate the experiences and perceptions, allow for more stability, and then plan and develop more comprehensive policies and guidelines. Leaders must take a balanced and cautious approach. At this point, both businesses and HEIs are exploring how to take advantage of the latest AI innovations. Generative AI is the current novel tech, and it is natural that it has been overhyped and accompanied by an aura that it will solve all of our problems. This pattern is typical in technology and tends to appear every few years. AI can bring new benefits and challenges, but it cannot do everything. As long as AI advances, HEIs and AI will co-evolve. Within that process, universities could also learn from partnering with AI firms or other universities.

The complexity associated with the rapid adoption of AI underscores the need for academic leaders who are system thinkers. They must study the feedback loops that define the value-creation structure and determine the system behavior. Moreover, AI can bring a substantial restructuring by creating new feedback loops, rewiring existing ones, and strengthening or weakening others. Leaders should aim to leverage those feedback loops for their benefit. A systems approach appreciates complexity, takes a whole-system view, understands that system behavior over time is often non-trivial and counterintuitive, and considers the unintended consequences. For instance, an overreliance on cost-cutting approaches can place an HEI into a self-reinforcing decline. Another underappreciated systemic risk arises from uniformly adopting identical AI models and practices across all HEIs, escalating academic competition.

5.2. Limitations and Future Research Directions

This article provides the first holistic map of AI transformation in HEIs. Future work could enhance and refine that map or go deeper into specific aspects of the map. While the level of analysis here is an HEI, future research could be more micro-focused, taking an in-depth look into particular aspects of a university. An example would be exploring the details of various learning methods and their impact on learning outcomes. Alternatively, future research could be more macro-focused, using the higher education sector as a unit of analysis.

At the sector level, 'superstar effects' may be significant in the longer term. A global education marketplace and ubiquitous online access create positive feedback loops where the positive reputation of a school, program, course, or instructor keeps increasing. As a result, superstars may emerge, similar to superstars in the sports or entertainment industries.

Our model suggests that the AI industry plays a significant role because it drives AI advances affecting businesses and HEIs. More work is needed on how established and startup tech and edtech companies affect the broader transformation of the higher education sector. More generally, higher education has a lot to learn from other sectors, such as media and advertising, already transformed by AI and related digital technologies, and this has to be a topic of rigorous future research.

Future dynamic research needs to explore the ethical implications of AI in education, examine the long-term effects of AI on student learning outcomes, or investigate AI's role in promoting inclusivity and accessibility in higher education. Another promising direction is to consider and evaluate novel business models for higher education.

Future research could study various scenarios or interventions in more detail. For instance, potential decreases or a plateau in AI capabilities through regulations, limitations of current AI approaches, another AI winter, black swan events, or otherwise, could cause significant economic shocks to HEIs and businesses. Approaches to prevent 'lemon market' effects, including exit exams, micro-certifications, and employment tests, should be examined. Future educational advances, like customized courses and AI tutoring, will need to be studied empirically.

Because generative AI lowers the cost of knowledge tasks [93], it can have a crucial impact on higher education. In essence, HEIs manage knowledge: they create new knowledge via research, deliver knowledge to students via teaching, and assess learning by asking students to perform knowledge tasks, such as essay writing. Future research could benefit from a thorough exploration of such a knowledge perspective.

Methodologically, the current article focuses on a CLD, or qualitative system dynamics. This does not allow for quantitative evaluation of policy interventions and planning. A natural next step is developing and analyzing quantitative models to derive additional insight into AI in higher education. For instance, a natural next step is to build a system dynamics simulation using a stock-and-flow model. Such a model could consider additional extensions, such as endogenizing HEI competition. However, one could also use other computational modeling approaches, such as agent-based, or analytical modeling, if the aim is to develop a simplified model.

6. Conclusions

This article presents the first causal loop diagram of the AI transformation in HE, providing a holistic view of how important variables interact to drive AI investment and impact. We show that several reinforcing and balancing AI feedback loops work together to impact value creation in an HEI that interacts with companies that provide jobs and the AI industry that drives AI advances. The model shows that the HEI invests in AI to improve teaching, research, and administration. Still, it must adapt to changes in the job market and take measures to deal with academic integrity problems. Student job placement is a crucial factor for the sustainability of the HEI model. Therefore, the HEI needs to emphasize AI complementary skills for its students. However, HEIs face a competitive threat and several traps that may lead to a decline. For instance, HEI policies focusing on excessive cost-cutting may reinforce its decline. In the long term, the current HEI model will not be viable if AI automation in companies becomes increasingly labor-displacing.

The article makes several contributions. It provides a systemic view of AI in education and proposes that academic leaders should become system thinkers to benefit from AI opportunities. It contributes to our understanding of the AI transformation of higher education from a complex systems perspective that focuses on the etiology and the consequences of AI-transformed value creation in HEIs. The article integrates systems thinking and economic concepts and contributes to higher education economics and strategy. Moreover, it contributes to our thinking of how AI can support the sustainability of HEIs and high-quality education, which is one of the UN's Sustainable Development Goals. Another significant contribution is connecting the HEI model affected by AI with job market factors, also affected by AI. Still, a systems approach to higher education suggests that we are just starting to explore the impact of AI on that sector. Therefore, the article outlines several directions for future research on AI transformation and provides a basis for developing quantitative models.

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Unleashing ChatGPT: Redefining Technology Acceptance and Digital Transformation in Higher Education

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Abstract: This article examines the effects of integrating ChatGPT, a generative language model developed by OpenAI, into educational and training contexts in higher education. The research takes as its conceptual framework models of technology acceptance and questions the relevance of these models to the acceptance and adoption of ChatGPT. A qualitative study carried out with teachers from various higher education establishments in France enables us to propose a model adapted to the specific features of generative AI. The ethical dimension and the controllability of the tools by users, made possible by a progressive training program, are two constructions that are essential to a proper understanding of whether or not these new tools are adopted. Additionally, this research contributes to the growing discourse on how generative AI innovations can be leveraged to enhance digital transformation in the academic sector, with a particular focus on business schools' stakeholders and strategies. Finally, the contributions and prospects for future research are discussed.

Keywords: ChatGPT; education; TAM; qualitative survey

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1. Introduction

Since 2022, the introduction of artificial intelligence (AI) technologies in the field of education has marked a significant turning point in teaching and learning methods. Among these technologies, ChatGPT, developed by OpenAI, stands out for its ability to generate text in a contextual manner and to explore different domains, thus offering new pedagogical perspectives (Moussavou 2023; Lo 2023; Rahman and Watanobe 2023; Mogavi et al. 2023). The aim of this research is to examine the factors influencing the perceptions, acceptance and use of ChatGPT, and its influence on the teaching practices of higher education practitioners. Through the application of Technology Acceptance Theory (TAM) as a theoretical framework (Davis 1986), this study aims to propose a TAM model specific to ChatGPT as advocated by Venkatesh (2022), considering the specificities of the application domain, namely education and university teaching. This will make it possible to understand the contexts in which the adoption of ChatGPT could modify teachers' pedagogical approach, in terms of course design, pedagogical experience, assessment methods and interaction with students (Klyshbekova and Abbott 2024; Karthikeyan 2023; Montenegro-Rueda et al. 2023).

While some teachers proclaim the effectiveness and usefulness of ChatGPT, others remain highly sceptical and fear the excesses of such a tool. Based on TAM theory, the aim of this research is to empirically examine teachers' perceptions and practices. By addressing this issue, this study contributes to the existing literature on educational technologies and the integration of AI into teaching, by providing an in-depth and empirical analysis of the impact of ChatGPT on pedagogical dynamics.

In the current academic landscape, the integration of ChatGPT into education is attracting increased research interest. However, an in-depth exploration of the literature reveals a lack of empirical studies on the use and actual impact of ChatGPT. To date, few field studies have been identified. Most of the published work takes a theoretical approach or focuses on the analysis of existing literature, offering conceptual perspectives on the potential applications and theoretical implications of ChatGPT without drawing on concrete empirical data.

This gap raises pertinent questions about the actual effectiveness of ChatGPT in practical contexts, particularly in teaching. The aim of this work is to fill in some of the gaps in the literature by means of an exploratory study of teachers who use or do not use AI in their daily work. This approach will not only enable existing theoretical hypotheses to be validated but will also identify ways of optimising the use of ChatGPT in various practical applications.

To achieve this objective, a qualitative approach was favoured (Bardin 2013). Semi-directive interviews were conducted with a targeted sample of university teachers who had or had not integrated ChatGPT into their teaching methods. The aim of this first stage was to gather detailed data on their perceptions, their experiences and the concrete changes in their teaching practices following the use of ChatGPT. Following the analysis of the interviews, this research proposes a version of the TAM model revisited and adapted to the adoption of ChatGPT in education.

First, we present an updated literature review on the use of ChatGPT in education, as well as on models of acceptance of the technology. The methodological choices are then presented. Finally, the main results of this exploratory study are highlighted, allowing us to propose a specific and adapted model.

2. Theoretical Framework

Our research is based on two main concepts: ChatGPT and technology acceptance models. The first part will discuss the evolution of ChatGPT, its impact on education and its opportunities and challenges. The second part will look at the models of the acceptance of the technology, highlighting how they have evolved over the years and the results obtained.

2.1. Evolution of ChatGPT: Impacts on Higher Education Sector

Humanity's ongoing quest to simulate human intelligence is not new. For many years, the ambition of scientists has been to create systems capable of thinking, understanding and interacting like a human being. Since 1950, the first Turing experiments have been exploring the possibilities of thinking machines by attempting to model complex cognitive processes. The first neural network computer was created, and Turing published the Turing Test used to evaluate AIs. These major advances went on to form the foundations of artificial intelligence. But it was not until 1956 that the word 'Artificial Intelligence' was officially used.

In 1989, the Frenchman Yann Lecun developed the first neural network capable of recognising handwritten numbers, an invention that was to lead to the development of deep learning. In 1997, IBM's Deep Blue system won against the world chess champion, the first time a machine had surpassed human capabilities. Over the following decades, AI continued to evolve, each time pushing the limits of what machines could achieve.

The launch of ChatGPT by OpenAI, in November 2022, represents a significant step forward in this evolution, illustrating both a great capacity to accumulate and process information and to generate a language identical to that of human beings. ChatGPT, derived from the GPT (Generative Pre-trained Transformer) family of models, is the fruit of several years' research into automatic natural language processing (ANLP). It is an 'encyclopaedic model that integrates a large number of references to the real world' (Langlais 2023). Its operating mechanism is based on a large corpus of data, on which it is trained and which enables it to respond to user queries in a superficially coherent and nuanced way (Langlais 2023). One of the special features of ChatGPT is its ability to perform fine-tuning, which allows the model to be specialised on specific tasks or domains, by re-training it on targeted datasets.

This ability to process large amounts of data and produce text in a consistent and contextual way has led to and facilitated its rapid adoption in several fields. The integration of AI in small- and medium-sized enterprises is marking a profound transformation of their environment and their working conditions (Berger-Douce et al. 2023). Indeed, this tool has been used in the healthcare sector to support research and clinical decision-making (Garg et al. 2023), in improving medical documentation (Baker et al. 2024), in business to improve employee productivity and customer service (Zhu et al. 2023), in entrepreneurship education (Dabbous and Boustani 2023) and in education in general to foster student engagement and improve learning (Lo 2023; Montenegro-Rueda et al. 2023). Thus, according to Kwan (2023), ChatGPT is an assistance tool for teachers, enabling more effective lesson preparation (Rahman and Watanobe 2023; Lo 2023) and offering personalised support to students (Montenegro-Rueda et al. 2023). Thanks to ChatGPT, we can indeed witness a transformation in teaching and learning methods, including personalised assistance, the creation of educational content, learner engagement, automated formative assessment and the diversification of pedagogical approaches. The table below summarises the main opportunities and threats of using ChatGPT in education (Table 1).

Table 1. The opportunities and threats of using ChatGPT in education.

	Opportunities		Threats
Assistant for teachers	**Help with course preparation** (Lo 2023; Rahman and Watanobe 2023) **Can generate plans and develop concepts** (Memarian and Doleck 2023) **Help in creating educational content** (Lo 2023) **Help with creating MCQs, QUIZZs** (Yu 2024) **Help with evaluation and correction** (Karthikeyan 2023) **Reduce teachers' mental workload** (Memarian and Doleck 2023)	**Ethics and academic integrity**	**Reliability of information and data generated** (Yu 2024; Rahman and Watanobe 2023) **The problem of intellectual property** (Mhlanga 2023) **The problem of authenticity** (Mhlanga 2023) **Integrity of examinations and assessments** (Pradana et al. 2023) **Facilitates student plagiarism** (Lo 2023; Grassini 2023; Rahman and Watanobe 2023; Yu 2024) **Threatens academic integrity** (Lo 2023; Grassini 2023; Yu 2024) **and creativity** (Karthikeyan 2023)
The learning experience	**Promotes self-training: individualized, self-directed training** (Yu 2024) **Can provide real-time feedback** (Lo 2023; Grassini 2023; Rahman and Watanobe 2023; Memarian and Doleck 2023) **Task optimization and performance** (Yu 2024) **Personalized learning** (Mhlanga 2023; Grassini 2023; Karthikeyan 2023) **Improving access to information** (Mhlanga 2023; Rahman and Watanobe 2023) **Enriches teachers' pedagogical and educational experience** (Karthikeyan 2023; Montenegro-Rueda et al. 2023) **Promoting educational digitization** (Yu 2024) **Fast, easy access to information** (Karthikeyan 2023; Rahman and Watanobe 2023)	**Technical aspects: bias and discrimination**	**Capabilities vary according to field** (Lo 2023) **Lack of equity and non-discrimination** (Mhlanga 2023) **Lack of transparency on algorithms** (Memarian and Doleck 2023) **Presence of algorithmic bias** (Mhlanga 2023) **Production of incorrect or fictitious information** (Lo 2023; Grassini 2023; Yu 2024)

Table 1. *Cont.*

	Opportunities		Threats
Student tutor	**Can question students and adapt to their evolving understanding** (Montenegro-Rueda et al. 2023) **Personalized learning for students** (Montenegro-Rueda et al. 2023) **Pedagogical support** (Mhlanga 2023) **Developing students' writing skills** (Karthikeyan 2023; Montenegro-Rueda et al. 2023)	**Legal aspect: privacy and security**	**Protection of privacy** (Memarian and Doleck 2023) **Use of collected data for improvement purposes** (Memarian and Doleck 2023) **The use of sensitive data** (Al-Mughairi and Bhaskar 2024)
Teacher–student interaction	**Facilitates collaboration, discussions and debates** (Lo 2023; Montenegro-Rueda et al. 2023) **Improves asynchronous communication** (B. Memarian and Doleck 2023)	**Psychological aspect: socio-psychological effect**	**Dependency** (Mhlanga 2023; Karthikeyan 2023; Al-Mughairi and Bhaskar 2024) **Lack of human interaction** (Al-Mughairi and Bhaskar 2024) **Decrease in students' cognitive development and critical thinking** (Rahman and Watanobe 2023) **Obsolescence of traditional teaching and learning skills** (Karthikeyan 2023)

In the higher education context, although ChatGPT has several advantages and provides a good opportunity (Adeshola and Adepoju 2023) to improve the educational experience (Grassini 2023), the integration of ChatGPT is double-edged. Although this technology has real potential for both teachers and students, it is not without risk and its integration is not as straightforward as one might think. Admittedly, in theory, this AI can be used by teachers as an assistant, a course creation tool, an assessment support tool (Klyshbekova and Abbott 2024), a tool for personalising learning (Mhlanga 2023; Grassini 2023; Karthikeyan 2023) and a tool for managing administrative tasks (Memarian and Doleck 2023). All of this makes it possible to enhance the teacher's experience and place greater emphasis on interaction and exchange with students (Lo 2023; Montenegro-Rueda et al. 2023). However, the problems of data security (Al-Mughairi and Bhaskar 2024), plagiarism (Lo 2023; Grassini 2023; Rahman and Watanobe 2023; Yu 2024), intellectual property (Mhlanga 2023), addiction (Al-Mughairi and Bhaskar 2024) and algorithmic bias (Memarian and Doleck 2023) hamper its rapid implementation. Furthermore, the empirical effectiveness and veracity of such promises have yet to be demonstrated, and their real impact on the depersonalisation of teaching and on students' cognitive abilities has yet to be proven (Rahman and Watanobe 2023). Hence, it is important to put into place a framework that optimises the benefits of ChatGPT while reducing the ethical, psychological, legal and technical risks.

2.2. Theories of Technology Acceptance: Evolution and Specificities

Our conceptual model is based on the Technology Acceptance Model (Davis 1986), which conceptualises the acceptance of technology by users (Venkatesh and Davis 2000). Meta-analyses of the TAM (King and He 2006; Yousafzai et al. 2007a, 2007b) show the extent to which this model is used in a variety of contexts and situations around the world. In the field of education, studies have tested the adoption and acceptance (or otherwise) of innovative technologies from the point of view of both teachers (Scherer et al. 2019) and students (Mohammadi 2015; Ibrahim et al. 2017; Rafique et al. 2020).

Under the name TAM, there are in fact several models of technology acceptance which have been enriched as studies have been carried out and results obtained, making it possible to obtain 'enriched' or 'extended' versions of the basic model. The first TAM model (Davis 1986, 1989) focuses on perceived usefulness and perceived ease of use, which determine behavioural intention. It is a simplified, even minimalist, model which has the advantage of being easy to understand and usable in many contexts. TAM 2 (Venkatesh and Davis 2000) proposes an enriched version of the model by highlighting seven antecedents of perceived usefulness. TAM 3 (Venkatesh and Bala 2008) proposes the addition of six antecedents of perceived ease of use. In parallel with the TAM models, the UTAUT model, known as the unified model (Venkatesh et al. 2003), allows several approaches to be considered to explain intention to use. It focuses on four moderating factors and four determining factors that provide a better understanding of intention to use. The UTAUT2 model (Venkatesh et al. 2012) is more consumer-oriented, and includes habits, price and pleasure as additional antecedents. The table below summarises the different models (Table 2).

Table 2. Comparison of the different versions of the TAM and UTAUT models.

Model	Moderator Variables	Explanatory Variables	Explained Variables
TAM 1 Davis (1986, 1989)	External Variables	1. Perceived Usefulness (PU) 2. Perceived Ease-of-Use (PEOU)	Attitude Intention to Use Actual Use/Usage Behaviour
TAM 2 Venkatesh and Davis (2000)	External Variables + ***Seven antecedents of PU*:** • Subjective Norm • Image • Job Relevance • Output Quality • Result Demonstrability • Experience • Voluntariness	1. PU 2. PEOU	Behavioural Intention Use Behaviour
TAM 3 Venkatesh and Bala (2008)	External Variables Seven antecedents of PU + ***Six antecedents of PEOU*:** • Computer self-efficacy • Perceptions of external control • Computer anxiety • Computer playfulness • Perceived enjoyment • Objective usability	1. PU 2. PEOU	Behavioural Intention Use Behaviour
UTAUT 1 Venkatesh et al. (2003)	Four moderating variables: • Gender • Age • Experience • Voluntariness of use	1. Performance Expectancy 2. Effort Expectancy 3. Social Influence 4. Facilitating Conditions	Behavioural Intention Use Behaviour
UTAUT 2 Venkatesh et al. (2012)	Three moderating variables: • Gender • Age • Experience	1. Performance Expectancy 2. Effort Expectancy 3. Social Influence 4. Facilitating Conditions + **5. Hedonic Motivation** **6. Price Value** **7. Habit**	Behavioural Intention Use Behaviour

This study is focused on the latest UTAUT model proposed by Venkatesh (2022), which focuses on the context of artificial intelligence. Indeed, the specificity of AI leads to significant modifications of the model that need to be considered. The author proposes an adapted research programme to study the adoption of AI by employees. Ten points of vigilance, grouped into three categories, are highlighted as follows: the intrinsic characteristics of artificial intelligence tools, the characteristics of the employees who will use them and the characteristics of the organisation in which the AI will be used. The figure below illustrates these different elements (Figure 1).

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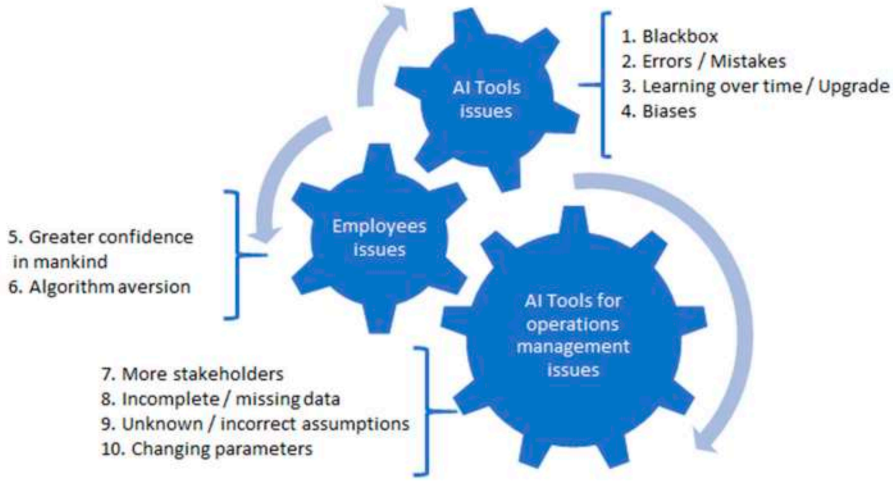

Figure 1. Ten special issues of AI studies (adapted from Venkatesh 2022).

Given these specific features, the proposed model incorporates four new moderating factors: individual characteristics linked to the personality of employees (acceptance or even search for risk, tolerance of uncertainty or desire to learn), characteristics linked to artificial intelligence technology (quality, errors and transparency), characteristics linked to the organisation in which the tools will be used (climate conducive to innovation, number of people involved and incomplete or missing information) and characteristics linked to training (regular training sessions, initiation and gamification). These four moderating factors can influence the classic determining factors of the model, namely performance expectancy, effort expectancy, social influence and facilitating conditions, which themselves help to explain the intention to use AI. Menon and Shilpa (2023) tested the model on ChatGPT users (students and employees) and found results in line with previous literature: performance expectancy, effort expectancy, social influence, facilitating conditions and privacy concerns were the predominant factors influencing the usage of ChatGPT. What about others who have not yet accepted this technique, such as teachers who have complete control over their teachings?

In the context of our study, we are going to question these different models of the acceptance of technology. The organisation considered will be represented by the higher education institutions considered, the employees will be the teachers interviewed and the artificial intelligence tool studied will mainly be ChatGPT. To do this, we used a qualitative methodology presented in the following section.

3. Methodology: A Qualitative Study

In order to gain a better understanding of the factors influencing the adoption of ChatGPT in the context of higher education and more specifically by teachers, a qualitative approach was adopted. The authors have conducted semi-directive face-to-face interviews. This method provides interesting and nuanced data on the participants' experiences, perceptions and attitudes.

The sample consisted of teachers working at various levels of university education and academic fields in public and private institutions across continental France. Participants were chosen progressively using purposive sampling, with the goal of increasing profile variety while maintaining qualitative representativeness (Paillé and Mucchielli 2021). Respondents possessed unique characteristics such as gender, age, seniority, area of competence, and interest in technology.

The individual semi-structured interviews lasted an average of one hour (the length of the interviews varied between 30 min and 90 min) and were conducted face-to-face by two interviewers between March 2024 and April 2024. After an initial introductory phase, during which the interviewers introduced themselves and explained the purpose of the study, the interviewees were asked to introduce themselves and their relationship with the technology. Seven main themes are then addressed (the interview guide is presented in Appendix A):

1. The experience of using ChatGPT;
2. Its perceived usefulness;
3. Its perceived ease of use;
4. Its perceived interest;
5. The users' attitude to generative AI;
6. Their intentions to use;
7. Subjective opinions and standards.

The interviewers used the classic techniques of reminder and reformulation. Interviewees were encouraged to express themselves freely about their experience with ChatGPT and generative AI.

All of the qualitative data (transcribed verbatim) was subjected to content analysis (Bardin 2013; Paillé and Mucchielli 2021) using an abductive approach, an analytical approach that is both deductive, based on the enriched TAM framework, and inductive, aimed at bringing out new relevant themes from the field.

To comply with an ethical approach to data collection and use (Kozinets 2019), we explained the research objectives to the interviewees, specifying that the results would be used in a scientific and/or educational context. Oral consent was systematically obtained. Anonymity and confidentiality were guaranteed both during data collection and data processing and analysis.

An in-depth examination of the verbatim transcripts by the researchers enabled us to identify the main trends and factors explaining the adoption of ChatGPT. Our empirical results confirm the relevance of the enriched TAM theoretical framework, while highlighting certain specificities linked to the singular nature of this conversational AI technology.

4. Results

The ten people interviewed had a wide range of characteristics. They ranged in age from 25 to 69. Six men and four women made up our sample. We were able to interview teachers specialising in various fields such as economics, management, finance, communication, marketing, mathematics and chemistry (Table 3).

Table 3. Characteristics of the sample.

Interview Number	Sex	Date	Field of Expertise	Age Bracket
I1	M	19 March 2024	Economy	50–60
I2	M	19 March 2024	Negotiation, Management	40–50
I3	F	21 March 2024	Chemistry, Environment	50–60
I4	M	18 March 2024	Marketing	60–70
I5	F	21 March 2024	Expression communication	50–60
I6	M	18 March 2024	Management	50–60
I7	F	23 April 2024	Mathematics	30–40
I8	M	2 April 2024	Finance	50–60
I9	F	23 April 2024	Economy	40–50
I10	M	16 April 2024	Numerical mathematics	20–30

This diversity of profiles ensures that the results are representative. Some of the people interviewed use ChatGPT regularly, which can be seen as '*a time-saving assistant for everyday tasks or tasks that we're not used to doing*' (I10). The uses may be professional, but also private. It quickly becomes apparent that this tool easily penetrates the different spheres of a person's life: '*So, on the other hand, the uses are extremely varied, ranging from preparing my future maths homework to finding the recipe for I don't know the last time a fish I don't know any more, in short finding recipes, preparing a road trip to Scotland or writing a paragraph to present a project,* etc.' (I7). On the other hand, other people had not yet used ChatGPT, or had used it very little, and some had only tried it: '*Apart from the test I've just told you about, I've never tried it*' (I8); they had no plans to use it for the time being: '*In any case, the attempt I made was a trial*' (I6).

The content analysis reveals that teachers' perception of the usefulness of ChatGPT is very mixed. While the productivity gains (the creation of resources, time saving, optimisation of research, reformulation and editorial benefits, etc.) are recognised, which is in line with the findings on the perceived usefulness of other educational technologies (Mugo et al. 2017), the profound pedagogical impact of ChatGPT on learning is divisive. Some see it as a tool that allows '*more flexibility for students depending on the subject, of course for students so that they can acquire more autonomy [...] so that students are more involved in their own learning*' (I6); others remain highly critical of these effects on learning: '*What I think about students is that they no longer think. They don't reason any more. They think they know everything because they've got ChatGPT. I'm afraid of the day when ChatGPT will take over from humans..., and I think that with young people now, it's OK, it's taken over*' (I1). Another aspect directly concerns the teacher, who wants to '*remain in control of my lesson. I'm not interested in being the spokesperson or microphone for a computerised lesson*' (I6). Teachers can thus feel that their role or status has been taken away from them. This profound questioning of the teaching profession goes hand in hand with a questioning of its credibility: '*they [the students] have the opportunity to check everything you say and the drift of course, we're not going to believe the teacher*' (I8). Between the leverage of personalisation and autonomy and the risk of disengaging students and calling into question the status of the teacher, this crucial dimension of perceived usefulness remains very mixed between advocates and opponents.

Despite an intuitive conversational interface, our results show that the optimal pedagogical integration of ChatGPT is perceived as complex by a majority of teachers, who may feel overwhelmed by the amount of information available: '*I have the impression that you can't get to grips with the subject because you haven't mastered it*' (I6); '*so there's too much information, which perhaps requires time to reprocess or to be able to stand back*' (I8). ChatGPT responses depend on the relevance of the prompts, which many teachers do not master: '*In fact, when the answer doesn't suit me, it's because the question was badly put. When it doesn't suit me, it's because the prompt was badly written and so I have to revise my prompt*' (I7); '*the tool is fairly intuitive. However, to specify the results obtained effectively, resources on prompting may be useful*' (I5).

The people interviewed are aware of the importance of training: '*If I had training, it would be easier to use it to master it*' (I8). They even went so far as to call for an appropriate training program: '*I'd like us to have support in getting to grips with it, whether for teaching or for research techniques, in a gradual way*' (I9). Without this training, teachers run the risk of abandoning ChatGPT and giving up using it: '*sometimes I'd give him a command and he'd give me the wrong answer, so I thought, «I don't have to give him the right information so that he can be reactive afterwards, so that made me angry»*' (I9). While ChatGPT may be perceived as magical by novices, experts will have more distance from its use and the reliability of the results obtained: '*We know that what ChatGPT gives us is an approximation of what we're looking for, and it always needs to be checked, so it's absolutely unreliable*' (I10); "*as the data isn't necessarily reliable, since it's everything that's on the Web, we're not necessarily sure of the result, so we need to be sufficiently trained and sufficiently wary about using this tool*" (I7). Training is therefore essential for the proper use of generative AI, and it must be progressive and ongoing. Indeed, after the 'Wow' effect of discovering the tool, there is always a 'Down' phase when the person realises that anything can be made to say anything and obtain completely false results. Training must help them get past this second stage to reach the 'Stabilisation' phase, during which users become aware of the tool's limitations: '*For me, that's the point of training. For me, that's the point of training. It's to ensure that when people come* *out of a training course, they understand the limits, the benefits and the uses they're going to be able to make of it*' (I7).

This highlights the limitations of the perceived ease of use construct as initially conceptualised in the TAM. A more explicit consideration of the systemic dimension and the profound adaptation of practices seems necessary. The use of ChatGPT in certain areas, coding for example, seems easier and more relevant. To reassure teachers, effective mastery of ChatGPT and its prompts is seen as a major prerequisite for its successful adoption. '*So in fact, I discovered that it was a tool that could be interesting for giving you the first bits of structuring, I find that in terms of structuring, you give a subject, very quickly, it is able to propose a good structure.... I took part in two videoconference training sessions with some guys, who talked about using ChatGPT and how to challenge it with prompts. I found it very interesting to discover that it's difficult to get out of Google where you type queries, but I realised as I used it that the question of exchange, challenge and prompts is important*' (I4).

The issue of the controllability and transparency of ChatGPT emerges as a central concern in all of the teachers' comments, and some even consider it to be '*a plundering or copying software. Moreover, there's a whole problem with copyright, which poses a real problem at that level*' (I6). The problem of data and its sources is '*an element that, in any case, will necessarily be considered. Depending on everyone's interests, particularly those of individual countries. I think that this notion of intellectual property rights will be settled when the two powers that are going to be at the forefront of AI have made their move, namely the Chinese and then the Americans, and it is on the basis of this tug of war that a code of property rights will emerge, and as I see it, we'll have two of them!*' (I3). This new construct that emerges from the data analysis is particularly illuminating in understanding the reservations and reticence observed. The 'black box' (Kleinpeter 2020) represented by the opaque internal workings of AI, the lack of traceability of the results generated and the unpredictability of possible biases or ethical abuses are sources of many questions and concerns. As a result, major efforts on algorithmic transparency (explanations of reasoning), data training (what happens to the information entered), data sources and auditability and user control seem essential to reassure the teaching profession. '*I don't use ChatGPT, because apparently there are risks in terms of personal data... I don't know who can do what with this data. You've always got someone behind it who manipulates as they please and does what they want with the data to sell it, to exploit it . . . so even for pedagogy, I don't really need it.*' (I2).

5. Discussion

Since its initial conception, TAM has been the subject to numerous theoretical extensions aimed at strengthening its explanatory power, particularly in specific contexts such as teaching (Scherer et al. 2019). However, the adoption of such an innovative and disruptive technology as ChatGPT raises singular issues that require some adjustments to the initial model.

Indeed, beyond its simple practical utility, ChatGPT raises ethical concerns and questions among teachers, such as plagiarism, intellectual property, the risks of dehumanization, the oppression of creativity and the reinforcement of biases and discriminations. This ethical dimension in the AIA2M model was considered as a complementary variable influencing the general attitude towards the tool. Moreover, the very nature of ChatGPT, as a conversational AI, implies specific issues of the controllability and transparency of data perceived by users. Understanding the internal functioning of ChatGPT, its training and the possibility of parameterizing and auditing its results, as well as the ability to explain its reasoning in an interpretable way would seem to be key factors in its effective adoption by teachers.

What emerges from this study is a TAM model that has been enriched and adjusted to the specific features of ChatGPT. This revisited model should enable a finer, contextualized analysis of the psychological, technical and ethical factors shaping teachers' perceptions, attitudes and intentions towards this disruptive innovation (Figure 2).

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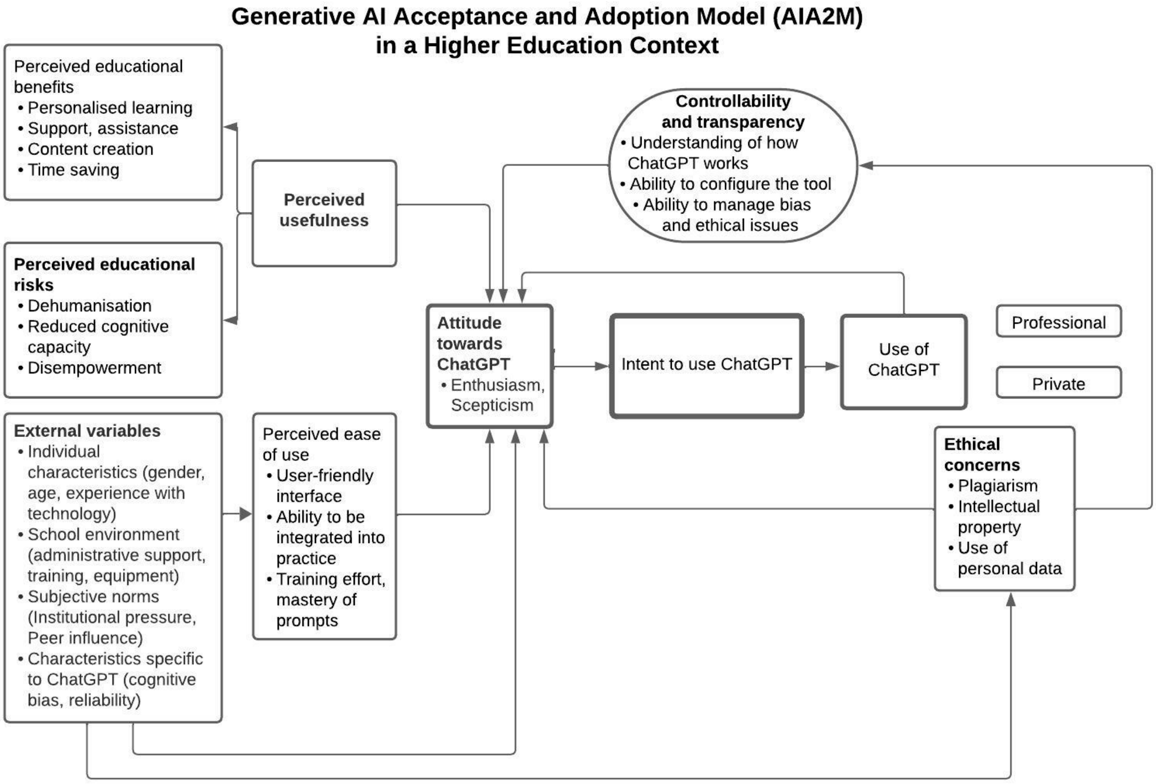

Figure 2. Generative AI Acceptance and Adoption Model (AIA2M).

The model proposed in this study represents a significant evolution of the classic Technology Acceptance Model (TAM), specifically adapted to the challenges posed by the adoption of ChatGPT in the educational context. The major contribution of this new model lies in the integration of new variables that reflect the specificities of generative artificial intelligence technologies in general and ChatGPT in particular. The introduction of the "Perceived controllability and transparency" construct at the heart of the model captures teachers' concerns about mastering and understanding the tool. In addition, the addition of "ethical concerns" as a moderating variable of general attitude demonstrates the importance of ethical, moral and deontological considerations in the adoption process. Furthermore, the distinction between "perceived educational gains" and "perceived pedagogical risks" within perceived usefulness provides a better understanding of teachers'motivations and disincentives.

It is therefore important to define a very clear ethical framework for the use of this tool and to put in place a well-defined institutional policy. This framework can be implemented by a protocol involving teachers, students and AI experts. This charter should define the fundamental principles (academic integrity, student interests, the primacy of human subjectivity, non-discrimination and data transparency) and the conditions for AI use (prohibited during assessments, limited by level and mandatory training for students). A monitoring committee must be set up to ensure that the charter is implemented and respected.

It is also important to encourage experimentation with ChatGPT through training courses and subscriptions offered to teaching teams to promote its integration and capitalize on the gains identified in the model. These training courses can be customized to suit individual needs and profiles. Similarly, awareness campaigns are needed to limit the risks associated with generative AI, including data security, the verification of the information generated and the risk of addiction. And let us not forget that AI cannot replace the sensitivity of a teacher, nor can it feel emotions when managing students.

The introduction of AI in general and ChatGPT in particular will not mean the disappearance of the teacher. Nevertheless, it will lead to a transformation of this profession.

The role of the teacher must no longer be solely that of transmission and assessment. They must evolve towards the skills of co-construction with the student, using the tools made available. Given the multiplicity of data sources, the teachers' expectations must evolve from teaching the student to search for information to sorting out existing information, detecting the true from the false and developing a sense of discernment.

Our findings have important implications for the enterprise sector in higher education, particularly with regard to performance promotion. Indeed, generative AI tools, such as ChatGPT, can facilitate distance learning solutions while stimulating student engagement and personalized learning experiences (Mallah Boustani and Merhej Sayegh 2021). ChatGPT is identified as "an assistant" by some of our interviewees, who anticipate an AI tutoring role for students. AI could, for example, help them identify which concepts need to be explored further, which options need to be chosen, which exercises they still need to work on. AI could become a veritable personalized guidance counsellor. This ability to manage large quantities of information and automate routine processes can streamline administrative tasks (such as resource management), reducing the need for human and financial resources.

Furthermore, these solutions also support the ongoing professional development of instructors/teachers and stakeholders, as AI can provide real-time information on market trends and emerging corporate strategies, enabling educators to cultivate a better-prepared workforce for the future.

From an educational policy perspective, business schools using generative AI can lead the way in supporting digital transformation and sustainable practices in higher education. By integrating AI-based tools into their courses, they help students acquire skills that are essential in today's working world, such as digital literacy, critical thinking and ethical decision-making. This is consistent with the broader aims of sustainable education, as it prepares students to tackle important global issues such as resource management, ethical business practices and environmental conservation.

It is important to emphasize here the impact that political leaders can have in the field: if school directors show a strong willingness and involvement in the use and adoption of these tools, then training sessions will be offered, and teachers will be accompanied and encouraged to use these tools, which corresponds to the traditional model of primary adoption (the organization decides to deploy a technology); then comes the decision of actual use by employees, which is secondary adoption (Gallivan 2001). However, Bidan et al. (2020) have proposed an inverted model, focusing on latent or dormant technologies. As the technology is available, the employee can seize it, accept it and use it without the organization even being aware of it. These are informal practices, born of the personal experience of the individual and/or those around him. Only then is the technology partly proposed by the organization, which is presented with a sort of fait accompli. The acceptance and adoption of generative AI seems to borrow from both models: indeed, the interviews enabled us to observe both the traditional and the inverted model, depending on the nature of the establishments concerned (private or public business schools), or the link with technology and the pedagogical innovation of the people interviewed.

In the long run, implementing AI in educational and business contexts can encourage a more responsible use of technology, instil a sense of accountability, and promote transparent decision-making processes, ultimately fostering a sustainability culture that extends beyond academic institutions and into the corporate world.

6. Conclusions

The main contribution of our study lies in questioning the traditional Technology Acceptance Model (TAM) and proposing a revisited TAM adapted to AI. This model takes into account ethics, data controllability, the control of the tool and its settings, knowledge of how personal data is used and intellectual property—elements often neglected in existing models. This enriched approach aims not only to address teachers' concerns about data security and privacy (Grassini 2023; Rahman and Watanobe 2023), but also to strengthen transparency and user trust, key aspects for a sustainable and responsible adoption of AI in education (Memarian and Doleck 2023). By introducing this new version of the TAM, we aim, based on field results, to establish a theoretical framework to better understand the factors driving teachers' acceptance of ChatGPT. This includes the identification of potential benefits such as time savings and the automation of repetitive tasks, but also the risks associated with plagiarism and the lowering of students' cognitive abilities. This model could thus serve as a basis for future research exploring in greater detail the implications of AI in education, particularly in diverse and multicultural contexts.

Furthermore, the contribution of this article lies in its empirical approach, which responds to a gap identified in the literature. Most studies on ChatGPT in education are based on theoretical analysis or commentary, with little empirical data (Pradana et al. 2023; Memarian and Doleck 2023). By collecting qualitative data from teachers, this research enriches the understanding of the real dynamics of ChatGPT adoption, considering the reality of practices and expectations specific to the educational context (Abdaljaleel et al. 2024).

This work has enabled us to study teachers' perceptions. Some see it as an opportunity for pedagogical enrichment, others as a risk to the quality of learning and the cognitive capacity of students. While ChatGPT is appreciated for its speed and ability to synthesize, the absence of critical reflection and the risk of cheating and algorithmic bias are causes for concern. This study thus clarified the role of ethics and the mastery of the tool in the acceptance of ChatGPT, highlighting the importance of appropriate, ongoing training and supervision. This ethical and pedagogical aspect is frequently highlighted in the literature as a condition for the beneficial integration of AI into educational practices, but remains underexplored. For a successful integration of ChatGPT, it becomes essential to formulate and formalize educational policies that take into consideration these dimensions of control and safety, thus offering a balance between technological innovation and the protection of fundamental pedagogical interests.

Despite the interest in this research on the integration of ChatGPT into teachers' pedagogical practices, it nevertheless presents certain limitations that deserve to be highlighted in order to contextualize the results and guide future research.

First of all, this model adds other external variables than the basic model. It is important to test it empirically to validate the relationships between the different variables and the most influential factors. A large-scale questionnaire is needed to validate the model. Secondly, the exploratory work was carried out in a limited geographical area and reflects only local perceptions and experiences. It would be more interesting to extend the research to other geographical contexts (Boustani and Chammaa 2023). International comparative studies would enable us to assess other variables, such as cultural specificities, which may influence the adoption of ChatGPT. From a methodological point of view, this research was conducted on the basis of semi-structured interviews. Other methodologies, such as observation and longitudinal studies, could provide a better understanding of the conditions under which ChatGPT is used. This study does not take into account the diversity and specificity of the different domains. It would also be interesting to conduct targeted research on specific disciplines and measure the impact of ChatGPT adoption between the hard sciences and the humanities and social sciences, for example. Exploring these additional dimensions will enable us to better grasp the potential and challenges of using ChatGPT in particular, and generative AI in general, in the field of education.

In terms of perspectives, this article paves the way for future research to explore how students perceive the integration of ChatGPT into their educational pathways, examining in particular the influence of this technology on their autonomous learning (memorization, creativity, assimilation and comprehension) and their capacity for critical analysis. Indeed, the majority of respondents believe that ChatGPT could weaken critical thinking, the ability to reflect and solve problems autonomously, particularly when students become too dependent on AI-generated suggestions. These aspects call for more detailed explorations, particularly on the impact of the tool on their academic performance and results. Studying ChatGPT's impact on students' motivation and engagement, as well as their ability to learn self-discipline and digital ethics, could also enrich the understanding of the use of this technology in an educational context (Pradana et al. 2023).

In conclusion, this exploratory study marks the starting point for a structured research project articulated in several phases, each aimed at deepening our understanding of this pedagogical revolution. The first phase will consist of a large-scale qualitative study of a wide range of teachers (permanent or part-time teachers, with or without research activity). This survey will not only enable us to refine the conceptual model, but also to question the uses of ChatGPT either in professional or personal dimensions. It will also provide an opportunity to draw up typical teacher-user profiles, the outlines of which are already emerging from this exploratory study. The second phase will focus on students' perceptions and practices through a quantitative study. The aim of this phase will be to shed light, from a dual perspective, on the dynamics of appropriating generative AI by comparing the views of teachers and students.

We are convinced that this ambitious study program will pave the way for a more holistic and in-depth understanding of the pedagogical mutations underway

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Informed Consent Statement: We obtain verbal informed consent from all participants in this study.

Data Availability Statement: Data are available on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Interview Guide

Presentation of the interviewees

Personal information (Sex, Age, Subjects taught, Research activity,. . .)

Link to technology and to innovative pedagogical practices

The experience of using ChatGPT

Have you already used ChatGPT?

IF YES:

In what context(s)? Describe your experience

How often do you use it?

Are you satisfied with the results?

IF NO: why not?

FOR ALL (those who use it and those who do not):

What are the main advantages of ChatGPT for you?

What are its main drawbacks?

Its perceived usefulness

What impact do you think ChatGPT has had or could have on enriching your teaching techniques? Has it or could it transform the way you teach?

Can you give us specific examples of how ChatGPT has helped or could help you achieve your educational goals more quickly and easily (creation of exercises, MCQs, quizzes, scenarios, articles, critical thinking, etc.)?

Its perceived ease of use

Do you find ChatGPT easy to use?

Why or why not?

What obstacles did you encounter? How did you overcome them?

To master ChatGPT, did you feel the need to use specific educational resources, such as training courses or guides (tutorials)?

Its perceived Usefulness

In your life as a teacher, how do you perceive the importance of ChatGPT as a useful aid/asset?

The users' attitude to generative AI

Are you enthusiastic or sceptical about using ChatGPT? Why

Their intentions to use

Do you intend to continue using ChatGPT for your teaching needs? What are the reasons behind your decision?

Would you recommend the use of ChatGPT? If so, in what area (pedagogical, personal, research, etc.)? under what conditions?

Subjective opinions and standards

What are the obstacles to using ChatGPT?

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