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AI's impact on higher education: transforming research, teaching, and learning

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AI’s impact on higher education: transforming research, teaching, and learning

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Editorial: AI's impact on higher education: transforming research, teaching, and learning

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Editorial on the Research Topic
AI's impact on higher education: transforming research, teaching, and learning

This Research Topic provides a comprehensive examination of how artificial intelligence (AI) is transforming higher education. The collected studies reveal several interconnected themes that illuminate both the opportunities and challenges of AI integration in academic settings. This editorial summarizes these themes and articulates their significance for the future of higher education.

Four critical themes on AI and higher education

Student perceptions and engagement

Research by Li et al. revealed that undergraduate students at a private university in China have moderate familiarity with AI tools, particularly ChatGPT, which is recognized by 94.3% and used by 90.4% of surveyed students. However, a concerning paradox emerged: while 89% of students use AI tools for academic tasks and 86.6% acknowledge their usefulness, only 39.7% report that these tools have significantly improved their understanding of course material. This gap between usage and perceived learning benefits demands further investigation.

Similarly, Sallam et al. explored health sciences students' attitudes toward generative AI, identifying factors that influence their perceptions and usage patterns. Their findings suggest that students generally view AI positively but express concerns about over-dependence, reduced independent thinking, algorithmic bias, and data security issues.

Wang et al. demonstrated that educating students about large language models can positively shift their perceptions and understanding of generative AI. After learning about AI mechanisms, students reported significantly greater approval of AI use in various contexts, suggesting that AI literacy is a crucial component for effective integration.

Supporting these findings, recent research from Jordanian universities revealed similar patterns of AI adoption among students. The study found that ChatGPT was the most recognized (94.3%) and frequently used (90.4%) AI tool among students across 27 universities, with 89% employing AI tools for academic tasks. However, echoing the concerns identified by Li et al., only 39.7% of Jordanian students felt that these tools significantly improved their understanding, despite 57.6% reporting a positive impact on their academic performance (Mashagbeh et al.). This cross-cultural consistency suggests that the gap between AI usage and perceived learning benefits may be a widespread phenomenon requiring global attention.

Pedagogical approaches and frameworks

Thoughtful pedagogical frameworks are essential for integrating AI into teaching practices. Schell et al. presented a case study of UT Sage, a tutor bot designed to provide personalized learning support while maintaining pedagogical integrity. Their work emphasizes the importance of aligning AI tools with evidence-based teaching practices and learning outcomes.

Malusay et al. demonstrated how professional development programs can enhance teachers" technological, pedagogical, and content knowledge (TPACK) in specific subject areas. Their research shows that teachers' TPACK progressed from "limited" to "expert" levels through targeted training, enabling them to effectively integrate technology into their teaching.

Temper et al. introduced the Higher Education AI Teaching (HEAT-AI) framework, a risk-based approach to regulating AI use in academic settings. This framework categorizes AI applications according to their risk levels, providing clear guidelines for their appropriate use while fostering innovation.

A systematic review conducted during the first 9 months after the release of ChatGPT provided valuable early insights into how AI has affected teaching, curriculum design, and assessment practices in higher education. The review identified the benefits and risks of AI integration, offering preliminary evidence to inform institutional policies and faculty practices (Liang et al.). As the authors note, this represents "a first wave" of research, acknowledging how quickly AI systems are evolving and changing educational landscapes.

Additionally, in specialized fields such as Mechanical Engineering Education (MEE), AI integration demonstrates unique applications and challenges. Research has shown that AI significantly enhances learning experiences through technologies such as computer-aided translation and natural language processing, making education more accessible and interactive. However, this integration demands substantial changes in teaching methods, emphasizing adaptability and responsible technology use (Alghazo et al.). The development of an "AI in MEE framework" provides a structured approach to implementation that could serve as a model for other disciplines.

Institutional leadership and administration

Khairullah et al. examined how AI is reshaping administrative processes in higher education institutions through "responsible strategic leadership." Their research highlights the role of AI in improving student success metrics, streamlining administrative tasks, and supporting strategic leadership initiatives.

Moreira-Choez et al. employed structural equation modeling to validate teaching models in higher education, distinguishing between traditional, collaborative, spontaneous, constructivist, and technological approaches. Their findings underscore the importance of adopting adaptive and evidence-based teaching methods to meet contemporary educational demands.

Ethical considerations and academic integrity

Kovari addressed strategies for maintaining academic integrity in the era of ChatGPT, offering comprehensive approaches to combat AI-induced plagiarism. These include regulating AI usage within curricula, enhancing plagiarism detection tools, and designing unique and creative assignments that are less susceptible to AI generation.

The path forward: five strategic imperatives

The research presented in this Research Topic revealed five strategic imperatives for the future of higher education. First, building AI literacy has emerged as an urgent priority for both students and educators to use these tools effectively and ethically. Understanding how AI works enables users to critically evaluate its outputs and make informed decisions about its appropriate use. Wang et al.'s findings suggested that education about AI mechanisms can positively influence perceptions and appropriate use. This literacy encompasses not only technical knowledge but also ethical considerations and practical skills for responsible AI integration. This imperative is further supported by Al Mashagbeh et al.'s findings from Jordanian universities, which revealed that while 90.4% of students use ChatGPT, only 39.7% reported significant improvement in their understanding of course material. This cross-cultural consistency with Li et al.'s findings from China suggests that mere access to AI tools without proper literacy leads to superficial engagement rather than meaningful learning. The gap between usage rates and perceived learning benefits highlights the urgent need for implementing structured AI literacy programs that educate students not just on how to use these tools, but on how to use them effectively for deeper learning.

Second, AI integration necessitates a fundamental reconsideration of traditional teaching approaches. Schell et al. and Malusay et al. demonstrated how AI can enhance pedagogical practices when aligned with evidence-based teaching methods and learning outcomes. The challenge for educators is to leverage AI while preserving and enhancing critical thinking and creativity. This reimagining of pedagogy involves developing new assessment strategies, creating more interactive learning experiences, and finding ways to use AI as a complement to, rather than a replacement for, human instruction. Liang et al.'s systematic review of early research following the release of ChatGPT provided valuable insights into how AI is reshaping the curriculum-instruction-assessment (CIA) triad in higher education. Their analysis of empirical studies published within the first 9 months after ChatGPT's launch identified both benefits and challenges of AI integration, offering preliminary evidence to inform pedagogical practices. According to their analysis, this work represents initial investigation in a dynamic field, highlighting the imperative for ongoing modification of instructional methods in response to developing AI technologies.

Third, as highlighted by Temper et al. and Kovari, clear ethical frameworks and guidelines are essential for the responsible use of AI in education. Risk-based approaches that categorize AI applications according to their potential impact on academic integrity and privacy can help institutions navigate this complex landscape. These frameworks must address data privacy, algorithmic bias, and the appropriate attribution of AI-generated content while still encouraging innovation and the exploration of 'AI's educational potential. The need for ethical frameworks is particularly evident in specialized fields. Alghazo et al.'s research on AI integration in Mechanical Engineering Education (MEE) highlighted discipline-specific ethical concerns, including data privacy and potential biases in AI-driven assessments. Their development of an "AI in MEE framework" demonstrated how ethical considerations can be incorporated into technical disciplines, providing a model that could be adapted across various academic fields. Their work emphasized that ethical frameworks must be tailored to the unique challenges and opportunities of different disciplines while maintaining the core principles of responsible AI use.

Fourth, the research suggests that AI integration may exacerbate existing educational disparities if not implemented thoughtfully. Ensuring equitable access to AI tools and training is crucial for preventing a digital divide that could further disadvantage certain student populations. Institutions must actively address how to provide equal opportunities for all students to benefit from AI technologies, regardless of their socioeconomic background, technical proficiency, or prior exposure to these tools. Liang et al.'s systematic review also pointed to geographical disparities in AI research and implementation, noting that while Asia accounted for a large number of studies, with emerging research from South America and the Middle East, there remains a need for "multi-lingual or culture-responsive studies" to ensure that AI integration addresses diverse educational contexts. This geographical imbalance in research mirrors potential inequities in AI access and implementation, reinforcing the importance of culturally responsive approaches to AI integration that consider diverse student populations and educational systems.

Finally, as AI becomes increasingly prevalent in higher education, institutions must prepare students for an AI-integrated future. This requires developing skills for working with AI rather than merely relying on it, fostering critical evaluation of AI outputs, and promoting the ethical use of these technologies. Educational programs should incorporate opportunities for students to learn about AI's capabilities and limitations, practice using AI tools responsibly, and develop the human skills that will remain valuable in an increasingly automated world.

A call to action

The contributions in this Research Topic represent a significant contribution to our understanding of the role of AI in higher education. By examining current practices, student and faculty perspectives, and institutional responses, these studies provide a roadmap for navigating the complex terrain of educational AI.

The imperative is clear: the AI revolution in higher education is not merely about adopting new technologies but about thoughtfully reimagining the educational experience for the digital age. The research presented here offers a foundation for this important work, highlighting both the transformative potential of AI and the need for careful and ethical implementation.

Furthermore, the geographical disparities in AI research and implementation identified by Liang et al. and the concentration of publications in developed countries noted by Alghazo et al. highlight the urgent need for "multi-lingual or culture-responsive studies." The future of AI in higher education must be globally inclusive, with particular attention to diverse educational contexts and equitable access across socioeconomic boundaries.

The integration of AI also presents opportunities for interdisciplinary approaches, as suggested by Liang et al.. By using AI to bridge "intersections of different disciplines" and incorporating ethical considerations into various courses, institutions can foster more holistic educational experiences that prepare students for the complex challenges of an AI-integrated world.

The future of higher education in an AI-enhanced world will depend on our ability to balance innovation with integrity, leverage technology to enhance rather than replace human connection, and ensure that AI serves our educational values rather than reshaping them. This Research Topic advances this ongoing conversation, providing insights that will help shape the future of teaching and learning in the age of AI.

Author contributions

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Ethical use of ChatGPT in education—Best practices to combat AI-induced plagiarism

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1 Introduction

The emergence of ChatGPT, a high-performance artificial intelligence language model developed by OpenAI, has generated both excitement and concern in academia (Li, 2024). Equipped with advanced natural language processing techniques, ChatGPT is able to generate human-like text that provides coherent and contextually relevant responses to a wide range of queries. This unprecedented capability has raised optimism and concern as it could fundamentally change traditional practices in academia, industry and everyday life (Cambra-Fierro et al., 2024).

The basic function of "ask me anything" and "I might have a good answer" is no longer just a concern in many fields. The scientific knowledge disseminated in journals is already struggling with the role that such technology will play. Questions arise about whether it will be, and can be, co-authored (Tang, 2024). Professors who create knowledge immediately face the challenge of assessing students in the presence of such technology. These are practical and legitimate questions.

While ChatGPT has many benefits in terms of increased student engagement, collaboration and accessibility outcomes, it also has very serious academic integrity implications: at its core is plagiarism. This paper offers comprehensive strategies on how educators can help mitigate these risks by promoting ethical use and fairness within the academic use of AI tools.

2 Challenges and risks of ChatGPT and generative AI

ChatGPT was truly disruptive, which should have surprised no one. It can be seen that these technologies are being adopted very quickly from university labs; ChatGPT reached one million users in its first 5 days and now has over 180 million (Duarte, 2024). This kind of rapid adoption demonstrates a remarkable property of generative AI: that it persists with coherent and contextually relevant text.

One of the main problems with AI models like ChatGPT is the range of threats they pose, including black box algorithms, including black box algorithms, discrimination, biases, vulgarity, copyright infringement, plagiarism, and many others, such as the generation of fake text content or fake media (Sloan et al., 2024). Therefore, organizations need disciplined risk management approaches to effectively address these threats. Considering the continuous evolution of artificial intelligence algorithms due to the rapidity of data sources, the review of heterogeneity and variability bias in periodic risk assessments should also be weighed against ethical considerations (Schwartz et al., 2022).

The experience was that the resulting text lacked an obvious logical structure, contained speculative information, did not elaborate on critical data, and did not provide original contributions (Giuggioli and Pellegrini, 2023). Any article on the topic would be conventional, lack logic and facts, and would not be critically engaging. In addition, ChatGPT references are generally incorrect; titles and authors, as well as other publication details, are misstated. Such inaccuracies require careful double-checking, especially in professional contexts such as journalism and software development.

Inaccuracy, poor logical flow, factual inaccuracies, lack of critical analysis, and lack of originality of AI-generated content can result from the current state of technology (Yang, 2024). This is based on deep learning models that are trained using very extensive datasets of prior information that may be outdated or of low quality. Although improvements in training models and data quality may improve the performance of AIs, it is not clear that improvements based on technical level necessarily lead to significant gains in innovation (Dwivedi et al., 2023).

The recent applications of generative AI in text, film and music production all indicate that these platforms will at best be partners in the innovation process, complementing rather than replacing human intelligence. In the case of complex activities requiring creativity and emotional intelligence, a well-formulated request alone is not sufficient for AI to produce markedly different and original outputs. Human oversight and collaboration remain essential (Liu, 2024). Research, practice, and urgent policy decisions in an era of rapidly evolving AI technologies require researchers, practitioners, and policymakers to critically engage with these changes. Building on the strengths of AI, while being aware of its limitations and making serious efforts to improve them, will foster an environment in which generative AI tools such as ChatGPT are used responsibly and effectively.

3 Addressing ChatGPT-induced plagiarism

Integrating ChatGPT into the scientific environment is not without its challenges. The primary concern is the possibility of plagiarism. Students may get used to using ChatGPT to create essays and assignments, which they then submit as their own work. This undermines the educational process and devalues academic credentials. Another challenge is the potential for inequality. Students who have access to ChatGPT can complete assignments in much less time and possibly better, giving them an unfair advantage over students who do not have ChatGPT. This may further increase existing inequalities in educational outcomes. On the other hand, it is difficult to distinguish content created by students from content created by AI. Because ChatGPT generates human-like, coherent text, the difficulty of distinguishing it from the "original" student content makes it difficult for educators to detect AI-assisted plagiarism.

While this work focuses on addressing the risks of plagiarism, ChatGPT and other AI tools hold great promise for improving learning outcomes and stimulating creativity. Through adaptive tutoring systems, these tools can improve personalized learning, provide immediate feedback and facilitate deeper interaction with course material. Furthermore, AI-driven creative applications allow students to experiment with problem-solving and critical thinking in new ways, ultimately resulting in a more dynamic and engaging learning environment.

3.1 Current educational strategies to counter unethical use of LLMs

The rise of large language models, such as ChatGPT, in education has led many educators and institutions to develop ways to prevent misuse. These approaches aim to protect academic integrity while adapting to the new environment of AI-enhanced learning environments. Different strategies have been introduced in different educational settings with varying degrees of success.

3.1.1 Regulating AI usage within curricula

This is probably the reason why many educational facilities have started to establish clear policies on how and when to employ AI tools such as ChatGPT. Many of these often tend to explain the emphasis on proper citation or attribution in the case of using generated AI content in a student's work. For example, some universities require students to mention what AI tool they used throughout the assignment, similar to citing sources from academic literature.

3.1.2 Enhancing plagiarism detection tools

A number of universities have now implemented high-tech, AI-detecting tools that work within plagiarism-checking programs. Indeed, services such as Turnitin have just this year introduced algorithms which detect AI-generated text by flagging submissions that are out of character for a student and/or contain unnatural patterns of speech. In addition, new software designed to detect AI-assisted content is being developed and implemented, further complicating student efforts to misrepresent AI-generated text as their own.

3.1.3 Promoting unique and creative assignments

Another effective strategy is the design of assessments that increasingly require a high level of originality and creativity on the part of the student, for which AI tools are less effective. For example, assignments of a personal reflective nature, or those which require original research questions or specific local contexts, make it harder for students to fall back on AI-generated content only. This strategy minimizes not only the chances of misuse of AI but also fosters deeper learning and critical thinking skills among students.

3.1.4 Incorporating oral examinations and presentations

Some educators have been adopting oral examinations wherein students are made to present and defend ideas, assignments, and research projects. These face-to-face or virtual exchanges permit the instructor to engage directly with the student to determine the depth of understanding of course material. In these oral exams, it will be almost impossible for the students to use AI tools because it involves real-time response and justification.

3.1.5 Collaborative group work and peer review

In contexts where group work is fostered, students often have to work in teams on elaborate projects, which already raises noticeable obstacles for AI-generated content to fit smoothly inside the final product. Group-based assignments by their very nature require communication, coordination, and collaboration among team members, aspects that no AI could imitate. Moreover, the mechanisms of peer review make students evaluate the work of their colleagues, thus automatically increasing the chances of identification of inconsistencies or any potential misuse of AI tools.

3.1.6 Reducing AI-assisted plagiarism through collaborative and reflective assessment

Empirical evidence supports the importance of using adaptive and reflective evaluation to reduce AI-related plagiarism. Successful pilot programs at highly regarded colleges that incorporate reflective and personalized tasks are highlighted by Moorhouse et al. (2023). These programs limit the misuse of AI by requiring individualized responses tailored to students. Furthermore, Dempere et al. (2023) provide evidence in favor of technology-based and ethics-based interventions, showing that ethical AI use campaigns in combination with AI recognition technologies greatly improve academic integrity compliance. Taken together, these studies show that integrating educational awareness campaigns and adaptive assessment provides a strong foundation for successful prevention of AI-enabled plagiarism.

3.2 Strategies to prevent plagiarism using ChatGPT

To address the challenges of using generative AI in education, educators can use a number of strategies to prevent ChatGPT plagiarism. Cotton et al. (2024) highlight the dual nature of ChatGPT in academia, highlighting the problems associated with scientific integrity and the prospect of increased engagement. They call for proactive institutional measures such as the integration of AI-recognition technologies, education of students on the ethical use of AI, and the creation of explicit policies on the use of AI tools. By implementing these tactics, universities can protect academic integrity and encourage ethical use of AI. Zeb et al. (2024) highlight the dual nature of ChatGPT in higher education, pointing to both its potential benefits for student engagement and its risks related to academic integrity. They recommend that institutions implement clear policies, create assessment tasks that require critical thinking, and provide training to guide ethical AI use. By integrating these measures, educators can harness the benefits of AI tools like ChatGPT while minimizing risks of misuse.

Strategies for the prevention of plagiarism, taking into account the opinions and suggestions:

Technological solutions

- There are various plagiarism detectors that can find copied content. If there is a possibility to search for texts in student submissions that match existing sources, a possible case of plagiarism is flagged. Educators can also invest in advanced technologies to detect artificial intelligence-generated content through language patterns and stylistic anomalies.
- Use learning analytics to track learner progress and detect unexplained patterns in learner performance. This could include sudden, unexplained improvement or different writing style, which is often a sign of AI-enabled plagiarism.
- Use adaptive testing methods where questions are modified or reformulated based on previous student responses. This will make the AI tools more difficult to work with, as it will be very difficult to generate or predict correct answers when incorporating dynamic approaches.

Pedagogical approaches

- Educating students about plagiarism is one of the most effective ways to combat plagiarism through education. Students need to be made aware of what exactly plagiarism is and the damage it does to learning and to the academic integrity built in the name of educational institutions. This can be achieved through teaching materials, classroom discussions, and clear communication of the consequences of plagiarism.
- Include reflective writing exercises in which learners should discuss the learning process, the challenges encountered, and the insights gained. This can help teachers to assess the credibility of students' work and understand their thinking processes.
- Peer assessment should be incorporated, where students are asked to evaluate each other's work. This both raises the quality of the work submitted and allows inconsistencies and possible plagiarism to be detected.
- Encourage projects in which pupils produce individual, creative outputs. Such products could include multimedia presentations that engage users through their senses. This could include podcasts or other digital communication tools that are unlikely to be replicable by AI.

General assessment design

- Design assessments that allow linking to personal experiences, local contexts, or specific curricula. These types of personalized tasks are less effective for general AI tools.
- In addition to the written essay, encourage students to communicate what they have learned through a variety of media, such as slide shows, audio recordings, films, and portfolios. AI has difficulty replicating these alternative

assessment methods, which encourage learners to develop more versatile skills.

Policy and institutional changes

- Setting clear guidelines for the use of artificial intelligence tools such as ChatGPT is essential. Students need to know how and in what context to use such tools, i.e., proper citation and attribution of AI-generated texts.
- Requiring students to submit an outline of their work can help instructors identify potential AI-generated content early in the process. This approach allows for timely feedback and guidance, reducing the likelihood of students resorting to plagiarism.
- Regularly checking student submissions and work. This could include thorough reading of assignments, oral presentations to check understanding, and the use of detection devices to flag suspicious content.
- Large tasks are broken down into smaller tasks structured by key points, with appropriate deadlines. This approach ensures that students build up their work gradually, making it more difficult to complete a whole project with AI.
- Oral examinations can be a sure test of originality; students have to justify their arguments and even defend their work with oral answers, which in a sense makes it impossible to include AI-generated content in this assessment scenario.

3.3 Designing assessments to minimize AI misuse

To further minimize the risk of AI-assisted plagiarism, educators can design assessments that are less prone to misuse. Some extended ways to minimize AI misuse:

Critical thinking and problem-solving tasks

- Tasks that require highly critical thinking or problem solving are unlikely to be performed satisfactorily by AI. This may include group discussions, project presentations, and interactive activities that require the individual to use their knowledge and skills.
- Designing open-ended tasks that encourage originality and creativity can create conditions in which AI tools are less useful. For example, having students formulate their own research questions or arguments fosters independent thinking.
- Refine tasks to focus on areas where AI tools fall short, such as in-depth critical analysis and personalized responses.

Real-life applications and practical assessments

- Demonstrate practical applications: create assessments in which students apply theoretical knowledge to practical, real-world problems. Case studies, simulations, and project-based learning activities are contexts in which AI's ability to generate relevant content is limited.
- Design assessments that replicate real-life tasks and situations in authentic contexts, such as service-learning projects, internships, or community-based research. Such tasks require personal engagement and cannot be easily outsourced to AI.
- Develop role-playing exercises and simulations in which students take on designated roles or characters. This is a great way to increase creativity and critical thinking, elements that are difficult for AI to simulate.

Personalized and reflective assignments

- Create personalized tasks for each student or cohort that include dynamic elements such as current events, specific local problems, or personal reflections. Individualizing tasks minimizes the applicability of general AI responses.
- Providing more personalized feedback and requiring follow-up actions based on that feedback, which fosters deeper engagement with material and reduces reliance on AI.
- In a portfolio-based assessment, the student collects work done over time. Portfolios show progress or improvement in learning, which is challenging for AI to simulate.

Collaborative and peer-based learning

- Group projects are those in which learners have to work together to create a final product, ensuring authentic input as collaboration requires communication and coordination that AI cannot replicate.
- Peer-assisted learning activities, where learners tutor or mentor their classmates. This reinforces knowledge and requires explanation and justification, which AI cannot provide.

Timed and proctored assessments

- Real-time or proctored exams prevent students from using AI in assessments. This approach greatly reduces plagiarism and ensures the work represents each student's abilities.
- Conduct timed assessments, such as in-class essays or timed online tests, to limit students' use of AI tools. This format emphasizes students' ability to think and respond quickly based on their own knowledge.

Multimodal and mixed assessment formats

- Use mixed forms of assessment: written work, presentations, and practical demonstrations. Multimodal assessments require diverse skills, making it difficult for AI alone to handle all elements.
- Interactive and adaptive learning systems, which vary the difficulty and nature of questions based on student performance, provide personalization that challenges AI.

Frequent and ongoing assessments

- Frequent, low-level assessments to monitor students' progress on an ongoing basis. This allows for early detection of irregularities and reduces the likelihood of last-minute reliance on AI.

3.4 Challenges in implementing anti-plagiarism strategies

Although the above-mentioned tactic offers a sound method for curbing AI-assisted plagiarism, its application may present a number of ethical and practical difficulties.

Some universities, especially those with limited resources, may find the high costs of using sophisticated plagiarism detectors and learning analytics prohibitive. Furthermore, the effectiveness of these technologies depends on frequent updates to keep pace with rapidly evolving AI capabilities, further increasing operational costs.

Many technology solutions, including learning analytics and adaptive testing, require the collection of large amounts of student data. This raises questions about data security and privacy, especially when sensitive data is required. The scope of information that can be collected and examined may be limited by the fact that schools and other organizations must ensure compliance with data protection laws.

Authentic student work can be mistaken for AI created using AI-based detection methods, especially when students use certain language patterns or have a distinctive writing style. This can lead to false claims that undermine student confidence and require manual investigation by teachers, a time- and resource-intensive process.

Teachers must devote a lot of time and energy to implementing pedagogical and policy-based measures, such as teaching plagiarism, oral exams, and dividing large tasks into smaller ones. It can be difficult for institutions to provide teachers with the tools and support they need to successfully integrate these changes into their daily routines.

A heavy reliance on technology detection techniques can divert attention from raising students' ethical awareness. While resources such as plagiarism detectors are helpful, a thorough awareness of academic integrity through education remains key to developing long-lasting moral behavior.

Since the AI is constantly changing, strategies need to be constantly modified and checked. Institutions must regularly adjust their strategies as generative artificial intelligence technology evolves, necessitating potential regulatory changes as well as ongoing teacher training. Administrative and faculty resources may be further burdened by this ongoing change.

3.5 Comparing strategies and extracting recommendations

These strategies discussed in this paper coincided with a number of approaches that educators globally have already begun to start. The next section will point out the similarities between these methods and make recommendations based on their relative success.

3.5.1 Educational awareness campaigns

This makes education perhaps the most effective form of plagiarism prevention. Nothing works better than awareness of the tools and the consequences of their incorrect usage. Institutions that are really involved in raising awareness among students about the ethical use of AI tools and consequences of plagiarism tend to show better compliance. In ensuring a culture of integrity, there is a need to have students taught how their learning and future careers will be affected by dishonestly passed practices. For example, some universities introduced workshops or online modules that teach how to use AI tools with ethics in mind-reminding about originality and proper attribution.

3.5.2 Dynamic assessments and continuous monitoring

These adaptive, updated assessments of performance-real-time quizzes or personalized work-are important deterrents in the growing misuse of AI. Adaptive tests adjust the questions based on previous responses, which makes it quite difficult for AI models to know the correct answers. Continuous assessment approaches-including continuous low-stakes assignments-help track the progress of students, underlining discrepancies indicative of AI misuse. As these approaches are implemented into practice, educators are then in a better position to follow students' learning through iterations and become less vulnerable to last-minute AI-generated submissions.

3.5.3 Diversified assessment formats

Multimodal assessments are becoming the preferred fighter against AI-assisted academic dishonesty in that written work, oral presentations, and practical demonstrations together raise the expectation that students will demonstrate a wider range of skills. Moreover, portfolio-based assessments-where students collect and present a body of work over a semester-offer a more panoramic view of the student's development and thus have made it more easily probable to spot changes in quality or style.

3.5.4 AI-detection tools

Already, many institutions have adopted or are Trialing detection software for this type of AI. Early data suggests these tools can often flag AI-generated content while the accuracy continuously improves; educators should consider blending AI detection with traditional plagiarism detection methods. Those few institutions that have applied these technologies so far recommend that their use be combined with instructor vigilance, since manual review of suspicious texts is still an indispensable part of the process.

4 Discussion

Despite all the benefits, the integration of ChatGPT into an educational environment raises some very serious ethical concerns. One major concern is that it facilitates plagiarism and other forms of scientific dishonesty. Students could use ChatGPT to write essays and complete assignments as if they had written them themselves. This practice emphasizes both the circumcision of the learning process and the devaluation of all forms of academic assessment. Above all, it challenges teachers to ensure high standards of academic integrity in their classroom practice. The problem has been compounded by the difficulty of distinguishing student-generated content from content created by artificial intelligence. Traditional plagiarism detection tools are unable to identify text written using advanced AI models such as ChatGPT, and therefore cannot alert instructors when AI-assisted plagiarism has occurred.

Many strategies avoid the risks associated with ChatGPT and try to manage its ethical use in education. Students should be made aware of the ethical use of AI tools and the need to prevent academic dishonesty altogether. Assessments should be designed to make the misuse of AI less likely, to further reduce the potential for AI-enabled plagiarism. Tasks or tests that require critical thinking, problem-solving or creativity will not be performed adequately by AI.

While useful, generative AI tools such as ChatGPT have the very real potential to facilitate scientific fraud. The implementation of these strategies, from plagiarism detection to curriculum redesign, requires a multi-faceted approach to this challenge. Educators, administrators, and policymakers need to stay ahead of the technology and democratically update it on an ongoing basis with the intention that the pace of development will keep pace with the advances in AI technology.

By detecting AI-enhanced content, AI detection techniques are essential to maintaining scientific integrity and preserving the integrity and trust of scientific work. However, these tools also raise ethical issues, such as the possibility of miscategorising genuine student work due to stylistic differences, which can lead to unfounded accusations. Furthermore, if perceptual technology is overused, attention may be diverted from promoting scientific ethics through education. With a well-designed strategy combining ethical teaching and AI perception, integrity can be maintained without compromising individual responsibility for learning.

Those few institutions that have already taken such steps prove that success lies in blending technology-based solutions with educational efforts: awareness campaigns, adaptive testing, personalized assignments, and diversification of assessment formats top the list of effective measures to minimize the risk of AI misuse. It will be important going forward to create a culture of responsible use of AI, where students realize the risks but are also informed about how to deploy these tools responsibly to advance their learning.

As AI advances, its impact on education is likely to grow, enabling more personalized learning and adaptive feedback that can improve outcomes and access. However, increased reliance on AI creates difficulties, including privacy issues, algorithmic biases, and the changing role of teachers in operating AI-augmented classrooms. Institutions may need to continually adjust rules to protect academic integrity as AI systems improve in learning and perception. The ethical and successful integration of AI into education depends on addressing these long-term impacts.

Researchers, practitioners and policy makers need to explore the ever-changing face of ChatGPT and other generative AI technologies. This paper moves in this direction by providing strategies for integrating AI tools into the university environment.

Author contributions

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Strengthening STEM education through a professional development program on enhancing teachers' TPACK in selected calculus topics

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One means to strengthen STEM education is providing appropriate and timely professional development programs among teachers. Hence, this study aimed to develop, implement, and evaluate a professional development (PD) program using training as the PD model on enhancing senior high school mathematics teachers' technological, pedagogical, and content knowledge (TPACK) on selected Calculus topics, namely, derivatives, integration, and their applications. The PD program consisted of a series of lectures and workshops in designing teaching–learning sequence of the topics. Employing the mixed-methods sequential explanatory design, initial and final TPACK of the 11 senior high school mathematics teachers were evaluated. Data analysis showed that teachers' TPACK progressed from generally limited to the expert level. At the end of the PD program, teachers were tasked to present a teaching learning sequence (TLS) as the output of the PD program and as evidence of their learning. These were rated by experts, and the results generally fall at the very satisfactory levels across all domains of TPACK. Supported by the teacher-participants' narratives, the PD program proved to be a transformative experience for teachers, thus enabling them to acquire technological, pedagogical, and content knowledge in derivatives, integration, and their applications.

KEYWORDS

derivative calculator, integral calculator, Desmos graphing, teaching learning sequence, pairing technique, STEM education

1 Introduction

Increasing the supply of STEM (science, technology, engineering and mathematics) educators through efficient and effective professional development for teachers is essential to the global interest in STEM education. Despite numerous studies on teacher professional development for specific subjects, quality research on professional development aimed at enhancing teacher's abilities to implement integrative and cross-disciplinary approaches in STEM education is still in its early phase (Morris et al., 2021). The importance of STEM education in the contemporary digital landscape is undeniable (Chai et al., 2021; Li et al., 2020; Williams et al., 2019). Nonetheless, most K-12 educators currently involved in promoting and facilitating STEM learning activities in schools have received training primarily in their respective subject areas (typically science, information technology, or mathematics) during their teacher education programs (Aslam et al., 2020; Cavlazoglu and Stuessy, 2017; Margot and Kettler, 2019; Knowles et al., 2018). Consequently, individuals may lack comfort in executing the integrative and cross-disciplinary methodologies promoted in STEM education (Margot and Kettler, 2019; Rich et al., 2018; Wang et al., 2020; Weng et al., 2020).

Teacher professional development, according to Postholm (Postholm, 2012), is the process by which educators learn new things, figure out how to keep learning, and use what they have learned to improve student learning. Additionally, key characteristics of high-quality professional development are complex and go beyond merely teaching core knowledge. A productive collaboration among educators, ongoing opportunities for learning, interactive and student-centered teaching approaches, and the use of technology to leverage teaching and learning processes are crucial indicators. When these elements are present, professional development programs can greatly enhance student learning and teacher effectiveness (Wei et al., 2009). Avery and Reeve (Avery and Reeve, 2013) recommended that STEM professional development providers should establish an environment that is as follows: (1) well-organized, (2) sensitive to teachers' personal and professional needs, and (3) values their points of view. Teachers become more engaged in and inclined to support STEM professional development programs if they do this. Borko (Borko, 2004) stresses that exceptional professional development should be rooted in classroom procedures and should promote active learning, partnership, and reflection. Professional development programs that integrate these characteristics benefit educators in both obtaining new knowledge and implementing it to further improve their teaching methods. Additionally, the said study emphasizes that the lasting value of professional development is vital in attaining long-term advancements in teaching and learning. Undeniably, many mathematics educators recognize the need to modify their teaching methods to address the requirements of learners entering twenty-first-century professions; however, they are novice about using technology-aided instruction and how to teach skills such as collaboration, innovative problem-solving, and the development of a well-crafted teaching learning sequence (TLS) or lesson plan. Research reveals a consistent gap between professional development programs and the needs of instructors, particularly in specialized areas such as advanced mathematics or calculus (Cohen and Hill, 2008).

Calculus is an important and fundamental field of study that has many practical applications including science, engineering, economics, and finance (Leithold, 1996). It is a branch of mathematics that deals with the study of rates of change and how things behave over time. It helps us understand better the principles of change, optimization, and prediction, thus, a powerful tool across many fields. Specifically, it is used in understanding the science of change of any phenomenon or entity such as blood pressures and heart rates of all living things, stock markets for economic activities and growth, rocket weights, runner speed, air pressure and temperature, and bacteria population which are essentials to life. Recognizing its importance, basic calculus is embedded as a specialized subject under the science, technology, engineering, and mathematics strand in the K-12 Basic Education Curriculum (DepEd Order 021 s. 2019). This integration of the course high school calculus is also a preparation of students for college calculus and higher math courses (Ayebo et al., 2017).

However, low students' mathematics performance in the high school particularly in calculus and mismatch between students' learning styles with teaching methods were observed (Salleh and Zakaria, 2011). With the adoption of the K-12 Education program, this has sparked greater concern among academics, particularly in mathematics (Casinillo and Aure, 2018). In this regard, innovation in teaching and learning the course have been done such as integrating technology to mathematics especially in STEM classrooms (Scharaldi, 2020). In addition, Simovwe (Simovwe, 2020) advised that intense regular in-service courses on calculus be offered to mathematics instructors as a means of enhancing their subject matter knowledge and teaching abilities through technology integration. For technology to become a tool for learning mathematics, teachers must develop an overarching conception of their subject matter concerning technology and what it means to teach with technological pedagogical content knowledge (TPACK) (Niess et al., 2009; Richardson, 2009).

In line with this, one of the famous models for teachers' training is the technological, pedagogical and content knowledge (TPACK) developed by Koehler and Mishra (2009). Developing teachers' competencies in technology integration has recently been one of the areas of attention (Njiku et al., 2021). It is an essential part of the education system today as it incorporates the growing demand on the use of technology in the classroom as well as continuing the focus on the content and how we deliver it. It guides teachers to design and integrate relevant, context-specific mathematics activities for learners (Koehler et al., 2013). Aside from the fact that TPACK has emerged as one of the most influential theories as both research and professional development activities extensively draw from it, its point is to understand how to use technology to teach concepts in a way that enhances learning experiences.

Shulman (1986) advocates that teachers must know both the subject matter (CK) and pedagogy (PK) and that these do not operate in isolation but interact forming the PCK. From this PCK, Koehler and Mishra (2009) add technology knowledge (TK) forming the three primary domains of teacher knowledge. It has been argued that the three do not operate in isolation but interact. Teachers need to know specific topics with relevant technology (Alemdag et al., 2019). This leads to the importance of these three knowledge domains interweave together (Njiku et al., 2020). Hence, under the TPACK framework, the three categories of knowledge TK, PK, and CK are joined and reconfigured in different ways. While pedagogical content knowledge (PCK) describes relationships and interactions between pedagogical practices and particular learning objectives, technological content knowledge (TCK) describes relationships and intersections between technologies and learning objectives. Technological pedagogical knowledge (TPK) describes relationships and interactions between technological tools and specific pedagogical practices. TPACK, which considers the connections between all three regions and recognizes that educators are functioning within this complex space, is then composed of these triangulated areas (Kurt, 2019).

However, reports concerning the use of TPACK training program for mathematics teachers are scant, limited, and concentrating only on pre-calculus topics such as algebra and the like (Erbilgin and Sahin, 2021; Gurl and Karamete, 2015; Niess et al., 2009; Njiku et al., 2021; Hernawati and Jailani, 2019; Bueno et al., 2021). Other teacher training programs in calculus even focus only on specific components or dimensions of TPACK. Wahyuni et al. (2020) evaluated a development training for teachers focusing only the pedagogical and content knowledge based on discovery learning model. In addition, Dockendorff and Solar (2018) investigated mathematics visualization skills and initial teacher education programs focusing on technological integration utilizing GeoGebra dynamic software. This is despite the various findings that developing teachers' entire TPACK in calculus have resulted to helping students learn better as they can creatively and flexibly teach the course. For example, teachers trained to use GeoGebra-supported calculus textbook models improved students' mathematical problem-solving and mathematical representation (Dewi and Arini, 2018). Liburd and Jen (2021) also discovered that pupils who were taught utilizing technology demonstrated a higher degree of conceptual knowledge than those who were taught using the traditional technique.

As of this writing, the researchers have not yet found a study on TPACK training for teachers which focuses on basic calculus particularly on derivatives, integration, and its applications using the derivative calculator, Desmos graphing app and integral calculator. The need to improve mathematics teachers' TPACK in basic calculus is equally important in pre-calculus. With this, to assist teachers in enhancing their TPACK domains in selected basic calculus concepts, this professional development program is developed, implemented, and evaluated.

2 Problem statement

This study aimed to develop and evaluate a professional development (PD) program on enhancing mathematics teachers' TPACK on selected topics in basic calculus. Specifically, it addressed the following questions:

1. What were the initial Technological Pedagogical and Content Knowledge of mathematics teachers on selected Calculus Topics?
2. How do mathematics teachers perceive the impact of a TPACK-centered Professional Development Program on their teaching effectiveness and students' learning outcomes?
3. What are the changes of teachers' TPACK levels as a result of participating in professional development program?
4. What are the qualities of teaching-learning sequence developed by the mathematics teachers as outputs of the professional development program?

3 Theoretical framework

3.1 Technological pedagogical content knowledge

The framework of Mishra and Koehler (2006a)'s technological pedagogical content knowledge (TPACK) lies at the core of understanding how technology can help remedy some of the problems of teaching and learning (Richardson, 2009). This means that mathematical TPACK refers to the intersection of technological knowledge, pedagogical knowledge, and mathematics content knowledge as shown in Figure 1. The twenty-first century mathematics teachers must advocate technology-oriented instruction for global competitiveness (Erbilgin and Sahin, 2021). This means that particular technological instruments (hardware, software, apps, related information literacy practices, etc.) are best employed to train and direct students toward a deeper, more thorough comprehension of the subject matter. Aside from possibilities that students may demand exposure to new software applications in mathematics, they need to adapt their teaching styles for online learning as the need arises. Technology aided instruction allows teachers and learners to spend more time exploring mathematical concepts in depth. For example, teachers and students can determine and verify the step-by-step derivative process of a certain function using the derivative calculator and examine the behavior of the said function through its graph using the Desmos graphing app. Time spent for computations and graphing is diverted to deeper engagement on the conceptual skills. With this, the TPACK framework was used to design the said professional development program and evaluate its effects on the senior high school mathematics teachers' knowledge.

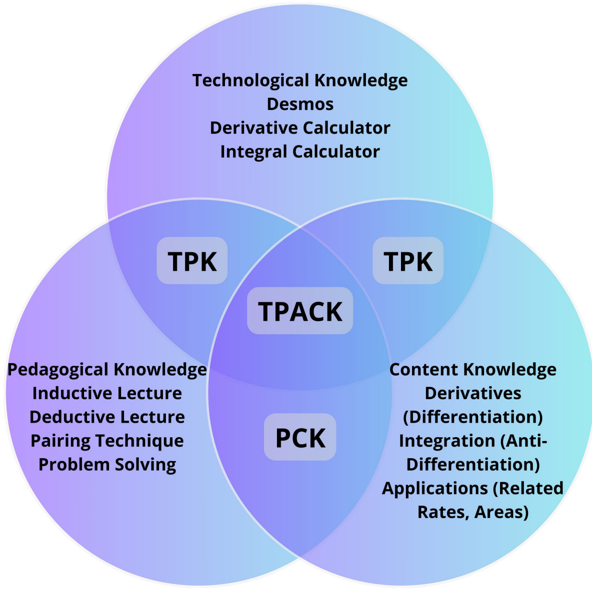

FIGURE 1
TPACK framework on selected calculus topics.

Each knowledge domain of TPACK and their relationships are defined in this study. CK refers to the core concepts, theories, and procedures on calculus topics of which teachers should have a solid foundation of. It focused on Differentiation, Anti-differentiation or integration and the applications of both particularly the related rates and problems involving areas. PK refers to the pedagogies in teaching. Inductive and deductive approaches were considered for the interactive lectures of the said program mixed with collaborative method through pairing technique in problem-solving. These approaches are characterized as constructivist methods. Piaget's constructivist theory has been prominent in recent research on mathematics learning and has provided basis for recent mathematics reborn efforts (Simon, 1995). Most high school students have positive responses to mathematics learning by an inductive-deductive approach (Rahmah, 2017). PCK is the intersection of PK and CK. This covered the said teaching approaches that are appropriately designed for the above-mentioned topics. TK refers to knowing the different software applications available for instructional delivery. In context, these were the digital apps that are accessible for free such as Desmos, derivative and integral calculators, and some other available software apps such as Symbolab and Wolfram Alpha. TCK is knowing which of the software applications available is appropriate to a particular content. TPK refers to the knowledge of mathematical software apps to be integrated as an instructional tool. It is knowing what technology can be applied for a particular teaching method. In this study, these were the software applications to be employed in the methods of teaching and learning. Finally, TPACK refers to the robust understanding of the technology to be applied in a particular method of delivering a specific content. This referred to the integration of the said software apps in the aforementioned pedagogical approaches in delivering the concepts of differentiation, anti-differentiation, and the applications of both, particularly related rates and problems involving areas.

3.2 Training as a professional development model

The training model remains to be recognized by teachers as a dominant paradigm because of its long history in education. It creates cognitive constraints to them or the difficulty of conceiving other models of PD (Kelly and Williamson, 2002). The model is characterized by one-shot workshop delivered by external experts through lectures, thus positioning teachers in passive roles (Dorph and Holtz, 2000). External experts in this setting may be colleagues, external teachers, or other resource individuals (Postholm, 2012). Given this characteristic, training is viewed as overly fragmented, disconnected to teachers' classroom practice, and misaligned with current theories of learning and school reform (Borko et al., 2010). The training model overshadows teachers' need to be proactive in identifying and meeting their own development needs (Kennedy, 2014) as it is often characterized to lack careful need analysis on the onset of its planning (Ayvaz-Tuncel and Çobanoğlu, 2018).

These characteristics are classified by Kennedy (2014) as drawbacks. Still, the model is considerably utilized to develop science and ICT pedagogical content knowledge (Rodrigues et al., 2003), introduce Inquiry-Based Science Education (Bernard et al., 2015), and train teachers in using the internet and preparing lesson plans (Junejo et al., 2018). In other words, the model is still recognized as an effective means of introducing new knowledge because of its transmissive nature which makes it suitable in delivering the aforecited contents. Further, it supports skills-based, technocratic view of teaching making it appropriate to the above contents, resulting in the provision of opportunity to teachers to update their skills and demonstrate their competence (Kennedy, 2014).

Darling-Hammond et al. (2009) reviewed the literature to address the prevailing drawbacks of training model. They suggested four minimal conditions for effective teacher training programs that should be intensive enough to cause behavioral change, connected to practice, continuous, and aligned with teacher incentives. It should also match to the existing needs of teachers and schools, involve teachers in planning, provide opportunities for active participation, be long-term, and have high-quality instructors (Bayar, 2014). In effect, these would redefine teacher's description of PD as a prepacked program which forms their professional identity. Instead, they would characterize it as collaborative where they are proactive leaders of reform having positive professional identities (Heba et al., 2015).

In the Philippines, training is a recognized PD method (DepEd, 2016). It is usually conducted by the division, school, or district for five days during semestral or summer break which they identify as in-service training (INSET). The purpose of INSET is to discuss and eventually tool or retool teachers on curriculum, strategies for instruction and assessment (Magulod, 2017). INSET is a continuing and practical activity for teachers to develop professional knowledge and skills throughout the education process. It can take different forms in attempting to achieve different objectives to bring change in education: professional education, professional support, and professional training (Altun, 2011). The latter is the most popular but such forms or methods are limited.

Martin et al. (2014) reviewed the literature, and they proposed new scheme of categorizing training methods based on seven criteria, namely, learning modality, training environment, trainer presence, proximity, interaction level, cost consideration, and time demands. These, respectively, refer to the mode of communication by which training contents are conveyed to the learners, the setting in which the training takes place, whether the method necessitates delivery of a trainer or some other source (e.g., computer), the locality of the trainer and trainees, the relative amount of interaction between trainer and trainee and among trainees, the most significant expenditures associated with each particular method and whether the expenses are initial or ongoing, and time commitment required of the trainees. Out from these criteria, they have proposed 13 training methods shown in Table 1. Of these training methods, only mentorship, apprenticeship, and some workshops are used because these are deemed appropriate in the present study. These are characterized by partnership between a novice employee with a senior employee. Mentorship provides support and guidance to less experienced employees, whereas apprenticeship develops skills and competencies.

3.3 Design and evaluation features related to the effectiveness of training

Arthur Jr et al. (2003) identified several designs and evaluation features associated with the effectiveness of training and development. These features are those which trainers and researchers have a reasonable degree of control, namely, (a)

TABLE 1 Comparison of training methods based on seven criteria (Martin et al., 2014).

Method	Learning modality	Training environment	Trainer presence	Proximity	Interaction level (minimally)	Cost	Time demands
Case study	Doing	Contrived	Yes	Face to face or distance	Variable	Low	Moderate
Games	Doing	Contrived	Yes	Face to face or distance	Interactive	Moderate	High
Internship	Doing	Natural	Yes	Face to face	Somewhat interactive	Low	High
Job rotation	Doing	Natural	n/a	Face to face	Not interactive	n/a	n/a
Job shadowing	Seeing	Natural	Yes	Face to face	Not interactive	Low	Low
Lecture	Hearing	Contrived	Yes	Face to face or distance	Not interactive	Moderate	Low
Mentorship & apprenticeship	Doing	Natural	Yes	Face to face or distance	Somewhat interactive	Low	Moderate
Programmed instruction	Seeing	Contrived	No	Distance	Not interactive	Moderate	Low
Role-modeling	Seeing	Stimulated	Yes	Face to face or distance	Not interactive	Moderate	Low
Role play	Doing	Stimulated	Yes	Face to face	Interactive	Low	Low
Simulation	Doing	Stimulated	No	Face to face	Not interactive	High	Moderate
Stimulus-based	Variable	Stimulated	Yes	Face to face	Somewhat interactive	Moderate	Low
Team	Doing	Contrived	Yes	Face to face or distance	Interactive	Moderate	Low

conducting a training needs assessment, (b) match between skills or tasks and training delivery methods, and (c) training evaluation criteria.

Needs assessment, or needs analysis, is an initial process of obtaining information on the employee efficiency level and the skill areas most in need of development to align the professional development program (Ludwikowska, 2018). Furthermore, it provides significant inputs to answer the following three important questions: who needs the training, what should be the training content in terms of skills and knowledge, and where the training is needed. These questions may be answered through the traditional trichotomy approach—organizational analysis, task analysis, and individual analysis. The organizational analysis provides information on where and when training is needed by an organization. The task analysis determines the knowledge, skills, and abilities (KSAs) needed to perform the tasks on the job of the trainees which specification of these provides critical inputs in designing the instructional process. Finally, the individual analysis, or person analysis, focuses on determining who should be trained and what training is needed by an individual. To carry out these analyses, Bansal and Tripathi (2017) outlined the steps in conducting the training need analysis. Initially, the trainer has to identify the professional competencies that relate to the prospect trainees' specific job/roles (i.e., TPACK in selected Calculus Topics in this case). Then, he/she has to identify competencies held by them on the job/roles they perform. The trainer will then compare the current competencies held by prospect trainees and those required in the job. Finally, the trainer outlines the requirement in sufficient detail and in appropriate format to prepare a training program. In this study, TPACK provided the lens for evaluating teachers' professional needs.

The training needs assessment results in identifying training objectives, which eventually specifies the skills and tasks to be trained and provides the basis for decisions on training delivery mode. These skills and tasks can be classified into three broad categories, namely: cognitive, interpersonal, and psychomotor. The cognitive skills and tasks relate to thinking, generating ideas, understanding, problem-solving, or the job's knowledge requirements. Interpersonal skills and functions relate to interaction with others. These encompass a wide array of skills such as leadership, communication, conflict management, and team-building. However, it is contended that practitioners (e.g., trainers) have restricted control over the preference of skills and tasks to be trained for the following reasons: they are mainly specified by the job and the result of the needs analysis, and training objectives. They only have more autonomy in terms of choosing and designing the training delivery method and the match between the skill or task and the training method. A particular training method may be effective on a specific task or training content, but a combination may be considered given that all training methods can transfer specific knowledge, skills, and attitude to the trainees (Arthur Jr et al., 2003). In this study, the training delivery methods were a combination of lectures and mentorship.

Finally, effective training should have evaluation criteria. Evaluation is defined as a systematic process of determining the worth, value, or meaning of something or determining the extent to which a program has met its stated performance goals and objectives. In training, "evaluation is a systematic collection of descriptive and judgmental data essential to make effective training decisions in terms of selection, adoption, value, and modification of various instructional activities" (Desimone, 2009). Hence, the choice of evaluation framework is a crucial and primary decision made when evaluating training effectiveness (Arthur Jr et al., 2003). Goldstein (Goldstein, 1980) contends that the amount of literature concerning these training evaluation frameworks which provide information on criterion development, evaluation designs, and mode of evaluating organizations has exploded (e.g.,Mulder, 2001; Eseryel, 2002). TPACK serves as the evaluation model for training effectiveness.

4 Research methodology

This section discusses the research design, the environment from where data were collected, and the statistical tools used for analysis. Moreover, data collection procedures were detailed in this section along with the appropriate data analysis methods.

4.1 Research design

This study employed the mixed method sequential explanatory design. Creswell et al. (2006) described this design as collecting and analyzing quantitative and then qualitative data. This research design included a multiple level strategy incorporating a systematic phase approach where in each phase, quantitative data provided general patterns and width and qualitative data are reflected upon the participants' experiences through narrative accounts (Newby, 2014). In other words, the qualitative interpretations were used to support or enrich the quantitative findings (Creswell et al., 2003). For the quantitative method, descriptive research was employed to describe teachers' initial and final TPACK prior to and after the PD program, and the quality of teachers' teaching-learning sequence plan (TLSP) after participating in the PD program where each TLSP done by pair of teachers was treated as one independent case. For the qualitative method, multiple case studies were used to provide an in-depth description and support the quantitative findings. Under this method, each pair of teachers who developed a TLSP is represented as a single case.

4.2 Data collection

There were four major phases to the research process: preparation, development, implementation, and evaluation. In the preparatory phase, researchers obtained necessary permissions and forwarded transmittals letters or letter of intent to develop and implement the PD program. Upon approval, mathematics teachers of the target school undergone training needs assessment (TNA) using a researchers adapted and modified instrument of Morales-López et al. (2021), and interviews regarding their TPACK in selected basic calculus concepts. Based on the TNA, a PD program was developed to enhance teachers' TPACK on the said topics. The training design of the said PD program was given feedback and recommendations of experts. Two of them are degree holders of Doctor of Philosophy in Mathematics (PhD Math) from Mindanao State University–Iligan Institute of Technology (MSU-IIT). They have been teaching basic and advanced calculus for more than 10 years. Another expert is a graduate of Master of Science in Mathematics (MSMath) who has been teaching higher calculus also for more than 10 years. All of them have been integrating technological advancements in teaching calculus. Revisions were applied based on consultations done.

In the implementation phase of the program, six lecture and corresponding workshops sessions were done. The initial TPACK of the participating teachers were collected before the said lectures and workshops. The details of this sessions are presented in the results section. There were monitoring and observations done to individual and group as well as interview schedules and documentation accounts throughout the PD program. At the culmination program, the participants' final TPACK were collected and the presentation and critiquing of the teacher's learning sequence (TLS) followed, concluding the implementation phase.

Finally, in the evaluation phase, teachers' final TPACK of the selected basic calculus topics were assessed using the same researchers adapted and modified instrument. Participants' narrative accounts explaining their responses in the post-assessment were also obtained. In addition, the quality of the proposed teachers' learning sequence plan as a result of the PD program were rated by evaluators using a designed rubric appropriate for the said learning output. The said experts were requested to provide written comments to enrich the ratings they assigned to each output. Efforts were made to maintain the privacy and secrecy of all data collected from the preparatory phase to the evaluation phase.

4.3 Research environment and participants

The PD program was physically conducted in one of the mega public high schools in Lapu-Lapu City, Cebu, Philippines. The school has a population of almost seven thousand students, 1,700 of whom are senior high school students and a total of 220 teachers including school heads. The target participants of said PD program were the 11 mathematics teachers in the Senior High School (SHS) department as shown in Table 2. These teachers were purposively chosen for the study. Almost all of these mathematics teachers earned units of master's degree programs with specialization in mathematics, engineering and accountancy. This means that these teachers have completed some (or even most) of the coursework required for a master's degree but have not competed all the requirements to graduate. They are all teaching mathematics courses as they were hired until the conduct of this study on the academic year 2022–2023. They are all teaching mathematics subjects on the academic year 2022–2023. They all have prior knowledge on the selected calculus topics and have expressed their need of a refresher course on calculus based on the training needs assessment. These teachers have varied number of years in teaching Mathematics subjects, two years is the least while 14 years is the highest. T1, T6, T7, and T8 are adjunct teachers as they are teaching mathematics courses and at the same teaching their specialized subjects under the STEM curriculum. However, none of them have received any TPACK training on specific topics in Mathematics,

TABLE 2 Profile of the teacher participants.

Participants	Sex	Tenure in service (years)	Highest educational degree earned	Specialization	Mathematics TPACK training attended	Preferred TPACK course
T1	Male	2	Bachelor's Degree	Engineering	None	Calculus
T2	Female	6	Master's Degree Graduate	Accountancy	None	Gen Math
T3	Female	3	Master's Degree (Units)	Mathematics	None	Calculus
T4	Female	2	Bachelor's Degree	Mathematics	None	Calculus
T5	Female	14	Master's Degree Graduate	Mathematics	None	Calculus
T6	Female	2	Bachelor's Degree	Industrial Engineering	None	Calculus
T7	Female	5	Master's Degree (Units)	Accountancy	None	Calculus
T8	Female	3	Master's Degree (Units)	Accountancy	None	Gen Math
T9	Female	2	Master's Degree (Units)	Mathematics	None	Calculus
T10	Female	3	Master's Degree (Units)	Mathematics	None	Calculus

thus making them a desirable participant of the PD program. The complete profiles of each teacher are shown in Table 1. Each of them was given a pseudonym as, T1, T2, T3,. . ., T11, to protect their identities on purpose.

4.4 Research instruments

The researchers adapted and modified an instrument developed by Mottier Lopez and Morales Villabona (2016). The said questionnaire was used to characterize the technological, pedagogical, and content knowledge exhibited by mathematics teachers in an initial training at the Universidad Nacional (UNA) This Likert-scale instrument consisted the seven TPACK domains. Each domain has corresponding number of items representing the units of analysis. In CK, there were eight-item statements assessing knowledge of the subject matter to be taught or learned. In PK, four-item statements describing strategies in teaching and learning assessment including classroom management. TK has five-item statements measuring knowledge of the above-mentioned technological applications including Power Point and video presentations. TPK has nine-item statements specifying the use of software apps and recognizing that technology has the potential to revolutionize how teachers instruct. PCK has six-item statements evaluating knowledge on blending of pedagogies and subject matter. TCK has six-item statements evaluating the ability to comprehend how technology should be integrated to create new content representations. Finally, TPACK has six-item statements describing the intersection of all the domains. Each item statement is rated with the following numerical scores and their corresponding descriptive rating, 5 as expert, 4 as advance, 3 as proficient, 2 as basic, and 1 as limited. The modification based on the construction of the units of analysis was subjected to a validation process with three experts in pedagogy, technology, and mathematical content on selected Calculus topics. Each of these specialists has more than 10 years of experience of teaching in their field. The said process was carried out using the Aiken Validity Index formula $V = \frac{S}{n(c-l)}$, where V is the value of the validity coefficient, S is the value of the rating scale minus 1, n is the number of assessors or experts used in the validation, and c is the highest score in the rating scale. Aiken's validity index value and interpretation ranges from 0 to 1, where $0 \leq V \leq 0.4$ as invalid, $0.4 \leq< V \leq 0.8$ as medium valid, and $0.8 < V \leq 1$ as very valid (Benson and Clark, 1982). Based on the results, the items with the lowest AVIs in PK, TK, PCK, and TCK domains recorded 0.611, 0.597, 0.625, and 0.542, respectively. These are classified as medium valid. These represent lowest AVIs of each domain. The items with the highest AVIs in CK, TPK, and TPACK recorded 0.917, 0.944, and 0.833, respectively. These are very valid with values. The said questionnaire was pilot tested to 10 teachers, and the reliability of the modified instrument was established with acceptable Cronbach's alpha values 0.756, 0.701, 0.839 on CK, PK and TK respectively. Moreover, PCK, TPK, and TPACK has values 0.729, 0.77, and 0.765, respectively, as the intersections of the first three domains.

On the other hand, interview questions and schedules were patterned on the philosophy of reflective thinking by Dewey (1933). The Reflective Thinking Open-Ended Questionnaire with the following items; " What I see?", " What I feel?" and "What I feel?", allows teachers to answer the questions in their own words in explaining the meaning of their own experiences.

4.5 Data analysis

Descriptive statistics was used to analyze the quantitative data gathered from the main instrument. Informational coefficients described and summarized trends and relationships within the pre-assessment and post-assessment levels of the teachers' TPACK on selected calculus topics (Fisher and Marshall, 2008). Progression between the participants' initial and final TPACK were determined by its differences. The Wilcoxon signed-rank test was utilized across all domains to determine whether the computed differences

TABLE 3 Initial distribution of the teachers' TPACK on selected calculus topics.

TPACK domains or components	Pre-assessment level of competence				
	Limited	Basic	Proficient	Advance	Expert
Content knowledge	6	4	1	0	0
Pedagogical knowledge	6	4	1	0	0
Technological knowledge	5	2	3	0	1
Technological pedagogical knowledge	5	4	2	0	0
Pedagogical content knowledge	5	4	2	0	0
Technological content knowledge	6	2	2	1	0
Technological pedagogical and content knowledge	7	2	2	0	0

between pre- and post-assessment were significant or not. The normalized gain formula was used to measure the degree of effectiveness based on the Wilcoxon signed-rank test results if the result is significant.

For in-depth discussion of the quantitative findings, descriptive case study was employed for the analysis of the qualitative data (Yin, 1994). A case study that provides descriptions of the teachers experiences on a particular phenomenon contributes to a better understanding of the said phenomenon (Smith, 2004). Teachers' narrative accounts were noted through pattern matching and developing themes. Similarities and differences in terms of what they see, feel, and think were identified and verified based on the interview responses and observational notes. Finally, the numerical ratings given by the panel of experts in each TLS plan were consolidated to obtain the average score per dimension in the scoring rubric and eventually added to get the total score per TLS proposal then averaged. Their written comments were used to substantiate the scores they gave.

5 Results and discussion

The findings of this study are organized in four parts. The first part discusses the initial TPACK of mathematics teachers in selected calculus topics. The second part describes the development of the PD program and its implementation. The third part presents teachers' initial and final TPACK after a PD program was implemented. The fourth part presents the quality of the teachers' TLS plan as perceived by the panel of experts.

5.1 Teachers' initial TPACK

Table 3 summarized the results of the survey conducted to determine the teachers' initial TPACK on the selected calculus topics.

In terms of both CK and PK, out of the 11 participants, ten perceived themselves between *limited* and *basic* levels while only one reached proficiency, meaning none made it to the *advanced* and *expert* levels. For TK, seven teachers assessed themselves in the *limited* and *basic* levels, three as *proficient* and one as *expert*. In TPK and PCK, nine participants viewed themselves at *limited* and *basic* levels, two as *proficient* but none were at *advanced* and *expert* levels. In addition, TCK and TPACK of the said participants indicated that more of them have rated themselves as *limited* while few of them as *basic*. The initial TPACK ratings were primarily supported by the narrative accounts of the said participants based on the three interview questions; " What I see?", "What I feel ?", and "What I think?" on each specific domain in the survey instrument. These questions are based on Dewey (1933) reflective thinking as an active, persistent, and careful consideration of a belief or supposed form of knowledge, of the grounds that support that knowledge, and the further conclusions to which that knowledge leads.

As of the CK and PK, almost all of the teachers shared the same sentiment about derivatives, integration and the applications of both as well as on ways how to deliver it. They argued that the topics are interesting yet difficult, complicated, and challenging to teach. They said the following:

> *"I see that calculus is interesting."* T_1
> *"I see topics are quite difficult for me."* T_9
> *"I see that calculus is very complicated subject but it can be learned."* T_7
> *"I see that teaching calculus will be great and bit challenging."* T_3

With this, they were motivated and felt the need to be retrained to improve their knowledge of the content and pedagogies.

> *"I feel motivated to learn more on calculus and how to teach it well."* T_5
> *"I feel that I should be refreshed and revived the long -time knowledge I had with calculus in my college days for my teaching."* T_8

They thought that they should revisit and relearn the specific topics. As quoted, teachers said the following:

> *"I think that I still have lots of things to learn about the course."* T_7
> *"I think that I need to refresh my learnings in the subject."* T_5
> *"I think that I still have so much to re-learn."* T_{11}

For TK and the rest of the intersection of the domains, teachers were thrilled of the technology that can be integrated in teaching the topics holistically and to be blended well with all the domains. They mentioned as follows:

> *"I see now that there are a lot software applications which are free to use for Calculus and it's a wow!."* T_3

"I think I will enjoy learning this subject (calculus) again and teaching this with the new technology to be integrated." T_2

"I feel like pursuing to learn the new ways of teaching calculus with technology and to review the concepts of the subject to be able to teach it the best way I can." T_4

With this, the initial TPACK ratings of the mathematics teachers were generally placed in the limited level. Calculus is often regarded as a challenging and difficult subject to teach due to its abstract nature and the level of mathematical rigor involved (Leithold, 1996). The study of Yan et al. (2020) found out that Mathematicians believed that the primary purpose of a calculus course is to communicate the nature of mathematics as a discipline.

In response to these assessments, a professional development program is carefully designed to meet their needs on the said TPACK domains. When the proposal was presented to them, they received it positively even though none of these teachers have experienced any TPACK training. Based on the observational notes and verbal response of the teachers, they viewed TPACK as a valuable process that could enable them to better comprehend how to use technology while blending it with all the other domains to enhance mathematics instruction.

5.2 Development and implementation of the PD program

This professional development program is designed for senior high school mathematics teachers to develop their TPACK on the selected topics in basic calculus by using appropriate application software which are accessible for free namely, the Desmos graphing calculator, derivative calculator, and the integral calculator. This proposal was based on the perceptions of the participating teachers who have given their initial TPACK and expressed their need to go through a program which aimed to develop their TPACK on the selected topics in basic calculus. The development of this proposal led to the formulation of its specific objectives as follows: (1) to improve the teachers' TPACK on Derivatives in an interactive deductive approach while utilizing Desmos graphing and Derivative calculator. Integral calculator is also used to integrate functions interactively. We also use both derivative and integral calculator to solve applications of both derivatives and integration employing both inductive and deductive approaches while employing pairing techniques in problem-solving. Desmos graphing, derivative calculator, and the integral calculator intends (2) to design TLS using teachers' improved TPACK in selected calculus topics. All the eleven (11) senior high school teachers at the target school recipient were officially registered as participants of the said development program. The participating teachers underwent a series of lectures and seminar-workshops on the specified topics covering all the TPACK domains organized in six sessions for one month. Each session was done in 4 h and another 4 h for its corresponding workshop. Teachers were asked to participate interactively during the inductive and deductive lectures. Research tagged these approaches as more student-centered specifically for mathematics courses as compared to traditional methods which are teacher-centered. Sapkota (2023) recommended that educators should be trained to better implement inductive and deductive lectures as these methods help students develop permanent concepts particularly in mathematics courses. In addition, participants were paired up for the workshop and mentoring in developing a fully TPACK integrated TLS in each covered topic since the beginning of workshop sessions. Paired teaching, in which a faculty member works alongside a more experienced colleague to share responsibility for all aspects of a course, is a promising and cost-effective method for helping instructors incorporate evidence-based teaching strategies (Stang et al., 2017). The teacher pairing was done based on two criteria: the mathematics subjects they taught in the recent academic year and their teaching experience. Teachers with more years of experience were paired with those having fewer years, fostering a balance of expertise and support in each pair.

The first session started with the discussion on the introduction of the geometric interpretation of derivatives and the differentiation formulas by inter-active deductive lecture utilizing Desmos graphing and the Derivative Calculator. The said pedagogical approach was demonstrated on the entire lecture where the speaker introduced the general principle of the said content breaking it down to the specific differentiation formulas and application software while questions and answers are intentionally embedded for active interaction. Then, the participants were paired starting for the first workshop on designing a TLS. The pairing technique was facilitated with an instructional guide given to the teachers to illustrate this technique as one of the pedagogical practices. In addition, each pair of teachers (representing the learners) was assigned with a mentor (representing the subject teacher).

The second session focused on the illustration of step-by-step procedures in problem-solving involving related rates and optimization as applications of derivatives using inductive approach and facilitating a pairing technique. To demonstrate this inductive lecture method, a set of instructional statements were provided to the participants while the speaker demonstrated the process embedding it in the lecture topic. Specific activities addressing the expected topic outcomes were given to the participants for them to discover patterns leading to the formulation of verified conjectures defining the concepts of the content. The pairs worked together to formulate solutions in the problem-solving tasks and in utilizing the Desmos graphing and derivative calculator. To illustrate the problem-solving approach as a learning pedagogy, each pair was given a set of problems involving the content and the integration of the appropriate technological software. Similarly, the same method of workshop was done for the topics in session two. The first two sessions addressed the TPACK needs of the mathematics teachers on derivatives and its applications. Based on the observations of the facilitators, the participants were very appreciative of their learnings and showed enthusiasm to participate during the lectures. They were actively giving answers to the speakers' questions. Moreover, they described their experiences on that day as awakening and have started gaining back their confidence.

"I see the beauty of Calculus again." T_7

"I feel good about learning calculus again. I cannot say that I am that confident yet because I think there's still a lot to learn." T_9

"I feel that through this training workshop, I can gain confidence in teaching basic calculus in our students in the future." T_3

"I think that my passion about the subject is awakened by the lecture/demo done by the speaker." T_5

The third session taught the teachers about the process of integration and its geometric representation. Anti-differentiation concept and formulas were introduced by interactive deductive lecture with the aid of an integral calculator. After which, the same pairing technique was implemented for the corresponding workshop of the topic. In the fourth session, the step-by-step procedures in problem-solving involving areas as an application of integration were explained and illustrated. Inductive approach and a pairing technique were again followed leading to its workshop on designing a TLS with their improved TPACK on integration and its application, that is, on solving area problems. The third and fourth sessions have fulfilled to the teachers' need in terms of their TPACK on Integration and its application. Once more, the participants were very much grateful for the opportunity of relearning again the said topics as noted by the facilitators. They were more engaged now in the discussion as they also asked questions to the speaker aside from responding to the questions on the discussion. The participating teachers highlighted their experiences on those sessions as motivating and exciting although some of them felt hesitant.

"I see the need to have a thorough review of the concepts of calculus. I feel motivated by the insights shared to us. Thankful to the speaker for sharing his knowledge to us math teachers regarding the forgotten concepts." T_2
"I feel excited and eager to listen to our versatile speakers who have so much inputs in the subject." T_6
"I am hesitant to do it on my own because of the less exposure on these topic and that it is almost like a new lesson for me." T_{10}

The last two sessions of the program were spent for the discussion and illustration of principles on how to design a well-crafted TLS with an improved TPACK on differentiation, integration, and its applications. The standard format of the Department of Education (DepEd) on lesson planning was adapted as the said TLS were meant to be actualized in their respective classes in the future. The same pairing technique was implemented for the last two workshops. The pairs were asked to choose only one among all the specific topics discussed. Each pair of teachers developed a TLS plan from their chosen. All of them were guided to make sure each TPACK domain was demonstrated in the TLS plan they worked on. On these sessions, they were still mentored by the speakers though giving constructive feedbacks on their outputs. The teachers are then asked to present and submit their final TLS for judging. A rubric was designed for the assessment of the said output. Three (3) experts were invited as judges to rate the TLS plan of each pair. All the pairs expressed their positivity to the speakers and facilitators during the workshop.

"We feel excited about the challenge of creating a lesson plan that will engage and inspire students and help them to develop a deeper understanding of calculus and its application especially now with a software." Mora and Gomez
"We think we can teach well the lessons with the TLS we make especially integrating the derivative calculator for our students." Pasigna and Yaun

"We see that there are a lot of ways to create a lesson plan using the various calculating software tools for student enhancement." Nino and Pino

Although Harris and Sass (2011) found no consistent relationship between formal professional development and teacher productivity, the teachers confirmed that formal training in the subject have more significant effects in their outputs.

5.3 Teachers' final TPACK

Table 4 shows the initial and final TPACK evaluation of the mathematics teachers and their level of progression across all domains before and after the PD program.

Columns 2 and 3 of Table 4 display, respectively, the initial and final distribution of teachers when grouped according to their TPACK levels. The last column shows the number of teachers who progressed from lower to higher competence levels. Ideally, a negative value should be reflected in the limited level or in the next lower competence levels and a positive value in the higher category of competence to indicate progress. It is noted that in CK, PK, and TK, most of the teachers progressed to the expert level except for one who rated herself at the advanced level. On the other hand, all teachers progressed to the *expert* level in the TPK, PCK, TCK, and TPACK domains. The interview responses of the participants have supported these improvements. As they have worked by pair since the first session of the training, they expressed their thoughts and feelings about their TPACK across all domains by teams of two. They communicated their realization, satisfaction, and improved confidence with the concepts, strategies, and software applications they learned on derivatives, integration, and the applications of both.

"We see the importance of this training especially in integrating technology with our lessons in calculus . . ." Pair 6
"We feel satisfied, contented and full of hope in teaching Calculus in the future." Pair 4

"The training is really a blessing to us teachers and we feel happy for the additional and refreshing knowledge in calculus." Pair 2
"We felt confident and eager to teach calculus." Pair 3
"We're so grateful for this opportunity." Pair 1

These positive results and feedback are parallel to the findings of Emmer (1986) in terms of the effects of teacher training. Based on this study, teachers frequently exhibit positive changes in attitude or in perceptions. In his results, it was confirmed that the training programs are apparently successful in eliciting teacher enthusiasm and support and are consistent with the teachers' role of expectations or preferences. Another study of Dede and Karakus (2014) supports these findings; however, their study indicated that teacher training programs effected the teachers' beliefs yet they were not significant enough for changing them. In relation to this, the Wilcoxon signed-rank test was performed to determine whether the teachers' TPACK Level in all domains of the selected calculus topics are significant or not.

Table 5 shows p-values which are below .01. This indicates that across all domains, the said progressions of the teachers' TPACK

TABLE 4 Initial and final distribution of teachers' TPACK in selected topics of basic calculus ($n = 11$).

TPACK domains or components	Pre-assessment level of competence					Post-Assessment level of competence					Level progression				
	Limited	Basic	Proficient	Advanced	Expert	Limited	Basic	Proficient	Advanced	Expert	Limited	Basic	Proficient	Advanced	Expert
Content knowledge	6	4	1	0	0	0	0	0	1	10	−6	−4	−1	+1	+10
Pedagogical knowledge	6	4	1	0	0	0	0	0	1	10	−6	−4	−1	+1	+10
Technological knowledge	5	2	3	0	1	0	0	0	1	10	−5	−2	−3	+1	+9
Technological pedagogical knowledge	5	4	2	0	0	0	0	0	0	11	−5	−4	−2	0	+11
Pedagogical content knowledge	5	4	2	0	0	0	0	0	0	11	−5	−4	−2	0	+11
Technological content knowledge	6	2	2	1	0	0	0	0	0	11	−6	−2	−2	−1	+11
Technological pedagogical and content knowledge	7	2	2	0	0	0	0	0	0	11	−7	−2	−2	0	+11

TABLE 5 The Wilcoxon signed-rank test of the teachers' initial and final TPACK on selected calculus topics.

TPACK domains	Wilcoxon test								
		N	Mean	SD	T	Z	p	$< g >$	Interpretation
CK	Pre	11	1.636	0.924*	66	2.994	0.003**	0.97	High
	Post	11	4.909	0.302					
PK	Pre	11	1.636	0.924	66	2.994	0.003**	0.97	High
	Post	11	4.909	0.302					
TK	Pre	11	2.091	1.300	55	2.836	0.005**	0.96	High
	Post	11	4.909	0.302					
TPK	Pre	11	1.727	0.786	66	2.98	0.003**	1	High
	Post	11	5	0.00					
PCK	Pre	11	1.727	0.786	66	2.98	0.003**	1	High
	Post	11	5	0.00					
TCK	Pre	11	1.818	1.079	66	2.98	0.003**	1	High
	Post	11	5	0.00					
TPACK	Pre	11	1.545	0.820	66	3.022	0.003**	1	High
	Post	11	5	0.00					

*$p < 0.05$, **$p < 0.01$ z = Wilcoxon signed-rank test, N = total number of students, g = normalized gain scale: ("High", $g > 0.7$), ("Medium", $0.3 < g < 0.7$), ("Low", $g < 0.3$) (Hake, 1998).

were all significant at the 99% level as shown in Table 5. The normalized gain scores, $\langle g \rangle \geq .96$, indicated that the development program on enhancing teachers' TPACK on selected calculus topics is highly effective in each domain. This confirmed the study of Chaipidech et al. (2021) on the incremental TPACK improvement of the STEM teachers after a development program intervention. Another parallel study of Chaipidech et al. (2022) on teachers' TPACK development has similar interpretation of these findings. Their study concluded that participants have significantly improved in knowledge-related TPACK dimensions. These results also validated the study by Bray and Howard (1980), claiming that a particular teacher training produced significant changes in the trainee's self-ratings of teaching ability. The PD program conducted has served its purpose in improving the initial TPACK assessment of the mathematics teachers. In the study of Treska (2014), this kind of training programs primarily target innovative and up-to-date practices, including changes in methodology that focus on student-centered teaching and activation of student's critical thinking. The importance of the PD program on enhancing the teachers' TPACK on selected calculus topics was observed when the participants gained new knowledge with dynamic enhancement of their pedagogical and technological competencies. This was evident on their final TPACK results compared to their initial self-reported assessment. Previous researches support the likelihood of positive effects on teacher trainings toward their teaching competencies. These positive effects were evident by the testimonies of the participants.

"We see the efforts of each speaker to deliver the lessons well and they did not fail because they made it easier for us to learn again." Pair 5

"We feel that the topic is useful not only for ourselves but also for our students and future's circumstances." Pair 2

"We think re-learning the subject is a good preparation in times that we will be given calculus subject to teach because honestly it is almost forgotten since we don't teach the subject for many years." Pair 3

"We think it was a very enriching training for us teachers." Pair 5

The trained participants also expressed their admiration on the training and suggested that the said development program must be re-echoed to all other teachers.

"We think that this training should be re-echoed and recalled in the LAC sessions of teachers." Pair 4

They supported their narrative accounts when they were all religiously doing their teaching learning sequence plan as the required final output of the PD program.

5.4 Quality of mathematics teachers' TLS plan on selected topics in calculus

A training matrix and guidelines for the development program were provided to all the teacher participants during the orientation. In all the workshops, participants worked by pair to also demonstrate cooperative learning for greater productivity. Millis and Cottell Jr (1997) explained many more positive effects of peer learning among faculty in higher education. As their final output in all the workshops, each pair was instructed to design a teaching learning sequence. They were tasked to only choose one specific competency among the selected Calculus topics. It is also noted that each pair have completed and submitted their distinct outputs on time for assessment. Table 6 summarizes the panels of experts' ratings.

Supposedly, there were only five pairs formed from the 11 participants but the teacher without a partner decided to be treated as two making the number of partners from 5 to 6. Experts rated the six pairs based on the rubrics which consisted of the seven TPACK domains. Each domain is represented by a criterion statement of which each part of the TLS is being rated as poor (1), unsatisfactory (2), satisfactory (3), very satisfactory (4) and outstanding (5). The scale comes with a descriptive requirement in each level.

The final ratings revealed that all the TLS have met the "very satisfactory" level across all domains. This means that the topic demonstrates strong achievement targets and SMART objectives; considers two or more perspectives in its motivation when appropriate; integrates illustrations and examples with analysis; explains the topic with clarity in the abstraction phase with two or more examples; shows completeness in skills in its application; and integrates appropriate assessment across all domains. The judges' narrative accounts are consistent with the tabulated result.

"I've seen that the teachers are serious in creating their outputs and they seemed competitive. Their TLS plan are carefully prepared. Their abstraction was articulated well and very comprehensive. All outputs are almost outstanding, some were just lacking some few points but generally I'm very satisfied with their works, just a little more push is needed especially in the last domain, the TPACK." Judge$_1$

"It's amazing that teachers have performed well through their outputs. Their TLS are well-thought. Its complete, very holistically presented with all the domains present, objectives are stated very clear and realistic. Some TLS have just met the standard enough but mostly, exceeded. I have not given an outstanding rating because I think they can still improve it more, but they are almost there." Judge$_2$

"Generally, all their outputs satisfy the criteria but I've seen a few who really exceeded well in some domains and at the same time I've noticed also in some outputs that there are missing points but only in some domains as well, the good thing is that TPACK domains are there as an element of the plan. Good job teachers!" Judge$_3$

"We think it was a very enriching training for us teachers." Pair 5

6 Discussion and conclusion

The TPACK construct has helped the teachers understand better why they need to adopt technology in their instruction. Hofer (2015), discussed the issues on why both novice and experienced classroom teachers been so slow to adopt technology in their instructions. Access to technology, technical training and the constraints of the K-12 teaching environment particularly time were considered the center of its barriers. These challenges were made even more daunting for the senior high mathematics teachers since technologies themselves are changing rapidly. This was evident by their initial TPACK results which was placed in the limited level. Implemented as technical training, a PD program was proposed and conducted with the goal of improving the teachers' limited TPACK and enhancing effectivity of their teaching with technologies not as an isolated tool that can be layered on top of their existing teaching practices but as a domain to be carefully intersected with appropriate pedagogical and content knowledge (Mishra and Koehler, 2006b). When the PD program started, it was not surprising that these teachers felt grateful yet overwhelmed just learning how to use newer technologies, let alone making decisions about how best it can be interwoven with pedagogical and content

TABLE 6 Assessment of teachers' TLS with their improved TPACK on selected calculus topics.

TLS/TPACK domains	CK	PK	TK	PCK	TPK	TCK	TPACK	Final rating	Descriptive rating
Pair 1	3.499	3.499	4.166	4.166	4.166	3.832	3.499	3.832	Very satisfactory
Pair 2	4.499	3.499	4.166	4.166	4.166	4.166	3.832	4.070	Very satisfactory
Pair 3	4.166	3.499	3.832	3.832	3.832	3.832	3.499	3.785	Very satisfactory
Pair 4	4.166	3.832	4.166	4.166	4.166	4.166	3.832	4.070	Very satisfactory
Pair 5	4.666	4.166	4.166	4.333	4.166	4.166	3.832	4.213	Very satisfactory
Pair 6	4.166	3.499	3.832	4.166	3.832	4.166	3.832	3.928	Very satisfactory

⟨ 4.50–5.00 O-Outstanding ⟩, ⟨ 3.50-4.499 VS-Very Satisfactory ⟩, ⟨ 2.50-3.499 S-Satisfactory ⟩, ⟨ 1.50-2.499 US-Unsatisfactory ⟩, ⟨ Below 1.499 P-Poor⟩.

area understandings (Kohler, 2015). Throughout the training, participants were taught that good teaching requires the thoughtful integration of technological knowledge, pedagogical knowledge, and content knowledge with the goal of designing a quality and discipline-based teaching learning sequence. Participants were provided with rich and diverse set of resources during the interactive lectures, mentoring during workshops and collaborative learning opportunities as they worked on their learning tasks by pair in every session.

One of the key outcomes of the PD program was the development of teachers' technological knowledge. Similar to the findings by Sugar and Wilson (2005), participants gained a deeper understanding of the diverse range of educational technologies available particularly in basic calculus, their functionalities and how it can best facilitate the pedagogy and content of a specific competency. Most teachers became expert in using derivative calculators, Desmos graphing app, and integral calculators as they integrate it in their designed TLS.

In terms of their pedagogical knowledge, the PD program exposed them to interactive—deductive and inductive approaches during the lectures together with innovative and constructive strategies during workshops. Confirming the findings of a similar study by Meichtry and Smith (2007), these pedagogies have strengthened participants' confidence on their teaching practices and have promoted active learning, critical thinking, and collaborative completion of the training outputs.

The PD program also emphasized the importance of deepening teachers' content knowledge in selected calculus topics. Teachers engaged in rigorous content-focused lectures and explored real-world applications in basic calculus. They became more confident with their enhanced content knowledge. Their narrative accounts were evident of their eagerness to handle the topics well. These positive impacts confirmed the findings of Jacob et al. (2017) on the effects of a PD program in terms of mathematical knowledge.

Finally, an essential aspect of the PD program was the emphasis of the TPACK framework, which determined the interplay between and among technological, pedagogical, and content knowledge. Teachers developed a more comprehensive and holistic approach to their instructional practices in the selected Calculus topics considering the dynamic relations of the said TPACK domains. They understood how to leverage technology as a tool to enhance pedagogy while ensuring a comprehensive and deep understanding of the subject matter. This confirmed the findings by Koh and Chai (2016) on the positive effects of teachers' improved TPACK toward twenty-first learning. These were supported by the quality of their TLS based on their enhanced TPACK. All their submitted TLS were rated by experts as "very satisfactory" with "outstanding" rating on some domains. This was also evident in the teachers' final TPACK evaluation. From limited, teachers progressed mostly to the expert level across all domains after the training. The said differences between the initial and final TPACK were all significant at 99 % level with normalized gain scores interpreted as "High". This means that the PD program was highly effective in significantly improving the teachers' TPACK on selected Calculus topics. Using the same framework, this validated findings by Absari et al. (2020) on the significant effects of the TPACK domain on learning. Based on the participants' narratives, the PD program proved to be a transformative experience for teachers enabling them to embrace a holistic acquisition of the technological, pedagogical, and content knowledge as a catalyst for enhancing their instructions in basic calculus. They felt they are now better equipped to create engaging and student-centered learning environments.

7 Implications/recommendation

This study reveals the potential of professional development programs centered around TPACK framework in improving teachers' level of competence in all the domains of the said framework. Teachers have gained significant increase in their pedagogical and content knowledge level while integrating technological innovations, particularly in the context of teaching basic calculus. Additionally, the research has observed notable challenges to technology adoption, such as inadequate financial resources, poor software application proficiency, and time constraints. Rahman et al. (2022) confirmed how lack of technological assistance and resources affected technology integration and altered instructors' attitudes regarding actively regulating pedagogy in the classroom and their proficiency with its use. The possibility for these challenges to be alleviated through the implementation of a professionally organized professional development program on TPACK was highlighted. The findings show that teachers have improved their pedagogical approaches, content expertise, and technological skills resulting in a more guaranteed, student-focused instructional methods. The program's efficacy was evident in the significant rise of teachers' TPACK level, which advanced from "limited" to "expert" . In addition, it was pointed out that professional development programs that adhere to the comprehensive integration of technology, pedagogy, and content teaching practices and improve student outcomes. Ensuring educators' adequacy for the dynamic challenges of 21st-century teaching and learning, schools and other educational institutions should prioritize and invest in comprehensive professional development opportunities that provide continuous support for teachers to improve their TPACK, particularly in technology-intensive subjects such as in science, technology, engineering, and mathematics.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the [patients/ participants OR patients/participants legal guardian/next of kin] was not required to participate in this study in accordance with the national legislation and the institutional requirements. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

JM: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. SC: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. JO: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. TE: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. GP: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. RD: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Exploring the applications of artificial intelligence in mechanical engineering education

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In an era marked by technological sophistication, Artificial Intelligence (AI) is increasingly being integrated into various fields, including Mechanical Engineering Education (MEE). This review paper presents a systematic examination of scientific publications in this field, spanning from 2018 to 2023. Utilizing the PRISMA framework, 228 research papers were selected and analyzed to identify research gaps and future directions in AI's application within the MEE discipline. The diverse applications of AI in MEE identified include personalized learning, smart tutoring systems, digitizing engineering drawings, enhancing simulation and assessment, and boosting student motivation and engagement. Additionally, a bibliometric analysis of AI in MEE was conducted, examining its role in different aspects of MEE, interdisciplinary collaboration, geographic distribution, and research focus. Accordingly, the scope of this review encompasses a comprehensive content analysis and bibliometric evaluation of AI applications in MEE. This review systematically identifies current applications of AI, maps research trends, and analyzes publication data to highlight interdisciplinary collaborations and geographical distributions. Furthermore, this study identifies critical research gaps and offers actionable recommendations, emphasizing future directions such as advancing Generative Artificial Intelligence (GAI) applications in MEE and reshaping curricula to integrate AI-based learning tools. The findings provide valuable insights to support stakeholders in evolving MEE to meet industry needs and enhance educational outcomes.

KEYWORDS

mechanical engineering, education, artificial intelligence, machine learning, educational automation

1 Introduction

Mechanical Engineering (ME) is a vast field, encompassing a wide range of disciplines such as mechanics, robotics, manufacturing, additive manufacturing (AM), aerospace, and computer-aided design (CAD). ME involves applying engineering principles and methods to solve real-world problems, from the initial stages of design and creation to the introduction of objects into the real world (Prabhu, 2019). Mechanical engineers critically evaluate their work using principles of motion, energy, and force, ensuring that their designs are safe, reliable, and effective. The significance of ME lies in its impact; mechanical engineers address various needs by developing technologies tailored to specific requirements. They are problem solvers who find solutions to challenges across multiple fields, including transportation, climate change, world hunger, healthcare, and more. This versatility is reflected in Mechanical Engineering Education (MEE), which plays a pivotal role in the innovations and challenges of various disciplines. Mechanical Engineers can design a wide array of machines, systems, and processes, from the smallest components to large-scale projects. Consequently, mechanical engineers need a diverse skill set, including problem-solving, creativity, and experiential skills (Prabhu, 2019). As technology evolves, MEE must provide students with an education that aligns with digital advancements, preparing them for the workforce. Students should be equipped with the necessary skills to navigate and address future challenges effectively.

The advent of AI has the potential to significantly facilitate the acquisition of key skills in MEE. By transforming MEE on various levels, AI enhances the educational experience and lessens the burden for both educators and students. It accomplishes this by offering sophisticated facilities such as personalized learning experiences, gamification of the learning process, and the digitalization of educational resources. AI is capable of personalizing education by monitoring students' performance, providing feedback, offering interfaces for human-computer interaction, and delivering suitable tasks (Zhai et al., 2021). However, the introduction of AI also brings forth concerns about academic integrity, student motivation and engagement, the need for more personalized learning, improved accuracy in engineering drawings and simulations, fault diagnosis in systems, digitization of engineering drawings, assessment, classification, automation of simulations, and the creation of safer learning environments (Cai et al., 2021).

This study is therefore dedicated to exploring and presenting a holistic perspective on the applications of AI in MEE. It achieves this through an in-depth examination of scientific publications focused on this area. By synthesizing and summarizing key findings, methodologies, and recommendations from a broad range of papers, this study offers a valuable resource for researchers, educators, and policymakers who are keenly interested in the integration of AI into MEE. This review paper contributes to the MEE field in several significant ways. First, it provides an extensive overview of the current state of AI in MEE, enabling researchers to identify prevalent themes and research trends within the field. Second, it combines findings and insights from numerous studies, offering a comprehensive perspective on the efficacy of AI in MEE. Additionally, this review pinpoints research gaps and areas that warrant further investigation, thereby guiding future research initiatives.

The methodology used for selecting and analyzing scholarly articles will be elaborated upon in the next section of this study. Subsequently, a detailed content analysis and synthesis of the findings and insights will be presented, highlighting various themes, trends, and prospective research pathways. Moreover, a bibliometric study will be carried out, examining publications related to AI in MEE, the extent of cross-disciplinary collaboration, and the geographical spread of research activities. In conclusion, this review will emphasize the significance of the consolidated findings and recommend future research avenues to propel the AI in MEE field forward.

2 Methodology

The research methodology used in this study adopts a structured strategy to collect and examine literature related to the incorporation of AI into MEE. This involves four main stages, as illustrated in Figure 1 and outlined as follows;

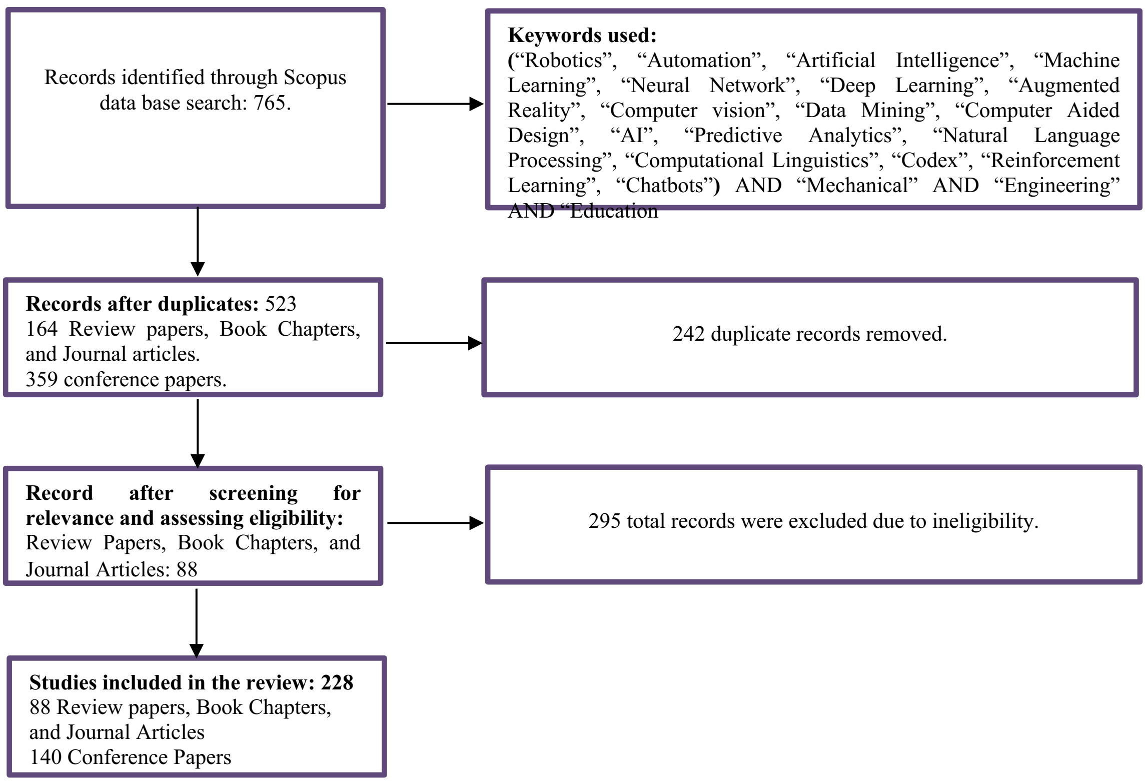

FIGURE 1
PRISMA flow diagram.

2.1 Literature retrieval

This phase involves the identification of relevant search terms and keywords to thoroughly identify significant publications pertinent to the chosen subject, marking the first and critical step in the data collection phase. A collection of existing articles and publications within the AI in MEE sphere was gathered from the Scopus database due to its credibility that results from its comprehensive coverage, quality control, global reach, frequent updates, and accessibility. Through the employment of a set of keywords, including "Mechanical," "Engineering," "Education," "Artificial Intelligence," "Machine learning," "Neural network," "Deep Learning," and "Augmented reality," "Computer vision," "Data Mining," "Computer Aided Design," "AI," "Predictive Analytics," "Natural Language Processing," "Computational Linguistics," "CODEX," "Reinforcement learning," and "Chatbots," the researchers performed a focused search through title, abstract, and keyword sections. This endeavor led to the compilation of 765 papers, covering the period from 2018 to 2023.

2.2 Literature screening

The procedure for reviewing literature in this study was influenced by the PRISMA guidelines, acknowledged for their comprehensive and clear methodology in the execution of systematic reviews and meta-analyses (Figure 1). The PRISMA framework provides a systematic approach for the identification, selection, and critical assessment of relevant studies, ensuring the review's credibility and the ability to replicate its findings (Anon.). Initially, a total of 765 papers were gathered. After removing duplicate entries, 523 documents remained, consisting of 359 conference contributions and 164 review articles, book chapters, and scholarly papers. We then conducted a meticulous evaluation of each document, carefully selecting only those papers that aligned with the study's objectives and met quality standards. This process led to the exclusion of studies not relevant to our research focus. Ultimately, our final selection included 228 works—comprising 140 conference contributions and 88 review articles, book chapters, and scholarly papers—spanning from 2018 to October 2023, ensuring a robust and relevant dataset for our analysis. Figure 2 displays the incremental growth in the quantity of papers throughout the mentioned timeframe. Scopus database was chosen due to its comprehensive coverage across diverse research fields including engineering, in addition to, its essential role as a reliable source of scientific information.

2.3 Bibliometric analysis

It functions as a methodical assessment of scholarly literature, primarily through the examination of citations and references within research papers. The 228 papers that were chosen during the literature screening process are encompassed in this bibliometric analysis which includes 88 review papers, book chapters, and journal articles and 140 conference papers. This bibliometric approach allows researchers to systematically examine the impact, trends, and interconnections among scholarly publications, providing insights into the development of research themes and collaborative networks within the field. By analyzing citation patterns, co-authorship relationships, and keyword frequencies, bibliometric analysis helps to identify influential authors, foundational studies, emerging research areas, and collaborative trends. This method thus offers a comprehensive view of the field's intellectual structure and the evolution of its major themes. In this review, we used co-citation, co-authorship, and co-word maps as key methods to highlight the relationships between studies, authors, and topics. To implement these analyses, VOSviewer was utilized to automatically generate occurrence and co-occurrence matrices, applying similarity measures (e.g., association strength) and post-hoc clustering to group related research areas. This combined approach not only visualizes research clusters but also identifies essential figures and studies, offering a detailed map of how AI is integrated into MEE. These methods were selected to reveal both the breadth of topics covered and the intensity of research collaborations, ensuring a comprehensive and insightful analysis of the literature (Chen H. et al., 2023).

2.4 Content analysis

This phase involves the meticulous review and systematic organization of extensive information, such as scholarly articles, to

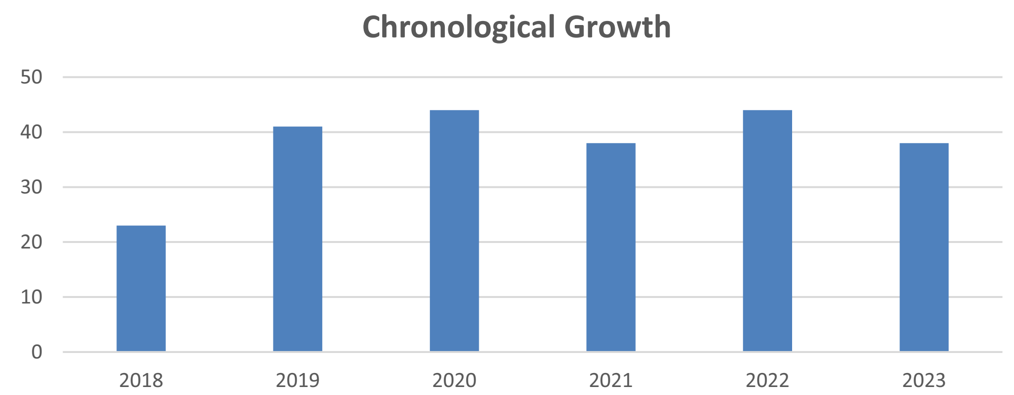

FIGURE 2
The number of papers and publications in relation to AI applications in ME (2018-2023).

discern prevalent themes and patterns. A further selection was carried out prior to the content analysis, retaining the most pertinent studies, with a significant proportion being journal articles (50 out of 88 journal papers and 36 out of 140 conference papers). The papers chosen for content analysis predominantly explored AI integrations within MEE, representing the most relevant works pertinent to the objectives of this review. The methodology entailed the classification and thematic grouping of the research articles, facilitating a deeper understanding of AI's influence on education. This structured approach aids in synthesizing key insights and drawing meaningful conclusions from the amassed data. Our content analysis was conducted through a thematic approach, where we manually reviewed and categorized each selected paper. This process involved identifying recurring themes and subthemes by carefully analyzing the content and focus of each study. This manual approach allowed for a nuanced interpretation, ensuring that the themes accurately represented the insights from the reviewed literature.

The following two sections of this paper present a bibliometric analysis, and a content analysis following the methodological steps described in this section.

3 Bibliometric analysis

In this section, an in-depth bibliometric examination is conducted, focusing on AI within the MEE framework. An improved understanding of the current research and development landscape in AI is pursued by analyzing a wide range of articles and studies, numbering 228 in total, sourced from the Scopus database. Additionally, this analysis is aimed at extracting critical insights, identifying emerging trends, and discerning the broader impacts of AI's integration into MEE through a meticulous review and evaluation of the literature. Through the utilization of the VOS viewer tool, a nuanced understanding of AI's current standing in MEE is offered through four distinct types of visual representations. These visual aids, featuring circles each symbolizing a specific research focus, with their size indicating the intensity of activity within that domain, are provided. Moreover, the spatial proximity between circles is signified as the strength of their interrelations, providing a visual image for the interconnected nature of AI research within MEE.

3.1 Co-occurrence map based on text data

By analyzing the text data from 228 publications selected through literature screening, the most relevant and frequently occurring terms were identified. This analysis, focusing on the titles and abstracts of these publications, aimed to isolate significant terms and establish a network of co-occurrence links among them. Through this process, it was possible to highlight emerging developments and pinpoint the most influential terms in the realm of smart technologies in MEE. From the data processed by VOSVIEWER, a total of 6,534 terms were generated, out of which 104 terms were selected based on a minimum occurrence threshold of 10. Following this, VOSVIEWER calculated the relevance scores for these terms, selecting the top 60% as the most relevant. As a result, 62 terms were illustrated on the map, as shown in Figure 3. According to Eck and Waltman (2018) Terms with high relevance scores were indicative of more specific subjects

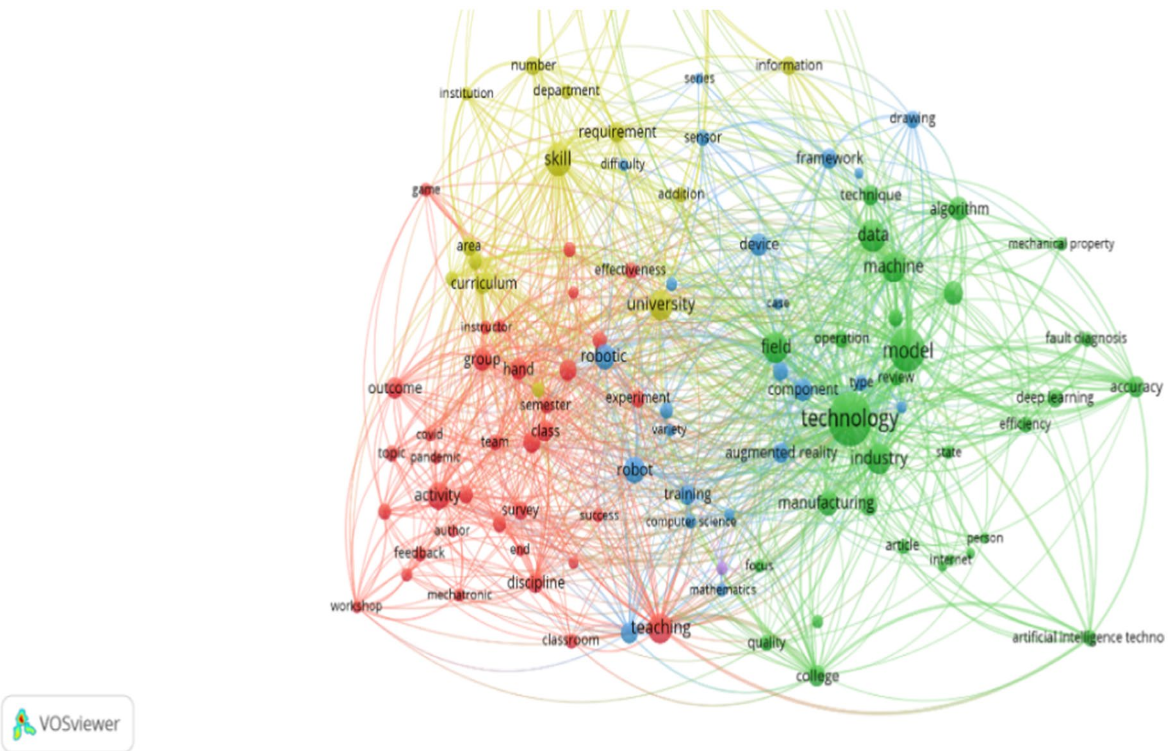

FIGURE 3
Co-occurrence map based on text data.

within the text data, whereas terms with low relevance scores were generally associated with broader concepts. Nonetheless, as demonstrated in Figure 3, the results have revealed a wide variety of research areas within the integration of artificial intelligence in MEE. The interconnected network of key terms indicates that the study of AI within MEE covers a broad spectrum of technological aspects.

As shown in Figure 3, various clusters reveal connections between different themes, the green cluster focus on "technology," which is closely associated with several key terms, including "Artificial Intelligence" "Robot" "Augmented Reality" "Machine Learning" and also extends to the educational field with terms like "educator" "feedback" "teaching." This emphasizes a technological focus within MEE literature, suggesting that AI and related technologies play a vital role in advancing the field. Moreover, the direct link between "technology" and "industry" further implies the necessity for MEE programs to align with industry trends, underscoring the importance of preparing students for the workforce through a technology-integrated curriculum. Furthermore, as illustrated in Figure 4, a detailed view of the connections with "technology" is demonstrated, emphasizing the strong connections that "technology" has with other terms across educational and technical aspects. The red cluster focuses on educational themes, with terms such as "teaching," "active learning," and "feedback" underscoring on the pedagogical approaches within MEE. Terms like "skill" and "curriculum" in the yellow cluster suggest an ongoing emphasis on developing student competencies and designing curricula that reflect both technological advancements and industry needs.

Figures 3, 4 show how research in MEE intersects technology and education, showing a balance between integrating advanced tools, such as AI, AR, and ML, and enhancing teaching methodologies. The clustering terms demonstrates the multidisciplinary nature of MEE, highlighting the potential of AI and related technologies to transform educational approaches and meet industry expectations. These insights offer a comprehensive view of the literature around the topic and emphasize the potential of technological integration in engineering education.

As shown in Table 1, the terms presented along with their rankings, frequency of occurrences, and relevance scores. Accordingly, it is demonstrated that technology occupies the first ranking with "244" occurrences and "0.4" relevance score, followed by model, and data as the top 3 in the table.

As depicted in Figure 5, the keyword "technology" appears as a central node, with numerous connections extending to related terms, indicating its foundational role in discussions on AI applications. Key terms such as "skill" (yellow cluster) and "accuracy" (green cluster) demonstrate strong associations with technology and AI, revealing that these areas are frequently explored in the context of AI-enhanced skill development and precision in engineering education. In addition, the green cluster involves terms like "machine," "model," and "learning," which connects directly to "technology." This suggests a focus on ML models and technological frameworks used for educational purposes in MEE. While, the yellow cluster emphasizes "skill" development, underscoring the educational applications of AI to enhance students' practical and theoretical skills, which are essential in ME fields. Finally, the red and blue clusters represent other themes, such as "robotics" and "curriculum" that are also connected to AI, demonstrating its broader impact across various areas of engineering education.

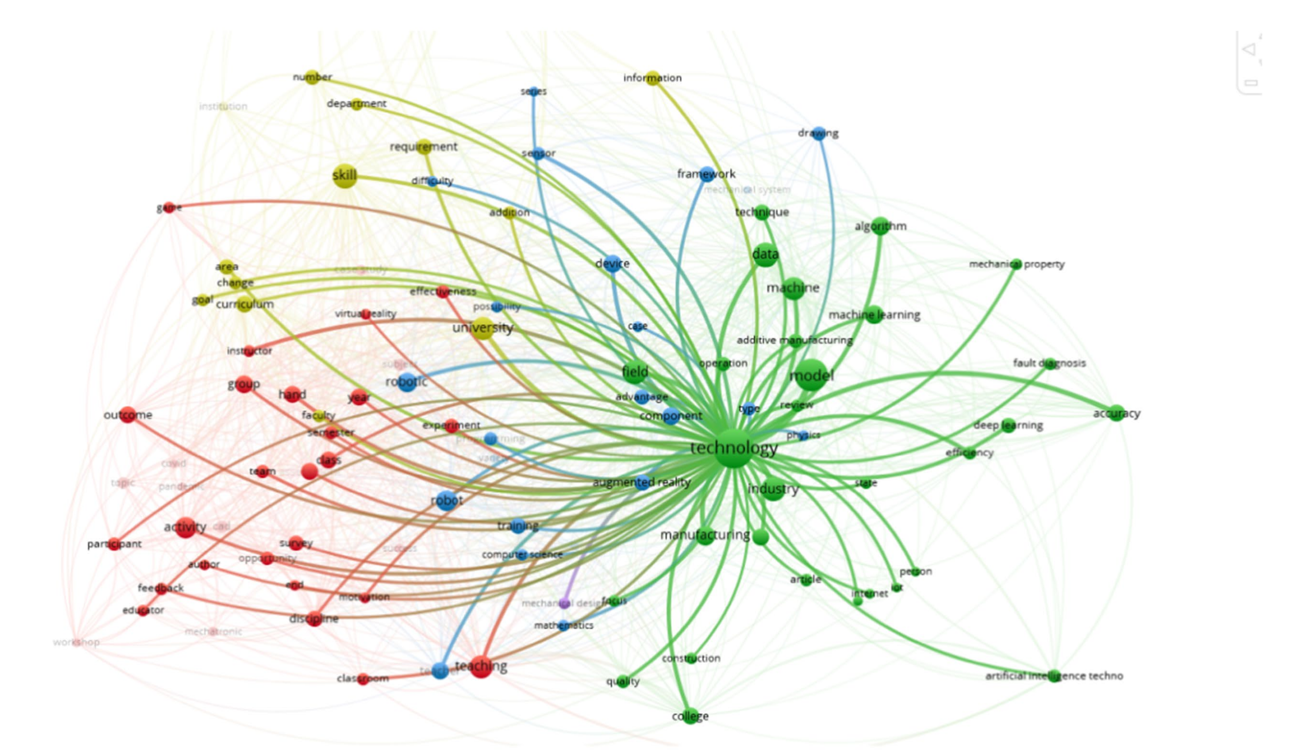

FIGURE 4
Technology links.

TABLE 1 Relevance of score texts.

Rank	Term	Occurrences	Relevance score
1	Technology	244	0.4
2	Model	157	0.59
3	Data	92	0.48
4	Skill	87	0.79
5	Field	83	0.17
6	Industry	82	0.36
7	University	78	0.54
8	Teaching	77	0.8
9	Machine	75	0.7
10	Activity	62	1.13

This visualization highlights the role of AI as a bridge between industry and academia. By linking technology, skill development, and accuracy, AI fosters enhanced learning experiences and prepares students for industry demands. Future investigators and educators can utilize this map to identify well-explores areas, like technology-centered skill enhancement, and to recognize emerging topics that may benefit from further research, such as robotics integration and curriculum innovation. All in all, this figure provides a comprehensive overview of how AI intersects with several educational and industrial themes in MEE, making it a valuable tool for understanding the scope and focus of current research in this field.

3.2 Co-occurrences map based on keywords

By analyzing the bibliographic data from the 228 chosen publications, as illustrated in Figure 6, a total of 2,165 keywords were discovered, from which 50 keywords were selected based on their frequency. A minimum threshold of six occurrences was set for keyword selection. The map displays two categories of keywords: authors' keywords and index keywords. Authors' keywords are those specified by the authors of the publications, while index keywords are created by indexes or databases to organize and categorize articles for the purposes of information retrieval and indexing.

As illustrated in Figure 6 and Table 2, "Engineering education" emerged as the keyword with the highest frequency (174 occurrences) and total link strength (725), indicating a strong connection with other keywords in the field. The total link strength here refers to the overall intensity of connections a keyword has, providing insight into its prominence and centrality within the research landscape. This central position indicates that "Engineering education" is a focal point of studies including AI and MEE, bridging multiple research topics and subfields. Following "Engineering education," "students" and "curricula" are revealed as the second and third most frequent keywords, respectively. This highlights a prominent emphasis on the educational facets of integrating AI into ME, specifically in terms of student engagement and curriculum development. The keyword map in Figure 6 also emphasizes the strong association between "Engineering education" and "artificial intelligence," highlighting the increasing integration of AI in engineering pedagogies. The map also demonstrates connections between "artificial intelligence" and specific mechanical engineering subfields, including "manufacturing processes" "3D printing" "machine design" "robotics," and "failure (mechanical)." These links suggest a keen research interest in the way AI can enhance specific technical areas among ME, potentially leading to innovations in design, process optimization, and predictive maintenance. Both (Figure 6) and (Table 2) highlight the multidisciplinary and transformative potential of AI in reshaping both the engineering curriculum and the technical competencies needed in the field.

The co-occurrence network in Figure 7 underscores the central role of "engineering education" in the research on AI applications, with strong linkages to advanced AI technologies like "machine learning" "deep learning" and "neural networks." This indicates a keen enthusiasm for incorporating these cutting-edge AI methods into engineering curricula. The network also reveals a significant relationship between CAD and "automation," suggesting a focus on automating CAD processes. However, the co-occurrence map in Figure 7 indicates that the integration of more sophisticated deep learning algorithms into CAD is still in its early stages, as the connection between CAD and "deep learning" appears less pronounced compared to the strong ties between other AI techniques and engineering education.

Furthermore, two supplementary keyword maps were produced. The first map, showcasing the author keywords, features keywords frequently used by authors with a minimum of five occurrences, leading to the identification of 17 authors as illustrated in Figure 8. In this figure, the red cluster includes terms such as "engineering education" and "machine learning," indicating a strong focus on AI's role in enhancing educational methodologies. On the other hand, the green cluster connects terms like "robot" and "mechanical design," indicating an interest in robotics and design-oriented applications of AI. Similarly, the index keyword map (Figure 8), also with a five-occurrence minimum, highlighted 74 authors, demonstrating a more detailed and complex network of keywords. In this figure, "engineering education" stands out as a central node, connected to several sub-themes across different colored clusters, including "augmented reality" and "internet of things" in the blue cluster, emphasizing the role of immersive technologies and internet of things in education, and it is connected with curriculum-related terms, such as "computer aided design" and "curricula" in the yellow cluster, underscoring how AI is integrated into course development' furthermore, it is connected to keywords related to advanced AI methods, such as "fault diagnosis" and "deep learning" in the red cluster, reflecting AI's growing applications in predictive maintenance and quality control within MEE. This visual clustering aids in identifying prominent research areas and thematic relationships among keywords used by authors in the field of MEE. Similarly, this analysis of keywords accentuates the emphasis on AI in MEE due to its significant connections with several aspects of ME. By identifying keywords clusters and their thematic associations, these maps provide a comprehensive overview of current research trends, guiding future studies toward areas with enriches academic interests, as well as gaps needing further exploration.

3.3 Co-occurrences map based on country of co-authorship

The analysis concerning the geographic origins of the publications reveals significant patterns in global contributions and collaborations. A map illustrating the collaboration between countries was developed,

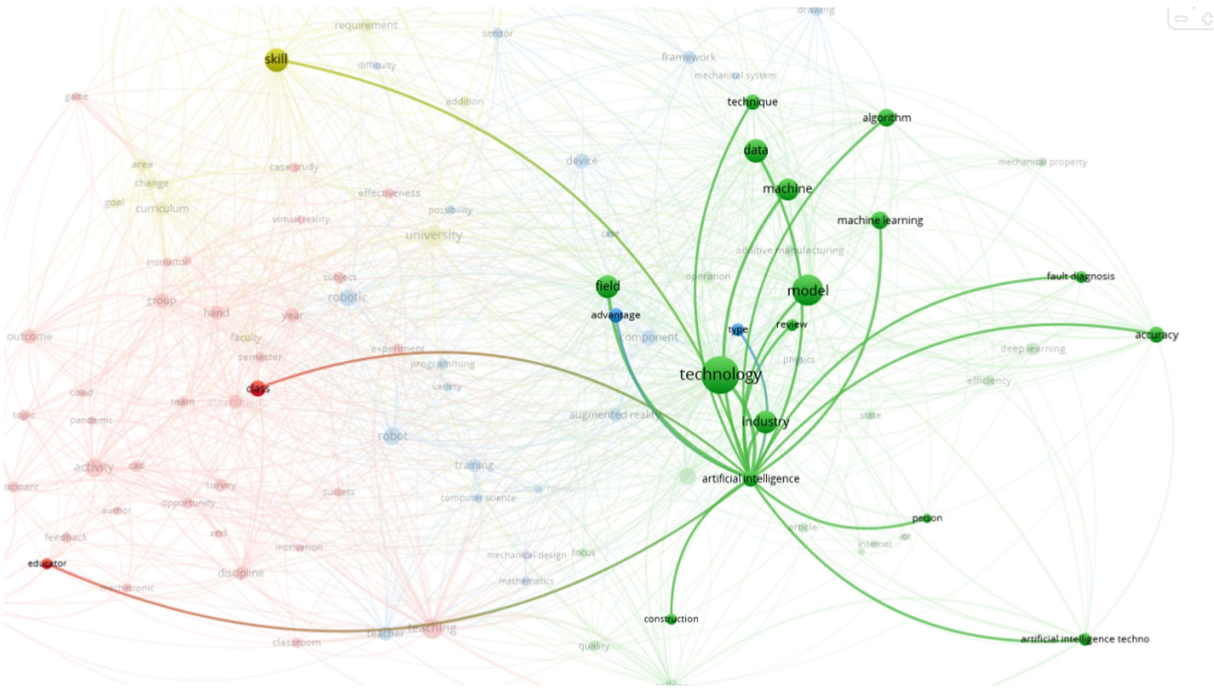

FIGURE 5
Artificial intelligence links.

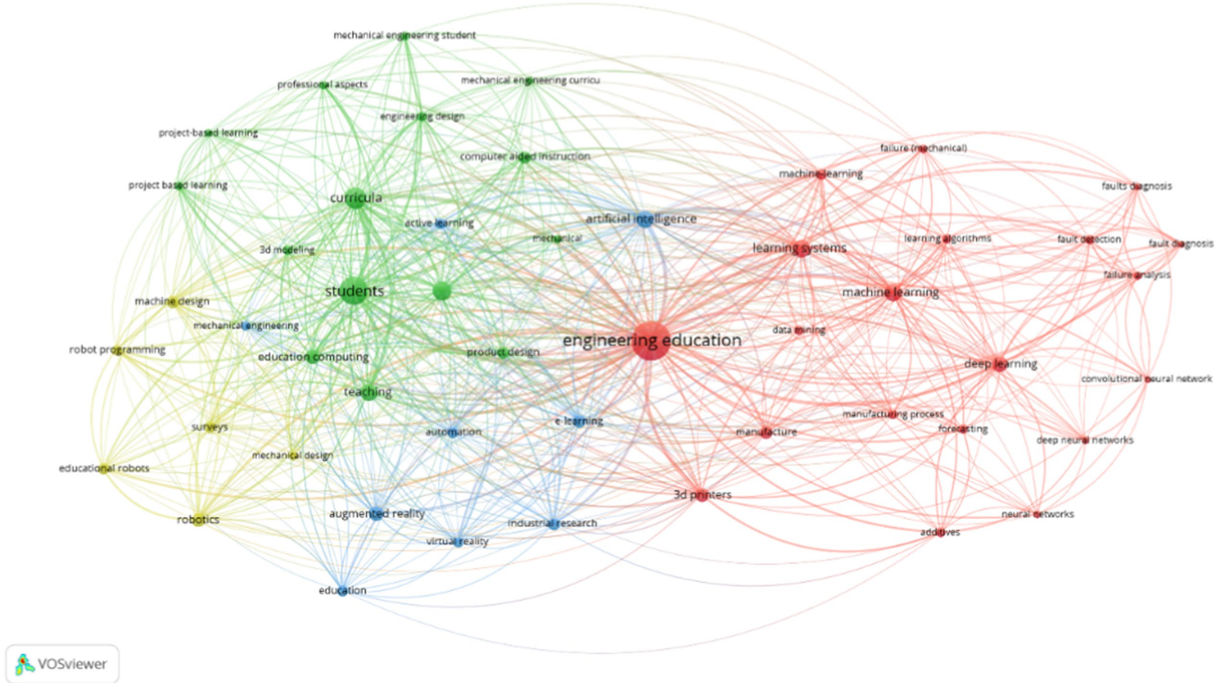

FIGURE 6
Co-occurrence map based on keywords.

applying a criterion where a country needed to have at least two documents to be considered. Hence, out of 51 countries that have published works, only 32 satisfied this condition, as illustrated in Figure 9.

As also shown Figure 9, a strong concentration is observed in some of the world's most developed countries, with the United States leading in publication volume, followed closely by China and the United Kingdom. This suggests the emphasis these countries place on

TABLE 2 Keywords total link strength.

Rank	Keyword	Occurrences	Total link strength
1	Engineering education	174	725
2	Students	90	450
3	Curricula	51	279
4	Computer aided design	40	203
5	Learning systems	34	192
6	Teaching	32	172
7	Machine learning	33	160
8	Artificial Intelligence	33	156
9	Deep learning	27	132
10	Education computing	25	129

research in AI and MEE, likely driven by advanced technological infrastructure, substantial research funding, and a high number of institutions with specialized AI research programs. The green and yellow clusters in the map depict collaborations primarily between the United States, China, and the United Kingdom, suggesting a robust global network where research is frequently shared and co-authored across borders. This collaboration is essential as it enhances the cross-pollination of ideas, standardization of AI methodologies in MEE, and sharing of innovations that address educational challenges internationally. On the other hand, Germany, India, and Australia are placed in smaller nodes which suggests that these countries' emerging contributions and their interactions with leading countries, yet they are presented on the map which indicates a growing interest in integrating AI into engineering education, potentially offering new insights from various educational and industrial contexts. This network analysis focuses on the international effort toward advancing AI applications in MEE, highlighting the importance of global collaboration in fostering innovation. Furthermore, it also points to geographic areas where research might be less active, suggesting potential opportunities for expanding AI applications in MEE in underrepresented regions.

The top-ranking countries, distinguished by their total link strength are presented in Table 3. This table highlights the most active nations in AI research within MEE, emphasizing both the volume of contributions and the extent of their international collaborations. As shown in the table, a broad geographic distribution of interest, with representation across four continents, including North America, Asia, Europe, and Australia. This widespread engagement reflects the global significance of AI integration into MEE. The table summarizes the countries in a descending order, showing the countries with highest total link strength to the least.

3.4 Co-occurrences map based on country of co-citation

A co-citation link is identified when two entities are both cited by the same document (Eck and Waltman, 2018). Numerous studies have explored the incorporation of AI into MEE, leading to the performance of co-citation analysis to highlight the most significant contributions by authors, as well as the interdisciplinary connections among them, especially regarding their focus on AI integration into MEE. The clusters are color-coded, grouping authors whose work is frequently co-cited, which suggests shared research interests or thematic overlap. For instance, the green cluster might represent the authors focusing on AI applications in the ME education to align with industry needs, while the red cluster could include the researchers who focus on enhancing the pedagogical methods and modernizing course materials through AI. These groupings reveal interdisciplinary connections and areas of focus within the field. A threshold was set, requiring a minimum of six citations for an author to be included, with the selection process capped at 100 authors to ensure the network reflects only the most significant contributions. Figure 10 illustrates the frequency with which authors are cited together within the field, while (Table 4) details the authors who possess the highest total link strength. Overall, this co-citation analysis helps map the intellectual structure of AI research in MEE, showing which authors and ideas are most interconnected and influential. It highlights the collaborative nature of the field and points to core contributors driving interdisciplinary advancements in AI-focused educational research.

3.5 Data analysis on article sources

From the 228 publications analyzed, the sources were ranked from highest to lowest based on their numbers. As a result, the top 10 sources, as displayed in Figure 11, were identified as those with the highest number of classified papers. According to Figure 12, the leading sources by publication count include the "ASEE Annual Conference and Exposition," "Journal of Physics," "Lecture Notes in Mechanical Engineering," and "Advances in Intelligent Systems and Computing," which accounted for 31, 9, and 6 publications, respectively.

The examination of the sources reveals a compelling overview of the cross-disciplinary interest with AI applications in MEE. Likewise, the wide array of studies drawn from various fields, including Physics, Mechanical Engineering, and Computer Science, underscores the importance of incorporating AI into MEE. This diversity highlights the necessity for further development and improvement of research in this area.

3.6 Data analysis on document themes

The variety of document types presented indicates a substantial interest in AI within ME. These documents cover a range of themes and subthemes identified in the content analysis, such as robotics, additive manufacturing, CAD, AI, and more. Additionally, the papers span various interdisciplinary fields within mechanical engineering, including robotics, mechatronics, and simulations. Moreover, numerous documents highlight the significance of introducing new curricula, considering ethical aspects, bridging the gap between industry and academia, and integrating AI into ME industrial systems, as detailed in the content analysis.

Figure 12 presents the themes identified in the analyzed papers, encompassing intelligent systems like VR/AR, AI, and robotics within the MEE sector. It also highlights the necessity for an updated curriculum that integrates these technologies, the application of AI in the mechanical engineering industry, and the effort to close the gap between industrial practices and academic research.

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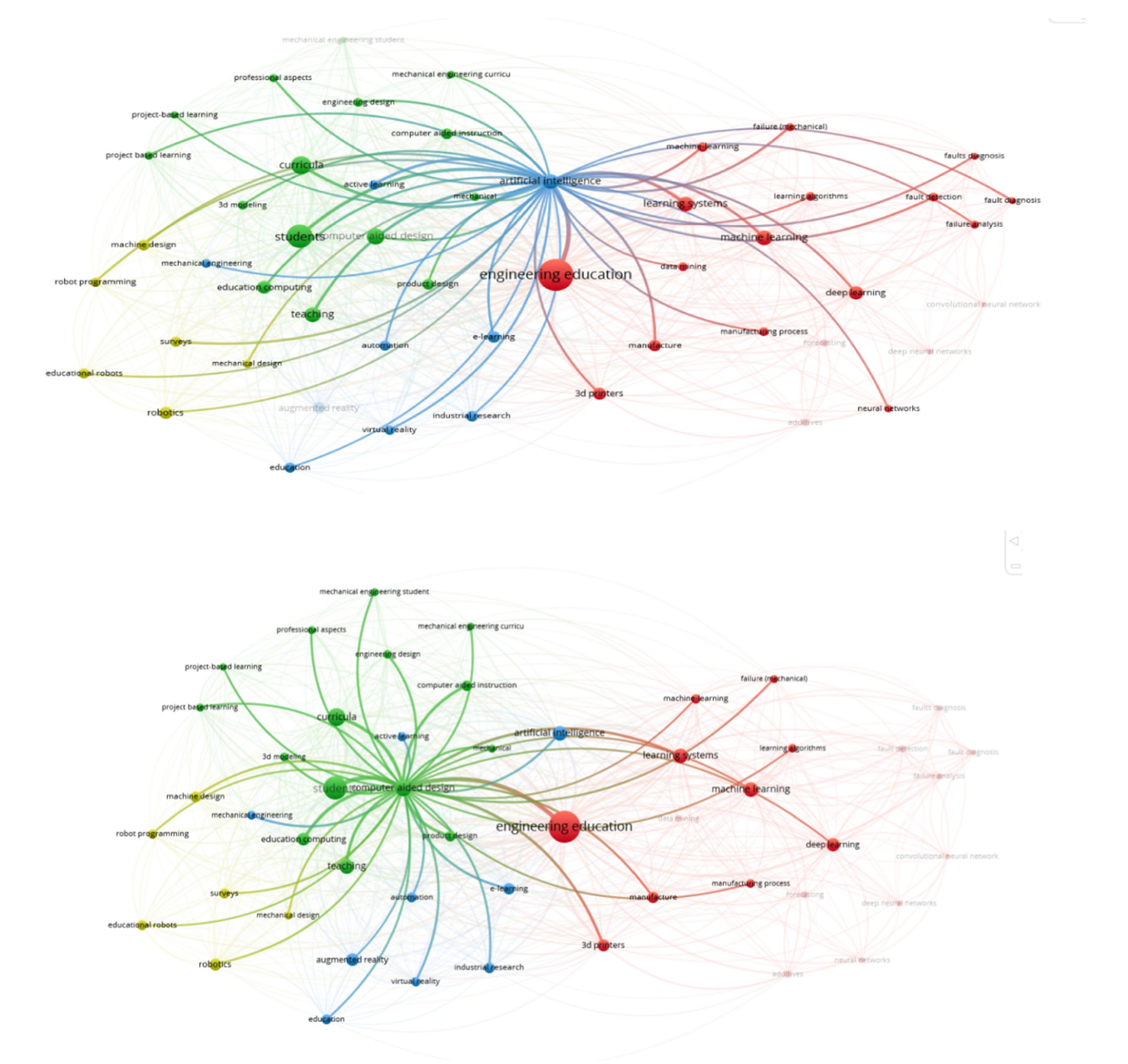

FIGURE 7
Network visualization of engineering education keywords: exploring connections between computer-aided design and artificial intelligence.

The bibliometric analysis reveals a strong emphasis in the literature on integrating AI technologies into MEE. Analysis of keyword linkages underscores essential connections between education, technology, and skills, highlighting the interdependence of these areas and their critical role in advancing MEE. Additionally, the global distribution of research contributions demonstrates widespread interest, underscoring the importance of expanding research in this field to achieve a more comprehensive understanding of AI's impact on engineering education. Key findings from this analysis point to emerging themes and research clusters that focus on personalized learning, intelligent tutoring systems, and simulation-based learning, which reflect the evolving landscape of MEE. These observations inform the subsequent content analysis, which will delve into the primary themes and insights identified across the literature, offering a nuanced view of current trends and potential areas for future research.

4 Content analysis

The primary focus of our exploration is the integration of AI in MEE. In this content review, our emphasis will be on identifying how AI is utilized in MEE, offering a comprehensive overview of scientific publications interested in this field. The key findings of these articles and their future directions that could aid future researchers in delving into this field will be shown. Additionally, this will help in identifying what has been done and what gaps have been found in the exploration of AI in MEE. Furthermore, the advantages provided to the

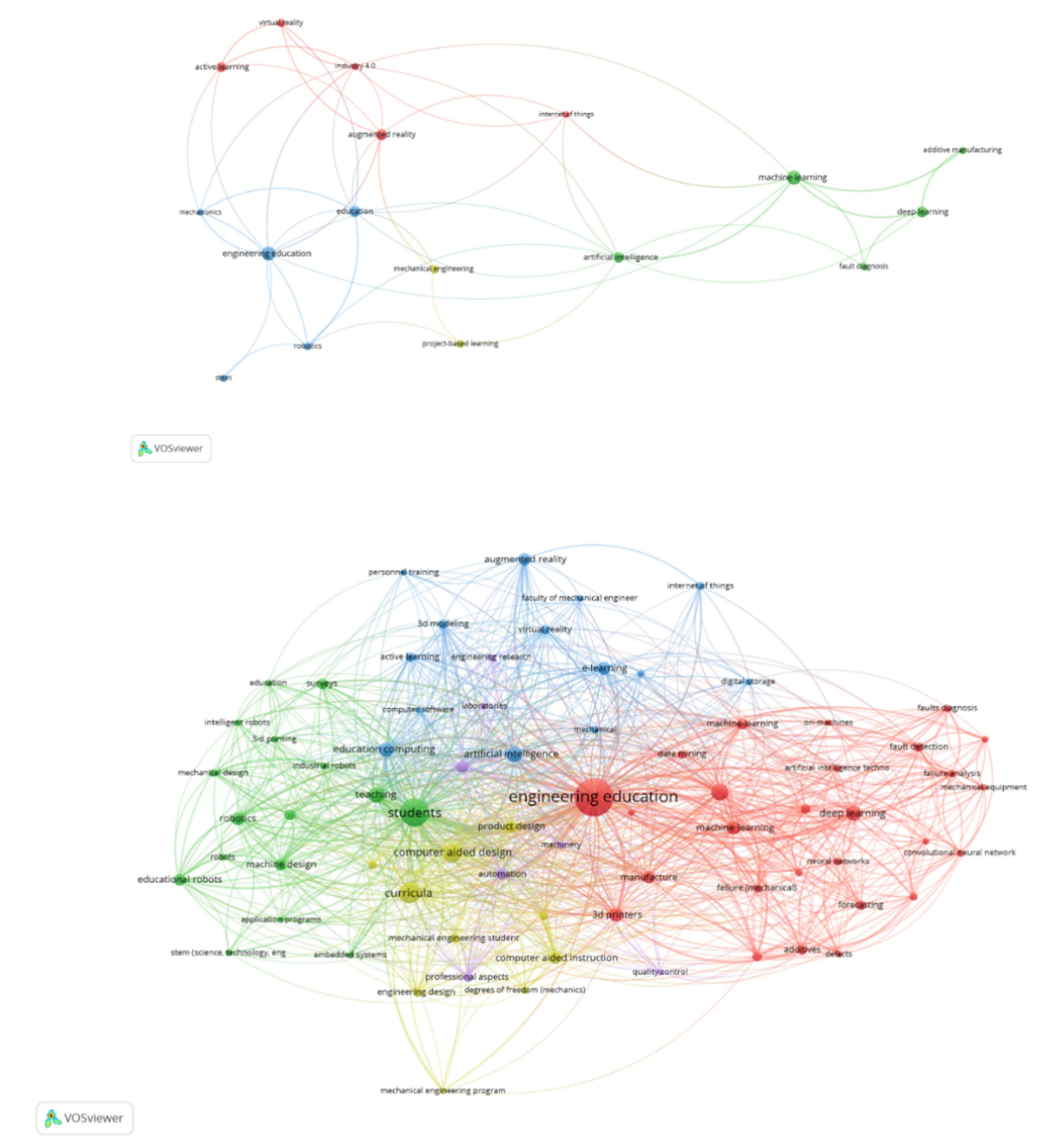

FIGURE 8
Keyword mapping in engineering education: author keywords and index keyword interconnections.

educational experience will be listed. Additionally, various aspects in the field of incorporating AI in MEE will be discussed by this section.

The publications are organized by topic for clarity and relevance. Papers on artificial intelligence in MEE are grouped together, as are studies on virtual/augmented reality, robotics, CAD, and additive manufacturing. This separation helps clarify the contributions and future directions of each technology. Similarly, discussions on the need for a new curriculum, the integration of industry practices into education, and the use of AI in the mechanical engineering industry are each categorized separately. This highlights the importance of incorporating new technologies in MEE. Additionally, breaking down these main topics into subthemes simplifies the explanation and enhances understanding of each specific aspect. The themes and subthemes in this review were categorized through a structured, multi-step process designed to ensure objectivity and relevance. First, the relevant literature was downloaded from the Scopus database and organized in an Excel file for systematic review. Next, each paper was carefully studied to assess its relevance to the scope of our review, and only those papers closely aligned with the study's objectives were retained for analysis. Following this, an

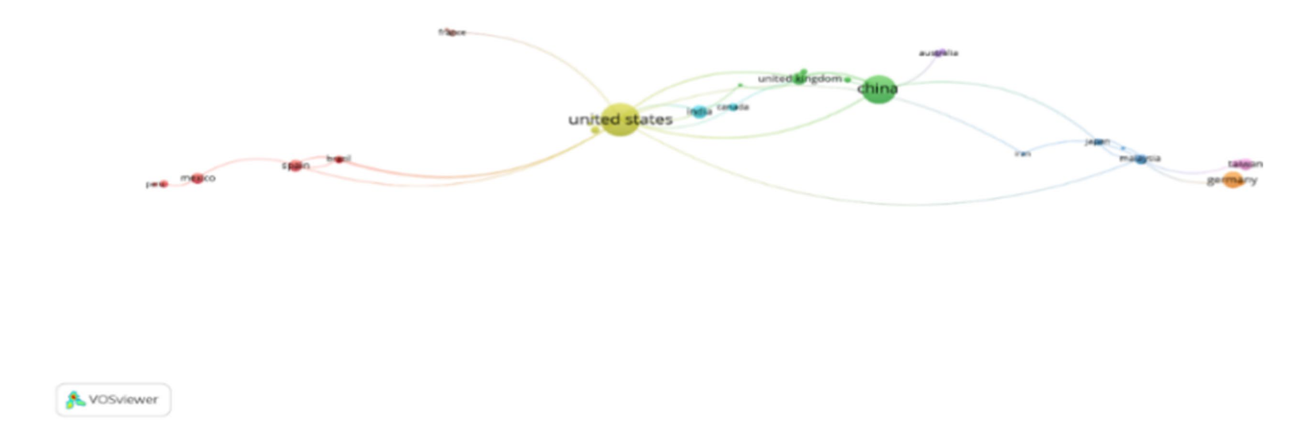

FIGURE 9
Co-occurrence map based on country of co-authorship.

TABLE 3 Country ranking table.

Rank	Country	Documents	Citations	Total link strength
1	United States	65	503	17
2	China	48	183	8
3	United Kingdom	9	155	8
4	Malaysia	6	10	6
5	Spain	8	71	4
6	Canada	4	18	3
7	India	10	10	3
8	Japan	3	0	3
9	Ukraine	3	11	3
10	Australia	2	4	2

initial scan of the selected papers was conducted to observe recurring patterns, allowing us to identify major and minor themes. To enhance the consistency and rationality of these classifications, we established clear criteria: themes had to appear in at least four different studies to be considered recurring, and subthemes were identified when specific applications or perspectives were frequently associated with a major theme. This process ensured that the themes reflected both the frequency and significance of topics within the literature, rather than subjective interpretation. The remainder of this section discusses the content analysis, providing insights into these themes and their implications for the integration of AI in MEE.

4.1 AI applications in MEE

AI applications are diverse, and integrating this technology offers substantial benefits to students, educators, and institutions in achieving their educational objectives. The incorporation of AI can significantly enhance students' comprehension of information and assist educators in tailoring assignments to align with individual students' knowledge levels. Furthermore, AI serves as an efficient tool for conducting assessments. Consequently, this section will highlight scientific publications that have explored the integration of AI into MEE, showcasing its multifaceted advantages in the educational landscape (Table 5).

The above table reveals a range of findings from literature that relate to the integration of AI in MEE. The cited papers show that AI can facilitate learning, promote personalized learning, and advocate for student centered learning through the integration of chatbots in mathematical concepts, smart tutoring systems with feedback provider by utilizing deep learning (DL) and reinforcement learning algorithms. As such, this has a positive impact on the creativity and efficiency of educational experience, as well as enhanced students' motivation, engagement, and industry preparedness. AI plays a transformative role in personalized learning by creating adaptive learning paths that guide students through step-by-step solutions tailored to their unique needs. Data is collected through various channels, including student interactions with course materials, performance metrics, and behavioral data during learning activities. This rich data is then analyzed using machine learning and deep learning algorithms, which identify patterns and adjust content delivery to match individual learning styles and pace. Key algorithms facilitate this personalization: supervised learning algorithms, like linear regression and decision trees, analyze student progress to suggest appropriate learning steps; reinforcement learning algorithms, such as Q-learning and Deep Q-Networks, adaptively refine these paths based on real-time feedback; clustering techniques, like K-means and hierarchical clustering, group students by learning style or performance to provide similar guidance; and collaborative filtering, such as matrix factorization, offers recommendations based on peer learning behaviors. Natural Language Processing (NLP) algorithms, including word embedding and sentiment analysis, enhance personalized interactions by understanding and responding to student language. Finally, neural networks, such as feedforward and recurrent networks, continuously learn from new data to provide increasingly effective and personalized learning experiences. Literature also reveals that some of the studies have delved into the integration of auto-assessment tools in MEE. Accordingly, some have discussed the usage of AI and others have stated the potential of integrating AI within assessment tools to provide better accuracy. Lastly, the publications have discussed the utilization of ML

FIGURE 10
Co-citation map.

TABLE 4 Authors of co-citation table.

Rank	Author	Citations	Total link strength
1	Wang Z.	36	5,041
2	Lee C.	24	4,557
3	Zhu J.	27	4,166
4	Zhang Y.	38	3,890
5	Li X.	41	3,426
6	Wang H.	27	3,415
7	Wang J.	40	2,593
8	Shi Q.	11	2,136
9	Zhang Z.	46	2,136

algorithms for the classification of group projects or task allocation, based on student's expertise within the course of their study which can be often challenging with human bias and complexity. Therefore, AI has shown promising results in theme allocation for tasks and group projects resulting in enhanced learning outcomes.

Further research is therefore imperative to identify best practices in personalized learning, to consider aspects such as ethics, gamification for active engagement, and NLP to facilitate human-robot interaction, to make sure that the field of MEE continually aligns with technological advancements and student's. There is also potential for further research to examine the integration of AI in the field of development of auto-assessment tools since there are insufficient number of studies that have investigated this field. Similarly, the investigation of using AI in assessment tools for better accuracy can be conducted. AI shows promise not only enhancing assessment accuracy but also identifying student retention rates. However, future research should consider ethical implications, AI-assisted peer assessment, NLP for written assessments, simulations for hands-on assessments, and the creation of intelligent grading and feedback systems. Moreover, it is crucial to explore the use of AI in theme allotment and task assignment across all ME courses, considering students' experience and skills. There is also a pressing need to develop AI techniques, encompassing ML, DL, and reinforcement learning algorithms, that can process larger datasets more effectively, yield more accurate predictions, and precisely gauge student performance.

4.2 VR/AR in MEE

Virtual Reality (VR) and Augmented Reality (AR) are transforming multiple sectors, including MEE, by providing immersive and interactive experiences. VR offers lifelike simulations that enable hands-on learning, foster collaboration, improve spatial skills, and facilitate the visualization of complex data. Concurrently,

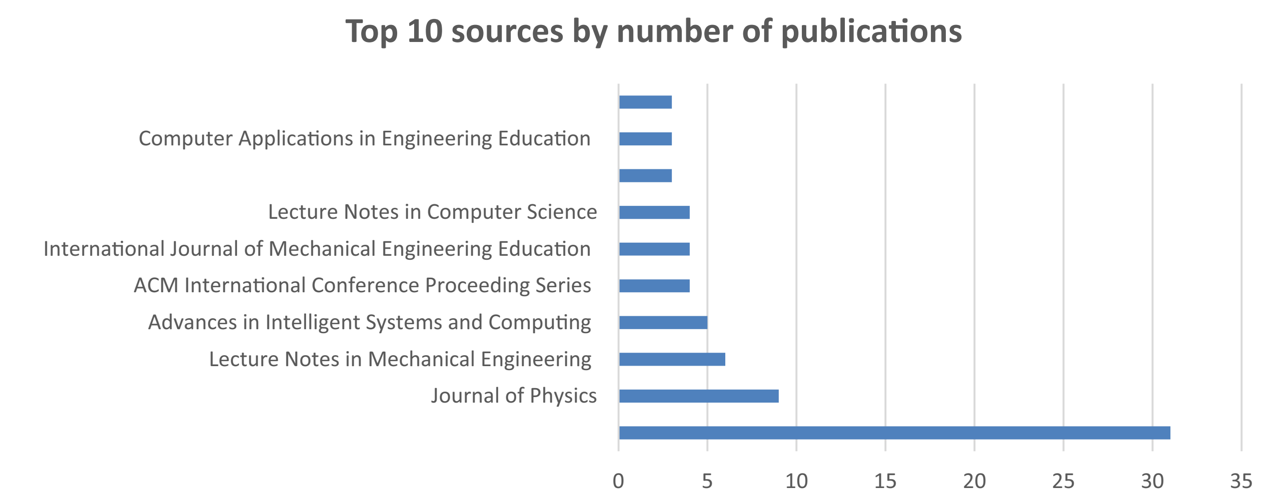

FIGURE 11
Bar graph of the top 10 sources by number of publications.

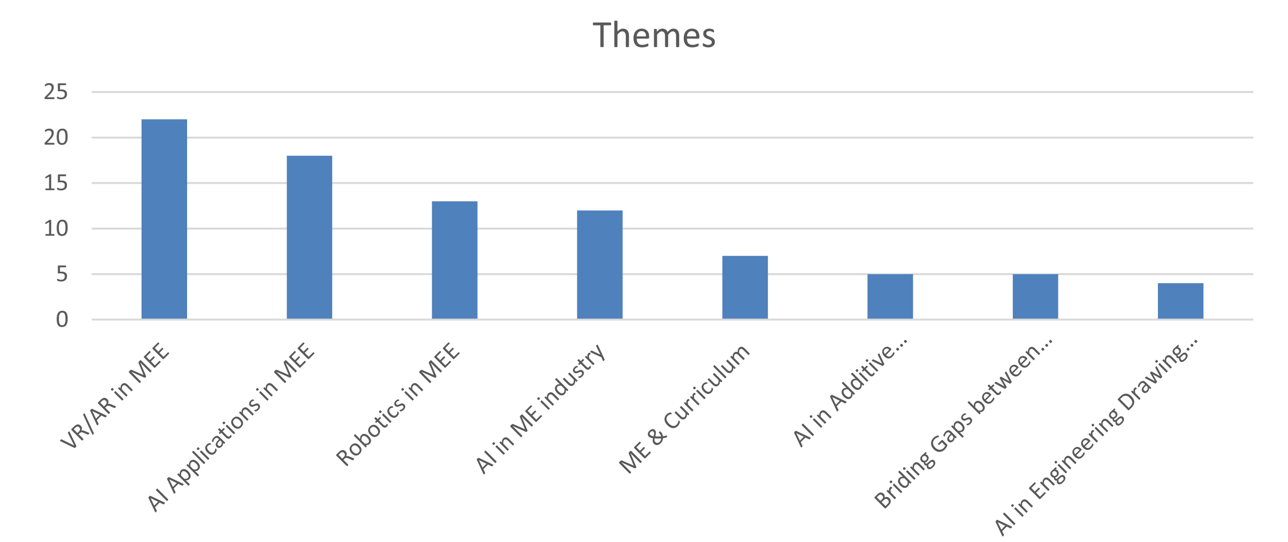

FIGURE 12
Occurrences of themes.

AR enhances real-world environments by overlaying digital information, offering features like remote assistance, and enriching traditional laboratory settings. These technologies significantly aid in the comprehension of ME concepts by creating dynamic, interactive learning environments. This section will delve into various publications that have explored the integration of VR and AR into MEE education, highlighting their impactful contributions to the field (Table 6).

The research papers in this section focus on the integration of VR/AR technologies in MEE. The papers show the integration of VR/AR technologies in MEE can simplify to students the visualization of complex engineering drawings and enhances their spatial abilities; also, these technologies can accommodate for higher number of students and provide them a safer environment which can be hazardous in real life. Thus, this resulted in positive impacts on students' academic journey as it boosted their motivation, understanding, and memory retention in the content of their study. Furthermore, these technologies have developed numerous advantages, including enhanced problem-solving, critical thinking, sustained attention, and reduced cognitive load on learners. Some of the studies have investigated the utilization of VR/AR technologies to encompass all ME laboratories which creates a safer environment to students; moreover, these technologies have been examined for assembly and disassembly of automotive components creating an interactive learning experience. Consequently, this offers students a hands-on experience and reveals a bigger opportunity for industry preparedness. A study has examined the integration of gamification within these technologies to increase engagement and joyfulness. Another study has investigated the integration of AI in VR technology using deep reinforcement learning algorithms to create interactive and intelligent simulations. It can aid learners by controlling objects, providing real-time feedback, and adapting to students' actions,

TABLE 5 AI in MEE.

Theme	Author	Focus
Artificial Intelligence in MEE in assessment context	Kahangamage and Leung (2019)	Focusing on the remodeling of engineering design subjects to enhance students' learning outcomes and educational approaches.
	Shyr et al. (2019)	Developing assessment indicators to gauge the learning effects in students resulting from AI-based robot design within engineering education, with a particular emphasis on evaluating AI's influence on learning outcomes.
	Kuzilek et al. (2021)	Utilizing an artificial intelligence algorithm to predict student success based on their exam behavior.
Assessment tools in CAD	Pando Cerra et al. (2023)	Exploring the benefits of integrating TrainCAD, an innovative self-assessment tool, into CAD learning methodologies and examining its impact on academic performance.
	Jaakma and Kiviluoma (2019)	Introducing two novel online auto-assessment tools designed to aid the development of both commands and strategic knowledge in CAD learning.
AI in classification and categorizing in MEE	Rodríguez-Martín et al. (2019)	Discussing the incorporation of short CFD simulation activities in fluid-mechanical learning, highlighting the use of machine learning in educational practices among a multidisciplinary student body.
	Belapurkar et al. (2019)	Implementing automated theme allotment to enhance learning outcomes, particularly in robotic competitions.
AI aids in Assisting students & Facilitate learning	Huang et al. (2023)	Exploring the intersection of Artificial Intelligence and design, delving into its history, present implications, and the challenges designers encounter when integrating AI into their work.
	Auerbach et al. (2019)	Investigating the use of robotics, specifically RoboGen, in inquiry-based learning, underscoring its role in enriching educational experiences and exploration in the realms of robotics and AI.
	Cai et al. (2021)	Introducing a chatbot designed to explain mathematical concepts, thereby facilitating personalized learning.
	Chen D. et al. (2023)	Incorporating precision machinery, AI, and learning materials into precision measurement courses.
	Clark and Clark (2018)	Developing a personalized learning tool specifically for thermodynamics.
	Bi (2020)	Natural Language Processing that translates STEM (Science, Technology, Engineering, and Mathematics) principles into English texts
	Hsieh and Li (2018)	Creating a system to assist students in learning G-code and mastering the necessary hardware-related concepts for Computer Numerical Control (CNC) programming.
	Liu et al. (2021b)	Focusing on the application of artificial intelligence, including BP neural network methods and hill climbing algorithms, in teaching and training for mechanical education courses at universities.
	Liu et al. (2021a)	Exploring the integration of Artificial Intelligence into the teaching of machinery manufacturing courses.
	Tsai et al. (2018)	Developing an Artificial Intelligence mechanical laboratory to facilitate advanced learning.
	Lin et al. (2020)	

improving their understanding of complex CAD designs. Nonetheless, the data is retrieved from 3D models and learner interaction with the environment. Hence, AI learns by conducting trial and error, improving the decision making by continuously interacting with the virtual environment by maximizing rewards for correct actions and minimizing penalties for errors.

Further research is imperative to investigate the use of sophisticated AI algorithms, including ML and DL, to facilitate the creation of personalized content, interactive simulations, and the provision of timely feedback all of which contribute to enhanced learning outcomes and a more enriching educational environment. However, the implementation of VR and AR is not without challenges. These include the necessity for faculty training to adeptly handle these technologies, the need for continuous updates and maintenance, ensuring accessibility to technology and internet connectivity, and addressing pertinent privacy and security concerns. Furthermore, there is a need for more comprehensive studies on student motivation and the inclusion of larger sample sizes to validate the impact of these technologies. The employed technologies must align with course delivery objectives, seamlessly integrate AI for customized learning experiences, and incorporate gamification elements to boost engagement and motivation. Additionally, leveraging NLP for personalized simulated environments can further tailor the learning experience to match the students' pace and course requirements. Hence, a deeper exploration into VR and AR technologies is warranted to fully harness their potential in achieving optimal learning outcomes.

4.3 Robotics in MEE

Robotics plays a significant role in reshaping the landscape of MEE. As a multidisciplinary field of engineering, electronics, and computer science, robotics introduces students to the practical applications of theoretical concepts. In MEE, robots serve as powerful tools for hands-on learning, enabling students to delve into control systems, mechatronics, and automation. The integration of robotics and robotics platforms in education not only fosters technical expertise but also cultivates creativity and innovation, preparing students for the evolving challenges in the field of ME. This section

TABLE 6 VR/AR in MEE.

Themes	Author	Focus
Using virtual reality and Augmented reality technologies for 3D and CAD designs.	Rossoni et al. (2024)	Exploring the adoption of VR in education to promote active learning experiences, with a focus on its potential to enrich educational methodologies.
	Coronado et al. (2022)	Investigating the portrayal of machines and mechanisms through AR for educational use, concentrating on its implementation and impact within engineering education.
	Kesler et al. (2020)	Employing VR technology in the instruction of CNC procedures to enhance the learning process.
	Yengui (2022)	Utilizing AR technologies to educate students about machine elements, providing a more interactive learning experience.
	Polhmann et al. (2020)	Leveraging AR to facilitate the visualization of engineering drawings by allowing students to scan QR codes and obtain 3D designs.
	Lin et al. (2020)	Merging Artificial Intelligence with virtual reality using Unity3D to enhance the educational experience in robotic systems.
Assembly and disassembly of components using VR and AR	Win et al. (2022)	Exploring the effectiveness of training methods that use both VR and AR in teaching automobile engine assembly in the context of MEE.
	Hernandez-Chavez et al. (2021)	Presenting the development of a VR Automotive Lab for Training, which uses VR technology to improve the educational experience of ME students.
	Wang and Ahmad (2020)	Exploring the potential of serious games in enhancing ME students' practical skills and working knowledge.
Teaching Assistant systems and Real-world scenarios using AR and VR	Qu et al. (2022)	Designing and implementing a teaching assistant system, specifically for mechanical courses, that employs mobile AR technology to elevate the educational experience.
	Caridade (2023)	Assessing the impact of project-based learning through AR in higher mathematics courses.
AR and VR in students' engagement and spatial skills.	Boboc et al. (2021)	Exploring how AR can boost student engagement and learning outcomes in comprehending the science of mechanisms within educational environments.
	Klaric et al. (2022)	Utilizing virtual tools in teaching dynamics to foster better student understanding and engagement in the subject.
	Awuor et al. (2022)	Enhancing students' spatial abilities in the context of engineering drawing using virtual tools.
	Probst et al. (2019)	Exploring the potential benefits and challenges associated with the integration of AR and Internet of Things (IoT) technologies in engineering education, with a focus on ME.
	Scaravetti and Francois (2021)	Investigating the potential of AR to enrich learning experiences and foster autonomy in the field.
VR and AR as laboratories in MEE	Lima et al. (2022)	Utilizing simulation environments in educational robotics to understand their benefits, features, and potential applications.
	Barroquillo et al. (2021)	Developing an interactive 360° walkthrough of MME shops and laboratories for specific engineering courses.
	Cordero-Guridi et al. (2022)	Employing virtual and digital technologies to amplify the learning experience of engineering students.
	Grodotzki et al. (2018)	Aiming to bolster MEE education using virtual labs.
	Mogylenko et al. (2020)	Enhancing students' laboratory experiences by employing AR to provide detailed education about the uniaxial tensile test.
	Okuno et al. (2020)	Implementing a virtual laboratory in a robotics course to enhance the educational process.
Use of mobile learning application designed to improve the quality of the teaching	Pop et al. (2019)	Evaluating the effectiveness of a mobile-learning application, ISO Checker, in teaching tolerances and dimensional control within engineering education.

will present publications that have discussed the usage of robotics in the MEE (Table 7).

The papers in this section highlight the widespread use of robotics in education to enhance the learning experience, particularly in MEE. Robotics, mechatronics, and AI integration are employed to stimulate students' interest in ME courses. Robotic educational platforms offer an inclusive educative system with tasks and tutorials in ME courses, and perform several tasks in 3D design, programming, controlling, operating, and planning. Similarly, they can simplify the concepts and enhance the learning experience, as they can provide instructional aid which enhances the learning experience and increases students' motivation. The usage of robotic kits can be an attractive opportunity to provide students with the hands-on experience which has been revealed to increase the engagement of students and develop better learning outcomes. Publications have shown that the integration of AI within these robotic platforms can

TABLE 7 Robotics in MEE.

Themes	Author	Focus
Using of robotics platform for educational purposes in MEE	Hsia et al. (2020)	Assisting students in learning programming through robot use, with potential for broader implementation in STEM subjects.
	Garces et al. (2021)	Aiding students in MEE through robotic platforms.
	Ali et al. (2018)	Implementing Robot for classroom teaching in MEE.
	Sawatzki and Muraleedharam (2021)	Exploring the benefits of cost-effective educational robotics kits in engineering education to enhance learning experiences.
	Wei and Berry (2018)	Designing and implementing modular educational robotics platforms suitable for multidisciplinary education.
Building and operating robots	Boya-Lara et al. (2022)	Enhancing STEM learning using robots.
	Bula et al. (2018)	Constructing robots from mechatronics scrap.
	Jovanovic et al. (2019)	Exposing students to the vast possibilities of STEM careers through hands-on activities with drones and robots.
Mechatronics systems in MEE	Tudic et al. (2022)	Assisting engineering students with the BPS platform for educational purposes in STEM technologies.
	Bello-Robles et al. (2021)	Implementing nonlinear control strategies for the Pendubot System.
	Zhang et al. (2023)	Presenting a platform of wireless sensor and control network (WSCN) for use in senior-level robotics courses for ME Technology Students.
	Ayub et al. (2023)	Incorporating robotic kits in problem-based learning (PBL) of the mechatronic module.
Use of robotics in MEE	Sheng and Wang (2023)	Illustrating the integration of robots in various tasks to transform manual processes into automated ones through an editorial.

add flexibility that accommodates different interests and skillsets in multidisciplinary courses. Other publications have emphasized that the integration of AI can facilitate the simulating process of mechatronics systems and simplify them to students.

The research has focused on specific fields and courses, indicating a need to expand the exploration of robotics education and problem-based learning across various educational settings. Additionally, further studies are necessary to enhance the capabilities and applications of robots, potentially through the use of AI. Integrating robotics with environmental and sustainability initiatives could also promote the use of recycled materials and energy-efficient designs in robotics projects. Finally, employing NLP could improve human-robot interactions, enabling more personalized learning experiences and facilitating interdisciplinary integration.

4.4 Mechanical engineering and curriculum

The dynamic nature of the world, and ongoing technological advancements in industries, necessitates the restructuring of the traditional MEE curriculum. This reshaping ensures that students are equipped with the latest skills, preparing them to face the ever-evolving challenges of modern engineering. In this section, we investigate scientific publications that emphasize the imperative need for reshaping the MEE curriculum (Table 8).

The papers in this section reveal the importance of integrating technologies in educational settings as they can greatly facilitate the learning process. Also, the publications discuss the evolution of delivery methods is essential to keep in pace with technological advancements, including the incorporation of advanced technological tools that can accommodate for both virtual and real worlds. The studies demonstrate frameworks of technologies for educative use to compromise for the rapid shift of educational delivery methods, underscoring the essential nature of adaptability in modern education. In particular, the incorporation of some technologies like Generative Artificial Intelligence (GAI) into MEE must be carefully managed to align with these evolving educational standards. The integration of technologies in the MEE curricula should adhere to the principles set forth by the Engineering Education Accreditation (EEA), with a focus on developing engineering professionals who are not only technically proficient but also globally conscious and capable of adapting to continuous economic and societal shifts. Also, with the utilization of advanced technologies like GAI, a cautious approach is paramount due to their potential for misuse. It is critical to implement strategies that counteract academic misconduct effectively. These strategies should encompass comprehensive education for students on the responsible use of technologies like NLP models, the establishment of clear and concise academic policies regarding technology use, and the integration of these tools in a manner that enhances critical thinking skills. Additionally, employing advanced plagiarism detection software capable of identifying content generated by AI is crucial. Equally important is the promotion of a collaborative learning environment and group work, which together play a vital role in upholding academic integrity while fully leveraging the advantages GAI offers in the academic sphere.

The integration of AI in MEE significantly enhances learning experiences, making education more accessible and interactive through technologies like computer-aided translation and NLP. This shift demands changes in teaching methods, with a focus on adaptability and the integration of digital tools. The careful incorporation of GAI is key, emphasizing the development of globally aware, adaptable engineering professionals. Addressing the potential for AI misuse is crucial, requiring strategies for responsible technology use, promoting critical thinking, and fostering a collaborative learning environment. This approach ensures the effective and ethical use of AI in enhancing MEE.

TABLE 8 Mechanical engineering and curriculum.

Themes	Author	Focus
Implication for academic integrity using GAI	Lesage et al. (2024)	Exploring NLP in MEE while emphasizing the implications of using AI for academic integrity within educational contexts.
Teaching methods and developing the curriculum	Ao et al. (2021)	Discussing the reform and exploration of the training model for cultivating professional talents majoring in ME and highlighting the importance of Accreditation as a quality assurance mechanism.
	Bencheva and Kostadinov (2023)	Discussing different learning styles and delivery methods in Engineering education.
	Mamedova et al. (2023)	Aiming to develop a curriculum that can increase the level of success of engineering students in the new format of studying.
	Dagman and Warmefjord (2022)	Emphasizing the importance of redesigning future CAD learning.
	Vogel-Heuser et al. (2022)	Highlighting the importance of emotional and subjective assessments in the learning process and suggesting the use of AI to enhance these topics.
Promoting Technologies in MEE	Sha et al. (2022)	Investigating the promotion of data science in ME research.

4.5 AI applications in engineering drawings and simulations

The field of ME heavily relies on CAD modelers, as nearly every ME process or system incorporates engineering drawings and simulations. These tools enable engineers to materialize any concept, allowing for testing in a cost-effective and safe environment. Consequently, advancing this aspect of ME is crucial, as it significantly contributes to enhancing the efficiency and performance of this subfield. Integrating AI into CAD modelers, engineering drawings, and simulations has the potential to unlock a myriad of benefits. This section will encompass scientific publications that explore this domain within the context of AI (Table 9).

The papers highlight the impactful integration of AI in CAD for ME, showcasing its effectiveness in enhancing learning, concept demonstration, and addressing spatial analysis challenges in drawing interpretation. AI, particularly through ML and DL algorithms, plays a crucial role in the digitization of engineering drawings, improving the accuracy and efficiency of detecting, classifying, and converting elements to 3D models. The digitization process involves several steps. First, preprocessing is applied, which includes binarization, noise reduction, and thinning. Subsequently, vectorization converts raster images into scalable and editable graphics, utilizing techniques like morphological operation and line detection to identify shapes and lines. AI plays a key role in shape and symbol detection through the usage of deep learning algorithms, classifying symbols by learning from labeled data and using graph-based approaches to detect connections. Feature extraction and classification then apply statistical and structural features to refine the digitized symbols, removing distortions, completing broken lines, and normalizing shapes. In the contextualization stage, AI infers relationships between symbols and analyzes how components are connected, utilizing both shape recognition and contextual rules. This process aids learners by recognizing mistakes in their CAD designs, suggesting corrections, automating design adjustments, and optimizing the design. Also, AI assists in the transition from 2D drawings to 3D CAD models by recognizing and reconstructing geometric shapes. This digitization not only enhances accessibility and preserves documents but also increases efficiency by automating the identification and interpretation of drawing elements. AI's integration into CAD is praised for automating design processes, analyzing vast data, fostering creativity, enhancing decision-making, and reducing design-related costs and time. Despite the challenges and time consumption in using CAD modelers, AI's role in automating and optimizing the design process is recognized as a significant advantage. The papers further identify the potential for future research in AI's role in manufacturing and product design, especially in developing algorithms for new product generation and advancing manufacturing research through 3D CAD model data analysis.

Several gaps have been identified in the digitization of engineering drawings. These include a scarcity of annotated examples, the absence of domain-specific datasets, and a lack of guidelines for interpreting drawings. There is also a need for further research on the contextualization of digitized information from specific types of engineering drawings, a lack of standardization across engineering drawings, and limited testing in the application of machine vision and ML techniques. Additional gaps include a limited scope of investigation, the need for a more judicious selection of ML models, and issues with generalizability. Consequently, further research in this area is imperative. This research should focus on extending to more complex shapes, enhancing accuracy, integrating with CAD modeling, exploring ML models, and addressing existing limitations. Moreover, the development of hybrid approaches that combine heuristic-based methods and document image recognition with DL techniques, the creation of specialized datasets, the introduction of advanced testing methods, the contextualization of digitized information, and the integration of emerging technologies like DL are also critical. Importantly, there is a significant need for continued research in implementing techniques that facilitate the generation of new products using CAD modelers.

4.6 AI applications in additive manufacturing (AM)

AM, commonly known as 3D printing, holds great significance as it transforms drawings into tangible 3D models. This process notably aids in the enhancement of students' spatial abilities and offers them enriched hands-on experience, thereby bolstering their skills, and deepening their knowledge base. Consequently, the advancement of

TABLE 9 AI in CAD and engineering drawing.

Theme	Author	Focus
AI in CAD modelers, engineering drawing, and simulation	Moreno-Garcia et al. (2018)	Exploring new trends in the digitization of complex engineering drawings, with a specific focus on the role of machine learning in the engineering drawing processes within an industrial context.
	Bharadwaj et al. (2019)	Developing a pilot manufacturing cyberinfrastructure utilizing information-rich mechanical CAD 3D models.
	Mane et al. (2019)	Utilizing artificial intelligence to predict polygon shapes in engineering drawings.
CAD modelers as a learning tool	Ravikumar et al. (2019)	Discussing the use of SolidWorks CAD modeler as a learning tool, this article focuses on developing innovative techniques that enhance the learning of ME topics such as kinematic synthesis, kinematic analysis, and fatigue failure theories.

AM is crucial, and this can be achieved by integrating AI, which promises to bring a multitude of benefits to these processes (Table 10).

The papers in this section were examined to illustrate the critical role of AM in MEE, particularly robotics education and to show how the integration of AI can positively impact these technologies enhancing the learning experience. The papers highlight the benefits of AM in MEE, as AM accelerates the design process and enables rapid prototyping and iterative refinement of robotic components. Moreover, AM's capacity to create complex and functional systems due to its adeptness in producing complex geometric and employing lightweight materials, makes it an invaluable tool in the ME field. Thus, the findings have concluded that this not only allow students to quickly test and adjust their designs but also significantly improve their understanding and practical skills in designing and manufacturing robotic systems, as it provides them hands-on experience, effectively preparing them for future industry challenges, as well as it cultivates creativity, boosts confidence, enhances design capabilities, and deepens understanding of core of ME concepts.

The integration of AI in AM significantly optimizes the process by controlling and enhancing various aspects. AI contributes to AM by improving process control, offering real-time monitoring, and enabling predictive outcome modeling. It also aids in designing new materials, reducing waste and production time, and decreasing costs through ML, DL, and reinforcement learning algorithms. Furthermore, AI is involved in detecting defects during AM process, showcasing its comprehensive utility in enhancing the efficiency and quality of AM. Additionally, AI strategically chooses processing parameters, optimizing product design, and notably accelerating delivery timeline from production to application.

Optimizing AM through the utilization of advanced AI techniques, such as improved ML models, is of great significance. Additionally, fostering a collaborative environment between humans and machines can significantly enhance the printing process, with generative AI playing a key role in customizing printed materials to meet specific individual needs. Moreover, further exploration into the use of AI for advanced simulation and modeling in AM processes is warranted. Ultimately, future research in this domain is crucial to identify and establish best practices in the integration of AI within the context of AM.

4.7 Bridging the gap between industry and education

As mentioned in the previous section, it is important for institutions to get students to acknowledge the industry, so they develop the required skills in using specific technologies during their academic journey which will prepare for the workforce. This section discusses the publications that have focused on combining industry and education to bridge the gap between them (Table 11).

AI technologies are rapidly evolving and finding applications in numerous fields, including both industrial and educational sectors. It is, therefore, crucial to examine scientific publications that focus on this area of interest. These publications are helpful in bridging the gap between industry and academia, and they aim to equip students with competencies needed to utilize in industry technologies effectively. This preparation is vital for students entering the workforce, as it promises to yield significant advantages in the industry's future. The papers in this section highlight the importance of integrating AI in the educational context of ME since students encounter equivalent challenges that are present in the industry. They also emphasize the importance of bridging the gap between academia and industry to bridge the gap between them providing students an enhanced preparedness for the industry and better practical skills. The publications have discussed the cruciality of students acknowledging AI and its uses in some of ME applications as employees in industry, as well as the importance of implementing a curriculum that can accommodate for such technology. Furthermore, the papers have highlighted the enhanced learning experience that has resulted by the usage of AI and VR.

However, there is a need for further exploration of improved digital simulations, and educational institutions should consider integrating AI technologies into their curricula. Such integration will familiarize students with industry standards, enhancing their knowledge and skills in engineering systems. Additionally, the curriculum should place greater emphasis on hands-on experience and practical exposure to industrial practices, ensuring students are well-prepared for the demands of the industry.

4.8 Application of AI in mechanical engineering industry

This section delves into the integration of AI within the ME industry, which plays an essential role in narrowing the gap between industry and academic learning, as illustrated in Table 12. This table categorizes relevant publications into three distinct areas: AI in the ME industry, AI in ME systems, and AI in the manufacturing industry. The significance of this classification lies in its comprehensive coverage of current industry practices. By familiarizing institutions and stakeholders with these practices, it enables them to equip students with relevant, industry-aligned knowledge and skills. This approach not only enhances students' understanding of real-world applications of their studies but also effectively prepares them for their future roles

TABLE 10 AI in additive manufacturing.

Themes	Author	Focus
Integration of additive manufacturing in MEE	Johnson, et al. (2020)	Reviewing the use of machine learning for material advancement in metals AM and highlighting its pivotal role in propelling this specific sector of industrial production forward.
	Guo et al. (2022)	Exploring the biomedical applications of powder-based 3D printed titanium alloys, with a particular emphasis on the contribution of machine learning in advancing metal printing technologies.
	Razaviarab et al. (2019)	Employing artificial intelligence in 3D metal printing to identify defects in printed layers and enhance overall quality.
Additive manufacturing to enhance students' understanding	Castelli and Giberti (2019)	Adopting FDM 3D printing for a hands-on robotics course, aiming to underscore the benefits of using AM in the education of robotics.
	Singhal et al. (2022)	Utilizing 3D printing to provide engineering students with practical, hands-on experience.

in the workforce, thereby effectively bridging the industry-education divide.

The development of technology and the progress of industries necessitate an examination of AI technologies used in industry 4.0 to determine the content of future curricula for ME students. The publications in this section emphasize the utilization of AI in many industries including manufacturing and aerospace industries, as well as in mechatronics systems. AI is being utilized for numerous purposes, i.e., enhance work efficiency, automate repetitive tasks, diagnose defects, provide predictive solutions, develop safer environment, and predict and evaluate mechanical properties using ML and DL algorithms. Furthermore, AI has boundless usage in manufacturing industry as to assist manufacturers in visualizing the challenges that were drastically difficult to acknowledge, uncovering concealed bottlenecks, and identifying unprofitable production lines. Also, AI improves accuracy of rotating machinery, reduces time and cost, enables online status detection and remote monitoring of mechanical equipment, and increases efficiency of detection. In addition, the incorporation of AI in Aerospace field has brought several benefits including enhanced automation in aerospace systems, intelligent robotics, autonomous control systems for unmanned vehicles, better sensor technology, and valuable educational opportunities with hands-on experience. Also, it is used for many purposes including image and speech recognition, predictive maintenance, and recommendation systems. Additionally, the publications have stated the potential of AI in mechatronics systems such as quality control, optimization of processes, providing autonomous systems, decision-making, and analyze data gathered from sensors to predict future damages. Industry's main objective is to achieve higher levels of efficiency, product quality, and productivity. Therefore, some of the future directions of the industry is to focus on the development of smart manufacturing, advanced robotics, digital twins, and predictive maintenance.

Nevertheless, the acknowledgment of the industry advancements in utilizing technologies is crucial for institutions as their main objective is to prepare students to the work field; thus, it is crucial to study industry and their advancement which will get the students with more familiarity regarding the technologies utilized.

The incorporation of AI in industry has brought diverse benefits as it has optimized the processes and has increased efficiency. Secondly, it has created a safer environment for employees as it has automated several operations. Also, it has helped in creating a valuable opportunity for educational and training by providing a hands-on experience with more enhanced technologies. Nonetheless, the advantages that AI has brought to industry reveals the cruciality of this technology to be integrated in many fields including MEE. Thus, this can enhance the learning experience and benefit students, educators, and institutions in a wide range of opportunities. Accordingly, it is important to address unresolved issues, advance AI techniques, and integrate AI with more technologies.

The conceptual framework presented below (Figure 13) inspired by Bahroun et al. (2023), offers a detailed visualization and categorization of publications that discuss the diverse applications of AI in MEE across various domains. The framework features a spider graph with a central dark black circle connecting to a two-tier structure: the initial tier represented by dark gray circles and the second tier by light gray circles. The black circle represents the overarching theme of "AI in MEE," the initial tier highlights primary themes of AI applications, while the second tier is linked to secondary themes. For instance, "3D Printing" is linked to themes like "Accelerated material research" and "Mathematical chatbots," showcasing areas where AI can enhance materials research and provide educational tools. The size of the circles in the spider graph varies, with larger circles indicating themes that are more prevalent and prominent. Conversely, smaller circles suggest fewer scientific publications have considered the theme they represent. This graphical representation provides a comprehensive overview for future researchers, offering insights into which areas require more development and enhancement, which have been less explored, and which exhibit the most significant gaps in the literature. Consequently, researchers in the field can target their investigations toward these areas, potentially contributing to their growth and development.

The content analysis in this review offers a structured overview of AI-driven tools and methodologies that can significantly enhance the pedagogical design of engineering education. By categorizing AI applications across various educational contexts, this review provides educators and curriculum developers with practical insights into integrating AI to create more effective, personalized, and industry-aligned learning experiences. The analysis reveals AI's potential to transform traditional teaching methods through adaptive learning systems, automated assessment tools, and simulation-based learning environments that support hands-on and experiential approaches. These insights are particularly valuable for designing courses that respond to individual learning needs, facilitating adaptive feedback and intelligent tutoring. Furthermore, the content analysis underscores the role of AI in fostering essential technical and analytical skills, preparing students for the technologies they will encounter in the workforce. By integrating

TABLE 11 Converging industry and education.

Themes	Author	Focus
Competence of students for industry	Chen et al. (2020)	Investigating the incorporation of artificial intelligence in interactive learning environments, with a special emphasis on its application in finite element analysis, offering benefits to both educational and industrial sectors.
	Afanasyev et al. (2018)	Developing an intelligent system specifically designed for corporate use in universities and enterprises to enhance engineering education.
Combining Industry and Educational fields	Brazina et al. (2022)	Applying Industry 4.0 principles and technologies in the teaching process to modernize and improve educational outcomes.
	Brezeanu and Lazarou (2020)	Aligning the engineering curriculum with skills development to meet the demands of Industry 4.0, ensuring that students are well-prepared for the future workplace.
	Grisales-Palacio and Garcia-Zaragoza (2022)	Creating Cyber-Physical Systems (CPS) that enable the convergence of industry and pedagogy, providing students with opportunities for professional experience and exposure.

TABLE 12 The applications of AI in ME industry.

Themes	Author	Focus
Artificial intelligence in mechanical engineering industry	Patange and Pandya (2023)	Explores how AI and Machine learning supports mechanical engineers, emphasizing their role in enhancing industrial processes
	Peloquin et al. (2023)	Focuses on using AI to predict the tensile performance of 3D printed photopolymer with the aim of guiding the extension of future models in the industry
	Sheng and Wang (2023)	Focuses on using machine learning to evaluate the distribution of pipeline steel mechanical properties, emphasizing its role in assessing material qualities in an industrial context
	Rizvi and Abbas (2023)	Evaluates how deep learning and advanced data collection methods enhance structural health monitoring, specifically focusing on their role in mechanical infrastructure within industry settings
	Yuan et al. (2023)	Simulation of Artificial Intelligence applications in the aerospace field, and provide insights to bridge the gap between education and industry
Artificial intelligence in mechanical engineering systems	Ma et al. (2023)	Investigates the utilization of physics-informed machine learning for degradation modeling in an Electro-Hydrostatic Actuator System, emphasizing its application in mechatronics systems within industry
	Faria and Barbalho (2023)	Analyze the scientific constitution of mechatronics and its association with innovative products.
	Chuang et al. (2022)	Deployment of non-intrusive intelligent sensor systems and 5G edge computing in smart factories
	Guo (2023)	Explores the integration of artificial intelligence in the detecting of rotating machinery states
	Kibrete and Woldemichael (2023)	The use of artificial intelligence in machinery for fault diagnosis
Artificial intelligence in manufacturing industry	Sanchez et al. (2021)	Explores the application of machine learning to highlight and determine factors affecting creep rates in laser power bed fusion, emphasizing its role in optimizing manufacturing processes.
	Choong and Cheng (2021)	Machine learning application in the failure analysis of optical transceiver manufacturing

these AI applications, educational institutions can enhance student motivation, engagement, and preparedness for industry, making the curriculum more dynamic and aligned with technological advancements in engineering fields.

However, the integration of AI in MEE is also accompanied by its challenges and limitations. Ethical concerns, such as data privacy and potential biases in AI-driven assessments, must be carefully addressed to ensure responsible application. Furthermore, the need for substantial technological infrastructure, including powerful computing systems and specialized software, poses a barrier to widespread AI adoption. Faculty training is also crucial, as instructors must be equipped to effectively use AI tools and adapt their teaching methods accordingly. Without proper training, faculty resistance to change and unfamiliarity with AI could hinder successful integration. Addressing these limitations is essential for realizing AI's full potential in MEE and ensuring that it enhances the learning experience rather than detracts from it.

5 Conclusions and future research

AI technology is rapidly evolving, and its applications are expanding across various fields, including MEE, where it is transforming education at different levels. In MEE, AI is utilized for a variety of purposes such as personalized learning, smart tutoring systems, digitizing engineering drawings, simulations, fault diagnosis, and more. The incorporation of AI in MEE has raised several concerns, calling for enhanced accuracy, more personalized learning approaches, improved simulations, increased efficiency, and academic integrity. These concerns are driving changes in the curriculum, elevating it to new heights. A thorough literature review has resulted in the analysis of 228 publications, with the most relevant papers being discussed in detail, showcasing their findings, and outlining future research directions.

First, a bibliometric analysis of AI applications in MEE has been conducted. This analysis began with an initial poll of 765 articles

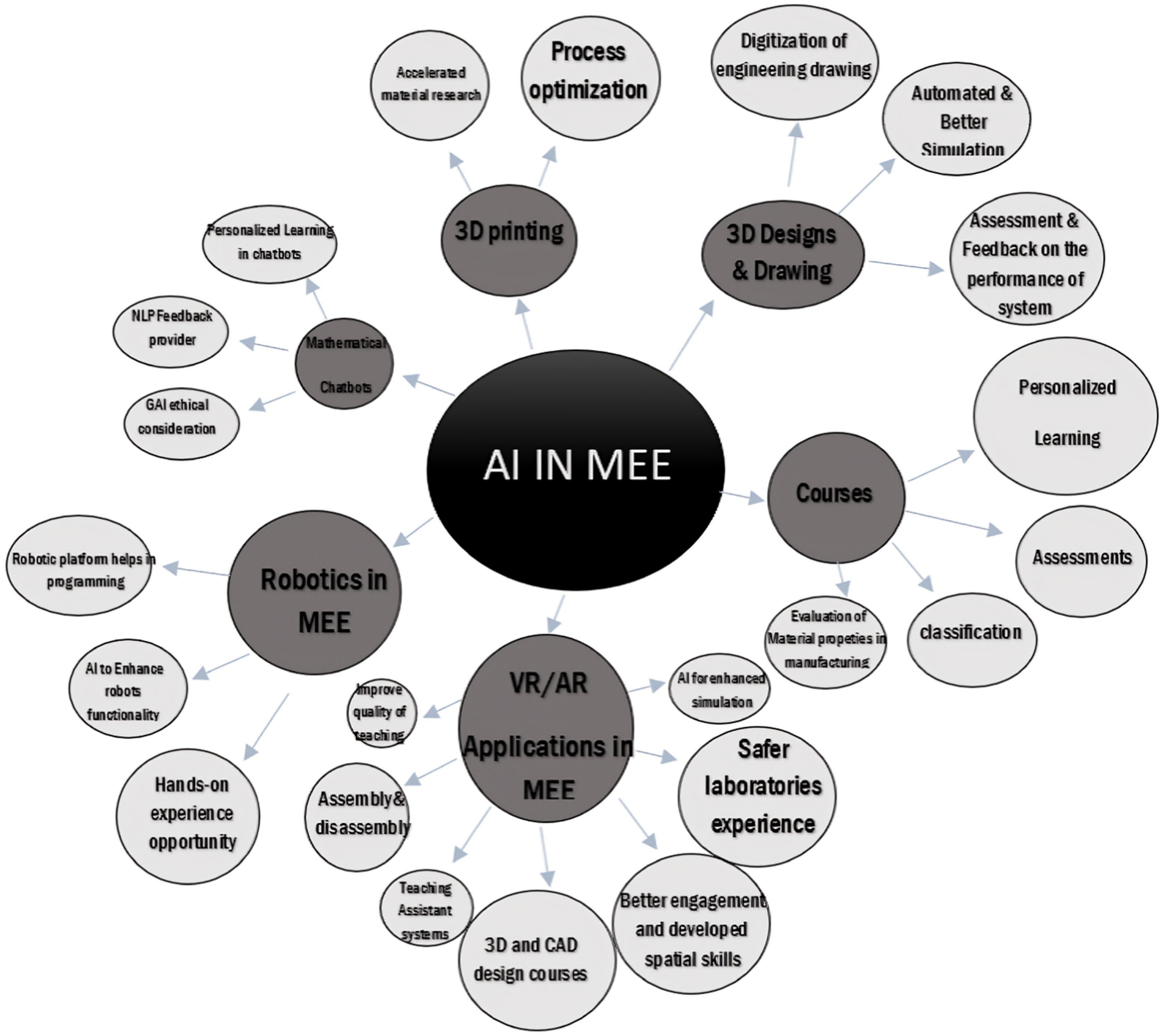

FIGURE 13
AI in MEE framework.

sourced from the Scopus database. After a meticulous process of literature screening and the removal of duplicates, the focus narrowed down to 228 publications specifically addressing AI in MEE, spanning the years 2018 to 2023. This comprehensive bibliometric analysis yielded several key insights. The results highlighted a range of interdisciplinary ME subfields globally incorporating AI. Moreover, it revealed a significant volume of scientific publications dedicated to this domain. Additionally, numerous authors have notably contributed to the discourse on integrating AI into MEE, bringing diverse perspectives and insights to the field.

Following the bibliometric analysis, the next step involved conducting a content analysis to thoroughly investigate the application of AI in MEE. This analysis yielded significant findings, highlighting the diverse applications of AI across various aspects of MEE, including manufacturing, AM, thermodynamics, simulations, and engineering drawings. Additionally, it brought attention to areas such as smart tutoring systems, classification, and personalized learning. AI tools like VR and AR have been noted for their substantial role in developing students' spatial skills and enhancing their motivation and engagement. Similarly, robotics and robotic platforms have proven beneficial in student learning within numerous robotic courses and other science education domains. Moreover, the integration of AI in robots and VR/AR technologies has shown positive impacts, enhancing their functionality. Furthermore, the reviewed scientific publications have revealed the numerous benefits that AI brings to MEE, with many papers stressing the importance of incorporating these technologies into the ME curriculum.

The promising outcomes that AI has brought to MEE have been notably highlighted in various studies. This review delves deep into the potential that AI unfolds in enriching MEE. Building on these findings, it suggests several future research directions that could further explore and expand the integration and impact of AI in this field.

Integrating GAI and Large Language Models (LLMs) like ChatGPT into the MEE curriculum offers a transformative opportunity to revolutionize this field. By leveraging LLMs that utilize NLP, educational approaches in MEE can be enhanced with personalized learning, intelligent tutoring systems, and effective feedback mechanisms. For example, ChatGPT, known for its advanced NLP capabilities, can be especially beneficial for MEE courses, facilitating tailored explanations of complex engineering concepts and improving interactive learning experiences. The vast potential of such technologies includes assisting in the instruction of challenging topics, providing instant feedback, and simulating real-world engineering problem scenarios. Specifically, GAI tools offer the potential to transform several aspects of the MEE curriculum. In simulations, AI can create complex engineering scenarios, enabling students to engage with real-world problem-solving in virtual environments. For coding exercises, these tools can provide instant feedback and code suggestions, accelerating learning for computational tasks. In research support, AI can assist students with literature reviews, trend analysis, and insights into emerging fields. For theoretical and computational problem-solving, AI offers step-by-step guidance on complex concepts and calculations, making abstract topics more accessible and interactive. However, these applications come with challenges, such as ethical risks (e.g., potential misuse and biases), accuracy concerns, faculty resistance, and a need for specialized training. Additionally, there are practical barriers, including possible reductions in critical thinking, technical limitations, accessibility, and compatibility issues with existing software. Addressing these challenges will be crucial to fully harnessing the educational benefits of GAI in a responsible and effective manner.

The future of MEE stands on the brink of significant advancements, primarily driven by the integration of AI. A crucial step forward involves developing theoretical guidelines or conceptual frameworks to assist educators and stakeholders in effectively implementing AI models, such as GAI, within the MEE curriculum. A key focus area is the automation of AM processes, where the use of machine learning algorithms is set to boost efficiency and performance. Additionally, advanced deep learning and reinforcement learning algorithms are expected to transform automated simulations, particularly in generating new products through 3D CAD model analysis. Another promising development is the creation of intelligent tutoring systems in mechanical engineering. These systems, which integrate GAI models with multimedia elements like animations and simulations, aim to simplify complex concepts for students. Efforts are also being made to enhance the precision of digitizing engineering drawings, utilizing AI for more accurate innovations. Moreover, addressing ethical considerations in using AI, particularly models like ChatGPT in educational settings, is essential for ensuring their responsible application. Finally, strengthening the connection between industry and academia is vital. This connection aligns academic learning with industry practices, equipping students with the skills needed to tackle real-world engineering challenges and meet industry standards.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

MA: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. VA: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Validation, Writing – review & editing. ZB: Conceptualization, Data curation, Investigation, Methodology, Supervision, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Higher Education Act for AI (HEAT-AI): a framework to regulate the usage of AI in higher education institutions

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The introduction of artificial intelligence (AI) into educational institutions is part of a global trend shaped by the capabilities of this technology. However, due to the disruptive nature of AI technologies, it greatly affects the way of teaching and learning. It is therefore essential to establish clear guidelines that not only ensure that all competencies required by the curricula are still effectively taught, but also empower students to use the new technology in a productive manner. Developing such guidelines for emerging and dynamic technologies is a very challenging task, as rules often struggle to keep pace with rapidly evolving advancements. The European Union found a good way to tackle this problem in its AI Act by introducing a risk-based approach to regulate AI applications of organizations. Depending on the level of risk, applications might be prohibited, require extensive analysis and safeguards, have transparency obligations, or need no further action. This paper adapts the core structure of the AI Act regulation for the education sector to provide teachers and students with a structured framework for dealing with AI. Various use cases, based on teaching and learning life cycles, are presented to illustrate the versatility of AI in teaching and the learning process. By establishing such a framework, we not only promote competence development in dealing with AI but also contribute to the creation of an ethical and responsible use of AI in education.

KEYWORDS

higher education institutions, artificial intelligence, education, large language models, rules (regulations), guidelines and recommendations, teaching

1 Introduction

Although artificial intelligence (AI) is widely used in research across all domains (Xu et al., 2021), the advancements of generative AI have led to many discussions about the right way to integrate this new technology into teaching and learning activities.

Higher Education Institutions (HEI) all over the world reacted in different ways to the new development. While some universities designed guidelines and policies on the usage of AI in courses, others tried to ban it. Recently, some universities even decided, therefore, to change the process of bachelor thesis.

As this rapidly developing technology is also going to change the world of work, it is vital that universities adapt their practices to this new situation and disruptive impact on education. It is indisputable that artificial intelligence offers numerous new applications for higher education institutions (HEI), both for educators and learners.

Knowledge workers have been shown to be much more productive with AI support (Dell'Acqua et al., 2023), for example when publishing (research) texts (Kitamura, 2023) or reducing administrative time (Bond et al., 2024). Another crucial benefit of AI in education is that with the help of generative AI, people with special educational needs can also be integrated into educational settings, allowing inclusive education (Khazanchi and Khazanchi, 2024).

Furthermore, the use of AI enables teachers to provide individual learning materials and learning pathways (Bond et al., 2024). Support for developing tailored educational content increases student engagement and learning outcomes (Holmes et al., 2019). These developments could lead to broader social impacts by increasing equality of opportunity for students.

The support of generative AI may also have economic effects, as the workload of faculty could be reduced. On the other hand significant investments in data-protected and safe AI infrastructure are required, which may strain budgets (Saidakhror, 2024).

The use of artificial intelligence also presents new challenges for academic organizations. Since the release of ChatGPT, numerous articles have pointed out that it was able to perform well in some assignments and exams. Various studies highlight that generative AI is already used by students to write assignments or essays (e.g., Oravec, 2023; Sweeney, 2023).

While generative AI tools have the potential to enhance personalized learning and engagement, there are concerns about their ability to undermine critical thinking and perpetuate misinformation. A recent study examining the relationship between students' use of generative AI and their exam performance reveals that students who use generative AI tend to score lower in their assessments (Wecks et al., 2024).

Further challenges such as data privacy, bias, and the need for ethical frameworks must be addressed to fully leverage its benefits in teaching and learning (Baek and Wilson, 2024).

As technology further develops and generative AI is more and more integrated into our daily routines and applications (e.g. Microsoft Co-Pilot), this challenge is going to increase.

If HEIs cannot ensure that AI is used in a responsible manner, it could lead to severe consequences. The improper use of the technology can lead to incorrect content (i.e., hallucinations). Therefore, it is crucial to establish rules that, on the one hand, encourage the use of AI and, on the other hand demand transparency and critical assessment of obtained results.

Therefore, in this paper we examine the following research questions:

- What do students and teachers need to be given in order to deal responsibly with artificial intelligence?
- How can a framework for higher education institute regulate the use of artificial intelligence?

The major contribution of this paper is the introduction of a flexible framework that regulates AI usage in HEI, which at the same time also shows the consequences of non-compliance.

Inspired by the AI Act of the European Union, the framework takes a risk-based approach (e.g., risk to privacy, risk to academic integrity). The term risk is defined by the EU AI Act (European Commission, 2024) as "…the combination of the probability of an occurrence of harm and the severity of that harm."

This paper focuses mainly on generative AI, addressing AI systems capable of creating text, images, and videos. However, the framework introduced can be further extended to encompass other approaches to artificial intelligence, such as machine learning techniques that facilitate decision-making, predictions, and recommendations. A pertinent example is personalized learning, where educational content is recommended based on student training data.

The remainder of this paper is structured as follows. Section 2 outlines our research methodology. Section 3 provides an overview of how AI technologies are currently used in HEI and what rules have been established to regulate usage. Furthermore, we briefly highlight those aspects of the European AI Act, which have been used to derive and develop our proposed Higher Education Act for AI (HEAT-AI). Section 4 introduces our novel approach to govern the usage of artificial intelligence, especially generative AI, in educational institutions. In order to clarify how the proposed framework can be used, we also included example use cases. In Section 5 we discuss and interpret our findings, before presenting our main conclusions in Section 6. Section 7 presents future work.

2 Methodology

In this section, we outline our research methodology to develop a framework to regulate AI technologies in higher education institutions.

Figure 1 depicts the main steps of our research methodology, combining theoretical (dark blue) and empirical (blue-green) steps.

Our first step was a collaborative analysis of the problems, challenges, and opportunities with key stakeholders at the St. Pölten University of Applied Sciences which offers bachelor and master programs in the fields of technology, business, social affairs and health.

- Open space with 23 bachelor and master program directors (March 2023).
- Round table within smaller groups (April 2023–March 2024).
- Their insights shaped our understanding of AI usage, concerns and opportunities in higher education.

To ensure the robustness of our findings and to get a broader view on the topic, we conducted a comprehensive literature review on the use and potential of artificial intelligence. This review, which included an exploration of AI's benefits and drawbacks, served as a solid foundation for our subsequent work.

Building on our literature review, we conducted a comparative study of the rules and regulations of leading higher education institutions. In addition, we analyzed the AI Act, the first AI regulation worldwide, to build knowledge for the development of a future-proof and flexible AI regulation for universities.

With the knowledge gained in the previous steps, we started to design an approach and asked key stakeholders, such as the committee for quality development in teaching or the committee for study law at the St. Pölten University of Applied Sciences, for feedback.

Based on our initial design and feedback, we began the development of a pilot version of HEAT-AI. The first draft was completed in June 2024. An iterative process with members of the University board (one of them with students) helped finalize the framework. HEAT-AI was approved by the University Board and went live in September 2024.

As AI is a highly dynamic field, the approach's effectiveness and usability a broad evaluation of the framework has already started.

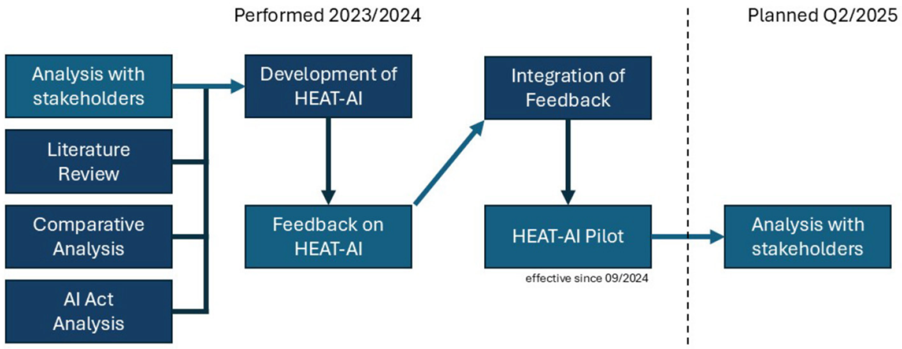

FIGURE 1
HEAT-AI research methodology.

Currently, we are collecting testimonials from all the departments regarding the use of the regulations within the supervision process of scientific theses. In addition, we actively collect questions from lecturers and students regarding the usage of the framework within teaching and learning processes. The focus groups with lecturers and students began in December 2024.

The framework will be evaluated at the end of the academic year 2025.

3 Related work

In this section, we highlight the use cases of AI in HEIs, their policies, and guidelines. Furthermore, we provide a short overview on relevant parts of the AI Act which build the foundation of our HEAT-AI approach.

3.1 Artificial intelligence in education

The use of artificial intelligence has made its way into various contexts of teaching and learning activities at universities. AI is both a part of digitalization and an independent field. The fundamental insights on digitalization in teaching, research, open science, and university administration can also be applied to changes brought about using AI. Especially generative AI brought a disruptive change to the way of teaching and learning. Text-to-image AI generators assist teachers to implement new art teaching concepts (Dehouche and Dehouche, 2023). Text-to-text AI generators provide personalized learning support and help teachers prepare lectures, support students, and evaluate their work. A systematic categorization has been developed based on a broad meta study (Zawacki-Richter et al., 2019). The researchers in this study related their use-cases for higher education to the student life cycle (Schulmeister, 2007), starting from guidance on study choices until the graduation. Their results lead to the following categories:

Profiling and prediction address f.ex. the likelihood of students dropping out of a program. This category focuses on admission decisions, course scheduling, dropout, and retention as well as student models and academic achievement. By applying machine learning methods, AI is used for recognizing and classifying patterns as well as to model predictive student profiles.

Intelligent tutoring systems focus on a teaching and learning level. This includes teaching and learning course content, where students and teachers use chat bots to help achieve learning outcomes. Furthermore, AI helps identify students' problems to achieve the intended learning outcomes and to provide automated feedback and learning material. Another use case is the facilitation of collaboration between learners by supporting online discussions or fostering collaborative writing.

Assessment and evaluation include automated grading, providing feedback, evaluation of students' progress as well as their academic integrity and the evaluation of teaching effectiveness.

Adaptive systems and personalization aim at individual course content delivery and learning pathways as well as teaching design. This includes monitoring and guiding students using academic data (Zawacki-Richter et al., 2019).

The above-mentioned categorization highlights how broadly AI can be implemented at different levels of a student's life cycle. Each of these categories involves various risks, such as unfairness, when it comes to admission processes (Marcinkowski et al., 2020) or inaccuracy when it comes to prediction of students' performance (Hemachandran et al., 2022).

As the category system of Zawacki-Richter et al. (2019) has been developed before the rise of broad access to generative AI tools, the corresponding use cases were not included. For the identification of specific use cases for teaching and learning, we refer first to the policies of the Top 5 Universities of the Times Higher Education World University Ranking 2024 (Times Higher Education, 2024).

Secondly, we analyze the typical lifecycle of teaching design and learning, cf. Sections 3.2, 3.3. Student-related use cases are defined as specific interactions in which generative AI is used to enable a specific learning process or to complete tasks. Use cases for teachers refer to all activities in which teachers use generative AI to design lessons, teach, examine, or adapt the curriculum. In order to provide a deeper understanding on the topic, in the following we highlight a selection of use cases divided by the different target groups.

3.1.1 Use cases according to the Top 5 Universities

According to the Top 5 Universities of the Times Higher Education World University Ranking 2024 [i.e., University of Oxford, Stanford University, Massachusetts Institute of Technology (MIT), Harvard University, and University of Cambridge] Teaching-centered use-cases include:

- giving formative feedback,
- evaluating students work,
- develop a grading rubric,
- providing questions for reflections on a specific topic,
- developing scenarios and cases,
- anticipating students' questions,
- planning learning activities and specifying assignments,
- design for individual learning pathways,
- design cognitive retrieval practice quizzes.

Student-centered use-cases include:

- relate to generative AI to find (new/alternative) learning techniques and study habits (e.g. asking generative AI to give examples for theories or create a test on a specific topic),
- access information using different senses (view/sound/etc.).

Both student-centered and teacher-centered use cases, as they apply for a lot of everyday tasks, including:

- translation of text,
- transcription of audio data,
- writing and Brainstorming assistance,
- generating ideas and specific examples,
- synthesizing information,
- summarizing bigger amounts of text or other data,
- research and analysis capabilities,
- project planning,
- generate visual summaries.

For an all-encompassing picture, the student lifecycle and the teacher lifecycle were used in the next step to identify possible blind spots.

3.1.2 Teachers lifecycle: planning and teaching a course

The teaching design lifecycle (see Figure 2) in higher education is a systematic approach to planning, delivering, and continuously improving courses in higher education. This lifecycle ensures that courses are effective, engaging, and aligned with both student needs and institutional goals.

The first step in the teaching design lifecycle is to conduct a needs analysis of the target group. This involves identifying the learning needs and the learners' prior knowledge through analyzing the current curriculum. Once the learning needs have been identified, the next step is to define clear, measurable learning objectives. These objectives should be aligned with the curriculums' goals and should be competency-orientated, student-centered and achievable.

A teacher then develops the course content as well as the course materials. According to the learning outcomes and the content the teacher chooses instructional strategies that facilitate learning. Appropriate learning and teaching methods include lectures, discussions, exercise, feedback etc. in different group forms (i.e. group work, plenary work and single work) and different learning spaces (on premise, online. in the field, on the job, etc.). The last design step is the assessment. Both formative and summative assessment techniques are useful tools for evaluating and grading the learning outcomes. Assessment design should be aligned to the learning process, the correspondent instructional methods, and the learning outcomes. The actual teaching situations involve communication between lessons as well as organization of learning materials (i.e. via learning management system).

The effectiveness and course satisfaction should be surveyed by collecting feedback and analyzing assessment outcomes. Teachers then can identify the course design areas to be revised and areas that should be maintained. The results if these reflections influence the next course planning (Lehner, 2019; Osterroth, 2018).

3.1.3 Learner's lifecycle: being a learner in a course

The first stage of the learner's lifecycle (see Figure 3) the introduction to the course structure, intended learning outcomes, and expectations. Students familiarize themselves with the learning management system (LMS) and course materials. In addition, they engage in initial activities to build community and rapport among students and with teachers. Students actively participate in lectures, discussions, group work and other learning activities. They interact with peers and instructors asynchronously through forums and collaborative tools. Students also engage with readings, multimedia, and lectures to understand the material to foster their learning and comprehension. They apply their knowledge through exercises, case studies, and practical tasks, which help reinforce learning. Office hours, tutoring, and study groups provide additional support.

(Peer-)Feedback and self-assessment help students to identify gabs in their learning outcomes. They revisit and revise course materials and seek additional resources or support for challenging topics. Students participate in formative assessment techniques, such as quizzes and assignments, to foster their understanding of the material. They complete their courses though summative assessment, such as continuous assignments, exams and projects, and demonstrate the achievement of the intended learning outcomes.

Ideally, students also reflect on their learning experiences and outcomes, assessing their progress toward learning objectives and their learning techniques. At the end of the course, they give feedback and/or evaluate the course on its' efficiency and their satisfaction with the learning and teaching process (Biggs et al., 2022).

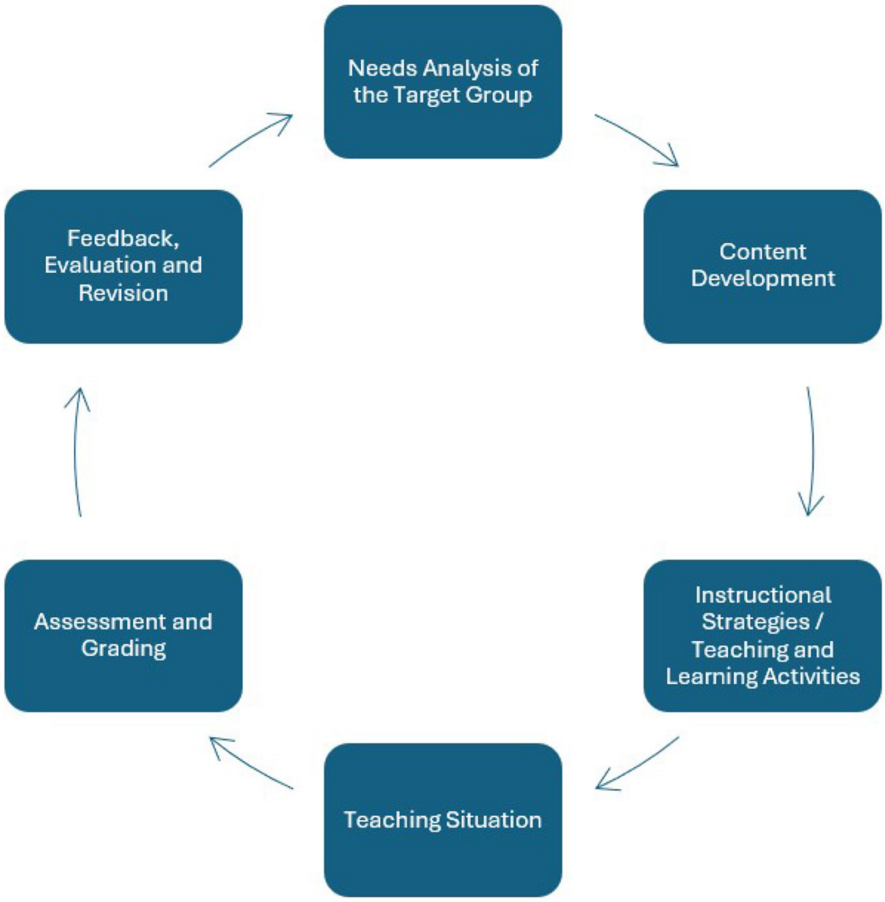

FIGURE 2
Teacher's life cycle.

These models in teaching and learning show which specific use cases should be addressed by policies on the usage of generative AI in higher education.

3.2 Policies and guidance documents

In this section, we will take a closer look at the major aspects of the selected AI policies that are currently in use.

The European Commission highlights in its ethical guidelines for the use of artificial intelligence and data in teaching and learning the importance of human agency, fairness, humanity, and justified choice (European Commission, Directorate-General for Education, Youth, Sport and Culture, 2022). The office for educational technology in the United States of America (USA) emphasizes "keeping humans in the loop" and stresses the importance of informing, training, and involving educators in policy making processes (Cardona et al., 2023).

Both the European as well as the USA policy address the same topic areas for using AI in general:

- security and privacy (e.g., data protection),
- equity and access,
- transparency,
- ethical considerations (e.g., human agency, environmental impact, bias, exploitation...),
- academic integrity (e.g., fairness, respect, honesty, ...),
- accountability.

Security and privacy are paramount, with a focus on protecting sensitive data, exemplified by regulations like the upcoming European AI Act. Equity and access underscore efforts to ensure fair distribution and utilization of AI tools across diverse student populations, advocating for inclusive access to educational resources and opportunities.

Transparency is emphasized, calling for clarity and openness in the development and deployment of AI technologies within educational settings. This involves revealing the inner workings of AI systems to foster trust and understanding. Ethical considerations are central, addressing concerns regarding human agency, environmental impact, bias, and exploitation in AI applications.

The guidelines aim to mitigate these risks, ensuring that AI in education upholds ethical standards and respects the dignity of all individuals.

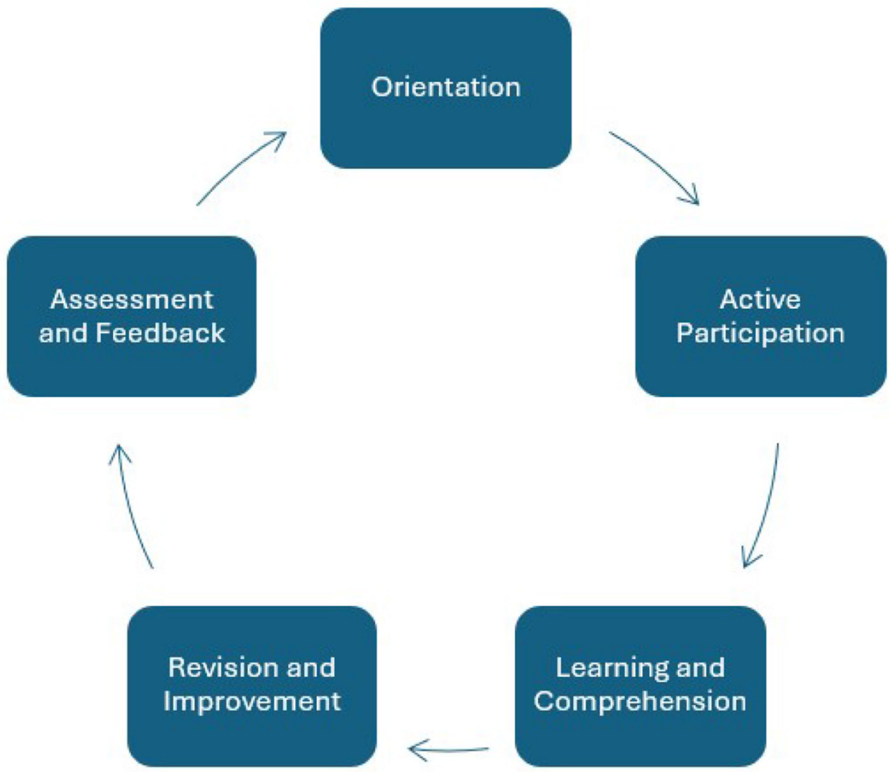

FIGURE 3
Learner's lifecycle.

Academic integrity is upheld through a commitment to fairness and honesty in research and educational practices involving AI. Collaboration and integrity are promoted to maintain the credibility and integrity of academic pursuits in the realm of artificial intelligence.

Accountability is emphasized, holding institutions and individuals responsible for the ethical and equitable use of AI in higher education. HEI need to ensure that stakeholders are accountable for their actions and decisions related to AI implementation.

Additionally, policies contain the understanding, identifying, and preventing of academic misconduct and the corresponding rethinking of assessment methods. Along those lines of thought, guidelines on AI should include how to correctly attribute the work of generative AI in students' assignments (Chan and Hu, 2023).

For policy making in higher education there must be a clear difference in addressing teaching with AI and teaching for AI. Teaching with AI leverages existing AI tools to enhance teaching practices, while teaching for AI equips students with the knowledge and skills needed to navigate the AI-driven world effectively. One research area dedicates its work on building curricula and offering electives that include the development of AI competencies (Chan, 2023).

For teachers to use AI tools with a high level of awareness, they should also be equipped with a certain level of AI literacy (European Commission, 2023). Artificial intelligence literacy should be prior to teaching with AI tools and focus on fundamental concepts related to computer systems, programming, machine learning, and data science. AI literacy ensures that teachers and students can navigate AI-driven environments confidently.

The Top 5 universities of the Times Higher Education World University Ranking 2024 include these elements of policy making. However, their approaches differ:

While Harvard, Cambridge, and Oxford focus on specific guidelines related to legal provisions regarding studies, MIT and Stanford also aim to sensitize educators and students as well as provide training for responsible use. None of the guidelines explicitly forbid the use of AI tools for teaching and learning. Some of these policies provide specific guidance on the overall institutional stance, positioning Artificial Intelligence as a future competence and integral part of the university's strategy.

All policies on AI in Higher Education should mitigate risks for students, teachers and the institution itself for supporting advantages and opportunities of using AI tools for education.

3.3 EU artificial intelligence act

As our proposed HEAT-AI framework has been strongly inspired by the structure of the EU's AI Act, in this section, we briefly introduce the cornerstones of the new regulation.

The European Commission's proposal (European Commission, 2024) for an AI Act aims at regulating the emerging developments in the AI sector and establishes as one of the first large economies harmonized rules for the development and usage of AI.

Similar to the ongoing debates regarding the use of AI in academia, the development of the AI Act was marked by numerous discussions and thorough reviews. The first proposal by the European Commission was already made public in 2021. After public consultations, many rounds of discussions of various stakeholder in the European Union (e.g., the European Parliament), a provisional agreement has been finally established in December 2023.

The key provisions of the upcoming regulation include the classification of AI systems according to their risks, thereby establishing obligations and responsibilities for providers and users of AI.

The AI Act uses the four risk categories: *unacceptable risk*, *high risk*, *limited risk*, and *minimal risk*.

Unacceptable risk refers to AI systems that violate fundamental rights or values of the European Union. Examples could be systems that compromise human dignity or make decisions that violate human rights. The category of high-risk AI systems refers to AI systems that pose a high risk to the safety, fundamental rights or health of EU citizens. Examples include AI, which is used in critical infrastructure, transportation or healthcare. AI systems with limited risk are AI systems that pose a certain risk, but less than high-risk systems. These can be AI applications in the area of customer management or recruitment, for example. AI systems with minimal risk include AI systems that are considered safe and therefore require less regulation. These include, for example, simple chat bots or voice recognition systems.

4 Higher Education Act for AI

As the AI Act provides a flexible framework for regulating the use of AI, the risk-based concept outlined in the regulation can serve as a blueprint for defining a flexible set of rules for higher education institutions.

In this section, we therefore present our developed Higher Education Act for AI (HEAT-AI), which is a framework for the secure usage of AI in teaching and research.

The development of HEAT-AI was based on the following principles:

- Students and faculty members shall be encouraged to make use of the new technology.
- Academic integrity shall not be impacted by the usage of AI.
- The new technology shall be used in a ethical and lawful manner.
- The use of AI shall not violate the privacy.

In order to provide a better understanding how HEAT-AI could be used in an university setting, we provide a detailed description on all risk categories followed by sample use cases for the individual categories, in the following subsections.

As the general framework of HEAT-AI is flexible, different higher education institutions may tailor the use case categorization according to their requirements and AI risk appetite and principles of the organization.

4.1 Unacceptable risks of usage

Areas that pose an unacceptable risk are prohibited for both faculty members and students. As indicated in the principles of HEAT-AI lawfulness and academic integrity has to be preserved. In the following, we are providing more detailed information on specific unacceptable risks or risk categories.

Unacceptable risk includes the usage of (generative) AI in a way that legal requirements are violated. An example of such a violation would be the transfer of personal data to an AI system without the consent of the concerned person (data subject) and thus a violation the General Data Protection Regulation (GDPR[1]) (European Union, 2016).

The EU defines personal data [or personal identifiable information (PII)] as everything, which could identify a person including surname and first name, a private address, an e-mail address (e.g., firstname.surname@company.com), an ID number, location data (e.g., the location function on cell phones), an IP address, a cookie identifier, the advertising identifier of your telephone and data held by a hospital or doctor that could lead to the unique identification of a natural person.

According to GDPR, personal data that has been anonymized in such a way that the data subject cannot or can no longer be identified, is not considered as personal identifiable information and thus can be used in any way. It is important to mention, that the data has to be truly anonymized and the anonymization must be irreversible. We are aware that there are also AI tools that do not violate the GDPR. Nevertheless, awareness should be created for the correct and lawful handling of personal data. The number of AI tools is growing and not every one is GDPR-compliant, so the transfer of this data without the explicit consent of the data subject in the educational setting to an AI falls under the prohibited category.

Furthermore, taking AI-generated content (text, images, program code, etc.) and presenting it as your own work would violate the academic integrity and therefore is also strictly prohibited.

Another unacceptable use of AI are situations where students' rights are undermined. Quality in teaching and research is an important asset. If students are assessed with the help of AI, the decision of AI cannot always be retraced. It is therefore essential to ensure that grading is not carried out automatically by AI systems, but remains in the responsibility of the teachers.

Furthermore, all attempts to use artificial intelligence to cheat are strictly forbidden. Example use cases include the usage of large language models as an unauthorized aid to answer exam questions or rephrase work in order to fool plagiarism detection.

For the effective implementation of the regulation it is essential to introduce sanctions. If an unauthorized use of AI is discovered, this can lead to far-reaching consequences. Teachers can be withdrawn from courses or receive warnings, while students can expect negative evaluations. Furthermore, any violations of the regulation is documented and reported.

1 Harmonizes the data protection laws within the European Union and regulates privacy requirements in the European Union.

TABLE 1 Use cases—Unacceptable risk of usage.

Use case	Teacher	Student
The transfer of personal data to the AI.	X	X
Outputting generated content as own work that is graded.		X
Assessment of coursework, exams and similar achievements using AI.	X	
Purely AI-based literature research. The AI searches for and summarizes publications.	X	X

In order to clarify use cases of this category, Table 1 highlights unacceptable use cases.

4.2 High risks of usage

The use of AI in teaching, which is considered a high-risk area, is strictly regulated. This category includes all areas of application where the integrity of science and knowledge transfer or a violation of the above mentioned principles are at risk.

In education, it is important to convey correct content, build knowledge, guarantee the networking of knowledge and train students to become critical and inquisitive experts. To this end, it is also important to promote a scientific approach.

Therefore, if AI-generated content is used, it must be carefully checked and documented. It should be noted at this point that generative models in particular are not suitable for generating knowledge, Large Language Models tend to hallucinate. They have been trained to create texts, images, etc. and are not expert systems. AI should only be used in the right context. In order to prevent incorrectly generated learning content, teachers and students should search for scientific publications or use search engines to find valid and verified sources; if the intent is to prepare texts linguistically, generative language models are suitable.

If AI is used by students or faculty members, it is important to consider what the requirements are. The focus here is on teaching and learning objectives. If the content is essential for the course or performance, the adopted AI content must be documented. It is also essential to provide full details on how and which AI tool was used.

In addition, it is crucial to take a critical look at how AI is used in high-risk areas. Questions such as the following help to critically examine the application of AI in high-risk areas:

- Are the results trustworthy?
- Is there a possible bias?
- Are the answers valid?
- Are the results distorted with the help of AI?

If HEI stakeholders (e.g., students, faculty members) decide to use the output of generative AI, they should adhere to the following procedure:

1. As usual in science, the source (in this case, the generative AI tool) must be cited as the original reference.

TABLE 2 Use cases—High risk of usage.

Use case	Teacher	Student
Transcribing interviews (without transferring personal data to the AI).	X	X
The creation of exams.	X	
The development of teaching materials.	X	
Supporting formulation of feedback on tasks and exams.	X	
The use of AI-generated content (texts, images, program code) in reports, exercises, assignments, theses, etc.		X

2. In addition, the content of the statement must be substantiated by citing original, traceable, and verifiable sources.
3. The prompts and the generated output have to be provided in the appendix of the student work. The following example shows how this can look like with a direct quote.

Of course, there are challenges for teachers when the main source is suddenly generative AI. It has to be judged at what point it is no longer considered as the students' own/original work. Here, it is important to clearly communicate the rules and what the learning objective of the course is. For example, if the learning objective is to learn the English language, it must be clearly communicated that generative AI is not permitted.

Sample Citation

"Linear regression is a statistical technique used to model and analyze the relationship between a dependent variable (also called the target variable or outcome) and one or more independent variables (also called predictors or features). The main objective of linear regression is to find the best-fitting linear equation that describes the relationship between the dependent variable and the independent variables, allowing for predictions of the dependent variable based on new data." (ChatGPT 4o validated through [1])

The original sources are listed in the list of references:

1. Weisberg, Sanford. Applied linear regression. Vol. 528. John Wiley & Sons, 2005.

There are many cases that can be considered high risk. Table 2 shows common use cases that in our opinion should be categorized as high risk.

4.3 Limited risks of usage

The concept of limited risk in the use of AI in teaching refers to the potential risks associated with insufficient transparency in the use of AI.

A transparency statement serves to protect faculty and students. It ensures that people are informed when AI is used. This strengthens trust. This means that a declaration such as "AI generated" is sufficient.

Figure 4 depicts an example of an AI-generated image.

10.3389/feduc.2025.1505370

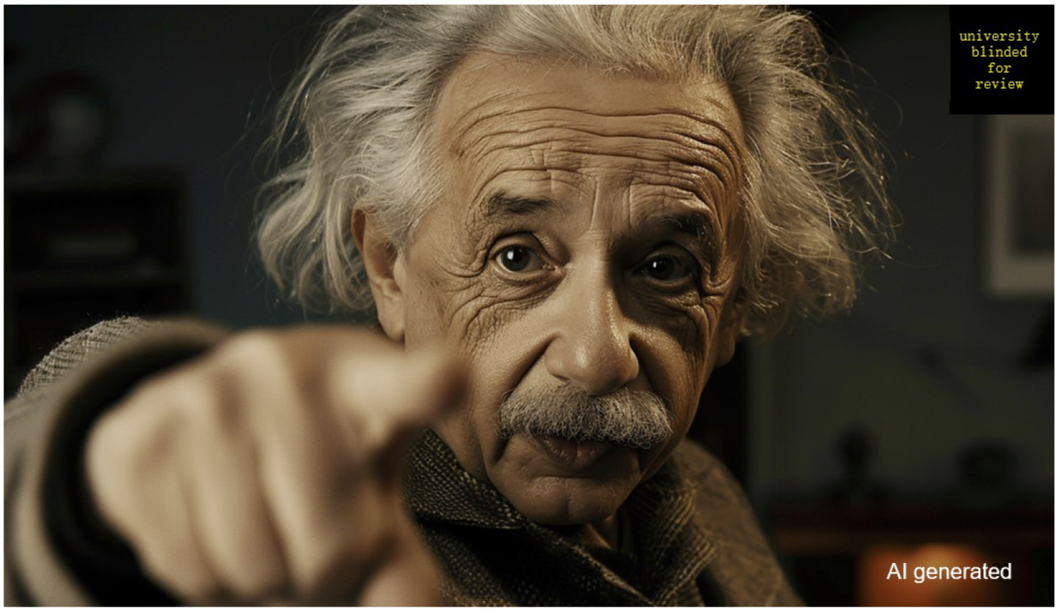

FIGURE 4
An AI generated image of Albert Einstein using Midjourney.

TABLE 3 Use cases—Limited risk of usage.

Use case	Teacher	Student
The creation of texts, images and videos indicating that generative AI has been used, unless the content is directly related to the learning objective. For example, AI-generated images can be used for the learning objective of creating a website independently.	X	X
Creation of complex scenarios or simulations to familiarize students with theoretical concepts and promote problem solving.	X	
The creation of use cases or example companies.	X	X
Optimization of own program codes.	X	X

Use cases considered limited risk are described in Table 3.

4.4 Minimum risks of usage

If the use of AI falls within Minimal Risk of Usage, unsrestricted use of AI is permitted. This is the case if AI is used as a support and is not part of an examination modality.

However, it is strongly recommended to check the content again afterward. However, it must be reiterated here that the use of AI is only allowed if the output does not contribute to the grade.

An example is a language course where the learning objective is to learn a specific language. Of course, in this case AI shall not be used for translations, and the output of an AI shall not be counted as the student's own work.

In this case, transparency is also particularly important to ensure fairness, as it might have effects on grades. Many grading schemes for submissions of assignments and essays also still consider style and wording as an important factor. However, with the advent of generative artificial intelligence, more and more students are using AI to correct and rewrite texts. This could lead to a situation where students who do not use this new technology face a serious disadvantage. Therefore, it is crucial to know where and how AI is used.

Use cases posing minimal risk are shown in Table 4.

5 Discussion

5.1 Result summary

We are currently implementing the approach at our University of Applied Sciences and gaining initial experience with it. Therefore, we held several workshops with key internal and external stakeholders, such as academic directors, program directors, heads of research institutes or researchers, lecturers, and students. To this end, care was taken to involve stakeholders from different domains such as technology, business, health, and social sciences. Different fields of study programs prefer different didactic concepts or examination modalities.

Curricula were reviewed, teaching and learning requirements were identified, and our framework was incorporated. In addition, we learned what program directors and lecturers need to implement HEAT-AI, such as explanatory slides and specific use cases.

From November 2024 until April 2025 the University Board is working on a process to deal with cases of misconduct, thus ensuring that the HEAT-AI guidelines are followed.

The development of the framework was driven by a comprehensive comparison of existing policies and self-collected

TABLE 4 Use cases—Minimal risk of usage.

Use case	Teacher	Student
Shortening, expanding, rephrasing, or linguistically correcting texts.	X	X
Use to enable inclusive teaching (live subtitling for people with impaired hearing or audio descriptions for people with low vision).	X	
Use of AI as an innovation tool to come up with ideas. If the ideas are further developed and the AI only served as a sparring partner, the own and further developed ideas do not have to be labeled.	X	X
Structuring and organizing reports, papers, etc.	X	X
Creation of curricula and learning objectives.	X	
Using Generative AI to inspire students and encourage creative writing projects. For example, they could start a story that students can then continue and edit.	X	
Creating interactive slides from trusted documents.	X	X
Using AI-powered tutors for individualized and personalized learning support.		X
Using AI to generate learning materials such as summaries, mind maps or flashcards to support their own learning process.		X
Use of suitable generative AI as a tutor.		X

teaching and learning concepts with stakeholders in our university. By analyzing these sources, we identified key elements that could inform the appropriate use of generative AI in higher education.

The categorization of the use cases of learning and teaching in the four distinct categories of our framework emerged through expert interviews, which provided valuable insights and ensured that the structure was grounded in practical experience. However, this categorization is not static; it is subject to regular evaluation and refinement based on continuous feedback and real-world experiences. This iterative approach allows the framework to remain flexible and responsive to evolving needs in the educational landscape, ensuring its ongoing relevance and effectiveness.

In the following, we briefly summarize our key findings for HEAT-AI:

- **Broad target audience:** artificial intelligence affects almost all disciplines at universities.
- **Harmonized rules with departmental flexibility:** the policy establishes harmonized rules throughout the university.
- **Encouraging innovation:** innovation in teaching and learning using AI is strongly encouraged.
- **Rapid technological development:** a flexible approach is essential to address the challenges posed by rapidly emerging AI technologies.
- **Risk-based approach:** the priorities of individual higher education institutions can be established using the four different risk categories.
- **Transparency requirements:** clear transparency requirements are established to ensure that the use of AI in teaching and learning is open and understandable to all stakeholders.

5.2 Interpretation

This section highlights the interpretation of the key findings mentioned above.

Broad target audience: during the development of the framework, when gathering requirements and meeting key stakeholders, it became clear that all university study programs were affected by the rapid development in the field of artificial intelligence. Therefore, it was crucial to have an approach that is suitable for a heterogeneous broad target audience. For the development of the university AI regulation, it was important to use as little jargon as possible and to ensure that all stakeholders can quickly understand the new rules. The development of rules around the risks to academic integrity and privacy supported the acceptance of the new rules.

Harmonized rules with departmental flexibility: an important requirement of the development was that departments could adapt or refine the university's AI regulations to eliminate ambiguities among lecturers and students in their field and tailor the regulations to their specific needs. Using use cases to tailor the harmonized rules to the specifics of a certain discipline has proven to be very useful and well suited for this purpose.

Encouraging innovation: as a higher education institution, an objective was to support the use of innovative artificial intelligence technologies that were useful. In addition, it was found that teaching students the critical skill of using AI responsibly and ethically could become a critical competence in the near future. Therefore, an approach that requires an assessment of the risks received broad support.

Rapid technological development: HEAT-AI provides a stable framework, particularly for high-risk scenarios, which can adapt to new developments in AI. Although the advantage definitely lies in the technology neutral definition, it provides more room for interpretation and sometime could require, by contrast to very specific rules, more effort to estimate the risk of using AI for a not defined use case.

Risk-based approach: having a risk-based approach for the use of AI raises awareness. We observed that communicating that risks have to be assessed, when using AI technology already leads to a certain degree of awareness amongst all stakeholders that the impacts have to be considered and must not be neglected. The risk-based approach also ensures that appropriate measures are taken depending on the level of risk.

Transparency requirements: being transparent about the use of AI is a key requirement. This is critical to be able to grade the competences of the students. In addition, technologies and applications that are used by some stakeholders might also be of interest to others. Transparently highlighting what and how AI was used therefore helps to better support all stakeholders in efficiently and effectively using the technology.

It should be mentioned that the introduction of the approach also requires training and support for all target groups. Since the introduction of the rules, we could observe broad support for the approach. However, more extensive evaluations in the future will extend the practical implications of this novel approach to regulate AI in universities and also show the limitations.

5.3 Comparison with existing research

In this section, we set our findings in relation to other research in the area.

In the past year, research worldwide has emphasized the need for clear, concise, and audience-oriented policies for higher education (Moore and Lookadoo, 2024). Studies highlight various areas that policies need to address. For example, while policies in the US, Japan, China, and Mongolia stress the importance of diversity, equity, and inclusion, they often lack clear discussions or actionable measures to address the digital divide.

This gap indicates a need for more focused efforts to ensure equitable access to generative AI technologies in education (Xie et al., 2024).

A survey in Australia revealed a divided perspective between institutions regarding the existence of guidelines and policies related to AI and data governance. This indicates that while some institutions have established frameworks, others are still in the early stages of developing such policies. The urgency of effective governance of AI in higher education is increasingly highlighted (Selvaratnam and Venaruzzo, 2024).

In African higher education, challenges include not only a lack of ethics and policies to govern AI use but also resource constraints and skill shortages (Maina and Kuria, 2024). On a global level, institutional policies regulate the accountability of learning outcomes, while human beings retain moral and legal responsibility for AI-related misconduct. Instructors have the freedom to decide how to incorporate generative AI tools in their courses, allowing personalized teaching methods (Dabis and Csáki, 2024).

Adopting a human-centered approach in AI ensures that stakeholder concerns about privacy and data control are adequately addressed (Alade and Aduwape, 2024).

The literature also shows that Generative AI can support both teachers and learners in many areas, but only if they use it correctly (Wecks et al., 2024). Due to the easy availability of Generative AI, its usage cannot be forbidden, but as with all technical aids, it is possible to determine when and how it may be used. In addition, it is difficult to estimate how the rapid development of AI will lead to which new tools.

Therefore a need for a highly flexible and adaptive policy framework in a rapidly evolving landscape of generative AI technology (Ghimire and Edwards, 2024).

When comparing our results and the policy idea of HEAT-AI respond to various issues presented in current research results. An institutionalized policy that is as clear and concise as possible (e.g., concerning data protection), but still allows teachers to find their own way in teaching their respective disciplines, seems like a good answer to the ambiguity concerning the regulation of AI usage in Higher Education.

5.4 Implications of the findings

Universities offer different study programs in a wide variety of fields such as technology, health, media, natural sciences, to name just a few.

But no matter which field, we have found that the use of AI tools has conquered all disciplines. Both teachers and students use especially generative AI in equal measure. Like any technological advancement, the easy availability of tools and perhaps lack of technical knowledge lead to misapplication.

One of our top priorities in university education is academic integrity. It is important that well-grounded content is taught, but also learned.

Learners must show that they can solve tasks independently and learn to think in a networked way in their domain. To achieve this, it is necessary to educate all stakeholders about the use of AI and to point out its limitations. Of course, not everyone needs to learn the technical details behind AI, but a basic understanding is nonetheless necessary when using technical tools. HEAT-AI uses a risk-based approach and specifies use cases to determine whether AI may and may not be used.

The framework also provides information on labeling requirements. Regulatory aspects are also included without everyone having to read the legislation in its entirety. All students should have the same chances of graduating successfully, not just the students who have easy access to the right tools. To do this, awareness has to be created that targeted support is allowed, but the learning process is the most important thing.

In the following paragraphs, we would like to briefly share our initial **learnings** from the application of HEAT-AI.

The brevity of the rules and the clear structure of HEAT-AI resulted in the feedback of university lecturers and students that the rules are transparent and understandable.

Communication is very important. The early involvement of the stakeholder (e.g., academic directors, student representatives, researchers) led to broad support. Active communication with students is also essential to answer open questions before introducing the approach.

Defining the use-cases in away that assignments are supported in a sound manner initially requires some effort. However, it could be observed that after a while, stakeholders get used to the framework.

What still needs to be investigated is the analysis of access to certain AI applications. The transparency requirements provide the opportunity to see which AI applications are being used. This is important to ensure fairness, for example, if paid versions of AI applications would provide significantly better results but are not accessible to students.

6 Conclusion

Due to numerous advantages of the usage of artificial intelligence, the increasing use of this new technology in higher education institutions is irreversible. The opportunities and versatile benefits of using artificial intelligence for teaching and research are undisputed. In this work, we therefore presented selected use cases at the time of writing to highlight the current state of practice.

However, as with almost any new technology that has a major impact on the way we research, teach, or learn, the risks of using it need to be carefully assessed by universities to mitigate any emerging negative effects. It is already clearly recognizable that in order to ensure academic integrity and ethical use, it is essential to establish clear regulations governing the use of AI.

The major contribution presented of this article is the introduction of a future-proof, and aforementioned flexible framework for the usage in academia, which on the one side encourages the usage of artificial intelligence technologies in order to provide a modern education and on the other side establishes clear rules, which also anticipates the rapid changes of this technology. In order to achieve this flexibility, the structure of our HEAT-AI policy adapts the risk-based governance approach of the European AI Act.

The presented approach should serve as a reference for other higher education institutions that are currently in the pressing need to define a framework for regulating the usage of artificial intelligence.

In line with European legislation, our introduced HEAT-AI categorizes the usage of artificial intelligence into four risk categories (according to their impacts on the core values of the institution, academic integrity, ethics, and privacy) that determine the different measures to be taken if AI is used in higher education institutions.

Based on the results of this article, St. Pölten University of Applied Sciences already established their rules for teaching and learning, which came into force this semester.

Although the effects on teaching and learning cannot be fully anticipated at the time of writing, many relevant stakeholders are supporting the approach and actively participating in its improvement by providing new use cases or experiences that can be incorporated in future versions.

An important factor that has been identified is the development of a new skill set for both teachers and students (e.g., prompting, limitations, and risk of using AI), which poses a substantial challenge due to the large number of individuals that must be trained in a relatively short period.

We are aware that the pace of AI advances and the pervasive nature of technology will require some changes in the future.

However, we are confident that the flexible structure will allow one to integrate new requirements in an efficient manner. The flexibility of the approach also allows other higher educational institutions to follow our introduced approach and tailor it to their specific needs and use cases.

7 Future work

As stated in the conclusion, St. Pölten University of Applied Sciences has already introduced its AI guidelines, based on the approach outlined in this article. In order to further improve the approach, we established various evaluation and feedback mechanisms with relevant target groups (e.g., lecturers, academic directors, students, didactic specialists), which can be also used for a more in-depth analysis of the effects on teaching, learning, and usage of AI.

The initial feedback from both students and lecturers is promising, suggesting that the herein-introduced approach facilitates the use of AI in the academic field while also providing clear rules. However, since the rules came into force quite recently, more data and feedback have to be collected over a longer period of time to perform a rigorous evaluation. A round table meeting is scheduled for December 2024 to align HEAT-AI with the requirements of the Ethics Advisory Board is scheduled for December 2024. During this meeting, issues of ethical compliance, among other topics, will be discussed.

Another area of research that we plan to tackle in the future focuses on the support that is needed by higher education institutions. In order to embed new rules in an organizational setting and to facilitate the adoption of HEAT-AI in other higher education institutions, we are currently working on the definition of a holistic governance and management framework, which incorporates our recent experiences and is based on the seven components of the widely adopted COBIT framework (i.e., Principles, policies, and frameworks; Processes; Organizational structures; Culture, ethics, and behavior; Information; Services, infrastructure, and applications; and People, skills, and competencies). A first activity, which already started, is the training concept of the internal and external lecturers.

The overall aim of our future research is the development of a holistic reference model for AI governance and management in higher education institutions, which can be tailored to specific requirements of universities and research institutions.

This article solely concentrates on the usage of AI, especially in the context of teaching and learning. As compliance requirements of higher educational institutions in Europe are constantly increasing (e.g., General Data Protection Regulation, Cyber Resilience Act, NIS2), future research activities could extend HEAT-AI to support further requirements (e.g., privacy, security, and resilience).

Author contributions

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

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Embracing or rejecting AI? A mixed-method study on undergraduate students' perceptions of artificial intelligence at a private university in China

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The rise of artificial intelligence (AI), particularly ChatGPT, has transformed educational landscapes globally. Moreover, the Beijing Consensus on Artificial Intelligence and Education and the 'Pact for the Future' propose that AI can support UNESCO in achieving development goals, especially focusing on SDG 4, which emphasizes quality education. Thus, this study investigates undergraduate students' familiarity with and attitudes toward AI tools, as well as their perceived risks and benefits of using AI tools at a private university in China. An explanatory sequential mixed-method design was employed with an online survey of 167 students, followed by a qualitative analysis of open-ended responses. Data were analyzed using the one-sample Wilcoxon signed-rank test and thematic analysis, supported by SPSS and ATLAS.ti 25. The findings revealed that students demonstrated moderate familiarity with AI tools, particularly ChatGPT and willingness to use them in coursework. Positive attitudes toward AI's value in education were evident, although concerns such as dependence and reduced independent thinking, algorithmic bias and ethical concerns, accuracy and information quality, data security, and privacy concerns were observed among students. Moreover, students generally viewed AI positively and perceived AI integration as inevitable and becoming common in academic settings. Students were concerned that the misuse of AI by their teachers was minimal and trusted their teachers to use AI effectively in teaching. Students also perceived AI's benefits, such as personalized learning, efficiency and convenience, career and skill development, and support for independent learning. This study contributes to the discourse on AI integration in higher education by highlighting students' nuanced perceptions and balancing their benefits with potential risks. The findings of this study were limited by the small sample size and institution. Future research should explore diverse contexts to develop comprehensive AI implementation frameworks for higher education.

KEYWORDS

artificial intelligence, familiarity, attitude, Beijing consensus on artificial intelligence and education, ChatGPT, private university, higher education, China

1 Introduction

The introduction of ChatGPT in 2022 has made Artificial Intelligence (AI) popular worldwide. AI makes higher education no exception to whether it should be allowed to be used in the classroom. Nearly 40% of universities in the United Kingdom (UK) stated that they might ban teachers and students from using ChatGPT; otherwise, it would be classified as academic misconduct (Housden, 2023). Several challenges manifest in various technological, organizational, societal, and ethical contexts. A notable challenge is the absence of thorough policies and guidelines for AI integration, leading to inconsistent and frequently ineffective implementation across institutions (Henadirage and Gunarathne, 2024). Moreover, challenges related to technology, including inadequate computational resources, scalability concerns, and the intricate nature of implementation, present significant difficulties (Buinevich et al., 2024). A significant issue is the lack of knowledge among educators and administrators regarding AI technologies, which greatly hinders their effective adoption and use (Ateeq et al., 2024; Henadirage and Gunarathne, 2024). Regarding the exploration and advancement of technology, significant deficiencies add complexity to the integration of AI.

Turing's (1950) famous remark, '*Can machines think?*' has become a reality and has prompted the world to unite in creating a pact for a better future (United Nations, 2024). In May 2019, countries convened to reach an agreement on the use of AI, also known as the "Beijing Consensus on Artificial Intelligence and Education" (UNESCO, 2019). The following year, UNESCO envisioned the use of AI to transform education and aid in achieving sustainable development goals (SGDs) (UNESCO, 2021b). Furthermore, UNESCO acknowledged the possibility of the misuse of AI and recommended ethical standards for AI (UNESCO, 2021a). Although the possibilities of artificial intelligence within educational contexts have been the subject of ongoing investigation in various sectors (Moonsamy et al., 2021), generative artificial intelligence has only recently begun to move from experimental settings to actual classroom environments and has gained popularity in the public eye (Bond et al., 2024). To date, there has been no consensus on the appropriate use of generative AI in higher education (Barrett and Pack, 2023). Moreover, the dangers associated with artificial intelligence cannot be overlooked. Large-scale language models may exhibit bias against certain groups because of the training data, which may not adequately reflect diverse populations, thereby producing biased outputs that exacerbate existing societal prejudices and inequities (Farrokhnia et al., 2024). Furthermore, the content—whether text, audio, or images—produced by artificial intelligence may contradict authentic information, allowing individuals to confuse falsehoods with reality, thus creating accountability dilemmas and perpetuating misleading information (Pavlik, 2023). Consequently, there is an urgent requirement for increased interdisciplinary investigation to tackle complex issues related to the incorporation of AI into higher education frameworks (Ullrich et al., 2022). Thus, this study aimed to investigate undergraduate students' familiarity with and attitudes toward AI tools, as well as their perceived risks and benefits of using these tools in higher education. The research was conducted within the context of a private university in China and addressed the following research questions:

1 What is the level of familiarity among undergraduate students with artificial intelligence (AI), and what are their attitudes toward AI's role in teaching and learning in higher education?
2 What do undergraduate students perceive as the risks and benefits of using AI tools in higher education?

2 Literature review

2.1 Students' familiarity with artificial intelligence (AI)

A survey indicated that students possess a general familiarity with generative artificial intelligence (GenAI) technology, and their engagement with GenAI is influenced by various factors, including the frequency of use (Chan and Hu, 2023). Another quantitative survey conducted in the UK revealed that students extensively utilized generative AI. The findings indicate that the majority of students are cognizant of generative AI, with approximately half having engaged in it or planning to do so for academic purposes (Johnston et al., 2024). Additionally, a recent survey conducted in Bulgaria indicated that local college students were highly familiar with the ChatGPT. The increasing prevalence of ChatGPT among college students suggests a growing eagerness to use this tool in the pursuit of high academic performance (Valova et al., 2024). A study conducted in Germany indicated that artificial intelligence tools have become integrated into the educational experiences of students across all disciplines, with learners discovering diverse applications for these technologies in their respective fields. Approximately two-thirds of students demonstrate familiarity with and practical experience in utilizing the tool, particularly in the fields of engineering, mathematics, and natural sciences (Von Garrel and Mayer, 2023). In a study conducted among medical students in Jordan, it was observed that while the majority were aware of AI tools, a limited number actively utilized these resources in their academic research endeavors (Mosleh et al., 2023). In a study conducted in Latin America, students from Ecuador, Peru, and Mexico recognized the significant contribution of Artificial Intelligence in enhancing educational quality and individualized learning processes (Ríos Hernández et al., 2024).

2.2 Students' attitudes toward using AI

A quantitative approach was employed to investigate the attitudes of users and students towards the adoption of ChatGPT, with a primary focus on Oman's residents. The investigation revealed that the student population exhibited a strong motivation to utilize the ChatGPT tool, with participants expressing that they perceived the tool as both beneficial and trustworthy within an educational context (Tiwari et al., 2023). An Australian survey indicated that college students experienced an increased sense of social support from AI with more frequent usage. However, it has also been suggested that prolonged exposure to AI can result in dependence, particularly in situations where human companionship is lacking (Crawford et al., 2024). In New Zealand, one study found that non-universal students and knowledge seekers were more inclined to utilize ChatGPT to accomplish their course requirements without reacting to its content (Stojanov et al., 2024). In a separate experiment, the students exhibited considerable interest in and enthusiasm for their first interaction with generative AI tools. However, when GenAI could not fulfill its advanced academic writing requirements, student satisfaction decreased considerably (Yang et al., 2024). An interview conducted with students from UK business schools revealed their perspectives, noting that generative AI tools often fail to capture the complexity and nuances inherent to real-world situations. Excessive dependence on

AI may overlook the significance of a multidisciplinary approach, constraining the scope of critical thinking (Essien et al., 2024).

2.3 Students' perceived risks and benefits of AI

The implementation of AI in education has the potential to provide personalized learning experiences according to the unique needs of each student, thereby improving both engagement and academic performance (Rizvi, 2023; Tyagi et al., 2022). A research initiative conducted in South Korea addressed the diverse learning needs of students through the customization of various courses for educators, simultaneously enhancing student engagement and academic performance (Lee and Kim, 2023). AI facilitates the innovation and enhancement of educational tools. The integration of artificial intelligence facilitates the advancement of intelligent tutoring systems, adaptive testing, and educational simulations, thereby enhancing the overall quality of education (Negi et al., 2024; Rachovski et al., 2024; Rizvi, 2023).

According to Tlili et al. (2023), the implications of AI include potential issues related to cheating, integrity of honesty, and truthfulness in ChatGPT, concerns regarding privacy, and risk of manipulation. Furthermore, the challenges associated with data privacy and security, along with the implementation of AI, present considerable apprehensions regarding confidentiality and protection of student information (Berendt et al., 2020; Qian, 2021). The integration of artificial intelligence within educational contexts raises significant ethical considerations, particularly regarding the implications for surveillance and the potential erosion of individual autonomy (Akgun and Greenhow, 2022; Berendt et al., 2020).

2.4 Theoretical underpinning

This study employed a descriptive mixed-method design, in which the theory used in the study serves as a guide for understanding the phenomenon. The Technology Acceptance Model (TAM), developed by Davis in 1989, serves as a prominent theoretical framework for comprehending and forecasting user acceptance and utilization of technology (Aljarrah et al., 2016). This model has emerged as a significant force in the field of Information Systems (IS). However, TAM theory has been adapted in education research to understand learners' intentions to use technology. The Technology Acceptance Model identifies two key factors that play a crucial role in an individual's decision to embrace a technology: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Perceived Usefulness (PU) denotes the degree to which a person believes that utilizing a particular system will improve their job performance (Aljarrah et al., 2016). This element is crucial to the adoption of AI technology. Studies show that when educators and students view AI tools as advantageous for enhancing teaching and learning results, their propensity to embrace these technologies increases significantly (Al Darayseh, 2023; Al-Abdullatif, 2024; Ma and Lei, 2024). Moreover, Perceived Ease of Use (PEOU) relates to the extent to which individuals feel that utilizing a specific system demands little effort (Malatji et al., 2020). The ease of use of AI tools plays a crucial role in their acceptance and integration into educational practice. When these tools are straightforward and user-friendly, they tend to be more readily adopted by educators and students (Al-Abdullatif, 2024; Supriyanto et al., 2024).

2.5 Research context

The private higher education sector in China has experienced significant growth and visibility, resulting in a considerable number of students enrolling in private institutions both within China and globally (Liu et al., 2022, 2023). In 2016, the Chinese government enacted a regulation requiring all private organizations to classify themselves as either for-profit or not-for-profit (Liu et al., 2023). According to the five-year trend, there were 757 private higher education institutions in 2019 (see Figure 1). Nonetheless, there is a notable increase in the number of private higher education institutions by 2020. In 2021, the government reclassified ordinary undergraduate institutions, undergraduate-level vocational schools, private higher vocational colleges (junior colleges), and adult education colleges and universities as independent entities, resulting in 764 private higher education institutions between 2021 and 2022 and a total of 789 institutions by 2023 (MOE China, 2020, 2022, 2023). Private higher education institutions sometimes have difficulty securing government funding for their research initiatives. They rely on students' tuition fees to finance their operations. Moreover, Chinese private higher education institutions face challenges in terms of educational quality and adherence to government laws (Welch, 2024).

With China enrolling the largest number of students in higher education, investigations into students' perceptions of Artificial Intelligence add to the discussion surrounding the increasing interest in this area, where the majority of AI research tends to emphasize nonempirical studies (Shahzad et al., 2024). A survey conducted among third-year interior architecture Chinese students revealed limited awareness of artificial intelligence (Cao et al., 2023). Moreover, Chinese students showed a moderate understanding of AI technologies compared to younger Chinese oncologist students, demonstrating a greater level of familiarity (Li et al., 2024). This study enhances the discourse on AI applications in private higher education from the perspective of undergraduate Chinese students.

3 Methodology

This study employed an explanatory sequential mixed-method design (Creswell and Creswell, 2023). The explanatory sequential mixed-method design was conducted first in the quantitative method using a survey, followed by qualitative data (Creswell et al., 2018). The researchers chose an explanatory sequential mixed method design to understand the familiarity and attitudes of Artificial, such as the Intelligence and their perceptions of the risks and benefits of AI.

3.1 Respondents and locale

The research locale of this study was a private higher education institution in eastern China. The institution now enrolls approximately 17,000 undergraduate students across 11 departments. The selected private higher education institution had a faculty of over 90% of

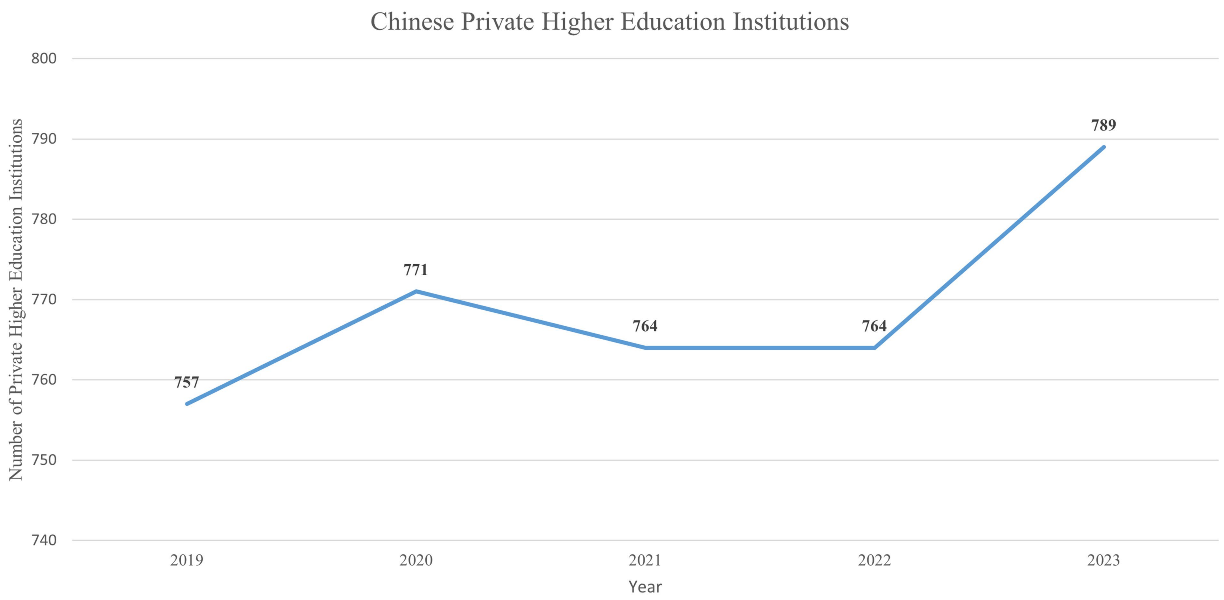

FIGURE 1
Chinese private higher education institutions. Source: Ministry of Education of the People's Republic of China.

instructors holding master's degrees, with 87% of instructors having prior experience working in renowned firms and holding expertise in their respective fields. This institution was chosen because of its strength in computer science studies and its ranking in China's private institutions, which ranges from 10th to 20th place (Table 1).

This study included 167 respondents (94 males and 73 females). The demographic characteristics of the participants are as follows. The proportions of male and female respondents were almost equal. In addition, 59.3% of the respondents were freshmen, and 26.3% were sophomores; the proportions of juniors and seniors were 9 and 6%, respectively. Most respondents were between 19 and 21 years old (74%). As many as 60.5% of the respondents were computer science majors, and 35.9% of the students were engineering majors. The remaining students were from the humanities and social sciences. The researchers calculated the sample size of the study using the Raosoft calculator online with a 95% confidence level and a 5% margin of error for the 17,000 target population. The recommended sample size was 376. However, during data collection, the researcher failed to meet the recommended sample size due to the limitations of voluntary participation and the randomized sampling technique applied in the study. The researchers sent an online survey to various WeChat groups on popular social media platforms in China.

TABLE 1 Demographic profile of the respondents.

Demographic profile	Frequency
Gender	167
Male	94
Female	73
Year level	167
First year	99
Sophomore	44
Junior	15
Senior	10
Age	167
16–18 years old	29
19–21 years old	124
22–24 years old	13
25–27 years old	1
Discipline	167
Engineering	60
Humanities	4
Social Sciences	3
Arts	0
Computer science	101

3.2 Instruments, procedure, and ethical considerations

The instrument used in this study was adopted and modified based on Petricini et al. (2023). Originally, the survey instrument was designed for faculty and students based on their familiarity with and attitudes toward AI. In this study, the researchers used eight items for the familiarity domain and 14 for attitudes toward AI. The researchers did not include items from the original survey; rather, they added more questions regarding the perceived risks and benefits of Artificial Intelligence in higher education in an open-ended format. All quantitative items were tested for reliability using Cronbach's alpha, and 0.834 using Cronbach's alpha, which is sufficiently reliable. The survey used a Likert scale, where 1 = strongly disagree, and 5 = strongly agree. Two open-ended questions on the survey questionnaire asked the students about the perceived risks and benefits of AI in education. The online survey was designed in both English and Chinese. Before its widespread distribution, it was first tested with 20 undergraduate students for face validity. Moreover, the first author is fluent in both English and Chinese. Responses to the open-ended questions were given in both languages; some were in English, while others were in Chinese. All responses in Chinese were translated into English.

Prior to data collection, the researchers ensured ethical considerations while conducting the surveys. The survey asked respondents for informed consent to collect their information and invite them to participate in the survey. Moreover, researchers do not collect identifiable information, such as real names and addresses. The questionnaire was published on the *Sojump* platform, a Chinese data collection platform. The survey was distributed through various WeChat groups in the selected research locale. The survey was conducted over a month during the second semester of the 2023–2024 academic year.

3.3 Data analysis

The one-sample Wilcoxon rank-sum test was first proposed by Wilcoxon in 1945. It is a nonparametric statistical test used to determine whether there is a significant difference between the median of a sample and its hypothesized population median. Using a Statistical Package for the Social Sciences (SPSS), the questionnaire data in Tables 2 and 3 can effectively handle small sample sizes, as they do not depend on strict sample size requirements. Second, for questions in the questionnaire designed as ratings (e.g., strongly agree, agree, neutral, disagree, and strongly disagree), the one-sample Wilcoxon signed-rank test can handle these ordered rating data and test whether there is a significant difference between the median familiarity and attitude of the student group and the hypothesized median familiarity and attitude of the population. This test focuses on comparing the median of the sample rather than the mean, which is consistent with the purpose of the attitude survey because the median can better reflect the central tendency, especially when the data distribution is skewed. By comparing the deviations from the median familiarity and attitude, it is possible to test whether students' familiarity and attitude tend toward a certain direction, such as whether they are generally positive or negative, which helps understand the overall tendency of the student group. The significance levels were $p < 0.05$ and $p < 0.01$. Based on this, for Tables 2, 3, corresponding to research question 1 the one-sample Wilcoxon rank-sum test was used to conduct an overall quantitative analysis of the data. Moreover, the researchers used ATLAS.ti 25 for word clouds and thematic analysis. Microsoft Excel and Power BI were used for data visualization.

TABLE 2 Chinese undergraduate students' familiarity with AI.

No	Question	Mean
1	I am familiar with the concept of artificial intelligence (AI).	3.329**
2	I am familiar with ChatGPT.	2.988
3	I have experience using ChatGPT.	3.168*
4	My instructors have addressed the use of AI (especially ChatGPT and other text and image generation tools) in my courses.	3.234*
5	My instructors have integrated AI generators like ChatGPT into their instruction.	2.928
6	I plan to use ChatGPT or similar tools for my coursework in the future.	3.521**
7	I have received instructions about how to use ChatGPT or similar tools.	3.132
8	I would be open to receiving instructions on using ChatGPT or similar tools.	3.719**

Significance level: $^{*}p < 0.05$, $^{**}p < 0.01$, (1: Strong Disagree-5: Strong agree).

4 Results

This study employed a mixed method design to explore the familiarity and attitudes of undergraduate students with artificial intelligence and the perceived risks, as well as the anticipated benefits of utilizing artificial intelligence in education. It invited 167 students from various disciplines to a private higher education institution.

Table 2 presents the familiarity of Chinese undergraduate students with artificial intelligence. The data were analyzed using a single sample Wilcoxon test, assuming that the median was 3 and the significance levels were 0.01 and 0.05, respectively. The results showed that Chinese students were familiar with the concept of artificial intelligence ($\mu = 3.329$, $p < 0.01$) and had experience using ChatGPT ($\mu = 3.168$, $p < 0.5$). The research shows that students are open to using ChatGPT and similar tools ($\mu = 3.521$, $p < 0.01$) for course tasks and

TABLE 3 Chinese undergraduate students' attitudes toward AI.

No	Items	Mean
1	Artificial intelligence (in the form of text and image generation) could be dangerous for students.	2.671**
2	Students use AI text-generation tools to complete coursework, which is prevalent in higher education.	3.240**
3	Students' use of AI text generation tools to complete coursework is inevitable.	3.357**
4	Something must be done to stop students from using AI.	2.545**
5	Artificial Intelligence has value in education.	3.754**
6	Students should not be restricted from using AI for coursework.	3.509**
7	The use of AI in education is very prevalent.	3.545**
8	AI is used in education for good and helpful reasons.	3.659**
9	AI is misused in education.	2.737**
10	Instructors misuse AI in academic settings.	2.5150**
11	Instructors use AI well in academic settings.	3.4012**
12	I would feel confident knowing an instructor was using an AI-created syllabus.	3.1437**
13	I trust AI to grade my course assignments and assessments instead of my instructor.	2.7246**
14	The use of AI text generation tools to complete coursework violates the university's academic integrity policies.	3.0060**

Significance level: $^{*}p < 0.05$, $^{**}p < 0.01$, (1: Strong Disagree-5: Strong agree).

to receiving guidance from ChatGPT and similar artificial intelligence-related tools ($\mu = 3.719$, $p < 0.01$), which is statistically significant. The results showed that the instructor talked about artificial intelligence in class (especially ChatGPT and other text and image generators) ($\mu = 3.234$, $p < 0.5$). However, the students believed that the instructor did not integrate these tools into their teaching ($\mu = 2.928$). Although the students knew all about artificial intelligence, they knew little about ChatGPT, which can be seen from the insignificant results ($\mu = 2.988$).

Table 3 introduces the attitudes of undergraduate students in China towards artificial intelligence. Research shows that students generally think that artificial intelligence is valuable in education ($\mu = 3.754$, $p < 0.01$), and the application of artificial intelligence is very common ($\mu = 3.545$, $p < 0.01$). There were sufficient and beneficial reasons for using AI in education ($\mu = 3.659$, $p < 0.01$). It was common ($\mu = 3.240$, $p < 0.01$) and inevitable ($\mu = 3.357$, $p < 0.01$) to use AI text-generation tools to complete course assignments in higher education. Artificial intelligence (in the form of text and image generation) could pose a danger to students ($\mu = 2.671$, $p < 0.01$), and measures should be taken to prevent students from using artificial intelligence ($\mu = 2.545$, $p < 0.01$). The students were not restricted from using artificial intelligence in their course assignments ($\mu = 3.509$, $p < 0.01$). Students generally held a negative attitude towards the view that artificial intelligence is misused (*item 9*, $\mu = 2.737$, $p < 0.01$), and Item 14 held a neutral attitude ($\mu = 3.0060$, $p < 0.01$) toward the view that using artificial intelligence text generation tools to complete course assignments violates the academic integrity policy of universities. In addition, students thought that teachers could use artificial intelligence in the academic environment in a standardized manner ($\mu = 3.4012$, $p < 0.01$). Moreover, students' concerns about the misuse of AI by instructors were minimal ($\mu = 2.5150$, $p < 0.01$), which is reflected in the significance of the analysis results. In addition, students still had a positive attitude toward teachers' use of AI to create teaching syllabi ($\mu = 3.1437$, $p < 0.01$). However, students were neutral in that artificial intelligence could replace their teachers in grading course assignments and evaluations ($\mu = 2.7246$, $p < 0.01$).

Figure 2 shows the respondents' reasons for using Artificial Intelligence. Individual learning had the highest frequency among respondents. Artificial intelligence, such as ChatGPT, provides personalized learning experiences. Asking questions was the second-most mentioned need. AI has significant advantages in quickly providing information, knowledge, and solutions and can significantly improve efficiency and convenience, thereby enhancing students' intention to use AI technology. In addition, the use of AI in learning helps respondents to save time when searching for information quickly. Learning-related courses, translation, coding, generating ideas, and getting help with homework are connected to the first factor that helps students with their individual learning. Career guidance is another interesting reason that appeared among most respondents who used AI to search for a job and prepare for the job market, which helps students in their future job prospects. Language practice was another benefit of using AI among the respondents. Respondents perceived that using AI provided them with an alternative to learning a new language on the Internet or in their classes. Research support, mental health support, and others received the least reason among the students to use AI.

In the survey, respondents were asked about the perceived risks and potential challenges of using Artificial Intelligence in education. According to the respondents, the integration of AI in education presents several challenges (see Figure 3), namely dependence and reduced independent thinking, algorithmic bias and ethical concerns, accuracy and information quality, data security, and privacy concerns. The following are the five major themes based on respondents' responses:

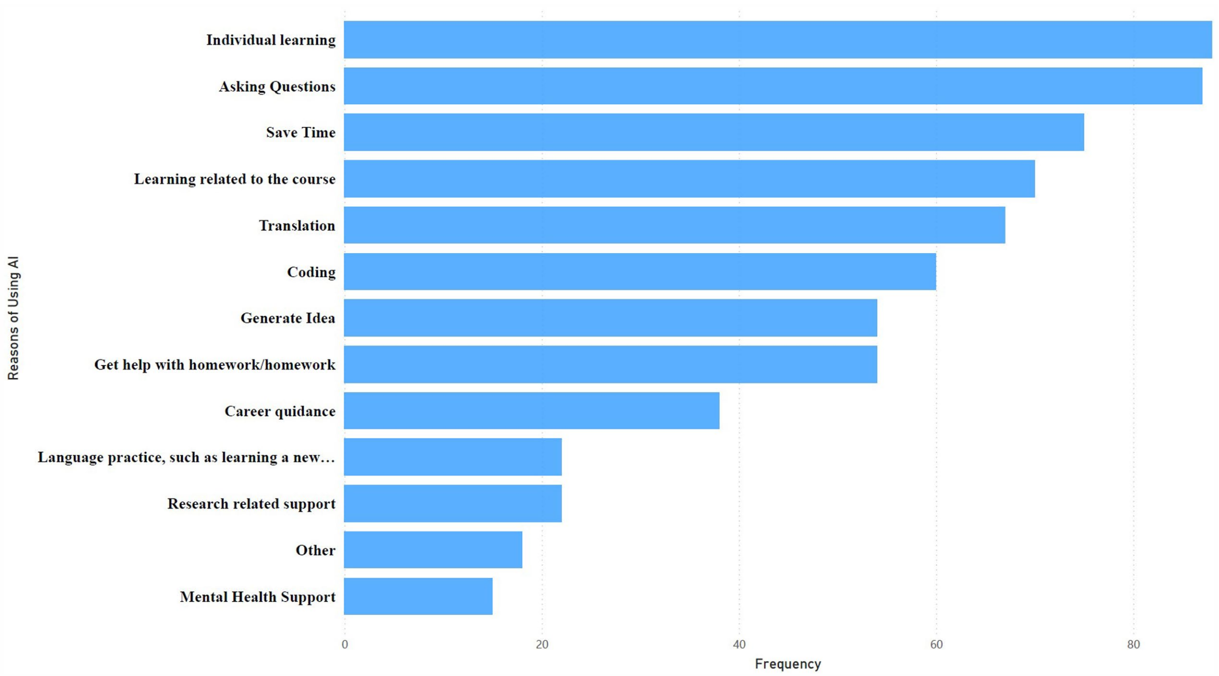

FIGURE 2
Perceived Benefits of Using Artificial Intelligence. Note. This figure is generated by the authors.

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4.1 Dependence and reduced independent thinking

Respondents' concerns about dependency on AI technology may result in over-reliance, thus impairing the development of human abilities and the capacity for autonomous decision-making. This reliance may impede students' critical thinking and problem-solving skills. Several respondents expressed concerns that students might prioritize AI-generated answers over their own reasoning. For instance, one respondent noted that students often turn to AI for quick solutions instead of engaging in their own thought processes, stating, "*Sometimes, if you encounter a problem in learning, in order to complete the task quickly, you will not find the answer through your own thinking for the first time, but directly rely on the answer generated by AI.*" Another participant highlighted that this reliance could lead to a lack of creativity and independent thought, mentioning, "*If there are any questions, they will first ask artificial intelligence without their own thinking, and the final thinking will only be limited to the answers given by artificial intelligence, which resulted to a lack creativity.*"

4.2 Algorithmic bias and ethical concerns

Based on their demographics, many of the respondents were from computer science and engineering. According to the respondents, the use of AI in education has ethical concerns, especially in relation to algorithmic bias and discrimination. These biases may influence decision-making processes and result in the inequitable treatment of students based on erroneous data or algorithms, thus compromising the integrity of educational evaluations. For instance, one respondent noted that biases could manifest in AI's recommendations, which might limit students' freedom of choice and affect their autonomy. One respondent mentioned, "*AI systems may influence students' learning decisions by recommending learning content and paths, which may limit students' freedom of choice and affect their autonomy and initiative.*" This reflects a broader ethical concern regarding the role of AI in shaping the educational experience.

4.3 Accuracy and information quality

Students noted that using AI to ask questions about their academic tasks was disadvantageous in terms of the quality and accuracy of information. Students considered apprehensions about the precision of the information supplied by AI (i.e., ChatGPT and DeepSeek). The respondents were concerned that AI might propagate inaccurate or misleading information that is potentially detrimental to their learning and decision-making processes. Respondents expressed skepticism about the accuracy of AI-generated content, emphasizing that it may not always meet professional or academic standards. One respondent noted,' *I do not think the authenticity of the generated content of generative artificial intelligence such as ChatGPT can be guaranteed. Its answers to some questions are not very professional and accurate.*" This reflects a broader concern that, while AI can provide quick answers, the quality of those answers may be lacking, which can lead to misinformation. Another respondent echoed this sentiment, stating,' *The main risk is that I do not think the reliability of artificial intelligence is very high. If artificial intelligence suddenly breaks down, it will lead to the stagnation of the whole project or industry.*" This highlights the potential consequences of relying on AI for critical tasks, which could have significant implications if inaccuracies are not addressed.

4.4 Data security and privacy concerns

Another issue raised by the respondents pertains to concerns regarding data security and privacy. Students observed that ChatGPT is not readily accessible in China and that access necessitates the use of a

FIGURE 3
Perceived risks of using AI in education. The authors generated this word cloud using ATLAS.ti 25 software.

Virtual Private Network (VPN). The integration of artificial intelligence into educational settings raises significant concerns regarding data security and personal information protection. Students expressed concern regarding the processes involved in the collection, storage, and utilization of personal data, which may lead to breaches of privacy and deterioration of trust in the provider. Respondents expressed apprehension about how AI tools require extensive data to function effectively, which raises serious privacy concerns. One respondent pointed out, "*AI systems usually need to collect a large amount of personal data to provide a personalized learning experience, which may include information such as students' grades, study habits, and personal interests. The collection and use of such data raises the risk of privacy violations.*" This highlights the potential for sensitive information to be mishandled or exposed, thereby leading to significant consequences for individuals. Another respondent echoed these concerns, stating,' *Once these data are leaked, it will be a great loss to individuals, society, and the country. Therefore, there are serious ethical problems*." This underscores the broader implications of data security breaches, not just for individuals but also for societal trust in educational institutions and technologies.

5 Discussion

This study investigated undergraduate students' familiarity with and attitudes toward AI tools, as well as their perceived risks and benefits of using AI tools in higher education. It invited 167 students from various disciplines to a private higher education institution.

Regarding the familiarity of students with Artificial Intelligence, the findings showed that students were moderately familiar with AI tools. Students had some experience in using ChatGPT; however, their knowledge of ChatGPT remained limited. Moreover, students showed an opening to AI tools such as ChatGPT and similar AI tools for completing their course tasks and opened with AI discussions in class. Comparing these findings with Petricini et al.'s (2023) study, students and faculty have mixed opinions on AI. However, the findings of this study demonstrate a level of familiarity with AI. Moreover, in a similar study by Horowitz et al. (2024), familiarity with AI comes together with trust to fully utilize it. However, there are certain aspects of AI that society must explore. In addition, studies have shown similar findings about students' high degree of familiarity with AI in their studies (Nikoulina and Caroni, 2024; Sahari, 2024).

Regarding students' attitudes toward AI, the findings revealed that they believe that AI has significant value in education and see it as an inevitable integration into higher education. Students support their teachers in using AI in teacher instruction but do not believe that AI can replace teachers in grading assignments. A systematic review of AI research has revealed that cultural factors play a significant role in the perception that AI cannot substitute for teachers in education (Kelly et al., 2023). This finding corroborates the research conducted by Tlili et al. (2023), which indicates a positive outcome and reflects the growing enthusiasm for its application in learning environments. Furthermore, a study conducted with secondary students in Pune city revealed a strong positive attitude towards AI, suggesting an overall favorable perception among the participants (Pande et al., 2023). Similarly, students in Spain pursuing studies in economics, business management, and education demonstrated awareness of the influence of artificial intelligence. They expressed a willingness to enhance their educational pursuits in this area, even though their current understanding may be somewhat limited (Almaraz-López et al., 2023).

In addition, respondents perceived the benefits of AI in education, including personalized learning, efficiency, information retrieval, career guidance, research support, and mental health support. AI helps students to improve their learning of new languages through independent learning. The benefits of AI in education are recognized in achieving development goals (UNESCO, 2019, 2021b). Furthermore, research indicates that AI facilitates individualized learning experiences by adjusting to the specific requirements of each student and offering customized material and feedback (Pan et al., 2023; Rizvi, 2023). However, despite their positive attitudes toward AI and its perceived benefits, students are worried about the potential dangers of AI. Students recognized substantial concerns concerning ethical use, dependence, reduced independent thinking, accuracy, data privacy, and security. Thus, it is crucial to address ethical concerns such as data privacy and algorithmic fairness to guarantee the responsible implementation of AI (Kaswan et al., 2024; Trivedi, 2023).

5.1 Theoretical implication

This study deepens the understanding of Artificial Intelligence in education research by examining it through the Technology Acceptance Model (TAM). These results underscore the importance of AI literacy for both students and educators. Furthermore, the function of AI as a substitute for human services, including career guidance and tutoring, broadens our understanding of its perceived usefulness. The findings indicate that students are more likely to embrace AI tools when they view them as easy to use and readily available, aligning with the principle that ease of use impacts acceptance. Nonetheless, the absence of complete confidence in AI among students highlights the essential importance of "trust" in this case. Context-specific adaptations are crucial for a deeper understanding of the factors that shape students' intention to utilize AI. Moreover, the results highlight ethical considerations, including algorithmic bias and data privacy, within the framework of TAM, indicating that these factors could greatly influence users' perceived trust and, in turn, their acceptance of AI.

5.2 Implications for higher education institutions

Based on these findings, this study offers recommendations for higher education to properly use AI in education.

1. Inclusion of AI in the student's curriculum. Higher education institutions (HEIs) may consider one course of AI learning to help students understand the use and proper utilization of AI in their studies. According to Aliabadi et al. (2023), artificial Intelligence should be included across the curriculum, transitioning from a topic of personal preference to an integrated component across many.
2. Creating an ethical framework or Guidelines for both students and teachers on AI. The implementation of an ethical framework for AI in HEIs can guide students and teachers in using AI in teaching and learning. HEIs may consider creating an inclusive framework grounded in the opinions of students and teachers. Utilizing frameworks that prioritize fairness, accountability, transparency, and ethics can effectively reduce risks (Sjödén, 2020).

3 Provide training for teachers on the proper use of AI. According to the findings, the students were aware that their teachers utilized AI in their teaching. HEIs can provide additional professional development every school year to help teachers update the development of AI in education, making them more responsive to change. Enhancing teacher training enabled teachers to deliver effective instruction, as students recognized teachers' positive attitudes toward utilizing AI in their teaching methods. Furthermore, allocating resources towards AI literacy and professional development for teachers can significantly improve their capacity to utilize AI in a manner that is both effective and ethical (AbuJarour and AbuJarour, 2023; Velander et al., 2024).

6 Conclusion, limitations, and future directions

This study investigated undergraduate students' familiarity with and attitudes toward AI tools, as well as their perceived risks and benefits of using these tools in the context of a private university in China. The findings revealed that undergraduate students demonstrated moderate familiarity with AI, specifically their awareness of using ChatGPT. However, students showed openness to using ChatGPT and similar tools in coursework and were willing to receive instruction using these tools. In terms of their attitude, students generally viewed AI positively and perceived AI integration as inevitable and becoming common in academic settings. Students were concerned that the misuse of AI by their teachers was minimal and trusted their teachers to use AI effectively in teaching. The perceived benefits can be summarized as personalized learning, efficiency and convenience, career and skill development, and support for independent learning. In terms of perceived risk, students are worried about being dependent and reducing their independent thinking, algorithmic bias and ethical concerns, accuracy and information quality, data security, and privacy concerns. Although this study used a mixed survey method to explore the situation of artificial intelligence in a private university, it has many limitations. Moreover, future researchers should consider studying a more comprehensive and extensive analysis of private universities, and data from multiple private universities should be combined for comparative analysis. Furthermore, this study recommends the integration of ethical AI into curricula, training teachers to guide students, and adopting the ethical framework suggested.

Data availability statement

The study data is available upon request from the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants or participants legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements. The researchers are committed to protecting participants by ensuring anonymity and voluntary participation, in accordance with the Declaration of Helsinki. No identifiable data were collected from the participants.

Author contributions

YL: Conceptualization, Data curation, Methodology, Writing – original draft, Formal analysis, Investigation, Visualization. NC: Conceptualization, Formal analysis, Methodology, Resources, Supervision, Writing – review & editing. XX: Funding acquisition, Methodology, Project administration, Resources, Software, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that Grammarly and QuillBot, as Generative AI tools, were used to enhance the readability and language quality of this manuscript.

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Implementing artificial intelligence in academic and administrative processes through responsible strategic leadership in the higher education institutions

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Artificial Intelligence (AI) has enormous potential to make a transformative impact in multiple fields. It has made significant strides in Higher Education by reshaping traditional administrative processes, learning, leadership, and teaching. This review explores the substantial impact of integrating AI in Higher Education Institutions (HEIs), from improving education delivery to enhancing student outcomes and streamlining administrative processes and strategic leadership. By catering to the diverse learning needs of students with the help of tools that directly affect academics, monitor student engagement and performance, and provide data-driven interventions, AI offers what the HEIs have long been waiting for to revolutionize the overall Higher Education landscape. This review also highlights that with AI's ability to streamline administrative tasks by enhancing admissions and enrolment processes, academic records management system, and financial aid and scholarships processes, AI not only facilitates improving the overall processes but also makes staff and faculty members focus less on mundane and monotonous tasks, hence concentrating more on the responsibilities and strategic initiatives that require focused attention. We identified that the key to unlocking the significant potential of AI is responsible strategic leadership. Strategic leadership requires aligning AI integration goals with the strategic mission of HEIs, fostering an environment ready to embrace innovation and ensuring that the required accountability and governance frameworks are in place for AI integration and usage. It is also the role of leadership to consider ethical considerations, collaborations with the relevant stakeholders, concerns about job displacement, and potential biases, ensuring that AI is used to its full potential for the benefit of faculty, staff, students, and society. We conclude the paper with AI-driven future implications, i.e., emerging technologies, continuous enhancement and AI-based enhanced research accomplishments.

KEYWORDS

higher education institutions (HEIs), artificial intelligence (AI), AI-driven administrative processes, strategic leadership, education—active learning

1 Introduction

Artificial intelligence (AI) has become predominant in modern society, affecting several domains and fundamentally altering the nature of work and various aspects of day-to-day activities (Khan and Yasir, 2024). In this regard, AI retains the potential to influence higher education institutions (HEIs) on a broader spectrum. Universities and other educational institutions actively investigate how to incorporate AI into their research capacities, administrative procedures, and pedagogical practices to enhance these imperative areas (Lee et al., 2024). However, introducing AI into HEIs brings a multi-layered potential and complexities that need scientific research for its wider acceptability and implementation (Saaida, 2023; Rashid et al., 2024). Higher education has seen a radical change due to AI technologies (Ozfidan et al., 2024), which have opened up opportunities for data-driven decision-making, individualized learning, and creative pedagogical approaches (Rahiman and Kodikal, 2024). Large volumes of data may be sorted through adaptive learning systems, allowing for the development of customized learning routes that complement each student's unique learning preferences, styles, and aptitudes, thereby improving their educational experience (Gligorea, 2023). AI-powered intelligent tutoring solutions provide students with immediate feedback and assistance, enabling them to understand different subjects and attain better learning objectives (Lin et al., 2023). Moreover, virtual learning assistants (Pogorskiy and Beckmann, 2023) are an AI-driven innovation that has the potential to enhance student engagement by providing prompt support and promoting communication. By reinventing how education is delivered and experienced in the twenty-first century, integrating these AI technologies in HEIs opens up novel pedagogical possibilities.

Previous research demonstrated that integrating AI in universities may result in cost-effective and efficient administrative process optimisation (Crompton and Burke, 2023). AI-powered solutions may automate repetitive processes like financial aid processing, enrolment management, and student admissions to facilitate several key projects. AI-driven predictive analytics helps academic institutions spot patterns and trends that help them make data-driven decisions about resource allocation, budgeting, and focused interventions that boost student achievement. Additionally, AI can improve research capacities by accelerating academic inquiry through data analysis automation, research gap identification, and insights generation from academic publications (Rafik, 2023). A new age of efficient and data-driven decision-making might be ushered in by integrating AI into administrative procedures, with far-reaching impacts on higher education.

The research study (Crompton and Burke, 2023) also focused on the challenges associated with integrating AI into higher education. The biases in AI systems (Varsha, 2023) raise questions about end-to-end accountability, transparency, privacy and security (Cen and Alur, 2024) by running the risk of sustaining current disparities. Robust data governance, informed consent, and cyber security measures are critical for guaranteeing the privacy and security of student data in AI-driven systems (Farayola et al., 2024). Another issue is how AI will affect faculty positions and lead to job displacement, i.e., proactive steps to assist faculty in this transformation are needed (Aithal et al., 2024). Careful strategic planning is necessary when institutions incorporate AI to guarantee its ethical and responsible application (Chan, 2023) in higher education environments.

The research study highlighted that considering the pedagogical consequences of AI integration in higher education is indispensable (Wang and Pange, 2023). Due diligence is required for the ethical use of AI in assessment, balancing human and AI-driven education, and analysis of the effects on student motivation and engagement (George, 2023). Furthermore, concerns about the use of AI in decision-making procedures that have historically relied heavily on human judgment, such as student admissions, may surface (Naseer et al., 2024). Hence, an evaluation of these aspects, where Higher Education Institutions (HEIs) incorporate AI, is crucial to ensure the appropriate and efficient application of AI technologies in HEIs.

This study reviews the advantages and disadvantages of integrating AI into higher education. It draws attention to how AI has the potential to transform education, streamline administrative procedures, and advance research capacities (Singh, 2023). However, it also raises questions regarding ethical issues, biases, the influence of AI on faculty positions, pedagogical consequences, and the overuse of AI in decision-making processes (Wang, 2021). The study highlights the necessity of using AI in higher education responsibly and morally. It also reports the significance of more research and cooperative efforts between academia, industry, and government to analyse and evaluate AI's potential for students, teachers, and society. The authors in Leoste et al. (2021) highlight that the implications of integrating AI into higher education offers both potential and obstacles, which is the pivotal point of this study. Concerns about biases, ethical issues, and the effects on academic duties are all covered by the possible advantages of AI (Alam, 2023a). It will allow AI in higher education to reach its full potential and benefit students, teachers, and society.

1.1 Objectives and motivation

The developments in AI have transformed various domains in the real world, such as education, finance, healthcare, etc. Personalized learning (George and Wooden, 2023), early intervention and student support (Zhao and Otteson, 2024), language processing and translation (Gayam, 2021), early detection and diagnosis of diseases (Saleh et al., 2022), medical imaging (Rajpurkar and Lungren, 2023), fraud detection (Javaid, 2024), customer support and quality assurance (Chen and Xiong, 2023) are just a few examples. However, the misuse of AI-driven technologies (Pöhler et al., 2024), fake news dissemination (Harris et al., 2023) and drastic effects of widespread AI-generated content (Mitrou, 2024) are also perceived. However, it cannot be denied that AI has driven efficiency, innovation, and personalisation, changing how we work, learn, heal, and interact in a world where everything is connected by technology. Thus, this review is aimed to highlight the impact of AI on HEIs and strategic leadership as shown in Figure 1. Table 1 presents the advantages and challenges of AI integration in HEIs. The objectives of this paper are as follows:

- Analyzing the uses of AI in HEIs and highlighting the development and current situation.

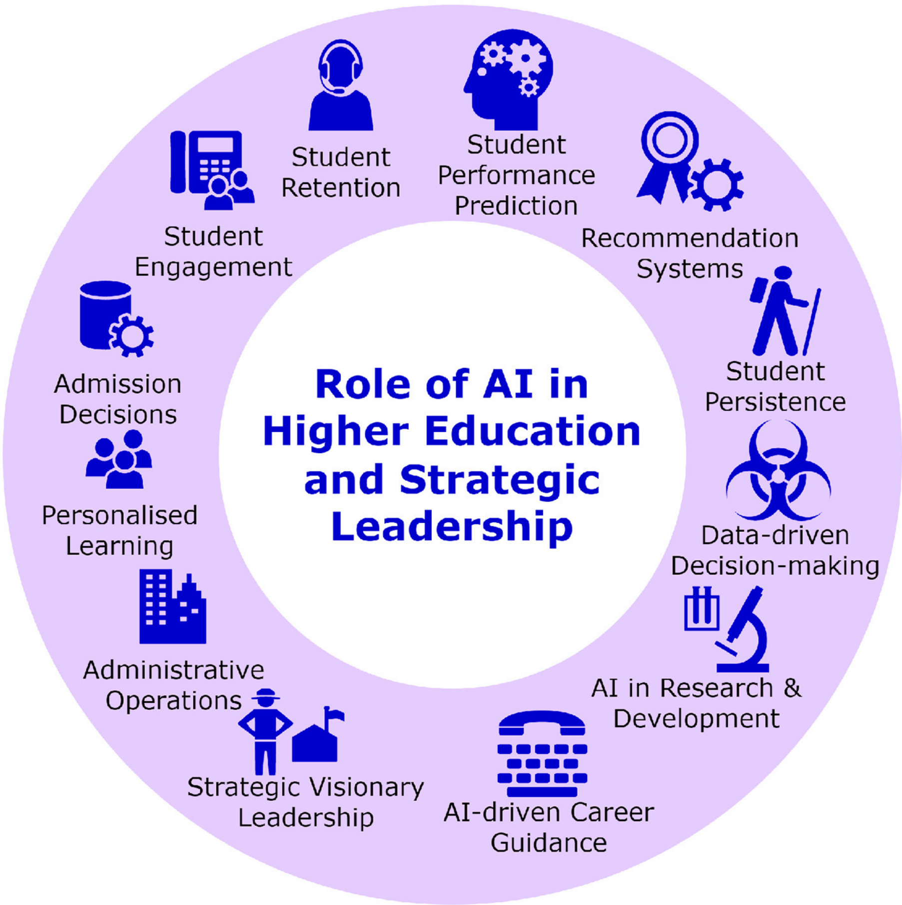

FIGURE 1
Various aspects of AI's role in higher education institutions (HEIs) and strategic leadership.

- Investigating the role of AI in improving the quality of education focused on personalized learning, student engagement, retention and performance prediction.
- Presenting the comprehensive overview of AI-driven career guidance and effects of AI in Research and Development in HEIs.
- Identifying how AI can facilitate data-driven decision-making, administrative operations and strategic visionary leadership.

1.2 Contributions to higher education institutes (HEIs) and leadership in AI era

This review analyses the role of AI in HEIs and its impacts on strategic visionary leadership, focused on progressive perceptions that are disregarded in the existing literature. The contributions of our review to the existing reviews on AI integration in HEIs are shown in Table 2. We also highlight the future research directions in this area. Thus, this review presents:

- Emphasizing the unparalleled benefits of AI to improve student success metrics (engagement, retention, persistence, performance prediction, graduation rates, and career placement) and designing relevant recommendation systems.
- Using AI's potential to address contemporary educational challenges, from making personalized learning possible to streamlining administrative processes, especially admissions-related processes.
- Highlighting how AI's potential can be harnessed to make informed decisions and facilitate research and development, enhancing the overall leadership capabilities.
- Exploring digital leadership in the age of artificial intelligence and the related challenges leaders face.
- Presenting a compelling call to action that challenges the researchers and HEIs' leaders to rethink traditional educational models and collaborative practices, ensuring that higher education not only endures but thrives with relevance, resilience, and responsiveness in the AI-driven era.

1.3 Comparison with the existing literature reviews on AI integration in HEIs

To highlight the contributions and significance of this review, we compared it with the related existing reviews

TABLE 1 Advantages and challenges of AI integration in HEIs.

HEIs aspects	Advantages of AI	Challenges of AI integration
Academics	• Personalized and adaptive learning systems • Personalized content for the students • Automated grading • Enhanced teaching efficiency and learning outcomes • Early warning of possible dropout issues • Preventive assistance • Monitoring attendance and success metrics	• Potential biases in AI algorithms • Privacy and data security issues • Over-reliance on technology
Administration	• Automated scheduling • Reduced administrative constraints • Robust processes • Efficient enrolment systems • Financial aid analysis • AI chatbots for assistance • Records management • Resource management • Security aspects • Career services	• Potential biases in AI-driven systems • Privacy and data security issues • Concerns about fairness • Challenges regarding wide-acceptability • Diminished human intervention
Strategic leadership	• Data-driven decision making • Enhanced strategic planning • Stakeholders' involvement • Diversity at all leadership and decision-making levels • Authenticity and accountability • Interdisciplinary collaboration • Effective management of institutional resources • Long-term plans to address social demands, technical breakthroughs, and worldwide trends • Ensures consistency with institutional values for advanced and equitable results	• Ethical concerns • Balancing innovation with privacy and security

in the field. The review in Zawacki-Richter et al. (2019) demonstrated the importance of AI integration in HEIs focused on Student Success Metrics, i.e., tutoring systems, grading and feedback support, adaptive learning platforms, predictive analytics, reinforcements for support and AI-based systems for admissions and enrolment. The literature review (Chen and Lin, 2020) expanded the existing areas of AI integration in HEIs and also discussed the role of AI-based career services and emerging technologies, such as Virtual Reality (VR) and Augmented Reality (AR). The researchers in Huang et al. (2021) concentrated on AI's role in Student Success Metrics and some AI-driven administrative processes, such as optimal course scheduling, security aspects, i.e., privacy challenges, and overall advantages and challenges of AI-driven automation along with emerging technologies in HEIs. The literature review (Ouyang et al., 2022) also focused on AI-driven student success metrics, resource management, optimal course scheduling and emerging technologies in HEIs. The research study (Crompton and Burke, 2023) highlighted the significance of AI integration in HEIs with its impact on tutoring systems, grading and feedback support, adaptive learning platforms and predictive analytics. The literature review (Chiu et al., 2023) also explained the effectiveness and challenges of AI-based automated mechanisms for tutoring systems, grading and feedback support, adaptive learning platforms, predictive analytics and reinforcements for support. The research study (Alqahtani et al., 2023) highlighted the efficacy of AI-driven mechanisms in HEIs by highlighting their role in current student success metrics and future implications and transformations in HEIs. The review (Bond et al., 2024) discussed the potential advantages and challenges of AI integration in HEIs and comprehended student success metrics, some administrative processes, such as admissions and enrolment, student record management, resource management and optimal course scheduling, career services and overall advantages and challenges. Our review fills the gap in the existing reviews by focusing on AI integration in HEIs concerning its adaptability to student success metrics with improvement in administrative processes and its impact on the role of responsible strategic leadership and AI-driven future implications and transformations in HEIs.

1.4 AI implementation process in HEIs

AI plays a transformative role in HEIs across three key domains, i.e., academic, administrative, and leadership, presented in Figure 2. The comparison with the existing studies indicates the significance of this review in terms of the AI Implementation process in HEIs shown in Figure 3, which is overlooked. In the educational sphere, AI enables adaptive learning systems that personalize content and automate grading, enhancing teaching efficiency and learning outcomes. The administrative sphere benefits from AI by automating critical processes, such as enrolment, record-keeping, and financial aid management, streamlining operations and reducing human error. In the leadership sphere, AI supports data-driven decision-making by providing advanced analytics for policy formulation, strategic planning, and resource optimization, helping institutional leaders make informed decisions that align with institutional goals and improve overall efficiency. This review also determines that integrating AI into HEIs involves several critical stages. It begins with strategic goal alignment, where specific goals for AI integration are defined to align

TABLE 2 Comparison with the existing literature reviews on AI in HEIs.

Ref + Year	AI's Role in Student Success Metrics						AI's Role in Administrative Processes							AI Integration and Role of Responsible Strategic Leadership				AI-driven Future Implications and Transformations in HEIs		
	Direct Effects on Academics			Student Progress & Engagement Monitoring	Data-driven Interventions in HEIs		Admissions & Enrolment	Students Record Management	Scholarships & Financial Assistance	Resource Management & Optimal Course Scheduling	Security Aspects in HEIs	Career Services	Advantages and Challenges	Effective Leadership Frameworks	Strategic Visionary Leadership and Goal Alignment	Importance of Fostering an Innovation-Driven Environment	Accountability and Governance Frameworks	Emerging Technologies	Continuous Enhancement	Enhanced Research Accomplishments
	Tutoring Systems	Grading & Feedback Support	Adaptive Learning Platforms	Monitoring attendance, engagement, and performance	Predictive Analytics	Reinforcements for Support														
[131] 2019	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	×
[132] 2020	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	✓	×	×	×	×	×	✓	×	×
[134] 2021	✓	✓	✓	✓	✓	×	×	×	×	✓	✓	×	✓	×	×	×	×	✓	×	×
[133] 2022	✓	✓	✓	✓	✓	×	×	×	×	✓	×	×	×	×	×	×	×	✓	×	×
[8] 2023	✓	✓	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
[130] 2023	✓	✓	✓	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	×
[136] 2023	✓	✓	✓	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	✓	✓	✓
[135] 2024	✓	✓	✓	✓	✓	×	✓	✓	×	✓	×	✓	✓	×	×	×	×	×	×	×
Our Review	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

with the institution's strategic policies and defined mission. Next is stakeholder collaboration, which involves engaging faculty, students, and administrative staff to ensure buy-in and collective support for the initiative. This process is followed by AI tool selection, where tools are identified to address academic, administrative, and leadership needs effectively. In the integration phase, AI is gradually implemented in processes, i.e., admissions, teaching, and records management. A robust framework for governance and accountability is developed, including ethical guidelines and governance mechanisms to ensure ethical and responsible use. Finally, evaluation and continuous improvement are undertaken by measuring outcomes, gathering feedback, and refining AI systems to ensure they remain effective and aligned with institutional goals.

2 Methodology

This literature review analyses and evaluates the existing literature on the Role of AI in HEIs and its impacts on strategic visionary leadership. This integrated approach covers comprehensive research studies in this domain. An empirical investigation using primary data is challenging since the widespread application of AI in HEIs and leadership is still novel. However, this study identifies and presents a comprehensive review of the practices and prospective approaches to integrate AI in HEIs effectively. The review paper overflow is presented in Figure 4, and the methodology for this literature review is detailed in Figure 5.

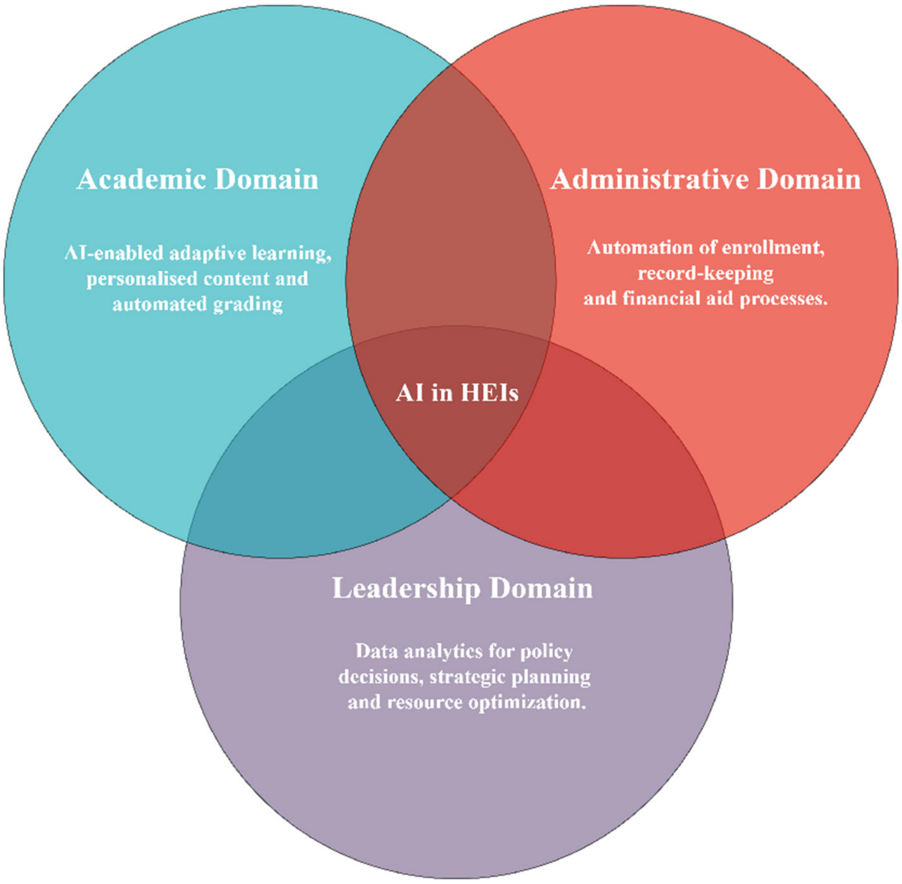

FIGURE 2
AI's role in academic, administrative and strategic leadership processes in HEIs.

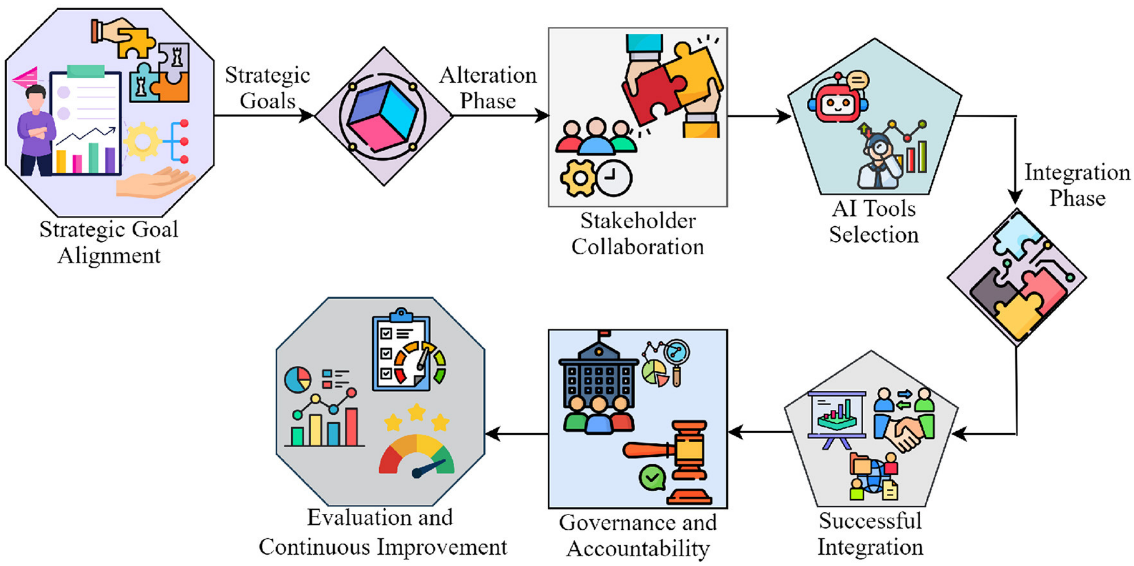

FIGURE 3
AI implementation process in HEIs.

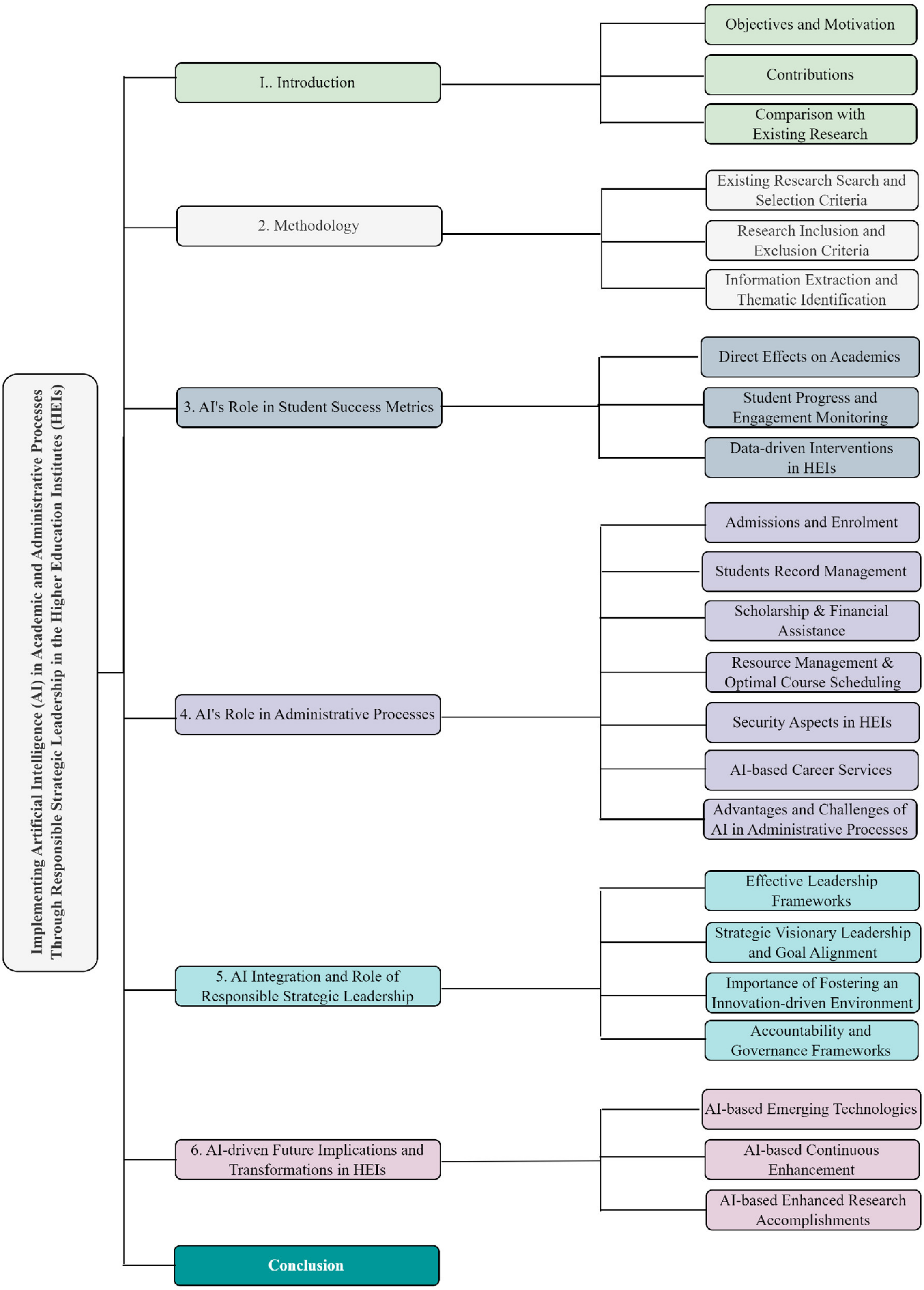

FIGURE 4
Review paper flow.

2.1 Existing research studies' search and selection criteria

The existing research offers valuable insights into the current state of AI in education, from the emergence of online learning platforms to the more complex uses of AI for administrative automation and personalized learning. However, the existing research studies overlook the current wave of AI in HEIs from various perspectives and strategic leadership. The focal point of the existing studies was digital transformation, which failed to highlight the role of AI in HEIs and its automation process in general. Therefore, this review presents the AI revolution in HEIs with its diverse impacts on students, administrative systems and strategic leadership.

We used different academic search engines comprehensively for the pertinent papers, such as Google Scholar, Semantic Scholar, Scopus, etc. Multiple keywords were used to acquire the relevant research studies. The terms "AI in Higher Education," "Higher Education in the AI Era," "Leadership in Higher Education in the AI Era," "AI Transformations in Higher Education," "Facilitating Administrative Processes through AI in Higher Education," "Enhancing Leadership Potential through AI in Higher Education" were considered and used for the literature search.

2.2 Research inclusion and exclusion criteria

The inclusion criteria were based on the most recent research studies. We used existing relevant research studies published in 2019 or later. The research quality criteria were based on being indexed in reputable databases like Google Scholar, SCOPUS or Web of Science. We excluded the research studies that did not address AI or its implications in the context of higher education.

2.3 Information extraction and thematic identification

The relevant identified research studies that met the selection criteria were examined and compiled for this literature review. This process identified recurrent themes, and thus, we arranged the acquired information into various categories. This enabled us to collect and correlate multidimensional research findings on the role of AI in HEIs and its implications in strategic leadership. We used an analytical approach in this literature review to enable a comprehensive understanding of how AI will affect higher education in the future. The results of this review will provide insights for academia, instructors, legislators, and researchers on how AI may revolutionize higher education.

3 AI's role in student success metrics

Education is one of the most important areas where AI is used. Several AI applications and processes in the HEIs have been implemented, i.e., in-person instruction and intelligent online learning, and e-learning, which uses dynamic learning, ontologies, conceptual systems, computational linguistics, and state-of-the-art models to enable direct and personalized learning processes. Therefore, AI has become more significant in forming and improving student success metrics, which aids in better decision-making for HEIs and instructors. Significant components of AI-based student success metrics in HEIs are presented in Figure 6. Some of the highlighted significant areas in Table 3 where AI is helpful in HEIs are discussed as follows.

3.1 Direct effects on academics

3.1.1 AI-based tutoring systems

AI-based tutoring systems are used for personalized learning experiences (Alam, 2023b) for students, which provide them with activities and material pertinent to increasing their level of engagement. In addition to making learning more engaging and relevant, personalized learning may boost motivation by giving students a sense of control and ownership over their education. Personalized learning has been demonstrated to enhance learning results, especially for students who might find it difficult to learn using conventional methods. Moreover, augmented and virtual reality (AR/VR) are used to create immersive learning experiences that allow students to explore and engage with virtual settings and simulations (Familoni and Onyebuchi, 2024). This also enables them to customize according to their unique needs and skills and offer real-time feedback on their progress. Online learning systems provide students more freedom regarding when and where they learn and access the educational resources and courses around the globe. Technology-enabled learning that adapts to the learning style, speed, and progress of the learner is known as adaptive learning. In order to achieve this, algorithms are used to analyse student data, including test scores, and modify the pedagogy or content (Shoaib et al., 2024) as necessary. However, personalized learning analytics presents several challenges and difficulties (Chinta et al., 2024), such as the requirement for trustworthy data sources and the risk that biased algorithms or tailored suggestions could reinforce already-existing disparities. Although learning analytics personalisation has the potential to increase educational effectiveness, it is crucial to carefully weigh the advantages and disadvantages of this approach to ensure that it is just and equal for all students.

3.1.2 AI-based grading and feedback support

AI-based grading and feedback support systems use artificial intelligence to assess student work, provide feedback, and sometimes assign grades (Jonäll, 2024). These robust systems enable the instructors to concentrate more on instructional design (González-Calatayud et al., 2021) and less on mundane duties. Thus, AI allows educators to focus on student engagement, course design, and meeting individual learning requirements by automating grading and feedback. Moreover, these systems provide automated grading efficacy with standards and real-time responses. Multiple-choice tests, short-answer assessments and true or false questions are a few examples of AI-based

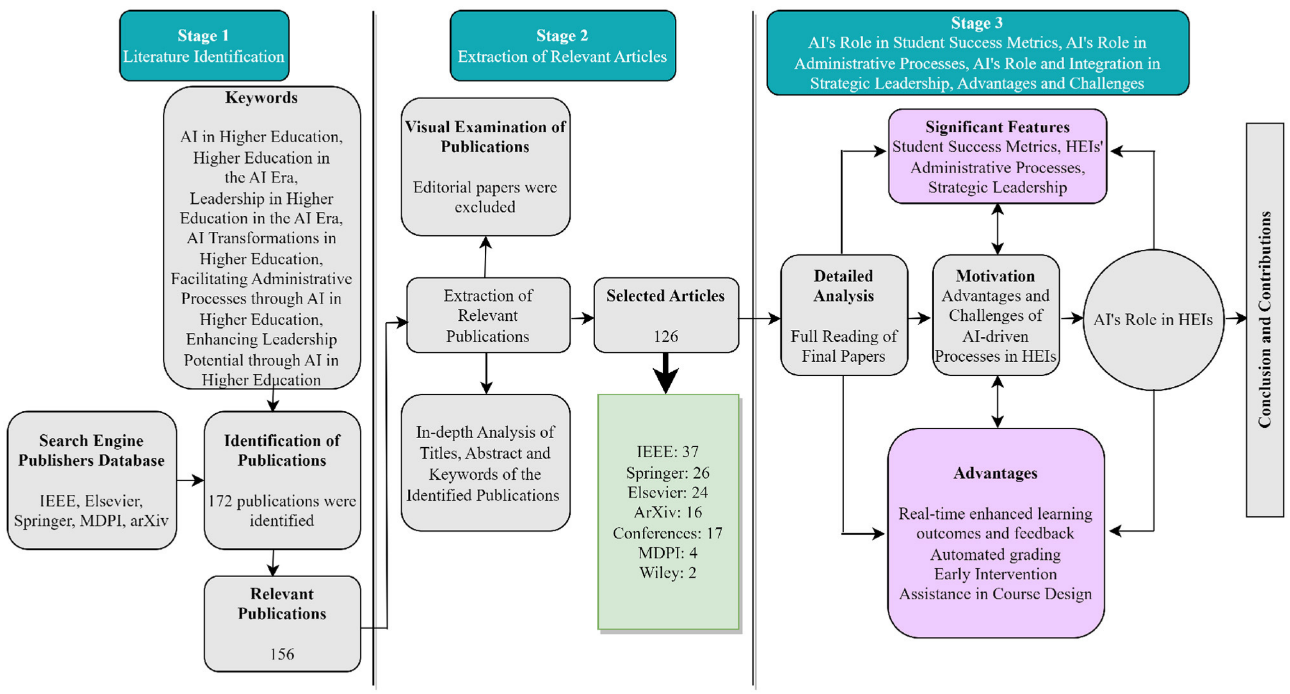

FIGURE 5
Literature review methodology and research studies' search and selection criteria.

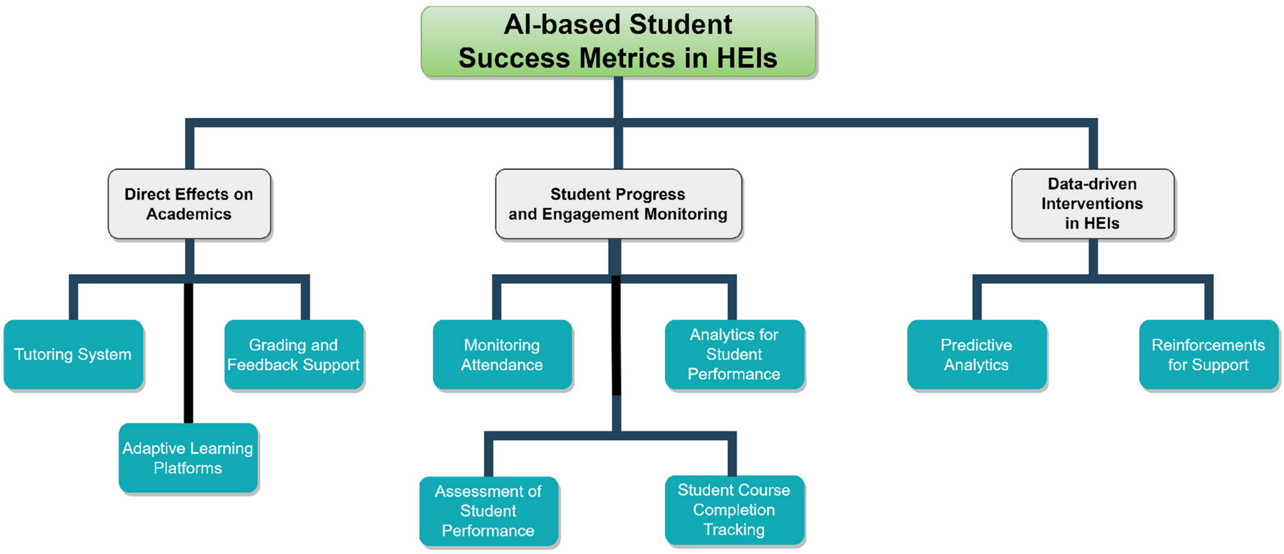

FIGURE 6
Significant components of AI-based student success metrics in HEIs.

grading systems (Owan et al., 2023). Additionally, these systems assess subjective assignments like essays by examining language, coherence, structure, and the logical flow of arguments using Natural Language Processing (NLP) techniques. Thus, AI-based systems offer prompt, tailored feedback and are helpful for big classrooms and online learning portals. As students advance through a course, these systems may also provide formative comments to assist them expound their abilities (Zhu and Lee, 2020). With its uniform methodology, AI-based grading reduces the biases present in human grading and produces more equitable results. These systems are helpful and scalable when dealing with courses where individualized feedback might be difficult. Long-term student achievement tracking by some AI techniques may yield insights for more focused help. However, AI-based grading has drawbacks, such as its inability to evaluate students' work for creativity or subtleties as well as a human teacher (Fagbohun et al., 2024). Lastly, algorithmic bias, data security, and privacy issues (Shwedeh et al., 2024) are important factors to be considered while deploying these systems in HEIs.

3.1.3 Adaptive learning platforms

AI-based adaptive learning platforms are tailored for student learning experiences (Kabudi et al., 2021) according to each student's unique needs, learning capability levels and their adopted pace. These systems include dynamic material and assessments, real-time feedback, individualized content delivery, scalability for different learning requirements, instructor assistance and insights, predictive analytics for early intervention, and improved student engagement (Ahamed and Hanirex, 2024). In order to provide individualized learning routes, personalized content delivery entails evaluating student preferences, inadequacies, and capabilities. Students may comprehend their success and areas for growth using real-time feedback. Videos, tests, interactive exercises, and simulations are dynamic content formats (Clark and Mayer, 2023) that keep students interested and accommodate various learning preferences. By identifying students who are in danger of falling behind or having difficulty with particular subjects, predictive analytics (Azcona and Smeaton, 2019) enables teachers to step in and offer more resources.

Presenting material in a thought-provoking way and at an appropriate degree of difficulty encourages students and lessens their frustration (Muir et al., 2019), which increases student engagement. These platforms' scalability enables them to accommodate learners ranging from novices to experts within a single system. Teachers may use each student's performance data to identify patterns, monitor development, and make informed decisions (Wise, 2019). Carnegie Learning, Smart Sparrow, Knewton, and DreamBox Learning are examples of AI-based adaptive learning solutions. However, these systems have issues like privacy and data, and uncertainties (Pedro et al., 2019) about relying too much on AI for learning. Notwithstanding these obstacles, AI-powered adaptive learning systems are a breakthrough in education, offering scalable, customized assistance to different learners and assisting students in HEIs.

3.2 AI-based student progress and engagement monitoring

3.2.1 Monitoring attendance

Automated Attendance records and monitors students' attendance using biometric devices or login credentials in virtual and real environments. AI can identify patterns in attendance behavior, such as persistent absences or late arrivals, which may be early signs of disengagement (Graven and MacKinnon, 2023). This data is combined with the student's performance in HEIs to determine the effect of attendance on grades and engagement. Once the data is analyzed, AI allows for proactive outreach by identifying possible attendance problems before they become more significant, followed by automated notifications (Atif et al., 2020) to the students in HEIs. Advisors and students receive alerts on poor attendance, which increases student accountability and permits prompt interventions.

3.2.2 Analytics for student engagement

Student contributions to online discussions (Ding and Orey, 2018) are tracked to distinguish between active and potentially disengaged students. Secondly, learning material-based tracking (Regan and Jesse, 2019) indicates how much time students spend on particular topics and provides information about their level of interest. Thirdly, it also tracks how frequently students interact with the course materials (Zhu et al., 2024), including how often they watch videos, take quizzes, and access resources. Analyzing peer collaboration helps distinguish between disengaged students and those who are well-integrated into peer networks (Darling-Hammond et al., 2020) by looking at trends in group interactions. Lastly, resource utilization evaluation examines how students in HEIs access learning resources (Chaka, 2020) to identify the most popular or effective materials. This offers a more thorough perspective of student involvement than just attendance and aids in detecting and filling in the gaps in students' interaction with the course materials. These results can be used to enhance the course design by emphasizing the most thought-provoking resources. However, it could result in excessive monitoring, compromising students' privacy and independence in HEIs. It can be incomprehensible to interpret engagement data because comprehension does not always correspond with the time spent on content. Diverse degrees of comfort with digital interaction may impact the data.

3.2.3 Student course completion tracking

Student Course Completion Tracking is an AI-driven method to track their progress in real-time, demonstrating that they have finished courses, online questionnaires and tests. AI-based systems in HEIs monitor their accomplishments of significant course benchmarks, enabling teachers to identify instances of students' lacking performance (Shoaib et al., 2024). Comparing current completion rates with previous data also allows for identifying patterns and predicting possible dropout spots (Prenkaj et al., 2020). Identifying common dropout points helps teachers take pre-emptive action by highlighting the phases at which students frequently drop out. It also enables examining success rates for various courses, and levels of success rate analysis offer valuable information (de Oliveira and Moreira, 2021) for developing curriculums. Thus, AI-driven systems present early warning signs of possible dropout issues, enabling preventative assistance (Ahmad et al., 2023) and allowing for a more focused strategy to lower dropout rates. It also assists HEIs in comprehending the components of course design that might influence student's success or failure. However, there are several challenges. Firstly, high dropout rates can be due to extracurricular variables, including personal or financial difficulties. Secondly, it focuses heavily on completion metrics by pressuring students to finish classes and online assessments quickly, which could lower the quality of education as particular courses may inherently have lower completion rates and require a sophisticated approach to data interpretation and response.

TABLE 3 Role of AI in student success metrics in HEIs with examples, real-world advantages and challenges.

AI-based student success metrics	Examples	Advantages	Challenges
Direct effects on academics	AI-based tutoring systems	• Personalized and customised Learning • Increased level of engagement and motivation • Immersive learning experience • Enhanced learning results • Real-time feedback	• Requirement for trustworthy data sources • Biased algorithms or tailored suggestions
	AI-based grading & feedback support	• Provide real-time feedback • Automated grading efficacy with standards • Robust systems • Time efficient • More freedom for the instructors to focus on instructional design, such as student engagement, course design, and meeting individual learning requirements • Formative comments for students • Uniform methodology and equitable results • Scalable, individualized feedback and long-term student achievement tracking	• Inability to evaluate students' work for creativity • Algorithmic bias • Data security • Privacy
	Adaptive learning platforms	• Specifically tailored for student learning experiences according to each student's unique needs, learning capability levels and adopted pace • Interactive and dynamic material and assessments, and individualized content delivery • Scalability for different learning requirements, instructor assistance and insights, predictive analytics for early intervention • Improved and increased student engagement • Real-time feedback • Predictive analytics for teachers to step in and offer more resources • Teachers may use each student's performance data to identify patterns, monitor development, and make informed decisions	• Creating adaptable content • Improving algorithms • Privacy and data security • Relying too much on AI for learning
AI-based student progress and engagement monitoring	Monitoring attendance	• Offers a trustworthy, up-to-date attendance and students' performance data • Early intervention for disengaged students • Automated mechanism to lessen administrative effort	• Privacy issues to monitoring online attendance and physical presence • Student participation may not be completely shown by attendance data alone • Potential biases in the event that absences are misunderstood with the missing context
	Analytics for student engagement	• A thorough perspective of student's involvement • Aids in detecting and filling in the gaps in students' interaction with the course materials • Results in suggestions for an improved course design	• Excessive monitoring, compromising students' privacy and independence in HEIs • Interpretation of engagement data may be challenging, as time spent on content does not always correlate with understanding • Diverse degrees of comfort with digital interaction may impact the data
	Student course completion tracking	• Early warning of possible dropout issues • Enables preventative assistance • Allows for a more focused strategy to lower dropout rates • Assists HEIs in course design	• High dropout rates due to extracurricular variables, including personal or financial difficulties • Focuses heavily on completion metrics • Pressuring students to finish classes and online assessments quickly • Lower quality of education
	Assessment of Student Performance	• Real-time view of each student's course standing with continued monitoring and tracking • Regular progress reports and real-time feedback • Students who may have difficulties can also be identified promptly • Teachers can take immediate action, such as providing resources or assistance • Data-driven interventions enhance student performance	• Excessive monitoring, compromising students' privacy and independence in HEIs • Bias in algorithms may perpetuate the existing biases

(Continued)

TABLE 3 Continued

AI-based student success metrics	Examples	Advantages	Challenges
AI-based data-driven interventions in HEIs	AI-driven predictive analytics	• Pre-emptive Measures • Personalized assistance for students • Customised resource allocation • Increased effectiveness of support services • Continuous improvement • Assessment of the impact of interventions	• Data privacy issues • Risk to Personal Identifiable Information (PII) • Limitations of predictive algorithms • Absence of contextual elements may influence performance results • Maintaining data quality is essential otherwise inaccurate data may result in ineffective measurements
	AI-based reinforcements for support	• Special tailored and targeted suggestions for each student's need • Possibility of positive results • Improved peer support • Support network • The most pertinent resources	• Speculated student's choices • Limited fair access

3.2.4 Assessment of student performance

AI-driven systems track student involvement in class activities, test results, and assignment completion, updating and monitoring performance data in real-time (Shoaib et al., 2024). A real-time view of each student's current course standing is possible by continued monitoring and tracking (Vashishth et al., 2024). Students who may have difficulties can also be identified promptly. Thus, teachers can take immediate action, such as providing resources or assistance (Makinde et al., 2024b) if a student's performance declines. Lastly, data-driven interventions can enhance student performance, which may prevent surprises when the course concludes by giving regular progress reports and providing students with real-time feedback to help them stay on course. However, continuous monitoring can lead to privacy violation concerns. Secondly, if there are biases present in the training data, it may lead AI systems to perpetuate the existing biases, hence resulting in unfair evaluations or feedback.

3.3 AI-based data-driven interventions in HEIs

Data-driven interventions (Makinde et al., 2024b) in HEIs use analytics to provide students with proactive and personalized assistance. These interventions improve student achievement and retention through early identification of students at risk and providing resources specifically tailored to their academic needs. The elements, advantages, and challenges of various AI-powered approaches in HEIs are discussed as follows.

3.3.1 AI-driven predictive analytics

AI employs predictive models to detect critical risk indicators, such as low attendance, subpar grades in required courses, or low levels of interest, that might impede their progress. By examining these variables, teachers may proactively connect with students in HEIs (Herodotou et al., 2019) who struggle with their performance. Using data from engagement metrics, current performance, and comparisons with comparable student profiles, AI determines each student's probability of success. This aids teachers in determining which students might need instant support and guidance (Almusaed et al., 2023). AI-driven mechanism improves support timing and determines when students may benefit from intervention. For instance, if a student is expected to have difficulties prior to midterms, an early intervention with extra help or tutoring might help avoid problems later. The impact of support measures is assessed by AI by monitoring the results of earlier initiatives. For instance, if an approach, such as tutoring, is successful for some students, the AI-driven algorithm will suggest the same measures for other students dealing with similar difficulties. Thus, pre-emptive measures allow prompt and personalized assistance by identifying students in danger of failing or dropping out. Secondly, customized resource allocation increases the effectiveness of support services by focusing resources on the students who require them the most. These measures, in the end, result in continuous improvement, and by assessing the impact of interventions, institutions may improve their tactics for increased efficacy. However, there are risks to data privacy. Therefore, there should be strict privacy regulations to collect and analyse the performance corresponding to the personal data to safeguard their Personal Identifiable Information (PII) (Mordecai, 2022). Secondly, predictive algorithms may incorrectly identify "at-risk" students or overlook contextual elements that influence performance, such as personal struggles. Thirdly, maintaining data quality is essential since inaccurate data may result in ineffective measurements.

3.3.2 AI-based reinforcements for support

AI uses performance and engagement data to suggest resources (Sayed et al., 2023), such as interactive exercises, articles, or videos tailored to a student's learning requirements. For instance, students who have trouble understanding mathematical topics, i.e., may be given extra arithmetic practice materials. AI-based approaches suggest interventions such as one-on-one tutoring (Srinivasa and Saritha, 2022) for students who require more academic help or flexible scheduling alternatives for those who need to balance work and study. AI-driven methods find students with comparable academic objectives or difficulties and recommend study groups to assist peers. Students can learn more collaboratively when grouped according to their complementary skills. AI also pairs students with tutors according to their learning preferences, subject-matter competence, and availability (Makinde et al., 2024a), guaranteeing that every student gets the most pertinent help. AI can recommend support services, such as career coaching, academic advising, or

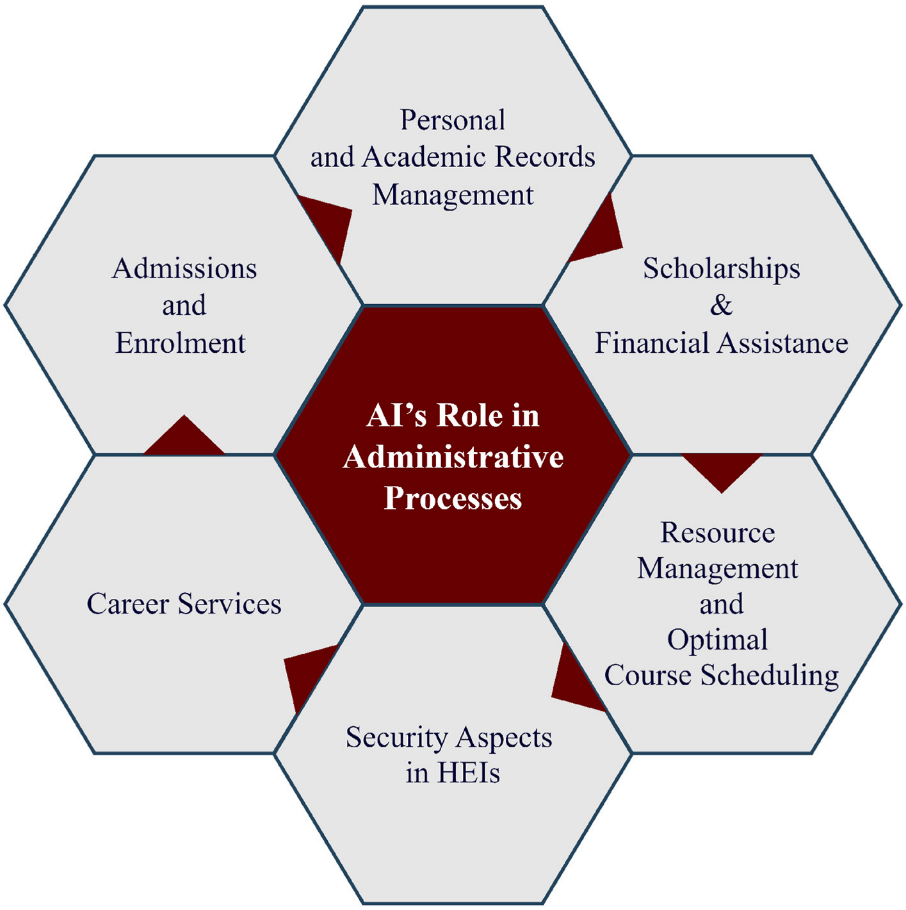

FIGURE 7
Salient aspects of AI's role in administrative process of HEIs.

counseling, to students who have difficulties with personal matters or particular needs to address non-academic complexities.

4 AI's role in administrative processes

AI significantly improves efficiency, decision-making, and resource allocation while simplifying administrative processes in HEIs (George and Wooden, 2023). AI revolutionizes the operations of HEIs (Funda, 2023) by automating monotonous jobs, analyzing large, complicated datasets, and offering insights. Figure 7 demonstrates salient aspects of AI's role in the administrative process of HEIs, and Figure 8 explains the advantages and challenges of employing AI for the administrative processes of HEIs. Lastly, this section elaborates the AI's roles, advantages and challenges in HEIs' administration as follows.

4.1 Admissions and enrolment in HEIs

AI-driven systems handle applications load and process these applications in a short time, retrieving and evaluating applicant data (Oladele, 2023) according to predetermined standards in HEIs. AI systems based on Natural Language Processing (NLP) tools evaluate essays and assessments. AI-based predictive models estimate a student's success through early intervention, explore the possible outcomes (Farhood et al., 2024) and predict suitable measurements for improvement. The admissions process is enhanced using AI-driven chatbots, which interact with potential students (Tritscher and Schlögl, 2023), responding to their multiple queries about classes, degree requirements, costs, student growth (Shoaib et al., 2024) and help with follow-ups. Moreover, by analyzing applicant demographics and histories, AI systems assist institutions in fairly and equitably (Barnes and Hutson, 2024) achieving their diversity and inclusion objectives to maintain diversity in HEIs.

4.2 Student's personal and academic records management in HEIs

In student information systems, AI reduces human error and enables administrative staff to perform various constructive duties by automating data entry, verification, and updates. Document management solutions facilitate swift access to information and compliance with HEI rules and regulations by making it simpler to retrieve, archive, and arrange records. This also protects and limits unauthorized access to students' PII.

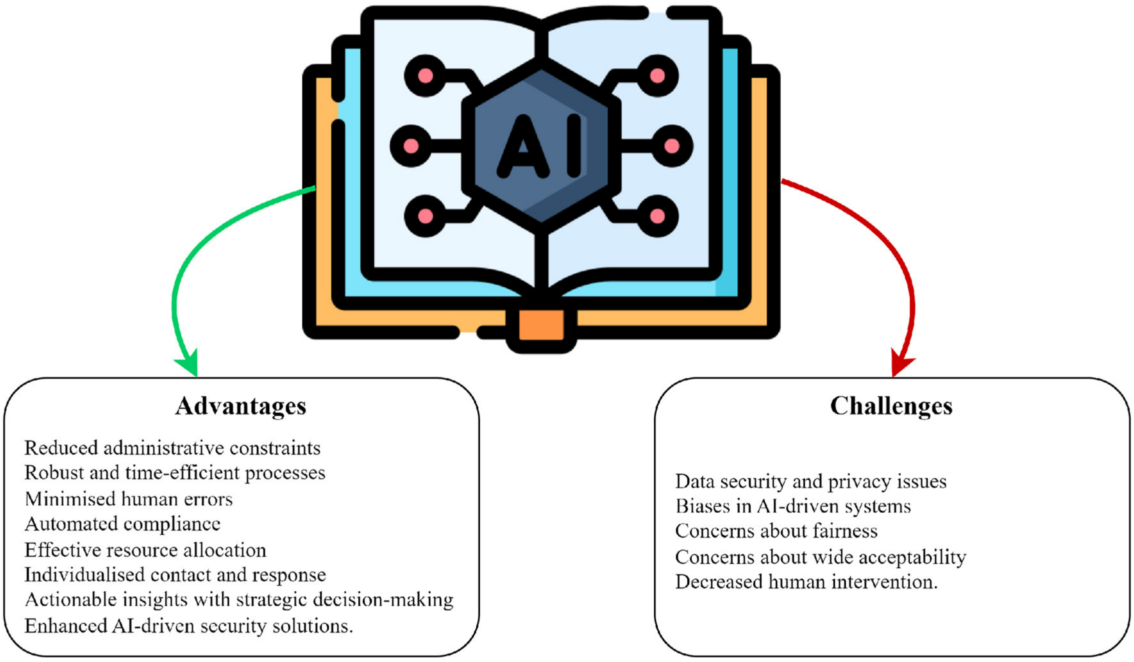

FIGURE 8
Advantages and challenges of AI in administrative processes of HEIs.

4.3 Scholarships and financial assistance

AI streamlines and improves the evaluation of financial assistance applications by evaluating academic standing, income, and other factors (Chisom et al., 2023). AI-based algorithms assist HEIs in identifying irregularities or frauds in financial data to lower the number of fraud cases (Kanagaraj, 2020), which also affect the HEIs' reputation (Utkirov, 2024). These algorithms can also predict internal and external financial aid needs, which aids in better budget planning for educational institutions.

4.4 Resource management and optimal course scheduling

AI-based optimal scheduling tools are automated to assign various facilities, such as rooms, maintain schedules, and avoid clashes (Taye et al., 2023). These schedules are maintained according to student enrolment, course requirements, and availability of different resources (Alam, 2022a). The automated mechanism can also predict the demand for faculty, equipment, and facilities, enabling organizations to manage resources effectively.

4.5 Security aspects in HEIs

AI lowers expenses and enhances sustainability by optimizing energy (Sutjarittham et al., 2019) use, maintenance planning, and space use throughout campus facilities. These systems are based on real-world scenarios and lessen the threats (Dunant et al., 2021) caused by natural and artificial calamities. The surveillance cameras and systems improve campus security by identifying illegal entry, odd activity, or possible threats. AI-driven resource allocation and privileged access management also decline and limit the impact of overall hazards (Dunant et al., 2021) and risks identified in the risk assessment (Tchassem, 2024) of resources from the department to the whole institution level.

4.6 AI-based career services

AI assists career services in providing customized job suggestions by matching students' academic accomplishments, interests, and talents (Sathish et al., 2024) with possible employment prospects [82]. AI-driven technologies monitor the professional development (Westman et al., 2021) of former students and encourage them to interact with the school through tailored messages (Makinde et al., 2024a), boosting their engagement and contributions.

4.7 Advantages and challenges of AI in administrative processes of HEIs

AI reduces administrative constraints on employees and speeds up processes (Parycek and Novak, 2024) by automating time-consuming operations like data input, application processing, and record keeping. It minimizes human error-causing blunders and the risk of bad reputation for HEIs, resulting in more dependable data processing with regulatory compliance in HEIs (Hina et al., 2019), which raises the accuracy of documents and reports. By giving institutions insights into resource demands, AI enables them to distribute resources efficiently, such as teachers, classrooms, and financial assistance, limiting waste and enhancing service. Students and applicants benefit from more individualized contact and robust response times. AI allows human personnel to manage more complicated and individualized student demands (Alam, 2021) by promptly responding to their multiple enquiries in real time. From budget allocation to enrolment projection, AI evaluates vast amounts of institutional data to produce actionable insights that enhance planning and strategic decision-making (Garcia and Adams, 2023). Lastly, AI-driven security solutions improve safety by enhancing monitoring capabilities and instantly notifying personnel of any threats or data and Information Systems (IS) breaches.

AI depends on large volumes of data that contain private student information, i.e., PII (Mita, 2022). This raises concerns about data security and privacy (Aswathy and Tyagi, 2022) because breaches or exploitation may undermine student trust and result in legal repercussions. Thus, it is imperative to ensure data privacy and cybersecurity aspects. AI models may inadvertently introduce biases if trained on outdated data. This raises concerns about prejudice and fairness and may result in judgments about admissions, financial assistance, or resource distribution that unfairly target particular demographic groups (Chinta et al., 2024). AI systems necessitate hefty infrastructure, training, and technology investments. Many institutions may find the initial expenditures prohibitive, particularly if they lack the requisite funding or technological knowledge and proficiency (Oladele, 2023). The richness and quality of data are essential to AI's efficacy. Outdated or inaccurate data might produce faulty insights, which lowers the accuracy of judgments made by AI. Staff members frequently need to adjust and undergo cultural changes while using AI. Teachers and administrators may be resistant to these changes (Selwyn, 2019) because they are unsure how AI will affect their jobs. If AI is used excessively, it may decrease human contact in administrative procedures (Robert et al., 2020), giving the organization an impersonal appearance. Therefore, to keep the atmosphere friendly and encouraging, it is essential to maintain a balance between automation and human judgment.

5 AI integration and role of responsible strategic leadership

The most crucial responsibility of university leadership is to address the technological, moral, cultural, and resource issues related to AI adoption coherent with educational principles and objectives. To get support from stakeholders around the university, leaders must present the advantages of AI in an open and accountable way (Zheng and Webber, 2023). Ethical and sustainable AI adoption must be facilitated and integrated through developing an astute strategic plan. Leaders must cultivate an institutional culture receptive to testing and assessing novel AI technologies. Initiatives such as AI skill development training programs and rewards for pilot participation may encourage adaptability (Zheng and Webber, 2023). Additionally, leaders must ensure diversity in AI design teams to reduce algorithmic bias. Assessing possible unequal consequences on excluded populations requires formal assessments of AI systems (Hagerty and Rubinov, 2019). Thirdly, leaders must reserve funds, personnel, infrastructure, and governance systems for deploying AI. A specialized AI oversight committee is essential to guarantee consistency with institutional principles (Cihon, 2019). Leaders should form alliances with peer universities to exchange best practices on the ethical use of AI in HEIs. Visionary leadership is essential to steer AI responsibly in a way that promotes education while respecting human values. Therefore, in HEIs, prioritizing education or research, visionary leadership entails foreseeing future developments and coordinating efforts to promote long-lasting change. A visionary approach to AI integration guarantees that technology promotes long-term institutional goals, values, and social advancement focused on current demands. Figure 9 demonstrates the integration of AI and the role of responsible strategic leadership in HEIs.

5.1 Effective leadership frameworks

Developing strong leadership and ethical frameworks is crucial for teaching, research, and administration when AI is integrated into HEIs. HEIs require leadership frameworks (Khalifa et al., 2023) to navigate problems, encourage innovation, and ensure their relevance in a robust global environment. A strong leadership framework (Ruben et al., 2023) combines ethical stewardship, collaborative governance, flexibility, and strategic vision to accomplish institutional objectives (Sharma and Sharma, 2021). Whereas, through ethical frameworks, AI applications are guaranteed to protect human rights (Díaz-Rodríguez et al., 2023), be consistent with institutional values, and advance sustainable and equitable results. Acceptance and integration of AI follow the phases of awareness, assessment, experimentation, and implementation as outlined in Everett Rogers' Diffusion of Innovations Theory. This emphasizes how crucial technology-oriented leadership (Rorink, 2024) is in adopting, integrating, and administrating AI tools. Purpose-oriented leadership creates a vision that supports the HEI's goals of advancing research, education, and social impact with a strategic focus (Doussineau et al., 2021) that defines priorities that correlate with innovation, operational effectiveness, and academic quality. This results in collaborative decision-making by including teachers, staff, students, and other stakeholders' involvement and promotes diversity at all leadership and decision-making levels. It also ensures that choices and procedures are explained in an authentic, understandable and accountable manner.

A leadership framework for HEIs (Ruben et al., 2023) considers various factors to satisfy the particular requirements of academic institutions, such as academic, operational, strategic and community leadership. Academic leadership (Leal Filho et al., 2020) promotes interdisciplinary research, encourages curricular innovation, and maintains academic standards (Dopson et al., 2019). However, operational leadership strives to manage institutional resources effectively and sustainably (Iqbal and Ahmad, 2021). These include managing human

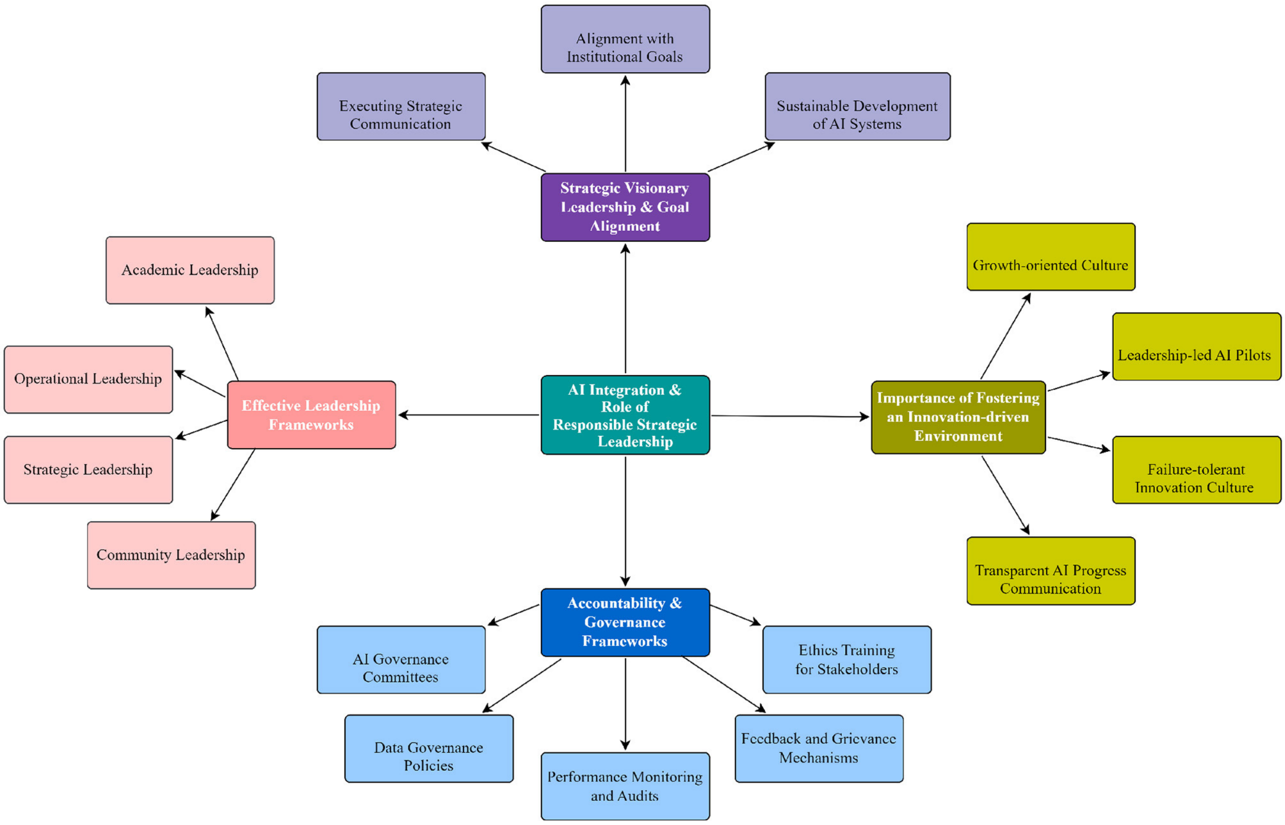

FIGURE 9
AI integration and role of responsible strategic leadership.

resources, technology, infrastructure, and budgets to guarantee efficient operations. Strategic leadership (Samimi et al., 2022) entails creating long-term plans that address social demands, technical breakthroughs, and worldwide trends. Community leadership increases the HEI's credibility by forming alliances with businesses, governments, and local communities (Shyiramunda and van den Bersselaar, 2024). Ethical leadership in HEIs guarantees accountability, transparency, and equity (Gonçalves, 2024). In HEIs, transparency is essential to fostering confidence in AI systems. HEIs ensure stakeholders can understand and access AI decisions and procedures using comprehensible justifications for their results, particularly in high-stakes contexts like financial aid distribution, grading, and admissions. Accountability guarantees that HEIs and stakeholders (Padro et al., 2023) accept accountability for AI effects on HEIs, i.e., information dissemination about the data sources, training procedures, planned uses and defined roles.

5.2 Strategic visionary leadership and goal alignment

The strategic mission of an HEI must correlate with the AI integration. Establishing a clear strategy for attaining HEI success requires objective alignment (Zabalawi and Aftimos, 2024). The leadership must create strategies for AI adoption and integration that are practical, feasible, and in line with the long-term objectives of the university. In HEIs, visionary leadership (Devika, 2024) entails foreseeing future trends, promoting innovation, and coordinating technology developments with institutional ideals. A clear, forward-thinking strategy (Asagba and Oshebor, 2024) is necessary to integrate AI into research, education, and administration while preparing institutions for long-term sustainable practices and implications. This results in multidisciplinary collaboration, AI-powered discovery, rapid insights, virtual classrooms, predictive analytics, and personalized learning experiences. AI in research has the potential to speed up and deepen disciplinary insights, promote interdisciplinary cooperation, and reveal patterns in intricate datasets (Górriz et al., 2020). Furthermore, AI can boost stakeholder participation, decision-making, and operational efficiency in administration. To sum up, to guarantee accountability and transparency, HEIs need to execute strategic communication, connect with institutional principles, and give priority to the sustainable development of AI systems.

5.3 Importance of fostering an innovation-driven environment

HEIs' leadership must establish an atmosphere that supports AI pilots, encourages experimentation, and prepares faculty and staff to accept AI-driven changes to cultivate an innovation-ready culture successfully. Lack of knowledge, a fear of becoming redundant, or worries about the moral ramifications are common causes of resistance to change (Gkrimpizi and Magnisalis, 2023). Strategic leadership (Samimi et al., 2022) that develops AI capabilities and synchronizes institutional objectives with human-centered innovation is necessary to address these challenges. Thus, it should foster an institutional culture that values inquiry, flexibility, and lifelong learning. Leaders should actively participate in AI pilot projects and provide an example of creative behavior. Faculty and staff may encourage innovation without penalizing failures by establishing a safe environment for experimenting. AI prototypes and pilots may test concepts, get insights, and improve implementation tactics. Resources and funds must be reserved for investigating AI tools pertinent to their roles. Feedback loops must be established to gather information from pilot initiatives and incorporate the knowledge gained into more comprehensive plans. For AI to reach its full potential, cooperation and interdisciplinary initiatives must be encouraged (Dwivedi et al., 2021). AI projects should be co-designed by interdisciplinary teams. Cross-departmental communication and invention sharing can be facilitated by collaborative platforms. To foster trust, AI must be in line with institutional ideals. Academic achievement, diversity, inclusiveness, and equity should be given top priority in an ethical AI charter. It is also critical to regularly communicate the goals, developments, and results of AI initiatives. AI has changed research and learning, among other aspects of education.

Assessments of faculty and staff members with current AI literacy levels, surveys, audits, and role-based requirements analyses are all necessary to develop AI competencies. This can be achieved by offering training courses and workshops, certification courses, learning laboratories and professional growth opportunities. Identifying early adopters or tech-savvy faculty members who may serve as mentors for peers can also be employed to establish peer learning and mentorship networks. HEIs must also ensure that the opinions of academics and staff are considered while developing AI policies and initiatives.

5.4 Accountability and governance frameworks

AI-driven practices in HEIs pose significant challenges in terms of ethical responsibility, transparency, and regulatory compliance. AI systems must be transparent and effectively convey to stakeholders their capabilities, constraints, and decision-making procedures to guarantee ethical practices (Felzmann et al., 2020). AI governance mechanisms, i.e., AI Governance Committees that supervise AI strategy, implementation, and ethical issues, must be formed and implemented. These committees must include students, academics, administrators, technologists, and external specialists. The committees must assign positions for AI supervision, such as Chief AI Officer (CAIO) and AI Ethics Officers, to guarantee adherence to legal requirements and HEI principles.

Data governance policies must be developed to ensure responsible data management used in AI applications. These policies should include data access controls, quality assurance, access restrictions and lifecycle management (Janssen et al., 2020). Performance monitoring and audits should be implemented to evaluate AI performance and outcomes. Feedback and grievance mechanisms should be established, allowing stakeholders to report issues or provide feedback on AI systems. Ethics training for stakeholders, such as training for professors and staff, seminars for students, leadership development, collaborative policy creation, stakeholder engagement, openness in governance procedures, and open access rules, should foster a culture of accountability. AI in HEIs must be flexible (Chan, 2023) and compliant with regulations. To ensure the ethical use of AI in HEIs, compliance with national and international laws, including UNESCO's AI ethics guidelines, the Family Educational Rights and Privacy Act (FERPA), and the General Data Protection Regulation (GDPR), is essential. All institutional stakeholders should also have access to AI through public reporting and open access rules.

6 AI-driven future implications and transformations in HEIs

AI integration in HEIs may revolutionize significant areas, such as research, teaching, learning, and administration, resulting in more developed, inclusive, adaptable, and future-ready institutions. AI can leverage SOTA technologies (Pedro et al., 2019) and accentuate continuous development to make education effective, comprehensive, and productive. In addition to addressing issues such as data privacy, equity, and ethical concerns, HEIs can promote collaboration between educators, technologists, and legislators (Pechenkina, 2023). This calculated approach guarantees that, in an AI-driven future, education will continue to be a vital component of societal progress. A detailed explanation of these implications and transformations is as follows.

6.1 AI-based emerging technologies

Real-world scenarios can be simulated in Virtual Reality (VR) environments driven by AI (Shirazi et al., 2024), allowing and promoting experiential learning. Students can investigate complex systems, historical locations, or virtual labs without physical limitations. For instance, medical students could use risk-free VR simulations to practice surgeries. Augmented Reality (AR) provides experiential learning opportunities by superimposing digital data on actual environments (Akpan, 2024). AI algorithms in AR tools can tailor instruction, changing the degree of difficulty according to a student's development (Hernandez-de Menendez et al., 2020). Thus, engineers, architects, and healthcare professionals may benefit from this technology. AI-driven intelligent systems can examine student's academic history, hobbies, and labor market trends to provide individualized career guidance. AI chatbots or virtual advisors can offer assistance with job applications, skill development, and career planning. When combined with AI, blockchain technology (Alam, 2022b) guarantees safe, unchangeable online records of academic accomplishments. The ease with which employers can confirm qualifications lowers the administrative load and fraud. The system has the potential to facilitate micro-credentialing for continuous education. Campus-based IoT devices (Samancioglu, 2022) with AI integration can track facility management, energy consumption, and attendance. AI-driven IoT data analytics can increase campus safety and optimize resource allocation. Smart classrooms can automatically adjust settings (such as temperature and lighting) according to student preferences.

6.2 AI-based continuous enhancement

AI can evaluate data from institutional operations to optimize procedures, such as resource management, course scheduling, and admissions. HEIs can predict issues like enrolment patterns (Tariq, 2024) or resource unavailability through AI-driven predictive analytics (Khan and Mahade, 2024). AI algorithms are continuously improved to guarantee increased accuracy in administrative work, learning analytics, and student assessments. The efficacy of AI-driven solutions can be improved through frequent feedback loops involving educators and students (Katiyar and Tiwari, 2024). AI-powered adaptive learning systems can offer individualized feedback, pacing, and content delivery. By providing staff and students with real-time support, virtual assistants can increase accessibility and engagement. HEIs can modify their curricula (Mohamed Hashim and Matthews, 2022) and methodologies to satisfy changing industry and societal demands due to AI's capacity to analyse global trends. For example, AI-powered simulations enable students to be inclined to cutting-edge disciplines like climate science or quantum computing.

6.3 AI-based enhanced research accomplishments

AI-Assisted Research Accomplishments for HEIs are significant accomplishments or standards that HEIs strive to reach by incorporating AI into their research environments. An institution's advancements in improving research quality, teamwork, creativity, and worldwide impact are frequently reflective (De Wit, 2019). AI can ensure that HEIs remain relevant by expediting the implementation of state-of-the-art (SOTA) educational research. Tools for research discovery and plagiarism detection driven by AI can improve academic integrity and creativity. Establishing specialized AI research labs with powerful computers, data storage, and cutting-edge AI tools can promote advancements in computer vision, big data analytics, and NLP (Harris et al., 2024). Developing AI education initiatives for students, faculty, and researchers may increase the ability to conduct interdisciplinary research by fusing AI with conventional domains such as the social sciences, engineering, and medicine. Developing or implementing AI tools to support data analysis, hypothesis development, and experiment design can boost precision and reproducibility (Ahmed et al., 2020) while expediting research workflows. AI may increase grant-writing success rates, discover funding opportunities, promote large-scale initiatives and increase research funding. AI-driven research results in real-world settings to tackle societal issues like healthcare, education, and climate change may exhibit the HEIs' dedication to innovation and societal wellbeing (Ramkissoon, 2024). Based on institutional research, launching spin-offs or start-ups with an AI focus can stimulate entrepreneurship and open up new business prospects. AI-driven research (Madanchian and Taherdoost, 2024) stimulates engagement with International AI research networks by participating in international AI consortiums and cooperative research projects. Lastly, creating innovative AI-based teaching can integrate educational findings with research findings to use AI for individualized learning and teaching support, which may result in improved student outcomes and instruction quality.

6.4 Current real-world examples of AI integration in HEIs

We explored AI-driven future implications for HEIs, supported by real-world examples and empirical evidence. Emerging technologies like intelligent virtual assistants, real-time performance tracking tools, and advanced predictive analytics systems (Rehan, 2023) will continue to shape the educational landscape. Continuous enhancement through AI can be seen in tools like Coursera, which evolves its recommendations based on changing user behavior, and Microsoft Azure, which refines interventions based on updated engagement metrics. These examples substantiate AI's potential to enhance research accomplishments and institutional strategies (Delello et al., 2025). Future advancements could also include integrating AI into strategic planning, enabling HEIs to remain agile in responding to societal and technological changes.

We present some examples of AI tools successfully implemented in HEIs globally to contextualize theoretical claims with real-world applications. For instance, IBM Watson for Education has been used to personalize learning experiences by leveraging its cognitive computing capabilities to analyse student performance, identify learning gaps, and provide tailored recommendations. This tool exemplifies how AI can enhance student outcomes by facilitating data-driven decision-making in educational contexts. Similarly, platforms such as Coursera and Duolingo employ machine learning algorithms to adapt to individual learner needs, optimizing course delivery and language acquisition. These practical applications demonstrate how AI can transform educational processes, validating theoretical frameworks on integrating AI in teaching and learning. Empirical evidence also highlights the use of AI in administrative processes within HEIs. For example, Georgia State University implemented an AI-powered chatbot, Pounce , to improve student engagement and reduce summer melt by answering student queries and sending reminders about deadlines. This initiative reportedly increased enrolment retention rates, showcasing the tangible benefits of AI in addressing institutional challenges. Another example is the University of Murcia in Spain, which adopted AI tools to automate grading and administrative processes, reducing faculty workload and enhancing efficiency with accuracy. These cases validate theoretical claims about the potential of AI in streamlining administrative tasks are supported by practical outcomes in real-world scenarios.

Moreover, documented case studies from HEIs worldwide provide insights into AI integration. For instance, the Open University in the United Kingdom uses predictive analytics to identify students at risk of dropping out and provide timely interventions (Saxena and Parivara, 2025). In Australia, Deakin University has integrated IBM Watson into its student services to offer 24/7 support (Scheepers et al., 2018), addressing queries related to enrolment, course selection, and campus resources. These examples contextualize theoretical discussions, emphasizing the transformative role of AI in improving both academic and administrative processes. Thus, AI's integration with a positive impact on HEIs globally is witnessed, and with wide acceptability, AI will improve the academic, administrative, and leadership of HEIs.

7 Conclusion and discussion

AI offers enormous transformative opportunities in HEIs, but responsible integration and implementation are crucial. The power of AI not only brings automation but also enhances human potential and administrative processes. It empowers educators to inspire and nurture the next generation of thinkers. However, collaborations with the relevant stakeholders and partnerships with AI experts and other educational institutions are significant in addressing the opportunities and challenges that AI brings with it. Additionally, emphasizing and prioritizing ethical considerations, including accountability, fairness, and protecting data privacy, are important aspects of responsible AI integration. As AI continues to evolve and transform, the leadership and higher education stakeholders need to collaborate, stay up-to-date, and be willing to adapt to this robust AI-driven landscape of HEIs. While challenges exist, AI promises a bright future where learning is adaptive, personalized, and truly understood, resulting in a more inclusive learning environment. With this evolving nature of AI, we intend to pursue further research efforts, maybe to explore how AI could facilitate addressing the pressing issues of access, diversity, and inclusion (ADI) in HEIs. Integrating AI in HEIs incorporates undeniable benefits, but a comprehensive understanding requires addressing the significant challenges accompanying this transformation. One of the foremost challenges is resistance to change, as faculty, staff, and administrators may be apprehensive about adopting new technologies. This resistance often stems from a lack of familiarity with AI tools, concerns about job displacement, and the fear of being rendered obsolete by automation. Additionally, ethical considerations pose a critical challenge in ensuring responsible AI implementation. For instance, biases embedded in AI algorithms can perpetuate inequalities, disproportionately affecting underrepresented groups in admissions, grading, or hiring decisions. The lack of transparency in AI decision-making processes, often called the "black box" problem, complicates accountability and trust in AI systems. Furthermore, concerns over data privacy and security are paramount, as the collection and analysis of vast amounts of sensitive student and institutional data make HEIs attractive targets for cyberattacks. Leadership must also navigate the delicate balance between innovation and the potential for over-reliance on technology, which could undermine human-centric aspects of education, such as personalized mentorship and critical thinking development. Addressing these challenges requires proactive strategies, including comprehensive training programs to build confidence in AI tools, establishing robust governance frameworks to ensure ethical use, and fostering a culture of collaboration and inclusivity that embraces AI as a complement rather than a replacement for human efforts. Only by addressing these multifaceted challenges can HEIs harness AI's potential responsibly and sustainably.

Author contributions

SK: Writing – original draft, Writing – review & editing. SH: Conceptualization, Writing – review & editing, Writing – original draft. HH: Writing – review & editing, Writing – original draft. RS: Methodology, Writing – original draft, Writing – review & editing. NA: Supervision, Writing – original draft, Writing – review & editing. MA: Funding acquisition, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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Glossary

Term	Definition
Artificial intelligence (AI)	The simulation of human intelligence by machines, including learning, reasoning, and problem-solving, often applied in HEIs for tasks such as data analysis, personalized learning, and automation.
AI-powered assessment	Automated systems that evaluate student performance using algorithms, often employed for grading essays, quizzes, and assignments efficiently and objectively.
AI-supported peer learning	Platforms that connect students with peers for collaborative learning, utilizing AI to match participants based on skill level or learning goals.
AI-driven insights	Actionable recommendations generated by AI systems from analyzing patterns in student data, helping institutions improve strategies and outcomes.
Academic records management	The use of AI to organize, secure, and analyse student academic histories, facilitating better decision-making for curriculum design and advising.
Automated Feedback Systems	Tools that provide instant feedback on student submissions, such as assignments or code, enabling continuous learning.
Adaptive learning platforms	AI-powered systems that tailor educational content and activities to individual students' learning needs, pacing, and preferences, improving engagement and outcomes.
AI governance	The framework of policies and guidelines ensuring the ethical and responsible use of AI within institutions.
Augmented reality (AR) and virtual reality (VR)	AI-enhanced technologies that provide immersive learning experiences, such as virtual lab simulations or historical reenactments.
AI-enhanced research tools	AI systems that aid researchers in literature review, data analysis, and hypothesis generation, improving efficiency and innovation.
Collaborative AI platforms	Systems that facilitate group projects and discussions by using AI to suggest relevant resources or optimize team composition.
Chatbots	AI-driven virtual assistants designed to handle queries and provide information in real time, commonly used in admissions and student support systems.
Data-driven decision-making	A process where institutional strategies and policies are informed by insights derived from analyzing large datasets using AI tools.
Ethical AI	Principles and practices ensuring AI systems operate transparently, without bias, and align with human values, especially critical in decision-making processes like admissions and grading.
Engagement metrics	Data points such as login frequency, time spent on tasks, and participation rates, tracked and analyzed by AI to measure student involvement.
Early warning systems	AI systems that alert administrators and faculty to students who are at risk of academic failure or disengagement.
Gamification in education	The integration of AI-driven game elements into educational platforms to enhance motivation and engagement.
Interactive learning environments	AI-powered systems that provide immersive learning experiences, such as virtual labs or simulations, to enhance understanding.
Intelligent tutoring systems (ITS)	AI-based tools that simulate a one-on-one tutor, providing personalized feedback, instruction, and learning pathways.
Learning analytics	The measurement and analysis of student data, such as engagement and performance, to enhance learning experiences and outcomes.
Natural language processing (NLP)	A subfield of AI enabling machines to understand, interpret, and generate human language, used in HEIs for grading, content summarisation, and language tutoring.
Plagiarism detection tools	AI systems like Turnitin that analyse written submissions to identify copied content and ensure academic integrity.
Predictive analytics	The use of historical data and AI algorithms to predict future outcomes, such as identifying students at risk of dropping out or underperforming.
Personalized learning	An AI-enabled educational approach where content delivery and pacing are tailored to each student's needs, preferences, and progress.
Recommendation systems	AI algorithms that suggest relevant content or resources to users, such as courses, research materials, or extracurricular activities.
Lifecycle management	AI systems that support students throughout their educational journey, from enrolment to graduation and beyond.
Engagement monitoring	AI systems that track student activity, participation, and interactions to identify trends and areas requiring attention.
AI-powered simulations	AI-powered tools that create realistic scenarios for skills training, such as medical procedures or engineering tasks.
Virtual assistants	AI tools, like Siri or Google Assistant, that automate routine tasks such as reminders, scheduling, and answering FAQs in HEIs.
Virtual labs	AI-enabled platforms that simulate lab experiments, allowing students to practice and learn without physical equipment.

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A learning module for generative AI literacy in a biomedical engineering classroom

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Purpose: Generative artificial intelligence (GenAI), especially Large Language Model (LLM)-based chatbots such as ChatGPT, has reshaped students' learning and engagement in higher education. Yet, technical details of GenAI are largely inapproachable to most students. This article develops a learning module for GenAI and seeks to examine whether this module can potentially affect students' perceptions toward GenAI.

Methods: We implemented a one-lecture (60-min) module on GenAI models, with primary focus on structures of LLM-based chatbots, during the last week of a Biomedical Engineering (BME) Machine Learning course. A mixed-methods survey on perceptions of GenAI was distributed to the students before and after the module. Paired t-tests and regression analyses were used to analyze the Likert-scale quantitative questions and thematic coding was performed for the free-response questions.

Results: Students (N = 13) reported significantly stronger approval on favorability to use GenAI in medicine (p = 0.015), understanding of LLM-based chatbots (p < 0.001), confidence on using LLM-based chatbots (p = 0.027), optimism on future development of LLMs (p = 0.020), and perception of instructor's attitude toward GenAI (p = 0.033). Students maintained a neutral view on accuracy of LLM-generated answers and a negative view on the ability of generating bias-free answers in LLMs. The primary contributors identified in students' intentions to use LLMs are self-efficacy in using the LLM outputs and lower precepted bias of LLMs. The impression of GenAI for students shifted from primarily LLM-based chatbots and generative work to components and training process of GenAI. After the module, students reported a clear understanding of tokenizers and word embeddings while expressing confusion on transformers.

Conclusion: A module on the details of GenAI models shifted the students' attitudes to GenAI models positively while still being acutely aware of its limitations. We believe that inclusion of such modules in a modern engineering curriculum will help students achieve AI literacy.

KEYWORDS

perceptions, generative AI, large language model, machine learning, learning module, pedagogy

1 Introduction

Generative artificial intelligence (GenAI) is often referred to as machine learning models that produce new information based on the training data (García-Peñalvo and Vázquez-Ingelmo, 2023). Despite the widespread attention received by GenAI products, such as large language model (LLM)-based chatbots including ChatGPT (GPT: Generative Pre-trained Transformer), the field with the most GenAI papers published in the past 3 years is medicine (García-Peñalvo and Vázquez-Ingelmo, 2023). In the aspect of education, GenAI products, especially LLM-based chatbots, have impressed students with their technical prowess and high accessibility (Yilmaz et al., 2023). These chatbots have been rapidly adopted by both students and educators alike. Estimates of actual adoption rates of these chatbots within the students vary, ranging from 24.6% (Abdaljaleel et al., 2024) in a survey conducted among undergraduates in multiple Asian countries, to a reported 58.2% among graduate students within a U.S. medical school (Hosseini et al., 2023), with varying numbers in between (Singh et al., 2023; Vest et al., 2024). Faculties have also reported using LLM-based chatbots in translating materials across languages (Kiryakova and Angelova, 2023), preparing lecture materials (Kiryakova and Angelova, 2023), generating assessments (Farrokhnia et al., 2023), and summarizing communication (White et al., 2024). Therefore, modern educators must pay special attention to the capabilities and limitations of GenAI products, while being acutely aware of their adoptions in classroom settings.

With more students think that using LLM-based chatbots is acceptable for coursework (White et al., 2024), especially for a specific subset of tasks (Vest et al., 2024), these chatbots will likely become an integral part of modern college programs, especially engineering programs. However, GenAI products, especially these LLM-based chatbots, differentiate themselves from other common engineering tools or office software, in ways that the performance characteristics of these chatbots are difficult to interpret and evaluate for non-machine learning (ML) experts (Singh et al., 2024). Most of the users of such LLM-based chatbots in current students, unfortunately, would classify as non-ML experts. OpenAI's website of their GPT models shows the performance of GPT on a series of text, video, and audio benchmarks. However, rarely do the users of the chatbots know what MMLU (Hendrycks et al., 2020), a prominent text-based benchmark that most modern LLMs get evaluated on, contains to make an accurate sense of the score on the MMLU benchmark. Neither do most users know the training data, the theoretical framework, or the structure of LLMs, making the nature of GenAI-based products inapproachable and incomprehensible.

The current education system is significantly challenged by these unknowns. The propagation of an unknown level of bias from the training data into GenAI products can pose ethical risks and perpetuate bias in education (Tlili et al., 2023). The high barriers to understanding the evaluation and components LLM-based chatbots contribute to the difficulty in evaluating the quality of responses generated by these chatbots (Ferrara, 2024), which can result in a sense of blind trust among the users (Jung et al., 2024) and potentially lead to degradation in students' high-order cognitive skills (Farrokhnia et al., 2023). These unknowns also discourage the users from taking responsibility for their actions in using these chatbots (Venkatesh, 2022) and thus, may encourage irresponsible behavior in learning, such as plagiarism and cheating (Farrokhnia et al., 2023), which in turn threatens academic integrity.

The goal of this paper is to investigate whether dispelling these unknowns by arming our BME students with knowledge of GenAI will affect the students' perceptions toward GenAI, especially toward the LLM-based chatbots. To achieve this goal, we designed a 60-min learning module on GenAI with a focus on construction of LLMs. We designed a 14-item survey from relevant theoretical frameworks for technology adoption to systematically investigate students' perceptions toward GenAI and LLMs. Through the survey, we characterized the effectiveness of this learning module and evaluated the most significant contributors to students' intention of using these chatbots. We intend to develop refined and tailored versions of our current learning module to fit various educators' needs.

2 Pedagogical framework and learning environment

The intervention, a 60-min lecture on GenAI models, was implemented as the last module of the "Machine Learning for Biomedical Engineering" technical elective course in the Spring 2024 term. Therefore, participating students tended to possess a high interest in machine learning and were knowledgeable in traditional machine learning methods. However, since full understanding of LLM requires knowledge in natural language processing (NLP) and deep learning, which were not covered in the course, we used the Cognitive Load Theory to guide the development of the learning module to achieve the best learning outcome when our students were not fully ready to tackle the material head-on.

The Cognitive Load Theory (Sweller, 2011) specifies that the extents of learning is affected by the intrinsic load of the material, which is the complexity of the knowledge presented. Even with the background and preparation level of our attending students, the intrinsic load of understanding LLM is extremely high. To reduce the intrinsic load, we designed the learning module which isolated the building blocks of a LLM model into its main building blocks, including tokenizers, word embeddings, and transformers. We also aimed to introduce more variability and promote interactivity by integrating discussion-based exercises after dense introductions of the concepts. A worked example was shown during the introduction of tokenizers to ease the transition to understanding difficult subjects. The 60-min lecture was structured as follows:

1 Introduction to flow of natural language processing (NLP) models and general structure of LLMs, assuming textual prompts and textual generation: *tokenizer* to *word embeddings* to *transformers* to *inverse word embeddings* and *inverse tokenization*.
2 Explaining the role of tokenizer, which converts sentences into a series of lexicographic tokens (in this case, an array of numbers). Students were reminded about the necessity of this step because computers can only understand numbers and not text. This section included a case study in Byte-Pair Encoding (Gage, 1994), the tokenizer adopted by GPT-series models, including GPT-4 (Berglund and van der Merwe, 2023; Hayase et al., 2024). A live demonstration of GPT-4o's tokenizer was

shown on the screen using the *tiktoken* Python package by OpenAI.

3 Introducing word embeddings as the way to project the word tokens into a lower-dimensional vector space with dimensions focusing on the meaning of the words instead of the words themselves. Students were first shown the size of the dictionaries used in GPT-4o's tokenizer, which includes 524,288 different words. Then, students were taught that the word embeddings used by GPT-4 can compress 524,288 dimensions into just 3,072 dimensions, demonstrating great savings in both time and space. The case study was an introduction to Word2Vec (Mikolov et al., 2013), a two-layer neural network-based approach to word embeddings. Students were informed that the GPT-4 uses a proprietary word embeddings model that is more complicated than Word2Vec.

4 Introducing transformers at a very high level. Transformers are neural networks that transform the input word embeddings (the processed prompt) into output word embeddings (the answer in numerical format). The transformation is made possible by the transformers learning about the statistical distributions of the training data. The case study was the network structure of the original transformer network (Vaswani, 2017), which closely resembles to the structure of the transformer in GPT-1 (Radford et al., 2018). The network structure was introduced at a block-diagram level without going into the details.

5 General training procedure of transformer networks, including estimates in size of network and data source, time, and monetary cost in training the transformer of GPT-4.

We assessed and identified relevant dimensions within the Technology Acceptance Model (TAM) (Davis et al., 1989), the Task-Technology Fit (TTF) Model (Goodhue and Thompson, 1995), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003, 2012) Models that were applicable toward using GenAI, especially those areas that have the potential to be impacted. These models were developed to explain adoption of emerging technology. The dimensions we identified as relevant include behavioral intention, attitude, performance expectancy/perceived usefulness, individual characteristics, and social influence. Behavioral intention and attitude were first identified as relevant due to the goal of the study, which is whether the perception of GenAI within the students will be changed due to this intervention.

We expect self-efficacy levels of using GenAI tools to increase after the intervention and be a potential positive contributor to students' intention of using GenAI. Although, we hypothesize that learning more about the components of LLMs may affect students' view of the performance expectancy of GenAI/LLM in conflicting ways. Knowing the components of how GenAI products are made can potentially enhance the interpretability of the contents generated by GenAI; however, the lesson plans also contained discussions on potential biases that GenAI could exhibit, which could cause students to trust GenAI less. Due to the transparency of the construction and evaluation of GenAI systems that this instruction module potentially brings to the students, we added self-efficacy and personality within the dimension of individual characteristics to our framework of examining GenAI. Additionally, we considered social influence to be a potential contributor to students' intention of using GenAI: the instructor of the module could potentially exhibit "advocacy bias" (Ellsworth, 2021) and thus affect the students' interest level or attitude toward GenAI.

Therefore, our research questions associated with this learning module are:

> *RQ1*. Is this module effective in developing understanding of GenAI systems within the participating students?
>
> *RQ2*. Is a better understanding of the inner workings of GenAI systems correlated with better self-efficacy of using GenAI products?
>
> *RQ3*. In which direction will students' perceptions toward GenAI products change when students have a better understanding of the construction of GenAI systems?
>
> *RQ4*. Will students recognize the instructor as a GenAI advocate if an instructor teaches a GenAI module in their course, irrespective of the instructor's stance of GenAI?

3 Evaluation methods

The class period was 80 min. At the beginning and the end of the class (10 min each), students were asked to complete a survey. The quantitative portion of the survey contained 11 statements based on levels of agreement. We chose a 6-point Likert scale (1: strongly disagree; 6: strongly agree) for better normality in the data (Leung, 2011) and having the participants take a position (Croasmun and Ostrom, 2011) so that we could better understand students' positionality on GenAI. Many statements were formulated to focus on LLMs due to the contents of the lecture. The 11 statements were based on areas of theoretical frameworks that we identified in the previous section: behavioral intention (Statement 5 or S5), performance expectancy (S7, 8, 10), attitude (S1, 2, 4), self-efficacy (S3, 6), optimism (S9) and social influence (S11). The wording of the survey questions can be seen in Table 1. To qualitatively assess the perception toward GenAI before and after the lecture, we included one additional open-ended question, "When you think of generative AI, what terms come to mind?." The post-survey also included two additional questions asking about the clearest points and the muddiest points from the lecture to evaluate and refine this lecture.

To ensure that the participants of the survey were actual participants of the intervention, the survey was distributed in person. Participants were informed that no grade bonus or penalty is associated with completing the survey, and they should not put their names on the survey. Instead, a number identifier was included in the surveys to link the pre- and post-surveys to a single participant. Since the machine learning course is a technical elective with a relatively small enrollment, adequate measures of ensuring anonymity were taken. The instructor left the room after the surveys were distributed and completed surveys were placed at the instructor podium facing down. For students who arrived late after the pre-survey had been submitted, they were instructed not to complete either survey but were allowed to attend the lecture. To further ensure anonymity,

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TABLE 1 Average agreement levels with statements 1–11 on a 6-point Likert scale (1: strongly disagree; 6: strongly agree) in the pre-survey (Pre) and post-survey (Post).

Statements	*N*	Pre (/6.00)	Post (/6.00)	*p*-value	Sig.
1	12	4.167	4.583	0.1753	NS
2	10	4.400	4.900	0.0150	*
3	13	2.769	4.615	0.0001	***
4	13	3.923	4.231	0.2188	NS
5	13	4.538	4.923	0.0961	NS
6	13	4.154	4.615	0.0269	*
7	13	2.615	3.231	0.0712	NS
8	13	1.923	1.846	0.6727	NS
9	13	4.154	5.000	0.0205	*
10	13	3.692	3.769	0.8193	NS
11	8	4.375	4.875	0.0331	*

The number of participants who answered the question in both the pre- and the post-survey is denoted by *N*. For significance (sig.), $^{*}p < 0.05$, $^{***}p < 0.001$.
Statements list:
1. I am favorable toward the use of natural language processing models in medicine.
2. I am favorable toward the use of generative adversarial networks in medicine.
3. I am certain that I understand the building blocks of large language model (LLM)-based chatbots, such as ChatGPT.
4. I am favorable toward the use of LLM-based chatbots in medicine.
5. I am likely to use LLM-based chatbots in my study or line of work.
6. I am certain that I can use the outputs from LLM-based chatbots effectively.
7. I think that LLM-based chatbots generate highly accurate answers.
8. I think that LLM-based chatbots generate bias-free answers.
9. I am optimistic about the direction of development in future LLM models.
10. I think that LLM-based models have potential to replace humans in daily tasks.
11. The instructor is favorable toward the use of LLMs.

transcriptions of the survey results were performed by the non-instructor authors on this paper. This study was designated as Non-Human Subject Research by UC Davis IRB office (IRB #2209830-1).

4 Results

4.1 Quantitative results

Thirteen copies of pre- and post-survey were collected at the end of the lecture. Due to the nature of surveys being distributed via paper copies and the full anonymity, not all questions were completed by the students. Student demographics were not collected as part of this study; however, the overall makeup of the course is 52% female and predominantly BME senior undergraduates.

On the quantitative portion of the survey, students reported a perceived favorable attitude from the instructor toward LLMs, and the perception was significantly reinforced after the lecture (S11, $p = 0.033$). Students lean toward agreeing on statements 1, 2, 4, 5, 6, 9 before the lecture was given to them; after receiving the lecture, the levels of agreement on S2 (use of GANs in medicine, $p = 0.015$), S6 (self-efficacy in using chatbots, $p = 0.027$), and S9 (optimism on future of LLMs, $p = 0.020$) significantly increased. The positionalities of S3, 7, 10 were not clear in the pre-survey. Among these statements, students reported a major increase in understanding of the building blocks of LLM-based chatbots (S3, $p < 0.001$), demonstrating the efficacy of the lecture. S8 (LLMs are bias-free) received a low level of agreement in the pre-survey, and this agreement level stayed low in the post-survey. Table 1 shows the full analysis of the Likert-scale questions and the full wording of these statements.

The results from the linear regression with RFE are presented in Table 2. The final model has only four predictors but achieved an excellent fit ($R^2 = 0.70$). Significant predictors on students' intention of using GenAI (S5) include their self-efficacy on using the LLM outputs (S6, slope = 1.68, $p = 0.001$) and their perception of LLM being bias-free (S8, slope = 0.78, $p = 0.016$). The favorability of using GenAI in medicine (S2, negative) and understanding of building blocks (S3, positive) are also contributors to this model, but these contributions are not statistically significant. The addition of any other statement into the model will cause the adjusted R^2 value to decrease, so we consider all other statements (S1, 4, 7, 9, 10, 11) to be non-contributors to students' intention of using GenAI.

4.2 Qualitative results

The final codebook for the free-response survey questions contains these major codes: components and training of LLMs, names of generative AI models, machine learning methods, generated data, medical AI, tool, ethics, and AI devices. The Cohen's Kappa for the coding was 0.840, demonstrating strong agreement between the two coders (McHugh, 2012).

We performed a Fisher's exact test on the coding frequencies in the common free-response question, "When you think of generative AI, what terms come to mind" (see Table 3). We found that the frequencies of the codes were significantly different ($p = 0.002$), further reaffirming our findings in the quantitative portion of the survey, that the students reported a significant increase in confidence in understanding of LLMs. Students have shifted from regarding GenAI as solely the names of GenAI products, such as ChatGPT and Dall-E, to components and training of LLMs. Another shift that we observed in the coding frequency is within the potential products of GenAI: more domain-specific codes in BME in "medical data processing" and "medical images" were identified instead of generic images, drawings, and letters.

We also applied this codebook to the other two questions in the post-survey, the clearest and muddiest points associated with the lecture. Students' answers to both questions, unsurprisingly, coded primarily into the category "Components and Training of LLMs." A more detailed analysis revealed that the students regarded the *tokenizers* as the clearest point, followed by *word embeddings* and *cost associated with training*; the structure and training of transformers remain the muddiest point for most students.

5 Discussion

In this study, we found that instructing the students about LLMs can shift students' perception of GenAI from naming the LLM-based chatbots to understanding the components of the products (S3, Table 3, codes 1, 2) as well as from general to domain-specific applications (S2, Table 3, codes 4, 5). These findings suggest that instructing students about GenAI, especially in a domain-specific context, may be beneficial for students to develop context for GenAI methods and products in their domain and develop students' critical thinking levels. The instruction module also builds self-efficacy (S6) toward the usage and development of LLM-based chatbots in students. Overall, the learning module successfully fulfilled the role of bringing more clarity and interpretability for understanding and evaluating GenAI, especially LLM-based chatbots.

RQ2 was not fully supported from our initial cohort. The level of students' perception of adopting GenAI in their study or work (S5) received a near-significant increase. According to our linear regression model, the main contributor from the intervention toward students' tendency to adopt may be from a higher level of self-efficacy of using the *outputs* from LLMs (S6, total effect $0.461 \times 1.68 = 0.774$). The contribution from increased understanding of LLM components (S3) was present but much less effective (total effect $1.846 \times 0.17 = 0.314$). This finding suggests that if an educator's goal is to increase adoption rates of LLM-based chatbots in their classrooms and/or increase students' levels of GenAI literacy, lectures focusing on using the LLMs, for example, prompt engineering and/or evaluating the outputs from LLM-based chatbots, may be more effective than teaching the students about constructing LLM-based chatbots.

We were only able to partially validate RQ3 in our initial offering of the module. Although we did find a significant increase in S9 (optimism in using and developing LLM-based chatbots) and a near-significant increase in S5 (adopting GenAI), the observed effects were mostly from an increased self-efficacy shown in RQ2. The authors have originally hypothesized that more knowledge about the components of LLMs will cause a decrease in S8, whether LLM models are regarded as bias-free. However, a prior module of this course has covered bias and equity issues in machine learning. Within the module, the study of word embeddings was used as an example for machine learning systems that exhibit bias. Possibly due to prior knowledge resulting from this prior module, students reported very low levels of agreement on S8 in the pre-survey. Therefore, we could not examine the effect in the awareness of bias level in GenAI in this cohort due to the pre-existing consensus. However, the regression model depicted that students who had a more optimistic view on bias and equity of LLMs tend to have a higher tendency of using LLMs in their study or work, partially confirming our initial hypothesis that better knowledge in biases exhibited in LLMs could potentially lead to a lower tendency of use. The previously proposed future work of developing a learning module for general students could potentially help us achieve better understanding in this RQ.

Although S11 (students' perception of instructor's attitude toward LLMs) was deemed a non-contributor to students' adoption of LLM-based chatbots, a lecture on constructing LLMs nonetheless increased an already-high level of perception that the instructor is favorable toward LLMs. From a post-lecture discussion with the students, the students were very surprised to know that the instructor is a complete non-user of LLM-based chatbots; the perceived favorability may have resulted from the identities of the instructor, i.e., a biomedical engineer teaching the course *machine learning in BME*, who *included a module of introductions to GenAI/LLM* in the syllabus and have multiple publications about *AI work in medicine*, including *generative AI work*. Therefore, the authors suggest that potential adopters of such modules in their own classrooms, whether teaching about components of LLMs or about using LLM-based chatbots, to be aware of students' perceptions about potential identities of the instructor, which can possibly affect the outcome of classroom instruction.

TABLE 2 Coefficients of the final linear regression model after RFE to predict S5 (behavioral intention).

Variable	Value	Standard error	Beta	*p*-value	Sig.
Intercept	−2.90	1.96	0.00	0.163	NS
S2	−0.35	0.25	−0.24	0.184	NS
S3	0.17	0.16	0.19	0.318	NS
S6	1.68	0.39	0.83	0.001	**
S8	0.78	0.28	0.49	0.016	*

The "Value" field is the value of the intercept and the slopes of all other statements. Value and Standard Error are unstandardized coefficients; Beta is the standardized slope. $^*p < 0.05$; $^{**}p < 0.01$.

6 Limitations and future work

Our implementation of the one-lecture module promoted GenAI literacy in our machine learning students. However, we would like to

TABLE 3 Codes, frequency (as measured by the number of references), and sample quotes in the question "when you think of generative AI, what terms come to mind" in both the pre- and the post-surveys.

Code	Pre-survey frequency	Post-survey frequency	Sample quotes
Components and training of LLMs	0	11	"Tokenizing, embedding, transforming" "…how complex and the amount of money put in to create these models"
Names of GenAI models	7	4	"ChatGPT," "DALL-E," "Google Gemini"
Machine learning methods	5	4	"Natural language processing," "neural networks," "machine learning," "deep learning"
Generative data	6	3	"AI-generated image," "create drawings or images," "form letters"
Medical AI	0	4	"…medical data processing," "medical images"
Tool	3.5	0	"…a tool that can assist us," "a useful tool"
Ethics	1	1	"…stolen work," "unapproved use of established works"
AI devices	1	0	"Robots"

Code frequency presented is the average of the two raters.

caution the readers on the results we obtained so far: participants of this study have almost completed a whole machine learning course, including modules on data exploration, visualization, linear regression, logistic regression, support vector machines, trees, fully connected neural networks, and clustering. These students are generally committed to learning more about AI and were receptive to knowledge related to GenAI. The cohort of students participating in the current study (maximum $N = 13$) is relatively small; more offerings of this course may be needed to increase the quality of statistics performed in this study.

Potential adopters of our strategies should mind students' level of background knowledge in machine learning and AI and should consider adjusting the complexity of the offering and/or increase the time allocated to this module for maximum benefits. With our students' preparation level, the topics that students have received adequate preparations for, such as the tokenizer and the word embeddings, were identified as the clearest points in the GenAI module. This course did not prepare the students to understand deep learning topics such as convolutional neural networks, and thematic analysis revealed that the details of deep learning-based transformers were too challenging for students to understand, even when introduced at the surface level.

One other future-facing challenge is the increasing opacity of GenAI products, especially LLM-based chatbots. The commercialization of LLM-based chatbots, now sometimes including audio, image, and/or video processing and generation capabilities, has shifted the scope of GenAI space. The training data, processes of word embeddings, the structure of the transformer network, and cost/time to train these chatbots, are no longer disclosed by commercial GenAI companies in their technical papers. The construction of this teaching module had to rely on best estimates in computer science literature and data from past models. We expect that our ability to update this module for adapting to future state-of-the-art GenAI products will be significantly challenged unless the companies become more transparent about the details of their GenAI products.

We intend to improve the module for the machine learning course: although understanding the neural network structures of transformers will be extremely challenging for students who are taking their first machine learning course, a more thorough introduction to deep learning methods will be beneficial in helping students understand important concepts such as layers, kernels/filters, and parameters. We also plan to develop two more instructional modules on GenAI. A technical module that assumes less background knowledge may be beneficial for easier adoption for interested instructors to develop their students' GenAI literacy and can be used as training for faculty to become more aware of GenAI. We also plan to develop a non-technical module, in collaboration with experienced LLM-based chatbot users, to increase participants' skills in prompting and evaluating the output of LLM-based chatbots. We intend to evaluate the outcomes of these modules with a more comprehensive survey among participants of these new modules.

Gamification has been reported to enhance students' engagement in class (Gari et al., 2018) and promote collaborative reasoning (Di Nardo et al., 2024) in a lecture-based context for assessment (Alhammad and Moreno, 2018). Our current machine learning course has integrated some major gamification components in instruction and assessment, for example, students are graded based on their placement on a leaderboard for the projects, which were private machine learning competitions. A way to address the absence of a formal assessment for the module in this course may be designing and implementing a bonus credit activity as an in-class GenAI trivia based on the materials of the module.

Data availability statement

The current version of the learning module can be accessed at https://cube3.engineering.ucdavis.edu.

Ethics statement

The studies involving humans were approved by University of California, Davis, Institutional Review Board. The studies were conducted in accordance with the local legislation and institutional requirements. The ethics committee/institutional review board waived the requirement of written informed consent for participation from the participants or the participants' legal guardians/next of kin because the study was designated as Non-Human Subject Research by the IRB Office due to the proposed activities not meeting the definition of human research (IRB 2219830-1).

Author contributions

XW: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. TC: Data curation, Formal analysis, Writing – original draft, Writing – review & editing. AT: Data curation, Formal analysis, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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A systematic review of the early impact of artificial intelligence on higher education curriculum, instruction, and assessment

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Introduction: The emergence of generative artificial intelligence (AI) presents many opportunities and challenges to teaching and learning in higher education. However, compared to student- or administration-facing AI, little attention has been given to the impact of AI on faculty's perspective or their curriculum, instruction, and assessment (CIA) practices.

Methods: To address this gap, we conducted a systematic review of articles published within the first nine months following the release of ChatGPT. After screening following PRISMA statement guidelines, our review yielded 33 studies that met the inclusion criteria.

Results: Most of these studies ($n = 17$) were conducted in Asia, and simulation and modeling were the most frequently used methods ($n = 15$). Thematic analysis of the studies resulted in four themes about the impact of AI on CIA triad: (a) generation of new material, (b) reduction of staff workload, (c) automation/optimization of evaluation, and (d) challenges for CIA.

Discussion: Overall, this review informs the promising contribution of AI to higher education CIA practices as well as the potential challenges and problems it introduces. Implications for future research and practices are proposed.

KEYWORDS

artificial intelligence, large language models, curriculum, instruction, assessment, systematic review

Introduction

Large language models (LLMs) aim to simulate the natural language processing capabilities of human beings (Cascella et al., 2023), particularly understanding, translating, and generating texts or other content. The introduction of LLMs, such as ChatGPT and other generative artificial intelligence (AI), has created interesting possibilities and challenges for all educational systems. For instance, while AI can provide opportunities for instructors to personalize learning and provide students with more immediate feedback (Fauzi et al., 2023), it can raise concerns about academic integrity and the propagation of biased or inaccurate information. Tensions over the legitimacy of AI in higher education have placed significant pressure on academics and students. Much of the extant research on AI has focused on students (e.g., Chan and Hu, 2023; Crompton and Burke, 2023) or administrators (e.g., Nagy and Molontay, 2024; Teng et al., 2023). However, how academics, in their role as educators, perceive, use, and adapt to AI tools is still under-researched, particularly when many academics have reported insufficient AI literacy (Alexander et al., 2023).

Given that AI tools are increasingly being used in higher education with a strong potential to transform higher education teaching, learning, and assessment, it is important to systematically synthesize early empirical evidence regarding AI's impact, identify trends and patterns in the literature, and further inform AI policy, research, and practices. Therefore, this study aims to fill the gap through a systematic review driven by the overarching question: How has AI affected the teaching, curriculum design, or assessment practices of academics in higher education (HE)? Specifically, this systematic review aimed to explore what the first wave of research following the release of ChatGPT in November 2022 had focused on and found with respect to the impact of AI tools in HE. In particular, we wanted to understand how AI technologies were affecting curriculum, instruction, and assessment processes to identify pros and cons that might inform promising pathways as well as potential challenges and problems. To complement those insights, we also wanted to identify where this early research was being conducted, what methods were used by researchers, and which aspects of AI were of concern. We hope this contextual information helps readers better understand the applicability of results to their own jurisdictions or situations. By doing so, we provide an overview of how the field is handling these new technologies to change or adapt academics' work in terms of curriculum, instruction, and assessment.

The higher education curriculum-instruction-assessment (CIA) triad

All educational systems must make decisions concerning what they teach (i.e., curriculum), how they teach it (i.e., instruction), and how they evaluate student learning (i.e., assessment). Normally, curriculum decisions (e.g., what to teach and the order in which to teach it) lead to instructional decisions (e.g., how the material is to be introduced, and which methods might best help students learn it), and culminate in assessment and evaluation decisions (e.g., how many assessments of what type and when those assessments will take place). Thus, curriculum, instruction, and assessment comprise the essential triad of all educational practices (Pellegrino, 2006). Higher education systems give academics considerable autonomy over these decisions based on their higher research degrees and contribution to research outputs within their disciplines. While professional certifying bodies have some control over what must be covered, universities give academics responsibility for deciding how to organize, teach, and assess learning in their courses.

The CIA triad has been demonstrated to be highly related to the quality of specific programs and the college students they prepare for the future (Merchant et al., 2014; Sadler, 2016). However, HE settings are likely to shift considerably in the AI era—the curriculum might not just reflect the logic of specific disciplines but also include AI-related content; instructional practices may need to adapt to the co-existence of AI teachers; and assessment practices might include students' understanding and competencies related to AI use. In this light, understanding the benefits that AI brings to HE curriculum, instruction, and assessment could help academics make full use of the technology to reduce workloads (Holmes et al., 2023; Pereira et al., 2023) and improve productivity. Meanwhile, noticing some threats can remind academics to be prepared for negative impacts on college students' engagement and learning.

Method

A systematic review of the literature was carried out by the first author in three databases: Scopus, Web of Science (WoS), and EBSCOhost. These databases are major research databases, varying in coverage content, disciplines, and languages (Stahlschmidt and Stephen, 2020). They can complement each other and provide us with high-quality and relevant literature. To establish trustworthiness, the research team made agreements on search terms and initial inclusion and exclusion criteria before the first author identified the literature. To answer the research question, search terms were trialed iteratively to retrieve relevant literature on how AI has influenced curriculum, instruction, and assessment in higher education (HE). Synonyms for "AI" (e.g., ChatGPT), "teaching" (e.g., instruction), "curriculum" (e.g., planning), or "assessment" (e.g., evaluation) were searched within the title, abstract, keywords, or anywhere in the record. Search terms were then finalized and used identically in each database: ("artificial intelligence" OR "generative artificial intelligence" OR "generative AI" OR "Gen-AI" OR "ChatGPT" OR "GPT*") AND (("higher education") AND ("teaching" OR "assessment" OR "evaluation" OR "feedback" OR "curriculum" OR "instruction*" OR "lesson" OR "planning" OR "delivery" OR "implementation")). A total of 2,810 articles were identified.

Filters were set only to include peer-reviewed journal articles published in English from December 2022 to the end of the search in August 2023. The first 9 months of literature could capture the critical early phase, when educators and researchers started to publish their responses to newly released AI tools, such as ChatGPT. Filtering only to include peer-reviewed journal articles helped ensure the quality of literature in the search phases. The time frame was chosen to return the earliest possible exploration of the impact of AI, immediately following the release of a demo of ChatGPT on 30 November 2022.

Moreover, articles in this review were limited to empirical articles on AI's impact on HE curriculum, instruction, and assessment (see Table 1). To be included, articles had to report a relationship between AI and any one or more of three aspects of HE curriculum, instruction, or assessment. Articles regarding the

TABLE 1 Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
1. Articles present an analysis of empirical data, written in English and published in peer-reviewed journal articles. 2. Articles about how AI influences any one or more of three aspects of HE curriculum, instruction, and assessment (e.g., curriculum design, instructional planning, delivery, assessment, evaluation).	1. Articles about HE curriculum, instruction, and assessment but not related to how AI impacts them. 2. Articles about broad perspectives on AI (e.g., benefits, weaknesses, preparation) rather than its impact on HE curriculum, instruction, and assessment. 3. Articles about the impact of AI on non-HE curriculum, instruction, or assessment (e.g., school contexts).

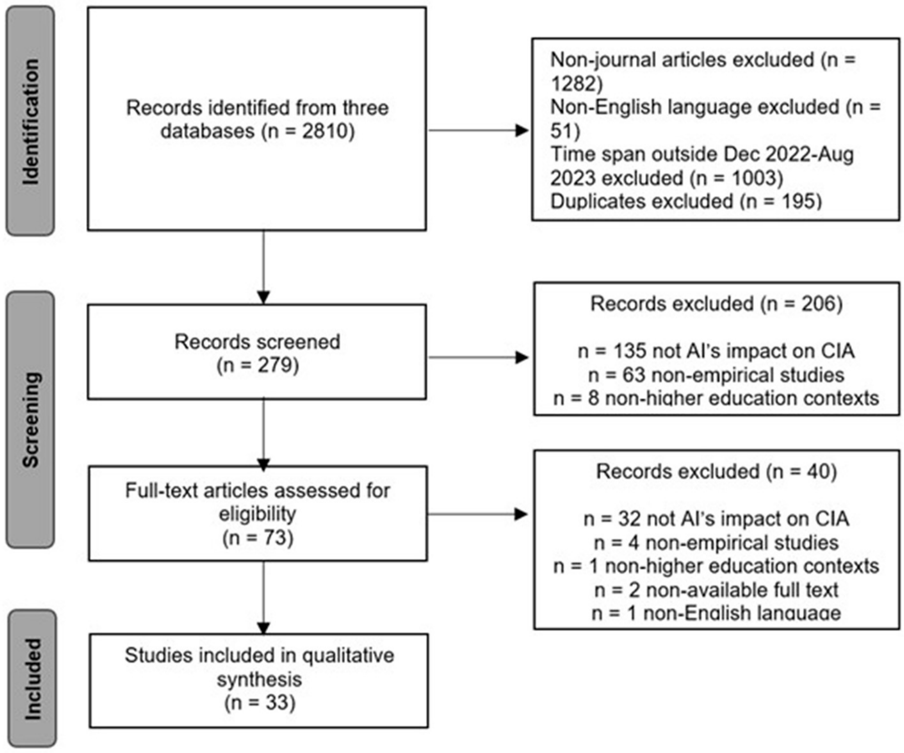

FIGURE 1
PRISMA flowchart of the literature search process.

impact of AI on curriculum, instruction, and assessment in non-HE contexts were excluded.

Search process

After removing duplications, 279 records were obtained for screening following the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines (see Figure 1; Moher et al., 2009). PRISMA guidelines provide a structured framework for searching, identifying, and selecting articles, as well as extracting, analyzing, and synthesizing data to address specific research questions. These guidelines help ensure the quality of the review, minimize bias, and maintain transparency and replicability (Moher et al., 2009) for researchers.

Specifically, the screening process involved title and abstract screening and full-text screening. The titles and abstracts of these records were assessed using the agreed inclusion and exclusion criteria (see Table 1), resulting in the exclusion of 206 records. These records were excluded because their titles and abstracts showed that (a) they did not investigate how AI affected HE curriculum, instruction, and assessment (n =135), (b) they lacked empirical evidence ($n = 63$), or (c) they did not focus on university contexts ($n = 8$).

The remaining 73 records were downloaded for full-text screening. The articles were read and evaluated against the inclusion and exclusion criteria. Ones that did not meet the inclusion criteria were removed. Specifically, studies that introduced AI or HE curriculum, instruction, and assessment but did not actually explore the relationship between them were excluded ($n = 32$). Other articles were removed because they (a) did not have empirical evidence ($n = 4$), (b) were in a non-HE context ($n = 1$), (c) were not available as full text ($n = 2$), and (d) were not in English ($n = 1$). Consequently, a total of 33 articles were included for review.

During the screening stage, either author was unsure if a specific article should be included, and then the content of this article was discussed against the research question and focus of this review. These discussions resulted in refining the inclusion and exclusion criteria and a consensus on included articles.

Data extraction and analysis

Due to the exploratory nature of this research, an inductive thematic analysis (Braun and Clarke, 2006) was conducted to identify key patterns of the impact of AI on HE curriculum, instruction, and assessment. The first author read the 33 articles thoroughly and extracted key information from each paper, including citations, context, sample size, data collection method, measurement, and the impact on HE curriculum, instruction, and assessment. With an eye to finding answers to the research question, meaningful segments, such as "AI tools allow educators to/provide students with..." and "the challenge is," were used to identify descriptive codes regarding how AI influences HE curriculum, instruction, and assessment.

Twenty-five initial descriptive codes (e.g., improve teaching effectiveness, challenge the role of educators, assess teaching effect) were captured. Then, the similarities and differences between each code were iteratively compared to identify high-level categories. For instance, codes such as "challenge instructors' AI teaching competencies," "ethical consideration," and "lack of support in AI teaching" were integrated into a category named "challenge existing teaching." Based on the raw data, research questions, and conceptual framework, similar categories were further reviewed and merged into four key themes. Articles could be arranged into more than one theme because of the presence of multiple themes. Please see Appendix A for complete details of themes, categories, and codes.

During the data extraction and analysis stage, the first author coded the key information from each study to address the research questions. The other authors critically read and reviewed the coding results, final synthesis, and interpretation of the themes. Any uncertainty on internal homogeneity and external heterogeneity (Patton, 2003) among codes, categories, and potential themes were discussed at regular meetings.

Results

Nature of studies

Table 2 shows the characteristics of the regions where the 33 studies were conducted, as well as the methods utilized to explore the impact of AI on HE curriculum, instruction, and assessment. Details of which papers are in each category are provided in Appendix B. There are 16 countries around the world contributing to this field. Asia, predominantly China, accounted for 17 of the 33 studies. As Table 2 shows, the balance was distributed widely across the world.

Regarding research methods, 15 of the studies used modeling or simulation methods to design, implement, and test the accuracy and effect of AI tools. For instance, Shi (2023) designed a teaching mode based on the neural network model to provide students with personalized resources and assignments in moral education. This intelligent mode was then tested by simulating different teaching scenarios, and its accuracy and practical effect were confirmed. Each of the following methods was used in six or seven studies, (a) experimental designs to compare AI with an intervention group and a control group, (b) surveys, or (c) interviews. For instance, Farazouli et al. (2024) conducted blinded Turing test experiments by inviting instructors to examine AI-generated texts and student-written texts, and interviewed instructors for their perceptions of the quality of assessed texts and whether they were worried that AI had written the text. A small number of studies used one of a set of diverse methods (e.g., case study, workshop, observation, discussions, etc.).

Three distinct foci of AI were examined. The most common focus in 16 studies was the technological dimensions of AI, such as designing and modeling an AI tool for HE curriculum, instruction, and assessment and testing the accuracy of this tool itself. Computer science and engineering researchers tended to focus on these technological aspects. The human dimension of AI experience was the focus of 10 studies and seen mostly in social science research. These articles examined how university teachers perceived the impact of AI on their curriculum, instruction, and assessment. Just seven studies highlighted how AI supported curriculum, instruction, and assessment.

TABLE 2 Study characteristics: number of publications by region, methods, and Foci.

Characteristic	*n*
The region where the study was conducted	
Asia (i.e., Mainland China, Hong Kong, India)	17
Europe	8
North America	5
Latin America (i.e., Brazil, not specified)	3
Middle East (i.e., Oman, Turkey)	2
Australia	2
Methods	
Modeling/simulation	15
Experiment	7
Interview	7
Survey	6
Others (e.g., discussion, workshop, open-ended questions, observation)	6
Case study	3
Mixed methods	2
Foci	
Technology	16
Human experience	10
Use of AI in class	7
Education dimension	
Curriculum	9
Instruction	21
Assessment	17

The number of included studies is more than 33 because some were conducted in cross-national contexts, used multiple research methods, and/or focused on multiple dimensions.

The focus of AI in higher education was classified according to the CIA triad. As shown in Figure 2, 22 of the studies addressed just one of the three aspects, with most being in instruction and assessment. Just 11 studies attempted an integration between two or more of the three aspects. Of the 33 studies, taking into account all overlapping categories, 21 (64%) papers had something to do with instruction, about half had something to do with assessment (17, 52%), and about a quarter focused on curriculum (9, 27%).

Thematic analysis

Based on thematic analysis of the articles (their purposes and findings), four key themes were identified: (a) generation of new material, (b) reduction of staff workload, (c) automation/optimization of evaluation, and (d) challenges

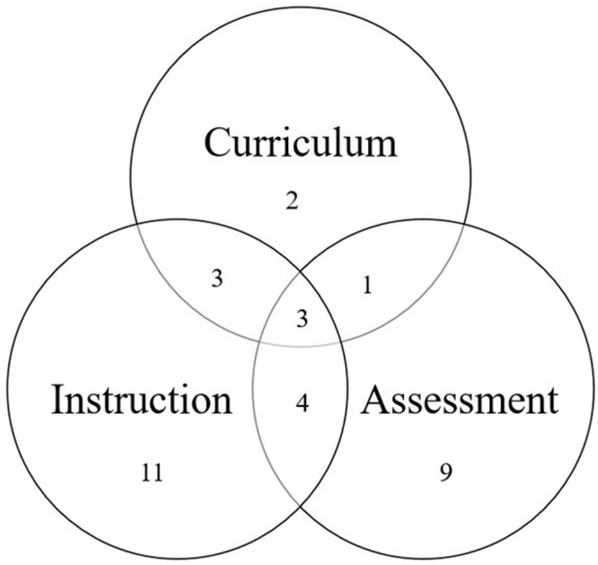

FIGURE 2
AI's impact on the CIA triad in HE: a Venn diagram of the number of published articles.

for curriculum, instruction, and assessment. While we analytically identify specific aspects, it needs to be remembered that mentions of curriculum or instruction or assessment separately, many of those studies have connections with one or more of the other topics. For example, reference to curriculum is usually related to how instruction could be done, while reference to assessment is linked with how AI resources can be used for instruction or curriculum, and so on.

Generation of new material

Ten studies described the ample new material AI provides for curriculum preparation and instruction implementation. Attributes mentioned include providing various resources and generating new teaching content, building an immersive learning environment, and improving or replacing existing teaching modes with a new teaching approach (Al-Shanfari et al., 2023; Chen et al., 2023; Guo, 2023; Pisica et al., 2023; Pretorius, 2023; Shi, 2023; Wang, 2023; Yang, 2023; Li and Zhang, 2023; Zhu, 2023).

Generate new curriculum content

Two studies examined how academics perceived the influences of AI on specific subject-related curricula and teaching, one in data science and one in English translation (Chen et al., 2023; Wang, 2023). Both studies conducted focus group interviews, and revealed that AI, at curriculum levels, could provide instructors and students with new, rich, and personalized materials, contributing to curriculum design and development and facilitation of course preparation. According to Pisica et al. (2023), 18 academics from Romanian universities reported the benefits of AI in curriculum, which included generating new content for existing courses and developing new curricula or disciplines.

Provide an immersive learning environment

AI technology, such as smart classroom, enables the simulation of the atmosphere of a "real" classroom, practicum, or internship, in which students could better understand and practice what they had learned (Wang, 2023; Zhang et al., 2023). For instance, Wang (2023) stated that AI could make teaching content visualizable; that is, students could practice key communication competencies in a virtual community of practice, which improves teaching efficiency. Additionally, Zhang et al. (2023) designed and experimented with an intelligent classroom for English language and literature courses in China, and found that this AI tool provided the experimental group with a good learning environment and enhanced students' language proficiency.

Offer a new teaching mode

A large body of research has designed and implemented an AI tool (e.g., speech recognition, ChatGPT) in HE teaching, providing a new teaching mode with good accuracy and effectiveness (Al-Shanfari et al., 2023; Chen et al., 2023; Guo, 2023; Pisica et al., 2023; Pretorius, 2023; Shi, 2023; Yang, 2023; Zhu, 2023; Li and Zhang, 2023). Guo's (2023) study, conducted in the Chinese context, showed that a newly designed speech recognition method, based on a recurrent neural network algorithm, had a better accuracy rate and faster convergence, and could replace the previous method and effectively address issues of the low speech recognition rate caused by noisy environments. In addition, two studies in multimedia teaching or moral education (Shi, 2023; Yang, 2023) conducted simulation experiments, suggesting that the new AI-powered teaching mode stimulated students' multiple senses, improved learning and teaching efficiency, and appeared to be much more effective than traditional teaching modes, which to some extent hindered students' originality and interest in learning. The simulation results also suggested that AI-powered teaching mode had the potential to be implemented in real classrooms.

Reduction of staff workload

Ten studies have demonstrated that AI could support staff in curriculum, instruction, and assessment, by reducing their logistical workloads, especially in terms of labor related to curriculum design, interactions with students, delivering personalized instruction, and preparing adapted or personalized assignments (e.g., Holmes et al., 2023; Pereira et al., 2023; Sajja et al., 2023; Devi and Rroy, 2023).

Work as a curriculum assistant

AI could work as a virtual curriculum assistant that helps address students' time-consuming and repetitive questions about curriculum (e.g., content, time, deadline), reduce instructors' logistical workloads and give them more time to improve teaching quality and support students' development (Sajja et al., 2023). For example, Sajja et al. (2023) used the syllabus and other teaching materials to design a curriculum-oriented intelligent assistant and found that this virtualTA effectively provided accurate course information and improved students' course engagement.

Additionally, AI has been demonstrated to help instructors reflect on curriculum and content difficulty. One study investigated using an AI toolkit to collect students' assessment data and further support teachers' reflections on curriculum design (Phillips et al., 2023). The study evaluated the reading demand (using skip-gram word embedding) of passages in assessments (e.g., exams) against the demand of texts and lectures used to support instruction, on the assumption that reading in an assessment should not be harder than that used in instruction. The AI tool predicted the difficulty of course materials, including recorded lectures and assessment materials, in a similar way to lecturers' self-reported material difficulty. Not only would this tool ensure the alignment of assessment reading materials with course reading materials, but also provide valid evidence for the assessment materials.

Personalized instruction

Applying AI technologies can facilitate analyzing students' learning procedures, performance, and needs, providing instructors with timely feedback, and assisting them in delivering adaptive instruction. Consequently, teaching and learning effects were somewhat improved (Al-Shanfari et al., 2023; Firat, 2023; Kohnke et al., 2023; Li L. et al., 2023; Li Q. et al., 2023; Pisica et al., 2023; Wang, 2023; Li and Wu, 2023). By implementing embedded glasses in real classrooms, Li L. et al. (2023) showed that this device helped instructors recognize and process students' real-time images and emotions and keep abreast of their learning status, and this information further provided timely feedback to instructors to change their teaching strategies. Therefore, compared to the control group, the teaching effect of the experiment group increased by 9.44%, and students reported more satisfaction with teaching. Similarly, a new piano teaching mode powered by a vocal music singing learning system has been demonstrated to be relatively successful: it not only made piano teaching more personalized and intelligent, increased teaching efficacy by 7.31% compared to the traditional teaching mode, but also motivated students to engage more in piano practice time and classroom participation (Li Q. et al., 2023).

Prepare personalized assignments

A new assessment method driven by AI tools could help instructors prepare personalized assignments. Pereira et al. (2023) described how an emerging recommender system generated equivalent questions for assignments and exams, to enhance the variation of assignments and support instructors in preparing individualized assignments and minimizing plagiarism. They also indicated that this recommender system was confirmed to be accurate after instructors evaluated the equivalence (e.g., interchangeability, topic, and coding effort) of AI-created questions to the questions instructors had provided.

Automation/optimization of evaluation

Many scholars have investigated the potential of using AI in HE assessment and evaluation.

Assess students' learning process and outcomes

AI is found to accurately assess students' learning process and outcomes, and further determine teaching effect (Novais et al., 2023; Saad and Tounkara, 2023; Wang et al., 2025; Zhu et al., 2023). For instance, Archibald et al. (2023) showed that an AI-enabled discussion platform accurately calculated students' curiosity scores to present their engagement in discussion, further reducing teachers' assessment workload and facilitating their intervention based on the quality of posts written by students. A new assessment method driven by AI tools (i.e., a backward propagation neural network) could automatically evaluate teaching, learning, and grading in an experiential online course in agriculture (Kumar et al., 2023).

Using experiments with small-samples, Zhu et al. (2023) developed in China an AI tool to predict students' performance based on their classroom behavior and previous performance. They suggested that this tool could be used to adjust instructors' teaching strategies and improve teaching quality. Similarly, Tang et al. (2023) discussed how a designed intelligent evaluation system could better recognize voices, face, postures, and teaching skills in microteaching skill training, accurately assess preservice teachers' teaching performance, and provide accurate guidance. Moreover, Saad and Tounkara (2023) used students' information, including class participation frequency and quality, absence rate, contribution to online group work, and utilization of learning resources, in distance learning, to establish a preference model for instructors that could quickly recognize students at risk of dropping out and leader students who could help their peers. They found that this model correctly assigned 85% of students to the correct clusters (i.e., at risk or leader), and assisted instructors in making correct decisions.

Besides evaluating students' cognitive-related outcomes, researchers have also used AI to assess students' non-cognitive outcomes (e.g., emotions, attitudes, and values). For instance, Novais et al. (2023) designed an evaluation fuzzy expert system and employed it to build profiles of students' soft skills (e.g., communication and innovation skills, management skills, and social skills). AI-generated scores were compared with real scores, providing reliable feedback to instructors and students.

Assess teaching effect

Wang et al. (2025) combined human-computer interaction and deep learning algorithm to design an intelligent evaluation system for innovation and entrepreneurship. The system could detect students' attitudes and behaviors and assess teachers' teaching preparation, language expression, content mastery, and teaching design. The operability of this system was further supported by assessing the teaching quality and effect of two classes, and the AI results showed that both classes' teaching quality scored almost 7 out of 10, suggesting a need to improve.

Challenges for CIA

Besides the above advantages, some challenges brought by AI in HE curricula, instruction, and assessment are described in six studies.

Challenge existing curricula

AI is found to bring many challenges to curriculum developers and existing curricula, especially in deciding what content is more valuable, how to integrate AI into the current curriculum, and how to prepare students with digital literacy. In order to address these questions, Lopezosa et al. (2023) interviewed 32 journalism faculties from Spain and Latin America about how they perceived this new technology; however, no consensus on whether to integrate AI into the curriculum was identified. Although most faculties embraced AI technology and suggested establishing AI as a standalone subject, some stated that challenges, limitations, and uncertainty about AI in education should be thoroughly researched before incorporating it into the curriculum. Some individuals suggested a compromise idea of integrating AI into communication subjects as a preliminary step (Lopezosa et al., 2023).

Challenge existing instruction

There are some concerns about using AI in HE instruction, including challenging teacher's AI teaching competencies, ethical considerations, and lack of teaching support. Chan (2023) indicated that AI may cause overdependence on technology and weaken social connections between teachers and students. In this light, Firat (2023) indicated that implementing AI may require educators to change their role from being instructors to guides or facilitators. Furthermore, based on interviews with 12 university teachers in Hong Kong, Kohnke et al. (2023) found that AI challenged participants' teaching competencies about teaching students how to judge AI-generated text critically, use AI tools ethically, and foster digital citizenship.

Ethical concerns in instruction include incorrect or fabricated information, accessibility, and algorithm biases (Firat, 2023). According to a teaching reflection of an educator from Monash University, Pretorius (2023) taught postgraduate students how to use generative AI effectively by giving them examples of communicating with generative AI to brainstorm and design research questions. Consequently, her course achieved good teaching feedback. However, Pretorius realized that incorrect or biased information produced by ChatGPT, as well as unequal access to AI caused by distinct socioeconomic status, required educators to shift their ability to prepare students with AI literacy for using AI professionally and ethically. Firat (2023) also mentioned over-reliance on AI, data privacy, and unequal access to AI tools as challenges.

Another concern centers on inadequate technical support and training in integrating AI into teaching. For instance, Al-Shanfari et al. (2023) utilized a mixed-method study to understand how aware, prepared, and challenged instructors were in integrating intelligent tutoring systems (ITS) in Omani universities. They found that most participants considered ITS effective in providing customized instruction; however, the lack of support and guidance in using ITS brought the instructors substantial challenges. As one participant said, "Teaching approaches at my university are not supporting the use of ITS" (p. 956). Similarly, Chen et al. (2023) interviewed 16 faculty members in data science and revealed that inconsistent definitions of data science, inadequate team support, and lack of collaboration platforms were major challenges.

Challenge existing assessment methods and strategies

While there are various opportunities for HE assessment, several challenges exist and need to be addressed. The most frequently mentioned challenge is that AI has been proven to pass many examinations and assignments. Consequently, some students may use it to cheat or plagiarize. For instance, Chan (2023) stated that new concerns in HE assessment have emerged, as most students and teachers are worried that some students use AI tools to cheat and plagiarize, and teachers could not identify such dishonesty correctly. Similarly, Kohnke et al. (2023) found that AI challenged the current assessment system, as instructors were worried that AI tools are too convenient for students making it easy to cheat and not work independently.

Moreover, it is hard for humans or AI detectors to identify AI-generated texts or assignments, which in turn challenges existing assessment practices and strategies. A case study conducted in an Australian Master's program for Geographic Systems and Science found that ChatGPT, acting as a fictional student, effectively completed most assignments (e.g., coding; Stutz et al., 2023). Although AI detectors identified it, lecturers did not recognize AI had generated the answers and gave a grade of "satisfactory." Stutz et al. (2023) also discussed the challenge ChatGPT poses to traditional evaluation methods and called on researchers and practitioners to rethink learning objectives, content, and assessment approaches. Assessments relying on oral exams or video conferences were suggested as alternatives that were resistant to AI dishonesty. In a similar study, both AI-generated and student-written texts were assessed by AI detectors and six English as a Second Language (ESL) lecturers from Cyprus (Alexander et al., 2023). It was found that AI detectors worked more effectively in identifying AI-generated texts than humans, and AI, to some extent, challenged lecturers' previous evaluation criteria and strategies. Lecturers seemed to conduct deficit assessment strategies and considered that AI-generated texts were characterized as having fewer grammar errors and more accurate expressions. Therefore, the authors recommended improving instructors' digital literacy and rethinking assessment policies and practices in the AI era. Similar findings were shown in Sweden, where Farazouli et al. (2024) conducted a Turing test among 24 university teachers in humanities and social sciences. They found that teachers tended to be critical about students' texts, underestimated students' performance, and doubted that some student texts had been finished by GPT. These concerns negatively influenced the trust relationship between teachers and students.

Discussion

This study examined how AI influences HE curriculum, instruction, and assessment by reviewing 33 recent articles. We summarize the review within a SWOT analysis (Gurl, 2017) framework to provide a structured framework about the strengths, weaknesses, opportunities, and threats of AI in terms of higher education curriculum, instruction, and assessment.

Benefits of AI in higher education

The analysis of 33 recent studies provides empirical evidence as to the geographical distribution of research, research methods, research foci, and the impact of AI on the CIA triad in higher education. Our results showed that most research was conducted in Asia, Europe, or North America. Consistent with findings indicating a rapid trend in Chinese research on AI in higher education (Crompton and Burke, 2023), China accounted for most studies in this review. One possible reason is that AI has been considered a priority in the Chinese government's agenda (State Council of PRC, 2017) and is thus highly emphasized in education.

This review also indicated that simulation and modeling were the most frequently used methods to assess the potential impact of AI in the HE context (e.g., Phillips et al., 2023; Saad and Tounkara, 2023; Sajja et al., 2023; Shi, 2023). This finding might be related to research foci, as more attention has been given to testing the effectiveness of AI tools rather than to academics' perceptions and practices of AI tools in the real world.

Several benefits were identified in this review, such as generating new material, reducing staff workload, and evaluating automatically or optimally (e.g., Kumar et al., 2023; Pretorius, 2023; Shi, 2023). This review first reveals that AI can create new courses and resources, promote curriculum development, address time-consuming workloads concerning curriculum (e.g., questions about syllabi, time, and deadline), and evaluate the material difficulty and quality (Chen et al., 2023; Lopezosa et al., 2023; Pisica et al., 2023; Wang, 2023). These findings reinforce earlier findings that the implementation of AI (e.g., ChatGPT) could contribute to generating a lesson plan and course objectives (Kiryakova and Angelova, 2023; Rahman and Watanobe, 2023) and to assessing general resources and textbooks (Koć-Januchta et al., 2022). AI has also been found to provide an immersive learning environment and a new teaching mode, where instructors facilitate students to conduct "trial-error" strategies and practice specific competencies in simulated scenes (e.g., Wang, 2023; Zhang et al., 2023). Meanwhile, AI, as virtual teachers, could take up logistical workloads (e.g., reinforce students' mastery of key concepts) and provide instructors time and energy to conduct personalized instruction and satisfy students' distinct needs (Al-Shanfari et al., 2023; Firat, 2023; Kohnke et al., 2023). These findings are in line with previous studies: AI, in most cases, worked well in sharing instructors' tutoring tasks, providing students with immediate and unique feedback, and reducing instructors' workload (Chou et al., 2011; Zawacki-Richter et al., 2019). Additionally, AI seems to benefit assessments by generating personalized assignments (Pereira et al., 2023), effectively assessing and predicting students' academic achievement (Wang et al., 2025) and non-cognitive outcomes (e.g., soft skills, Novais et al., 2023), identifying disadvantaged students (Saad and Tounkara, 2023), and assessing teaching effectiveness (Wang et al., 2025). This review finds evidence that AI-empowered assessment can effectively assess students' learning and teachers' teaching (Hooda et al., 2022; Zawacki-Richter et al., 2019).

Thus, AI has been found to bring benefits to HE curriculum, instruction, and assessment, including generating new materials, alleviating faculty workloads, and automating or optimizing assessment, in alignment with progressive literature (Chou et al., 2011; Rahman and Watanobe, 2023). These findings pave the way for future studies to ascertain the generalizability of the early promising results and the identification of conditions in which the early benefits actually occur. The benefits identified here suggest directions in which HE policy could go, provided appropriate infrastructure and training are given to academics.

Weaknesses in the research

This early research, however, is potentially problematic because of its narrowness. Specifically, research conducted in many regions, especially developing countries, is poorly represented. The currently available research has been conducted largely in Western, Educated, Industrialized, Rich, and Democratic (WEIRD; Henrich et al., 2010) societies. This means that there is a bias in what we can know since participants from other regions of the world are excluded. To the degree that cultural, historical, and developmental factors impinge upon the practice of higher education, more work with such populations is needed. Such research would enhance our understanding of how academics perceive the threats and opportunities of AI.

Another gap in the literature is the absence of research into the real world of higher education classroom pedagogical activities, course development, and assessment design. Comparatively, few studies have focused on the human experience of using AI, especially in classrooms (e.g., Al-Shanfari et al., 2023; Archibald et al., 2023; Farazouli et al., 2024). Related to this is the lack of cross-disciplinary collaborative research between computer scientists and social scientists. If AI tools are meant to make a difference to classroom teaching, learning, and evaluation, researchers from different backgrounds will need to collaboratively explore how AI technology could be used in educational practice.

Based on this review, future research will need to explore the following questions:

- How does AI influence the teaching, curriculum design, or assessment practices of academics in higher education in the Global South contexts? How does it differ from research conducted in the Global North? How can AI tools, policies, and practice become more culture-sensitive based on this comparison?
- What are the best practices of academics in teaching students to use AI ethically and responsibly?

Opportunities of AI in higher education

The presence of AI seems to create opportunities for academics in terms of revisions to existing courses and freeing up time to focus on improving existing curriculum, instruction, and assessment quality. These opportunities point to the development of interdisciplinary courses with the help of AI, especially in terms of course content and assessment design. One way to implement interdisciplinary approaches would be to integrate ethical considerations of using or relying on AI in philosophy or research methods courses. Another way is to use AI to bridge the intersections of different disciplines (e.g., Arts-Arts disciplines, Science-Science disciplines, and Arts-Sciences disciplines). An example in the Science-Science disciplinary intersection could be using AI to predict how air pollution (environmental science) affects health outcomes (healthcare).

Given the benefits AI brings to academics' instruction by providing an immersive learning environment and a new teaching mode, it may be feasible to establish a collaborative teaching system, where virtual teachers (i.e., AI) share intensive and repetitious teaching workloads (e.g., immediate feedback, knowledge reinforcement), and where human teachers pay attention to student's personal, emotional, and development needs and conduct one-to-one adaptive instruction. For instance, AI teachers could automatically grade and constantly offer targeted practice for students, which would provide adaptive support to teachers. Consequently, developing AI-empowered student and teacher assessment models could be important research and practice directions.

Additionally, we suppose that student-facing AI assessment models can be implemented in three steps. Before the classroom, AI can be used to diagnose students' knowledge bases and help instructors better understand students' learning preferences, motivations, and needs. During the classroom, AI techniques (e.g., speech recognition, facial recognition) can be combined to collect students' facial expressions, emotions, gestures, classroom dialogue, and so on, and promptly analyze their learning engagement, behaviors, strategies, and difficulties. This information can inform instructors about students in need, possible changes in teaching strategies, and early advice on where to intervene. After the classroom, AI, working as a teaching assistant, could provide students with targeted assignments, facilitate individualized learning, and predict future performance based on current performance. Similarly, instructors' information (e.g., preparing lessons and teaching) could be collected into a digital profile for each instructor, informing assessments of their teaching performance, abilities, and professional development needs. It could inform faculty professional development programs. Nevertheless, caution is still needed when embracing AI-generated assessment results, as some indicators (e.g., instructors' professional ethics) cannot be assessed effectively or, depending on programming, or could even be overlooked. Therefore, combining AI-generated and human-based assessments is necessary, respecting human beings' values and educational principles. The challenge of students' unsanctioned use of AI within assessment processes will require higher education to find valid ways of implementing or managing AI.

Threats AI brings to higher education

Indeed, an important threat AI brings to education is the requirement that all teaching and learning has to happen in an ICT environment, which could be seen as antithetical to the human in the human experience of learning (Brown, 2020). While AI seems to be able to do many things, it is simply programming and thus not human.

The literature reported here makes clear substantial challenges to curriculum, instruction, and assessment. Despite the importance of curriculum, this review found less research into AI's integration into HE curriculum than on the two other aspects of the CIA triad. In terms of existing curricula, there is considerable debate as to what students need to be taught about or with AI and how it could be integrated (Lopezosa et al., 2023). AI creates the possibility that skill with large language models (e.g., to analyze data, to compose communication) is what students might need in the future. Considerable enthusiasm exists for the integration of AI skills with other graduate attributes such as the 4C skills (i.e., communication, collaboration, critical thinking, and creativity). This is an extension of the long-standing arguments advanced by technologists that the best way to prepare future citizens and workers is to ensure they develop generic competencies rather than disciplinary specific knowledge and ability (Chickering and Ehrmann, 1996; Cuban, 2001). Consequently, faculty members need to consider the intersection of disciplinary structure and AI affordances and constraints in terms of integrating contemporary capabilities with long-standing traditions of knowledge.

The threat of AI applies also to instructors' role and their teaching abilities. Most academics have little understanding of how AI tools are designed and what large language models can do. Thus, few have thought constructively about how to integrate AI into their teaching. The question is how AI tools, with their capacity to translate text, analyze it, and compose fluent but potentially meaningless text, can or should be integrated into diverse fields such as engineering, medicine, studio art, laboratory science, and so on. Application within humanities may be much more feasible with the current capacities of GenAI, but still academics have to learn how AI can be an adjunct to teaching rather than potentially a substitute for the instructor's knowledge and skill. Enthusiasm of technologists for using machines to replace the labor of humans (Brown, 2020) is clearly a threat to the human-in-the-loop. This is all the more important because currently AI cannot identify fabrication or error in the text that it assembles.

The most important challenge centers around assessment and evaluation of learning. With the free access students have to powerful AI language models, it is difficult to ensure that the work submitted by students is their own genuine intellectual contribution. The fear and possibility of non-detectable academic dishonesty will require substantial efforts to ensure the integrity and social warrant (Brown, 2022) of course grades and academic qualifications. A possible response to generative AI capabilities is to impose invigilated in-person examinations without access to digital resources and without bring-your-own-devices. Another way to ensure the integrity of evaluation is to require students to participate in an oral examination of their learning; a solution that will have a large impact on workloads, efficiency, validity of sampling, and accuracy of scoring. It is clear generative AIs will force academics to rethink the purpose of assessment (e.g., student-centered or knowledge-based learning), the content and format of what is assessed, the design of assessments (e.g., process evaluation, outcome evaluation, or value-added evaluation), and the formative use of assessed performances.

Given the interactive and integrated nature of curriculum, instruction, and assessment processes, there simply is little research on AI's impact on their intersection. Indeed, only three papers attempted to address all three legs of the CIA triad. Future research will need to examine the integration of AI impact, rather than studying each aspect of the triad in isolation.

Limitations

Although this review explored three major education databases to minimize selection bias, the recent articles were published in English rather than in other languages, such as Chinese and Spanish. Therefore, the generalizability of these findings needs to be taken with caution for use in non-English contexts. Considering that Asia accounted for a large number of studies and that an emerging number of studies were conducted in South America and the Middle East, multi-lingual or culture-responsive studies should be conducted in the future. More importantly, this review was limited to the first 9 months following the release of ChatGPT on 30 November 2022; hence, it is very much a preliminary exploration of how AI has impacted higher education. In light of how quickly AI systems are being developed and changed, new research is being published constantly. Hence, the findings presented in this review have probably been superseded already.

Conclusion

This review contributes to a better understanding of the benefits and threats of AI that recent research has identified in the higher education context. It also identifies challenging opportunities for higher education institutions and faculty members. This paper offers a first step toward understanding the impact AI on the CIA triad in higher education. While the future remains uncertain, several of the trends found in the study are likely to continue for some time to come. In particular, it seems very likely that China will continue to lead the way in research outputs and that studies using stimulations/modeling are likely to remain the most common method, perhaps because they are relatively easy to conduct. It is also likely that the challenges associated with meaningful integration of AI into curriculum, instruction, and assessment will remain difficult for years to come.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JL: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. JS: Conceptualization, Writing – review & editing. GB: Supervision, Writing – review & editing, Funding acquisition.

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Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2025.1522841/full#supplementary-material

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Validation of a teaching model instrument for university education in Ecuador through an artificial intelligence algorithm

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Introduction: In the context of university education in Ecuador, the application of Artificial Intelligence (AI) for the assessment and adaptation of teaching models marks significant progress toward enhancing educational quality. The integration of AI into pedagogical processes is increasingly recognized as a strategic component for fostering innovation and improving instructional outcomes in higher education.

Methods: This study focused on the validation of an AI-based instrument, specifically designed for the evaluation and adaptation of pedagogical strategies in the Ecuadorian university environment. A quantitative methodology was adopted, employing multivariate statistical analyses and structural equation modeling (SEM) to examine the internal consistency, construct validity, and interrelations among various didactic dimensions. The instrument was applied to a statistically representative sample of university professors across both undergraduate and graduate levels.

Results: The statistical analysis demonstrated high levels of internal consistency and discriminative validity among the constructs representing different teaching models. The confirmatory factor analysis and SEM procedures verified the adequacy of the theoretical structure and the robustness of the proposed measurement model. Coefficients obtained for reliability and model fit met or exceeded established thresholds in educational research.

Discussion: The findings confirm the empirical soundness of the AI-based instrument and support the feasibility of using such tools to assess and enhance teaching models in higher education. These results underscore the importance of adopting innovative, data-driven methodologies that respond to the demands of contemporary educational environments. Furthermore, the use of AI in the validation process enables a more precise interpretation of educational information, reinforcing the relevance of AI-supported models in optimizing teaching and learning processes.

KEYWORDS

teaching, artificial intelligence, assessment, educational sciences, algorithm, educational model, pedagogical innovation

1 Introduction

In the current context of rapid digital transformation and the proliferation of emerging technologies, the educational sector, particularly at the university level, encounters a multifaceted landscape marked by both challenges and opportunities (Apata, 2024; George and Wooden, 2023; Moreira-Choez et al., 2024c). Within this framework, the integration of Artificial Intelligence (AI) is increasingly recognized as a pivotal factor in enhancing and adapting contemporary educational demands. According to Lameras and Arnab (2021), AI supports the development of personalized and efficient teaching strategies while teaching strategies while also transforming pedagogical interactions at various levels, thereby redefining the dynamics of teaching and learning.

The evolution of teaching models reflects a transition from traditional, teacher-centered approaches to interactive, student-focused methodologies. This shift has been influenced by both pedagogical imperatives and technological (Bakar, 2021; Kanwar et al., 2019). Constructivist, collaborative, and other innovative frameworks have replaced rote memorization, emphasizing critical thinking, problem-solving, and learner autonomy (Einum, 2019; Murphy et al., 2021). Despite these advancements, a gap remains: the absence of validated tools capable of evaluating and adapting teaching methodologies to specific contexts, which limits the effective implementation of these models.

AI emerges as a viable solution to this issue, offering capabilities that enable the processing of large datasets, identification of patterns, and provision of adaptive recommendations (Dwivedi et al., 2021). In the context of this study, AI is for the validation of an instrument designed to evaluate teaching models in higher education. By utilizing advanced analytical techniques, AI ensures the reliability, internal consistency, and discriminative capacity of the instrument, making it a robust tool for application in diverse educational environments (Cowls et al., 2023).

The relevance of this research is underscored by its potential to address critical deficiencies in university didactics. The integration of AI in the validation process not only contributes to the development of more effective and personalized teaching processes but also aligns with broader goals of improving educational quality (Naseer et al., 2024). This alignment is particularly pertinent in Ecuador, where the adaptation of teaching models to meet the needs of students represents an essential objective (Ingavelez-Guerra et al., 2022; Ruiz-Rojas et al., 2023). The instrument validated in this study is designed to enable educators to assess and implement innovative teaching methodologies, addressing contemporary educational challenges and supporting the evolution of quality education in the face of technological advancements.

In response to this problem, the research question is formulated: ¿How to validate a teaching model instrument for university education in Ecuador using an artificial intelligence algorithm? To address this question, the following general objective is established: validate a teaching model instrument for university education in Ecuador through artificial intelligence algorithm. The formulation of this question and objective seeks to address the specific needs of evaluating and adapting teaching models within the context of Ecuadorian university education, utilizing advanced technological tools to ensure precision and efficiency in the results.

To fulfill both the problem statement and the study objective, the following hypotheses are proposed, serving as the foundation for the scientific validation of the proposed instrument.

- H1: The factorial loadings of the regression items and each teaching model are acceptable in the questionnaire for higher education teaching through artificial intelligence.
- H2: The factors are significantly related to the teaching model, with parameters obtained from the best model fit.
- H3: The variance coefficients are statistically significant for the observed variables and the teaching models.
- H4: The teaching models in higher education are distinguishable from one another through discriminant analysis, convergent analysis, and the Heterotrait-Monotrait (HTMT) ratio.

2 Theoretical framework

2.1 Traditional didactic model

The traditional didactic model is defined by a teacher-centered approach, where the unidirectional transmission of knowledge predominates (Hoidn and Reusser, 2020; Yang, 2008). In this paradigm, learning is conceived as a passive process of information reception, evaluated primarily through memorization and repetition of data. The assessment used in this model tends to be summative, focusing on final outcomes while neglecting a comprehensive evaluation of the learning process. Although this approach has been widely employed, critics such as Paul (1989) highlight that it fails to foster the development of critical skills and independent thinking, which are essential in contemporary education.

The evaluation of this model involves analyzing key attributes, such as reliance on teacher authority, the hierarchical structure of the learning process, and the emphasis on outcomes over procedures (Stufflebeam, 2001). These attributes are crucial for understanding how the model impacts the development of student competencies (Gamage et al., 2023; Hu et al., 2023). Specifically, measuring the predominance of unidirectional transmission and limited interaction helps identify its influence on students' ability to apply knowledge critically and autonomously.

The importance of measuring these attributes lies in the need to assess the relevance of the model in current educational contexts, which demand transversal competencies such as problem-solving and adaptability. The literature provides evidence that validates these measurements as relevant elements of the construct (Sarstedt et al., 2019; Yang et al., 2004). For instance, studies have shown that teacher-centered approaches correlate with limited performance in tasks requiring analysis and creativity (Oyelana et al., 2022; Wagner et al., 2020). Furthermore, criticisms of the model suggest that its lack of emphasis on the educational process can perpetuate superficial and fragmented learning.

2.2 Collaborative didactic model

The collaborative didactic model, in contrast to the traditional model, is based on the importance of social interaction within the educational process (Kaasila and Lauriala, 2010). This approach fosters collaboration among students, creating an environment conducive to the exchange of ideas and joint problem-solving. Beyond improving social skills, this model enriches learning by providing it with greater depth and meaning. According to Mora et al. (2020), it is particularly effective in developing competencies such as critical thinking, problem-solving, and teamwork.

The evaluation of this model involves analyzing key attributes such as active peer interaction, the ability to construct knowledge collectively, and the inclusion of diverse perspectives in learning (Lombardi et al., 2021). These elements are crucial to understanding how the model promotes essential competencies that go beyond academic content and translate into skills applicable in various contexts. Active social interaction and structured collaboration are measurable indicators that reflect the model's ability to facilitate meaningful and transferable learning experiences (de Freitas and Neumann, 2009; Patel et al., 2012; Qin and Yu, 2024).

The importance of measuring these attributes lies in the need to assess the effectiveness of this approach in meeting the demands of contemporary educational environments, which require transversal skills and social competencies. The literature supports the validity of these measurements, as studies have shown that collaborative settings enhance deep learning and improve performance in tasks requiring creativity and critical thinking (Chen et al., 2018; Graesser et al., 2018). Moreover, collaborative dynamics allow students to develop negotiation, leadership, and conflict resolution skills, which are fundamental in professional and social contexts.

2.3 Spontaneist didactic model

The spontaneist didactic model emphasizes the significance of direct and spontaneous student experiences, framing learning as a natural and organic process that should be facilitated rather than imposed (Green, 2015; Reigeluth, 2013). Within this paradigm, students' curiosity and personal interests serve as primary drivers of their educational journey, positioning the teacher as a facilitator who supports exploration and discovery rather than a source of unidirectional knowledge transmission. According to Alkhawalde and Khasawneh (2024), this approach proves particularly effective in fostering creativity and intrinsic motivation, as it aligns closely with the learner's internal inclinations and interests.

The evaluation of this model requires examining attributes such as the degree of autonomy afforded to students, the role of curiosity in guiding learning activities, and the extent to which the learning environment supports spontaneous exploration (Ten et al., 2021). These attributes are critical for understanding how the model influences student engagement and promotes competencies like creative problem-solving and self-directed learning (Loyens et al., 2008). Measuring these elements allows for the identification of how effectively the model facilitates adaptive and meaningful learning experiences.

The importance of assessing these attributes lies in their potential to provide insights into how well the spontaneist model aligns with the demands of modern education, where adaptability and lifelong learning are increasingly valued (Kergel, 2023). Research evidence supports the validity of these attributes as relevant components of the construct. For instance, studies have shown that environments promoting student autonomy and curiosity are associated with higher levels of engagement and deeper learning (Arnone et al., 2011; Tas, 2016; Tu and Lee, 2024). Furthermore, such settings foster resilience and the ability to navigate complex, real-world problems, outcomes often linked to the development of intrinsic motivation and creativity.

2.4 Constructivist didactic model

The constructivist didactic model posits that learning is an active process through which individuals construct new knowledge by engaging with their experiences and interacting with their environment (Loyens and Gijbels, 2008; Zajda, 2021). This perspective shifts the role of the educator from a transmitter of information to a facilitator who designs diverse and meaningful contexts that enable students to integrate new knowledge with their prior understanding. According to Tsui (2002), this model is particularly effective in promoting a deeper and more lasting comprehension of the subject matter, as it encourages learners to internalize concepts through meaningful connections.

Evaluating the constructivist model involves examining attributes such as the degree to which students actively participate in their learning process, the richness of the contexts provided, and the strategies employed to encourage reflection and critical thinking (Honebein et al., 1993; Le and Nguyen, 2024; Lee and Hannafin, 2016). These attributes are essential for understanding how this model supports the development of higher-order cognitive skills, such as analysis, synthesis, and evaluation (Kwangmuang et al., 2021; Richland and Simms, 2015). Measuring these elements helps to determine how effectively the constructivist approach facilitates the application and retention of knowledge in diverse and complex situations.

The importance of measuring these attributes lies in their alignment with contemporary educational demands, which prioritize lifelong learning, adaptability, and the ability to transfer knowledge to real-world problems (Aithal and Mishra, 2024; Zamiri and Esmaeili, 2024). Empirical evidence supports the validity of these measurements, as studies have consistently demonstrated that constructivist environments foster active engagement and critical inquiry, leading to improved problem-solving abilities and long-term retention of knowledge (Huang et al., 2010; Kwan and Wong, 2015). For instance, student-centered activities that require reflection and application of concepts to new scenarios have been shown to enhance comprehension and foster intellectual independence (Klemenčič, 2017; Peters, 2010).

2.5 Technological didactic model

The technological didactic model emphasizes the integration of information and communication technologies (ICT) into the teaching-learning process, responding to the demands of contemporary society and leveraging digital tools to enrich the educational experience (Didmanidze et al., 2023; Okoye et al., 2023). This model recognizes technology as a transformative agent in education, providing diverse advantages, including access to extensive digital resources, opportunities for personalized learning, and the development of essential digital competencies. According to Kirkwood (2014), the model has the potential to revolutionize educational methodologies by facilitating more flexible, interactive, and accessible approaches to teaching and learning.

The evaluation of this model involves analyzing critical attributes, such as the extent of ICT integration in instructional design, the promotion of digital literacy, and the adaptability of learning processes to individual student needs (Mohammadyari and Singh, 2015; Valverde-Berrocoso et al., 2021). These attributes are essential to understanding how the technological model enhances learning outcomes by fostering engagement, interactivity, and autonomy. For example, measuring the use of adaptive learning systems and digital tools to support diverse learning styles provides insights into the model's effectiveness in personalizing education (Moreira-Choez et al., 2024b; Sajja et al., 2024; Truong, 2016).

The importance of assessing these attributes lies in the necessity to evaluate the model's relevance and impact within modern educational environments (Angeli and Valanides, 2009; Schunk, 2003). The increasing ubiquity of technology in all spheres of life necessitates a focus on developing students' digital fluency and their ability to navigate, evaluate, and utilize technological resources effectively. Empirical studies underscore the validity of these attributes, with research demonstrating that technology-rich environments can enhance student engagement, improve access to education, and support the acquisition of transferable skills (Aljehani, 2024; Lajoie et al., 2020). Furthermore, ICT-based approaches have been shown to facilitate collaborative learning, critical thinking, and problem-solving, all of which align with the broader goals of 21st-century education (Moreira-Choez et al., 2024a; Peña-Ayala, 2021).

3 Materials and methods

The methodology adopted in this study was framed within the positivist paradigm, employing a quantitative approach that allowed for objective and systematic data analysis. The research design was non-experimental, with a descriptive-correlational level, which facilitated the characterization of the participating faculty and the exploration of significant relationships between relevant variables for instrument validation. A deductive method was applied, starting from the theoretical analysis of conceptual frameworks related to artificial intelligence and educational innovation, and arriving at specific conclusions regarding the relevance of the instrument in university contexts.

The study population consisted of active university professors during the 2023 academic year at two higher education institutions in Ecuador: The Technical University of Manabí (UTM) and the State University of Milagro (UNEMI). According to institutional records, the total population included 843 professors: 276 at UTM and 567 at UNEMI. A representative sample of 413 professors was determined using the statistical formula for finite populations, with a 95% confidence level and a 4% margin of error.

The sampling technique was non-probabilistic by convenience, due to the voluntary nature of participation and logistical constraints. However, considering that the study employed inferential statistics, specifically Structural Equation Modeling (SEM), a normality test was conducted prior to model application. Kolmogorov-Smirnov and Shapiro-Wilk tests, as well as skewness and kurtosis coefficients, indicated an acceptable normal distribution for most variables, justifying the use of SEM for exploratory and validation purposes.

TABLE 1 Sample distribution by university, gender, and academic level.

University	Gender	Academic level	Frequency	Percentage (%)
Technical University of Manabí	Male	Undergraduate	38	9.2
		Postgraduate	41	9.9
	Female	Undergraduate	27	6.5
		Postgraduate	29	7.0
Subtotal UTM			135	32.7
State University of Milagro	Male	Undergraduate	56	13.6
		Postgraduate	75	18.2
	Female	Undergraduate	61	14.8
		Postgraduate	86	20.8
Subtotal UNEMI			278	67.3
Total			**413**	**100.0**

The information presented in Table 1 reveals a heterogeneous distribution of the sample based on university, gender, and academic level, which enhances the representativeness of the study. Most participants belong to the State University of Milagro (67.3%), while 32.7% are from the Technical University of Manabí. This difference may be attributed to the larger faculty size at UNEMI or a greater willingness among its professors to participate in research related to educational innovation. Additionally, a slightly higher female participation (56.9%) is observed, reflecting a growing trend toward gender parity in the Ecuadorian academic field. This gender diversity strengthens the analysis of results by allowing the identification of possible differences in the perceptions of the validated instrument.

Regarding academic level, 55.9% of participants are involved in postgraduate programs, while 44.1% teach at the undergraduate level. This overrepresentation of postgraduate faculty may be linked to their greater familiarity with research processes and topics such as artificial intelligence in educational environments. Specifically, postgraduate faculty from UNEMI constitute the largest individual subgroup in the sample (20.8%). The combination of these variables demonstrates a solid and diverse sample composition, which supports the external validity of the study. Nevertheless, it is advisable to conduct additional analyses to determine whether the observed differences significantly influence responses to the instrument, which would enable contextual adjustments and enhance its applicability.

This integrated table provides a detailed view of the sample's composition based on key sociodemographic variables, facilitating a more analytical understanding of the study participants. The inclusion of faculty members of both genders, various academic levels, and from two institutions contributes to the diversity of the sample and strengthens the external validity of the validated instrument. It is recommended to conduct comparative statistical analyses to determine whether sociodemographic differences significantly influence perceptions and evaluations of the instrument.

3.1 Statistical analysis through artificial intelligence

Figure 1 illustrates the structure of relationships between different teaching models applied in the university context and how artificial intelligence contributes to their development and efficacy. This schema is presented as a structural equation model, where different latent variables representing specific teaching models, such as the Traditional, Technological, Constructivist, Spontaneist, and Collaborative models, can be observed. Each of these models is associated with various indicators reflected by the observed variables, denoted with the letter "P" followed by a number.

In this research, a quantitative approach supported by artificial intelligence tools is employed. For this purpose, the Statistical Software for the Social Sciences (SPSS), version 25, and the structural equation modeling software AMOS, version 24, were used. These programs operate in an integrated manner to validate the coefficients of the instrument designed to evaluate teaching models in Higher Education.

Multivariate statistics are utilized, specifically the Principal Component Analysis (PCA) technique, both confirmatory and exploratory, to examine the underlying structure of the observed variables. To assess the reliability of the content and the construct, an internal consistency analysis is conducted using Cronbach's alpha coefficient, which measures the homogeneity of the items, and McDonald's omega, through additional extensions of the software (Omega, Alpha, and All Subsets reliability Procedure).

Additionally, a plugin in AMOS called Model Fit Measure is incorporated, used to evaluate the goodness of fit of the structural model. The criteria for excellence are set according to the Comparative Fit Index (CFI) with a threshold above 0.95 and the Root Mean Square Residual (RMR) lower than 0.08. To further strengthen the model, through the use of artificial intelligence, the Root Mean Square Error of Approximation (RMSEA) is also considered with an optimal value lower than 0.06, following the recommendations of Schubert et al. (2017) and McNeish and Wolf (2022).

The selection and calibration of the models are based on the Akaike Information Criterion (AIC), according to Portet (2020) and Asadi and Seyfe (2024). Regarding the functionality of artificial intelligence, the extension for validity and reliability tests is used, which facilitates discriminant analysis, the Average Variance Extracted (AVE), the Maximum Shared Squared Variance (MSV), and the correlation between each dimension of the teaching model, based on Wang and Wang (2022).

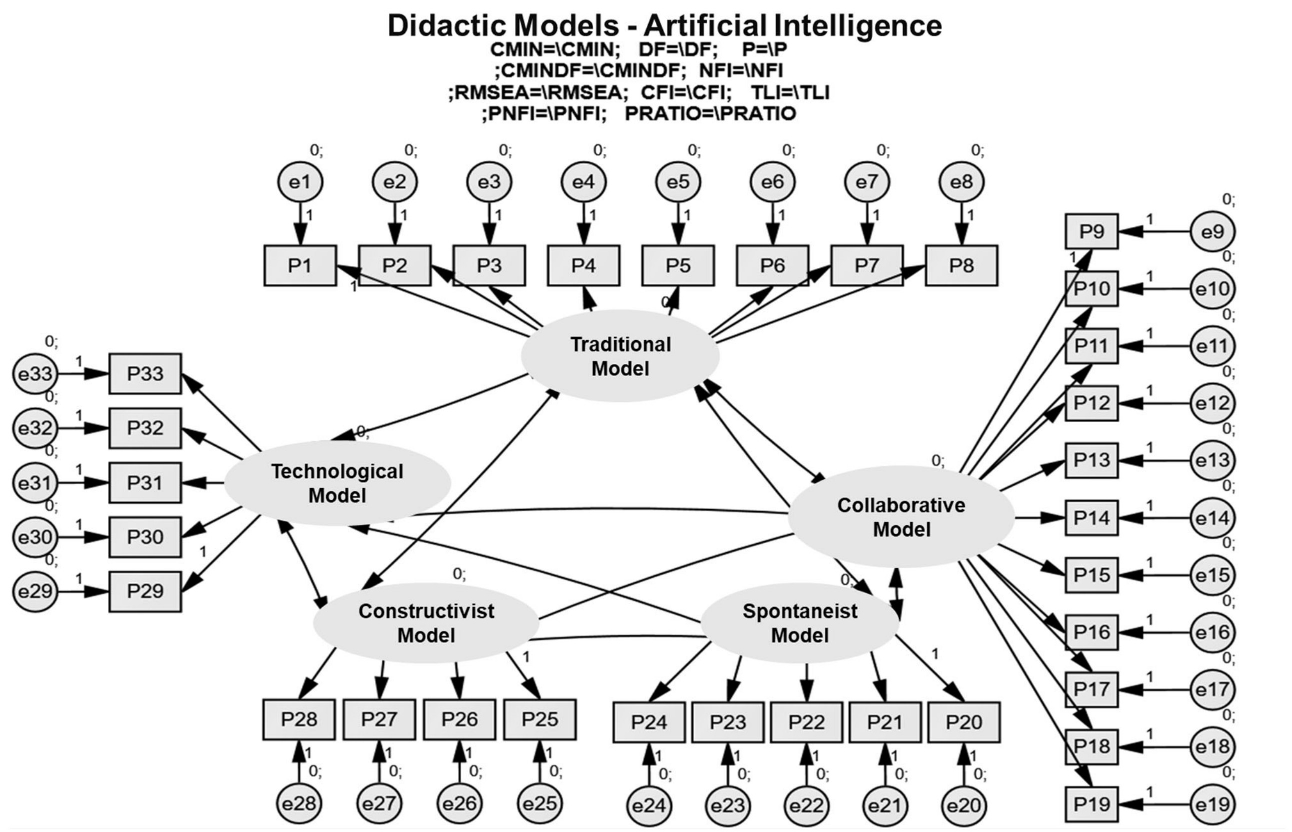

FIGURE 1
University teaching models generated by artificial intelligence.

After establishing a neural network for each dimension with its corresponding observed variables, the extension to name unobserved variables (Name Unobserved variables) is implemented. To measure the correlation between dimensions, the Draw Covariances tool is used. Finally, in AMOS, the analysis properties are activated to apply the Maximum Likelihood estimation and various outputs are selected for the interpretation of results, which have included standardized estimates, squared multiple correlations, simple and implicit moments, residual moments, modification indices, factor score weights, covariances and correlations of estimates, critical ratios for differences, and tests for normality and outlier detection.

4 Results and discussion

Table 2 provides a quantitative evaluation of the internal consistency and discriminative ability of five teaching models applied in university education. The reliability analysis is performed using Cronbach's alpha coefficient, while Critical Reliability (CR) and the Average Variance Extracted (AVE) are measures of the consistency and convergence of the evaluated constructs. Lastly, the correlation (R^2) offers a perspective on the relationship between the observed variables and the theoretical construct they represent.

Table 2 compiles the results of the reliability and validity analysis of the constructs of the university teaching models. Through the application of Cronbach's alpha coefficient and the factor loadings of Critical Reliability (CR), the internal consistency of the scales is determined. The Average Variance Extracted (AVE) and the Pearson correlation among the dimensions of the teaching models provide a measure of the convergent and discriminant validity, respectively.

Regarding the reliability of the dimensions, the results indicate a reliability above the generally accepted threshold of 0.70, suggesting excellent internal consistency for the measured constructs. According to Taber (2018), a Cronbach's alpha above 0.70 is indicative of good internal reliability, corroborating the accuracy of the scales in the context of higher education.

In parallel, the Critical Reliability for each teaching model reveals values exceeding the recommended minimum standard of 0.70, indicating strong consistency and reliability of the items within each construct. Authors such as Sujati et al. (2020) assert that CR values above 0.70 denote adequate composite reliability, which strengthens the legitimacy of the construct measurements.

The Average Variance Extracted, surpassing the parameter of 0.30 suggested in relevant literatura (Dos Santos and Cirillo, 2023), reflects the amount of variance that a factor has in relation to the variance due to measurement error. The values obtained in this research demonstrate that the constructs possess acceptable convergent validity, as they capture a significant proportion of the variance in the observed variables.

Moreover, the Pearson correlation for each teaching model exceeds the coefficient of 0.50, indicating positive and strong relationships between the variables. This is consistent with the findings of Diamantopoulos et al. (2012), who maintain that substantial correlations between the items and the underlying construct are indicative of high construct validity.

Next, Figure 2 presents a detailed analysis of a structural equation model applied to university teaching models, where the relationships between theoretical constructs and their corresponding items are evaluated. The values in the schema reflect the factor loadings, indicating the magnitude of the relationships between the items (observed variables) and the constructs of each teaching model, as well as the metrics of the overall model fit, providing evidence of the quality of the model's fit to the collected data.

The confirmatory factor analysis (CFA) carried out on the teaching models in Higher Education, for which artificial intelligence tools were used, is reflected in Figure 2. A Chi-square fit index over degrees of freedom (CMIN/DF) of 3.681 is observed, which, despite exceeding the ideal value of 3 suggested by Pasamonk (2004), is considered acceptable within the tolerance range in Social Sciences. A significance value (p) of 0.000 confirms the statistical relevance of the model, resulting from ten computational iterations.

Regarding the model fit, the Root Mean Square Error of Approximation (RMSEA) reaches a value of 0.081, which is close to the excellence threshold established at 0.065, as proposed by O'Loughlin and Coenders (2004), implying a satisfactory fit of the model to the data. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) yield values of 0.827 and 0.812 respectively, indicating an acceptable level according to the recommendations of Yildiz and Güngörmüş (2016). In turn, the Parsimony Normed Fit Index (PNFI) of 0.715 and the elevated Akaike Information Criterion (AIC) of 2003.301, although not optimal, reflect manageable complexity and an adequate specification of the model respectively, in line with the contributions of Zacharia et al. (2011).

The robustness of the instrument is attributed to the high factor loadings of the items in each dimension, as detailed in

TABLE 2 Reliability and discriminant analysis for university teaching models.

Number of items	Teaching models	Cronbach's alpha (α)	Critical reliability-CR (λ)	AVE	Correlation (R^2)
8	Traditional teaching model	0.778	0.797	0.323	0.568
11	Collaborative teaching model	0.925	0.927	0.536	0.732
5	Spontaneist teaching model	0.859	0.859	0.578	0.760
4	Constructivist teaching model	0.747	0.776	0.448	0.669
5	Technological teaching model	0.855	0.862	0.559	0.748

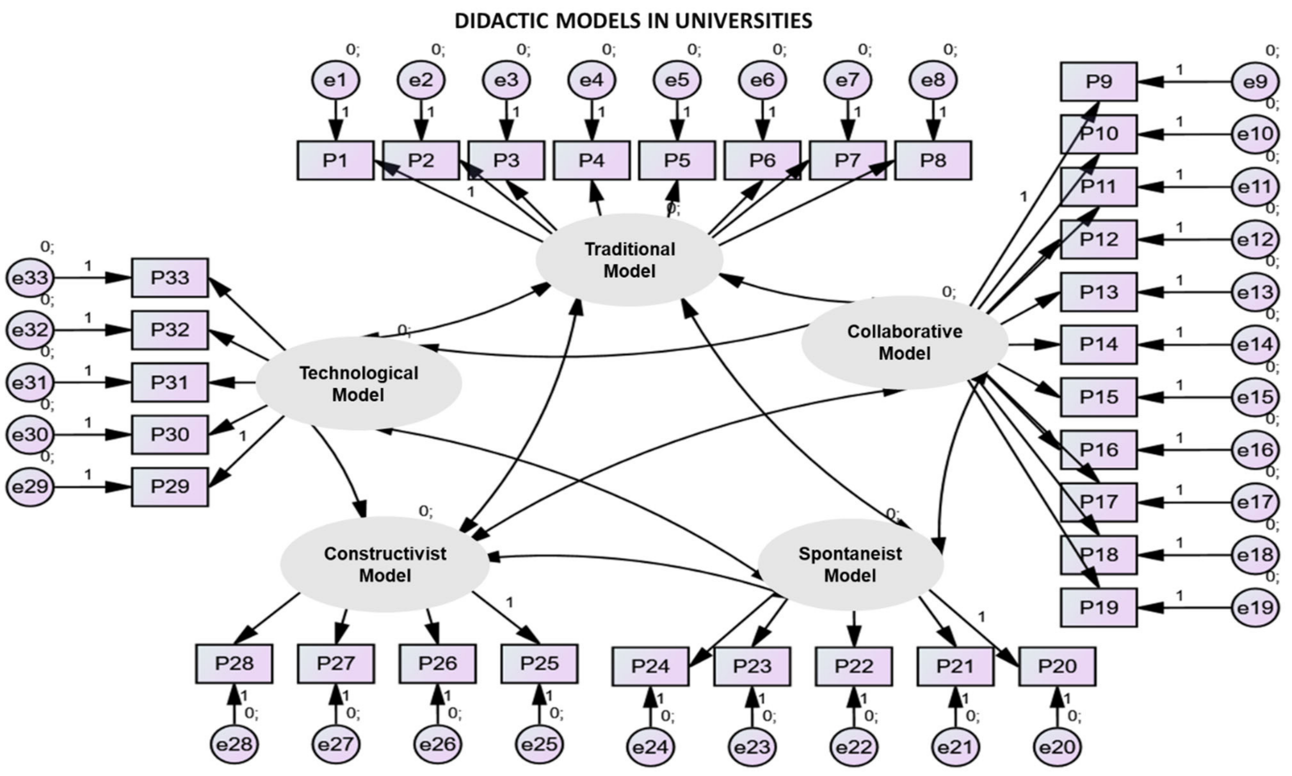

FIGURE 2
Adjusted model and factor loadings of the items and construct of the questionnaire.

Figure 2. In the collaborative model, factor loadings range from 0.62 to 0.84, this value exceeds the standard of 0.50, indicating a significant association with the underlying construct, in line with what was reported by Shrestha (2021). The spontaneist model presents loadings ranging from 0.66 to 0.84, and reflects a strong relationship with the established questions. The items of the constructivist model exhibit loadings from 0.51 to 0.81, while the technological model shows values from 0.64 to 0.83, both denoting a substantial contribution to their respective constructs.

Conversely, the traditional model displays the lowest factor loadings in some items, below the established coefficient of 0.50, which could indicate lower internal consistency or relevance in these indicators, according to Fayers (1997). However, other items within the same model show loadings from 0.54 to 0.76, suggesting that, mostly, the questions are suitable for assessing the proposed construct. The correlation between dimensions reveals the highest covariance between the spontaneist model and other constructs, suggesting a possible conceptual overlap or shared didactic approach, as might be inferred from the observations of Høgheim et al. (2023). The results allow for the acceptance of the alternative hypothesis H2, which asserts the relevance and adequate fit of the factor loadings ($p < 0.001$).

Regarding the lowest correlation observed in the traditional model, this could suggest, according to Raykov et al. (2016), that certain observed variables have lesser congruence with the construct. This could be interpreted as an indication that revising or eliminating certain items could enhance the correlation of the traditional model with other constructs.

Table 3 presents the results of the regression analysis applied to the items grouped according to five teaching models: Traditional, Collaborative, Spontaneist, Constructivist, and Technological. For each item, the estimated coefficient, standard error (S.E.), critical ratio (C.R.), and p-value are reported. The table also indicates which items were used as reference indicators (with a fixed regression weight of 1) to identify each latent construct.

The use of artificial intelligence (AI) has enabled the development of estimators, such as standard error (S.E.), critical reliability (C.R.), and statistical significance (P), which are essential in the evaluation of teaching models. These indicators are consolidated in Table 3 for each observed variable, facilitating a detailed understanding of the effectiveness of various pedagogical approaches.

In particular, the analysis revealed that the traditional model, when examining responses to eight specific questions, generated estimators significantly different from zero, showing high critical reliability and notable statistical significance (indicated with three asterisks ***). This finding suggests robustness in predicting educational outcomes when employing this model, reaffirming its validity in specific didactic contexts.

Similarly, the collaborative model, which incorporates eleven observed variables, yielded estimated values greater than one, accompanied by critical reliability exceeding 10 points, indicating outstanding statistical significance. This result not only emphasizes the effectiveness of the collaborative approach in teaching but also reinforces the importance of interaction and cooperation in learning.

TABLE 3 Validation of the regression model coefficients for the items of the instrument.

No.	Items	Models	Estimate	S.E.	C.R.	P
P1	The teacher assumes the role of expert and is solely dedicated to transmitting content.	Traditional	1			
P2	The teacher's lectures are based on one-way communication; information is transmitted to a group of students.	Traditional	1.106	0.09	12.263	***
P3	Students absorb, transcribe, memorize, and repeat information for specific activities such as tests or exams.	Traditional	1.047	0.083	12.683	***
P4	Learning is individual and competitive.	Traditional	0.959	0.079	12.079	***
P5	The teacher informs what is expected of the student (presentation of the teaching objectives and learning competencies).	Traditional	0.288	0.05	5.821	***
P6	The teacher presents and explains advance organizers.	Traditional	0.282	0.051	5.568	***
P7	The teacher dedicates the first 15 minutes of class to motivating the students.	Traditional	0.211	0.056	3.753	***
P8	The teacher presents and explains the class in a masterful way.	Traditional	0.609	0.064	9.51	***
P9	Teachers have the role of facilitator, tutor, guide, co-learner, mentor, or advisor.	Collaborative	1			
P10	Students take the responsibility to learn and create partnerships between student and teacher.	Collaborative	1.391	0.111	12.476	***
P11	Teachers seek to improve students' initiative and motivate them. Students are seen as individuals who can learn on their own.	Collaborative	1.270	0.113	11.251	***
P12	Teachers allow students to include content, activities to solve, gamification, and other playful aspects.	Collaborative	1.636	0.125	13.13	***
P13	Teachers allow and encourage the so-called celebration of cooperative learning.	Collaborative	1.659	0.117	14.23	***
P14	Teachers enable positive interdependence as a feature of group work.	Collaborative	1.627	0.112	14.509	***
P15	The teacher encourages the student to take the lead in their learning by solving mysteries, dilemmas, and problems.	Collaborative	1.555	0.116	13.369	***
P16	The teacher forms small groups of students to interact with him/her and provides feedback.	Collaborative	1.435	0.111	12.943	***
P17	The teacher conducts activities for students to actively participate in problem-solving.	Collaborative	1.384	0.103	13.407	***
P18	Consultation and analysis of information with sources such as academic pages, texts, articles, among others, are encouraged.	Collaborative	1.243	0.099	12.532	***
P19	The teacher promotes the defense of team ideas, through presentations with audiovisual resources.	Collaborative	1.388	0.108	12.793	***
P20	The teacher arouses interest in up-to-date knowledge in extracurricular areas, including some non-disciplinary foundations.	Spontaneist	1			
P21	The teacher observes, takes into account the students' interests, and assesses their skills, abilities, and competencies accordingly.	Spontaneist	0.974	0.066	14.863	***
P22	The teacher combines directed discovery learning and spontaneous discovery.	Spontaneist	0.989	0.064	15.572	***
P23	Activities and events of an open and flexible nature are allowed.	Spontaneist	1.054	0.071	14.802	***
P24	The teacher generates project activities linked to the environment or society for students to execute.	Spontaneist	1.074	0.086	12.51	***
P25	The teacher allows and favors free grouping and organization of team works.	Constructivist	1			
P26	The teacher conducts peer assessments.	Constructivist	2.074	0.231	8.995	***
P27	The teacher employs teaching cartography allowing creativity in the student.	Constructivist	2.223	0.225	9.884	***
P28	The teacher assesses with logs, pedagogical paths, and outdoor activities.	Constructivist	2.051	0.227	9.038	***
P29	Effective use of web pages and virtual platforms is taught, evidenced, and managed.	Technological	1			
P30	The use of technological tools such as Educaplay, Powtoon, Quizzes, Geogebra, Viox, and others is carried out.	Technological	1.679	0.128	13.144	***
P31	Teaching processes are channeled through the use of mobile applications.	Technological	1.500	0.117	12.775	***
P32	Methods, tools, and interactive resources are used for the understanding of texts, hypertexts, transtexts in the mass media.	Technological	1.589	0.117	13.60	***
P33	Simulators for exploring the world of science are used.	Technological	1.721	0.143	12.072	***

The spontaneist, constructivist, and technological models showed similar patterns, with estimators significantly different from zero, high critical reliability, and statistical significance for each evaluated question. These findings corroborate the hypothesis that the pedagogical approaches examined have a measurable and significant impact on the teaching-learning process, allowing for the validation of the alternative hypothesis H3. This posits that the estimators generated through linear regression, under the auspices of artificial intelligence, are significant and, therefore, of great value for educational research.

The significance of these results lies not only in the validation of the investigated teaching models but also in the potential of AI to enrich teaching methodologies. According to Chen et al. (2020) the application of advanced technologies in education facilitates a more precise and personalized analysis of learning needs, allowing for the development of more effective and tailored didactic strategies.

Table 4 presents the estimated variances, standard errors (S.E.), critical ratios (C.R.), and significance levels (p-values) for each of the five teaching models Traditional, Collaborative, Spontaneist, Constructivist, and Technological as well as for all 33 items that compose the measurement instrument. All variances were statistically significant at the 0.001 level, suggesting strong internal consistency and robust construct identification.

Table 4 details the variance coefficients corresponding to the teaching models, along with data from the associated questions. This analysis reveals that the five examined teaching models present elevated estimators, reduced standard errors, high critical reliability, and notable values of statistical significance (indicated by three asterisks ***). This uniform pattern, observed across all analyzed variables, underscores the robustness of the results and the reliability of the methods employed to evaluate the variances associated with the dimensions and questions of the teaching model instrument.

The presence of high estimators suggests a strong influence of the teaching models on the variables of interest, while the minimal standard errors indicate precision in the estimations made. The high critical reliability reinforces the consistency of these findings, and the significant p-value confirms the statistical relevance of the observed variances. Such a conjunction of factors strongly supports the acceptance of hypothesis H3, which posits the significance of the variances for the dimensions and questions included in the analysis of the teaching models.

The importance of these results lies in their ability to validate the teaching models from a statistical perspective, thereby providing empirical evidence of their effectiveness. The significance of the variances, in particular, highlights the relevance of the differences between the models, pointing toward a clear differentiation in their impact on the teaching and learning processes. According to Lawless and Pellegrino (2007), variance analysis is crucial for understanding how different didactic strategies can be adapted to specific educational needs, thereby improving the quality and effectiveness of education.

Table 5 reports the values for Composite Reliability (CR), Average Variance Extracted (AVE), Maximum Shared Variance (MSV), and Maximum Reliability (MaxR(H)) for each of the five teaching models: Traditional, Collaborative, Spontaneist, Constructivist, and Technological. In addition, it includes the inter-construct correlation coefficients. The results provide the necessary indicators to confirm that each model is statistically distinct from the others, based on established thresholds for discriminant validity.

TABLE 4 Validation of the estimators for variances for the teaching models and questions.

Models and items	Estimate	S.E.	C.R.	P
Traditional model	0.916	0.127	7.193	***
Collaborative model	0.148	0.021	7.168	***
Spontaneist model	0.371	0.048	7.778	***
Constructivist model	0.146	0.029	5.118	***
Technological model	0.254	0.037	6.941	***
P1	1.080	0.091	11.933	***
P2	1.018	0.091	11.197	***
P3	0.744	0.071	10.477	***
P4	0.830	0.073	11.445	***
P5	0.673	0.048	14.036	***
P6	0.711	0.051	14.067	***
P7	0.944	0.066	14.232	***
P8	0.836	0.063	13.208	***
P9	0.208	0.015	13.702	***
P10	0.304	0.023	13.490	***
P11	0.390	0.028	13.792	***
P12	0.325	0.025	13.235	***
P13	0.198	0.016	12.459	***
P14	0.161	0.013	12.120	***
P15	0.265	0.020	13.114	***
P16	0.270	0.020	13.318	***
P17	0.206	0.016	13.093	***
P18	0.238	0.018	13.471	***
P19	0.268	0.020	13.378	***
P20	0.402	0.031	13.060	***
P21	0.203	0.017	11.894	***
P22	0.152	0.014	10.953	***
P23	0.243	0.020	11.955	***
P24	0.548	0.041	13.264	***
P25	0.418	0.031	13.439	***
P26	0.833	0.068	12.343	***
P27	0.370	0.041	8.982	***
P28	0.789	0.064	12.275	***
P29	0.362	0.028	13.057	***
P30	0.435	0.039	11.259	***
P31	0.421	0.036	11.810	***
P32	0.293	0.029	10.238	***
P33	0.759	0.061	12.511	***

TABLE 5 Discriminant validity analysis for the teaching models.

Models	CR	AVE	MSV	MaxR(H)	Traditional	Collaborative	Spontaneist	Constructivist	Technological
Traditional	0.768	0.323	0.141	0.833	0.568				
Collaborative	0.927	0.536	0.698	0.933	0.318***	0.732			
Spontaneist	0.872	0.578	0.698	0.883	0.305***	0.835***	0.760		
Constructivist	0.759	0.448	0.620	0.794	0.376***	0.668***	0.787***	0.669	
Technological	0.863	0.559	0.472	0.873	0.335***	0.632***	0.652***	0.687***	0.748

***The correlation is significant at the 0.001 level (two-tailed).

TABLE 6 Heterotrait-Monotrait (HTMT) ratio analysis for the teaching models in higher education.

Correlation models	Traditional model	Collaborative model	Spontaneist model	Constructivist model	Technological model
Traditional model					
Collaborative model	0.549				
Spontaneist model	0.528	0.834			
Constructivist model	0.536	0.710	0.859		
Technological model	0.463	0.641	0.678	0.723	

Table 5 sheds light on the coefficients of discriminant validity, these values demonstrate the establishment of different levels of acceptance for the evaluated teaching models. This approach emphasizes the precision with which the construct validity reflects each dimension of the instrument through its observed variables. Specifically, it is observed that the dimensions associated with the teaching model in higher education achieve an acceptable reliability, which exceeds the 0.70 threshold for composite reliability, as indicated by Pérez Rave and Muñoz Giraldo (2016). This measure of composite reliability suggests robust internal consistency within the evaluated dimensions.

Regarding discriminant and convergent validity, indicators such as the square root of the Average Variance Extracted (AVE) and the Maximum Shared Variance squared (MSV) are crucial. For the technological teaching model, an AVE of 0.559 and an MSV of 0.472 are reported, indicating satisfactory discriminant and convergent validity, reflected through a correlation of 0.748. These results demonstrate that the technological dimension maintains a clear distinction from other dimensions while showing internal consistency in its variables.

When applying the contrast technique, it is found that the collaborative and spontaneist models present AVEs greater than 0.50, which meets the criterion for discriminant validity. However, the high MSV of 0.698 in both dimensions indicates a limitation in their ability to be distinctly differentiated from each other, as established by Blustein et al. (1989). This situation raises questions about the precise delimitation between similar constructs within these models.

On the other hand, the traditional and constructivist models do not meet the standards for discriminant nor convergent validity, failing to meet the established parameters. However, a high correlation is noted between the variables of these models, extending to all the teaching models included in the study. This universal correlation underscores the interconnection among the different pedagogical approaches evaluated and provides substantial evidence to accept hypothesis H4. This acceptance implies that the instrument used demonstrates reliability, discriminative capacity, convergence, and significant correlation across the various teaching models examined.

The instrument's ability to reflect these crucial aspects suggests a robust and versatile assessment tool, capable of capturing the complexity and interrelationship of the teaching models in higher education. In turn, these results emphasize the importance of discriminant and convergent validity as essential criteria for evaluating constructs in educational research, as supported by previous studies in the field by Cheung et al. (2023). The identification of strengths and limitations in the discrimination and convergence of the teaching models provides a solid basis for future research, aimed at optimizing pedagogical strategies and fostering effective and differentiated learning.

Table 6 displays the HTMT ratio values calculated among the five teaching models: Traditional, Collaborative, Spontaneist, Constructivist, and Technological. Each value represents the degree of correlation between constructs. Lower HTMT values indicate greater discriminant validity, suggesting that each model captures a distinct pedagogical approach within the framework of higher education.

Table 6 presents the Heterotrait-Monotrait (HTMT) ratios, crucial for determining the correlation between different traits, derived from the discriminant analysis (as shown in Table 4). This analysis focuses on the correlation between traits of teaching models, providing a critical measure of discriminant validity between constructs, as highlighted by Touron et al. (2018). The results indicate a weak correlation of the traditional model in relation to other models, with scores below 0.50. This finding suggests that the traditional model possesses significant distinctive characteristics compared to the other models evaluated.

On the other hand, the collaborative model shows coefficients close to 0.850, which is considered acceptable according to criteria established by contemporary researchers such as Tarkkonen and

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Vehkalahti (2005). This level of correlation implies proximity in characteristics between the analyzed models, although it remains within limits that allow for adequate discrimination between them.

More specifically, it is observed that the spontaneist model and the constructivist model present a statistical indistinction, with an HTMT index of 0.859. This result, interpreted through artificial intelligence, finds support in the research of Henseler et al. (2015) and Hamid et al. (2017), who argue about the difficulty of statistically distinguishing between constructs when HTMT coefficients are high. This phenomenon highlights the conceptual and operational similarity between the spontaneist and constructivist models, suggesting that, although different, they share common elements that make them statistically indistinguishable in certain respects.

Overall, these coefficients provide empirical evidence in support of hypothesis 4, proposed by Ibrahim and Nat (2019), which anticipated that the teaching models employed in higher education significantly discriminate against each other. The data suggest that the teaching models are empirically distinguishable through this instrument, establishing the discriminant validity of the evaluated dimensions, as described by Salessi and Omar (2019). This finding is crucial as it confirms the instrument's ability to effectively differentiate between pedagogical approaches, providing a valuable tool for educational research and the improvement of teaching practice in Higher Education.

The identification of discriminant validity among the teaching models underscores the importance of developing and employing rigorous assessment instruments in educational research. These instruments should not only be capable of capturing the subtleties of the different pedagogical approaches but also effectively distinguish between them, to facilitate a deeper understanding of their impacts and relative efficiencies. Consequently, these findings pave the way for future research aimed at exploring and optimizing teaching methods in Higher Education, with the goal of improving educational outcomes and adapting to the changing needs of students and society.

After confirming the factorial validity of the theoretical constructs, the structural model's hypotheses were tested. This stage allowed for the statistical verification of the proposed relationships between the teaching models and the observed variables, employing structural equation modeling (SEM). The analysis was conducted using the maximum likelihood estimation method, complemented by standardized coefficients, critical ratios (CR), and significance values (p-values), which collectively provided empirical support for the proposed theoretical model. The specific results of the hypothesis testing, including the direction, strength, and statistical significance of each relationship, are detailed in Table 7.

The results of the structural equation modeling analysis confirmed the statistical validity of the four hypotheses initially proposed in the study. Each hypothesis demonstrated a highly significant relationship ($p < 0.001$), with standardized coefficients and critical ratios (CR) exceeding accepted thresholds, thereby providing robust empirical support for the theoretical model of teaching practices in higher education mediated by artificial intelligence tools.

Hypothesis H1, which assessed the factorial validity of the items within each teaching model, revealed regression weights ranging from 0.211 to 2.223 and CR values between 3.753 and 15.572. These findings are aligned with psychometric standards, indicating satisfactory item representativeness within each latent construct. The significance of these results underscores the structural coherence of the questionnaire and its utility for evaluating pedagogical strategies in university settings. This is consistent with prior research that validates structural models through confirmatory factor analysis, demonstrating strong item reliability when factor loadings exceed 0.40 (Sukkamart et al., 2023).

TABLE 7 Hypothesis testing using structural equation modeling.

Hypothesis	Coefficient range	CR range	p-value	Result
H1	$0.211 \leq \times \leq 2.223$	$3.753 \leq \times \leq 15.572$	***	Accepted
H2	$0.320 \leq \times \leq 0.790$	$0.759 \leq \times \leq 0.927$	***	Accepted
H3	$0.146 \leq \times \leq 0.916$	$5.118 \leq \times \leq 7.778$	***	Accepted
H4	$0.463 \leq \times \leq 0.859$	$0.759 \leq \times \leq 0.927$	***	Accepted

***The correlation is significant at the 0.001 level (two-tailed).

Hypothesis H2 examined the predictive associations between latent factors and the overall model, reporting standardized coefficients from 0.320 to 0.790 and CR values from 0.759 to 0.927. These values suggest that the factors integrated into the model are statistically capable of anticipating the behaviors associated with each teaching modality. Such results reinforce the idea that well-structured instructional models can predict teaching performance and educational innovation outcomes. In line with findings from educational contexts focused on sustainability and digital readiness, properly identified causal constructs show predictive power when embedded in higher-order structural models (Pimdee, 2020).

For H3, the results showed statistically significant variance estimators across the observed variables and teaching models, with coefficients ranging from 0.146 to 0.916 and CR values between 5.118 and 7.778. These findings confirm that the teaching models are consistently measured and that the variability explained by each item is not due to random error but rather to latent factors grounded in empirical evidence. This coincides with previous studies that emphasize the importance of robust variance structures for interpreting complex educational phenomena (Chuenban et al., 2021).

Finally, H4 confirms that teaching models in higher education are statistically distinguishable through discriminant analysis, convergent validity, and the Heterotrait-Monotrait (HTMT) ratio. The observed coefficient range (0.463–0.859) and CR values (0.759–0.927) meet the criteria for adequate discriminant validity. According to Yusoff et al. (2020), HTMT values below 0.90 indicate a strong distinction between related yet conceptually different constructs. Therefore, the acceptance of H4 supports the instrument's ability to differentiate between teaching models within university contexts.

5 Conclusions

This study has demonstrated, through a rigorous methodology and the application of advanced tools such as artificial intelligence, the ability of different higher education teaching models to distinguish themselves from each other in terms of internal consistency, discriminative capacity, and their relationship with the observed variables. The reliability analyses, using Cronbach's alpha coefficient along with Critical Reliability (CR) and Average Variance Extracted (AVE), have corroborated the consistency and convergence of the evaluated constructs, surpassing thresholds established in the literature as indicative of excellent internal consistency and convergent validity.

The integration of these models into a detailed analysis, using a structural equation model, has effectively assessed the relationships between the theoretical constructs and the observed variables, reflecting the depth of the association through factor loadings and confirming the quality of the model's fit to the collected data. The results obtained, such as the fit indices and factor loadings, have provided a solid basis for asserting the reliability and validity of the constructs within the context of higher education.

Crucially, the empirical validation of the model was substantiated by the acceptance of the four hypotheses formulated (H1, H2, H3, and H4), which further reinforces the robustness and relevance of the instrument. Hypothesis H1 confirmed the factorial validity of the items, with statistically significant factor loadings well above recommended benchmarks, ensuring the representativeness of each indicator within its respective latent construct. Hypothesis H2 identified strong predictive relationships between latent factors, supported by standardized coefficients and critical ratios (CR) exceeding conventional thresholds, validating the model's explanatory capacity in capturing the dynamics of innovative teaching practices. Hypothesis H3 verified the significance of the variance coefficients across dimensions and indicators, thereby strengthening the instrument's internal reliability. Lastly, Hypothesis H4 confirmed discriminant validity among the five teaching models evaluated traditional, collaborative, spontaneist, constructivist, and technological—through cross-loading analysis, Heterotrait-Monotrait (HTMT) ratios, and shared variance measures (MSV and AVE), ensuring the conceptual distinctiveness of each construct.

The discrimination between the teaching models, as demonstrated through measures of discriminant and convergent validity, and HTMT ratios, reflects a clear and significant differentiation in their approaches and methodologies. This distinction has been further reinforced by the correlation between the dimensions of the models, revealing the conceptual coherence and uniqueness of each model in its contribution to the educational process.

The confirmed empirical differentiation between teaching models demonstrates their unique methodological orientations and contributions to the educational process. This distinction is not only statistically significant but pedagogically meaningful, highlighting how different instructional paradigms shape the delivery and outcomes of higher education. Furthermore, the integration of artificial intelligence facilitated the processing and interpretation of complex datasets, enhancing the precision of the validation process and enabling a deeper understanding of the latent structures that underpin teaching effectiveness.

This study contributes significantly to the body of knowledge in the field of Didactics and Pedagogy, offering valuable insights into how different pedagogical approaches impact the teaching-learning process. The results underscore the importance of adopting adaptive and evidence-based teaching methods to meet contemporary educational needs and prepare students for future challenges.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The study received formal approval from the Graduate School of the State University of Milagro and was conducted in strict accordance with applicable institutional guidelines and national ethical standards. All participants provided their prior informed written consent through a digital form incorporated into the initial section of the instrument. It is important to note that the research did not include or process any human images or biometric data. The study's purpose was solely to identify, evaluate, and validate latent dimensions associated with university teaching models through statistical and artificial intelligence-based analysis. The exclusive use of self-reported survey data ensured the anonymity and protection of participants, thus complying with ethical principles of confidentiality, integrity, and voluntary participation.

Author contributions

JM-C: Writing – original draft, Writing – review & editing, Conceptualization, Investigation, Supervision, Visualization. TR: Conceptualization, Data curation, Methodology, Visualization, Writing – original draft, Writing – review & editing. AN-N: Conceptualization, Investigation, Supervision, Visualization, Writing – original draft, Writing – review & editing. ÁS-G: Data curation, Formal analysis, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. MR-Á: Conceptualization, Formal analysis, Supervision, Visualization, Writing – original draft, Writing – review & editing. CO-M: Conceptualization, Data curation, Investigation, Writing – original draft, Writing – review & editing. DN-L: Conceptualization, Data curation, Investigation, Writing – original draft, Writing – review & editing. JS-E: Conceptualization, Data curation, Investigation, Writing – original draft, Writing – review & editing.

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Apprehension toward generative artificial intelligence in healthcare: a multinational study among health sciences students

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Background: In the recent generative artificial intelligence (genAI) era, health sciences students (HSSs) are expected to face challenges regarding their future roles in healthcare. This multinational cross-sectional study aimed to confirm the validity of the novel FAME scale examining themes of Fear, Anxiety, Mistrust, and Ethical issues about genAI. The study also explored the extent of apprehension among HSSs regarding genAI integration into their future careers.

Methods: The study was based on a self-administered online questionnaire distributed using convenience sampling. The survey instrument was based on the FAME scale, while the apprehension toward genAI was assessed through a modified scale based on State-Trait Anxiety Inventory (STAI). Exploratory and confirmatory factor analyses were used to confirm the construct validity of the FAME scale.

Results: The final sample comprised 587 students mostly from Jordan (31.3%), Egypt (17.9%), Iraq (17.2%), Kuwait (14.7%), and Saudi Arabia (13.5%). Participants included students studying medicine (35.8%), pharmacy (34.2%), nursing (10.7%), dentistry (9.5%), medical laboratory (6.3%), and rehabilitation (3.4%). Factor analysis confirmed the validity and reliability of the FAME scale. Of the FAME scale constructs, Mistrust scored the highest, followed by Ethics. The participants showed a generally neutral apprehension toward genAI, with a mean score of 9.23 ± 3.60. In multivariate analysis, significant variations in genAI apprehension were observed based on previous ChatGPT use, faculty, and nationality, with pharmacy and medical laboratory students expressing the highest level of genAI apprehension, and Kuwaiti students the lowest. Previous use of ChatGPT was correlated with lower apprehension levels. Of the FAME constructs, higher agreement with the Fear, Anxiety, and Ethics constructs showed statistically significant associations with genAI apprehension.

Conclusion: The study revealed notable apprehension about genAI among Arab HSSs, which highlights the need for educational curricula that blend technological proficiency with ethical awareness. Educational strategies tailored to discipline and culture are needed to ensure job security and competitiveness for students in an AI-driven future.

KEYWORDS

technophobia, anxiety, ChatGPT, artificial intelligence, Chatbots, higher education, health education, psychology in education

1 Introduction

The adoption of generative artificial intelligence (genAI) into healthcare is inevitable with evidence pointing to its current wide applications in different healthcare settings (Yim et al., 2024). As genAI advances rapidly in its capabilities, it would fundamentally transform healthcare with subsequent revolution in operational efficiency with improved patient outcomes (Sallam, 2023; Verlingue et al., 2024; Sallam et al., 2025a). Nevertheless, the integration of genAI into healthcare practices is expected to introduce formidable challenges (Dave et al., 2023; Sallam, 2023). Central to these challenges is the expected profound implications on the structure and composition of the workforce in healthcare (Daniyal et al., 2024; Rony et al., 2024b).

On a positive note, the potential of genAI to streamline workflow in healthcare settings is hard to dispute (Mese et al., 2023; Fathima and Moulana, 2024). As stated in a commentary by Bongurala et al. (2024), AI assistants can decrease documentation time for healthcare professionals (HCPs) by as much as 70% which would enable a greater focus on direct patient care. To be more specific with examples, the improved efficiency provided by genAI can be achieved through automated transcription of patient encounters, data entry into electronic health records (EHRs), and improved patient communication as illustrated by Small et al. (2024), Tai-Seale et al. (2024), Badawy et al. (2025) and Sallam et al. (2025b).

On the other hand, alongside the aforementioned opportunities, genAI introduces complex challenges in healthcare where even minor errors can lead to grave consequences (Panagioti et al., 2019; Gupta et al., 2025). An urgent concern of genAI integration into healthcare is the fear of job displacement (Christian et al., 2024; Rony et al., 2024b; Sallam et al., 2024a). As genAI abilities to handles routine and complex tasks in healthcare is realized, the demand for human intervention may diminish, prompting shifts in job roles or even losses (Rawashdeh, 2023; Ramarajan et al., 2024). However, this genAI anticipated impact is not uniform and it could vary across healthcare specialties and cultural contexts. This variability demands careful study to identify determinants of attitude to genAI and devise strategies that maximize genAI benefits in healthcare while addressing critical concerns, including job security (Kim et al., 2025).

Research studies have already started to examine how health science students and HCPs perceive the genAI tools such as ChatGPT mostly in the context of Technology Acceptance Model (TAM) (Sallam et al., 2023; Abdaljaleel et al., 2024; Chen S.Y. et al., 2024). In the context of concerns of possible job displacement, (Rony et al., 2024b) reported that HCPs in Bangladesh expressed concerns about AI undermining roles traditionally occupied by humans. Their analysis highlighted several concerns such as threats to job security, moral questions regarding AI-driven decisions, impacts on patient-HCP relationships, and ethical challenges in automated care (Rony et al., 2024b). In Jordan, a study among medical students developed and validated the FAME scale to measure Fear, Anxiety, Mistrust, and Ethical concerns associated with genAI (Sallam et al., 2024a). This study revealed a range of concerns among medical students, highlighting notable apprehension regarding the impact of genAI on their future careers as physicians (Sallam et al., 2024a). Notably, mistrust and ethical issues predominated over fear and anxiety, illustrating the complicated emotional and cognitive reactions that are elicited by this inevitable novel technology (Sallam et al., 2024a).

From a broader perspective, Nicholas Caporusso introduced the term "Creative Displacement Anxiety" (CDA) to define a psychological state triggered by the perceived or actual infiltration of genAI on areas that required human creativity (Caporusso, 2023). The CDA reflects a complex range of emotional, cognitive, and behavioral responses to the expanding roles of genAI in areas traditionally dependent on human creativity (Caporusso, 2023). Caporusso argued that a thorough understanding genAI and its adoption could alleviate its negative psychological impacts, advocating for proactive engagement with this transformative technology (Caporusso, 2023).

Extending on the previous research on genAI apprehension in the context of healthcare, our study broadens the FAME scale's validation to a diverse, multinational sample of health sciences students in order to offer a more comprehensive understanding of attitude to genAI in healthcare. Key to our inquiry was the delineation of "Apprehension" as a distinct state of reflective unease that differs fundamentally from the immediate, visceral responses associated with fear or anxiety based on Grillon (2008). Herein, Apprehension was defined as a measure to reflect the awareness and cautious consideration of genAI's future implications rather than acute, present-focused threats.

Thus, our study objectives involved the assessment of student apprehension toward genAI integration in healthcare settings, with confirmatory validation of the FAME scale to ensure its reliability in measuring anxiety, fear, mistrust, and ethical concerns. Specifically, our study addressed the following major questions: First, what is the degree of apprehension toward genAI among health sciences students across various disciplines, including medicine, dentistry, pharmacy, nursing, rehabilitation, and medical laboratory sciences? Second, does the FAME scale effectively capture and measure the specific determinants underlying this apprehension? Finally, which demographic variables and FAME constructs are significantly associated with apprehension toward genAI among health students in Arab countries?

2 Methods

2.1 Study settings and participants

This study utilized a cross-sectional survey design targeting health sciences students, spanning fields of medicine, dentistry, pharmacy/doctor of pharmacy, nursing, rehabilitation, and medical laboratory sciences. The study group comprised students of Arab nationality enrolled in universities across the Arab region, as outlined in the survey's introductory section.

Recruitment of the potential participants was based on snowball sampling convenient approach as outlined by Leighton et al. (2021). This approach depended on widely-used social media and messaging platforms, including Facebook, X (formerly Twitter), Instagram, LinkedIn, Messenger, and WhatsApp, starting with the authors' networks across Egypt, Iraq, Jordan, Kuwait, and Saudi Arabia and encouraging further survey dissemination. Data collection started on October 27 and ended on November 5, 2024.

Adhering to the Declaration of Helsinki, the ethical approval was granted by the Institutional Review Board (IRB) at the Deanship of Scientific Research at Al-Ahliyya Amman University, Jordan. Participation was voluntary without monetary incentives, and all respondents provided electronic informed consent following an introduction of the survey that detailed study aims, procedures, and confidentiality issues.

Hosted on SurveyMonkey (SurveyMonkey Inc., San Mateo, CA, USA) in both Arabic and English, the survey access was limited to a single response per IP address to ensure data reliability. All items required mandatory responses for study inclusion, with rigorous quality checks to ensure data integrity. A minimum response time of 120 s was set, guided by a median pre-filtration response time of 222.5 s and a 5th percentile benchmark of 111.85 s. Additionally, responses were screened for contradictions: participants who selected "none" for genAI model use but indicated the use of specific genAI models were excluded for inconsistency.

Our study design adhered to Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) guidelines which suggest a minimum of 200 participants for sufficient statistical power (Mundfrom et al., 2005). Considering the multinational scope, we targeted over 500 participants to robustly estimate apprehension to genAI across diverse populations.

2.2 Details of the survey instrument

Following informed consent, the survey began with demographic data collection including the following variables: age, sex, faculty, nationality, university location, institution type (public vs. private), and the latest grade point average (GPA). The second section inquired about the prior use of genAI, frequency of use, and the self-rated competency in using genAI tools.

The primary outcome measure in the study was "Apprehension toward genAI" entailing assessment of the anticipatory unease about genAI's future impact on healthcare. Apprehension was assessed through three items adapted and modified from the State-Trait Anxiety Inventory (STAI) (Spielberger et al., 1971; Spielberger and Reheiser, 2004). These items were: (1) I feel tense when thinking about the impact of generative AI like ChatGPT on my future in healthcare; (2) The idea of generative AI taking over aspects of patient care makes me nervous; and (3) I feel uneasy when I hear about new advances in generative AI for healthcare. The three items were assessed on a 5-point Likert scale from "agree," "somewhat agree," "neutral," "somewhat disagree," to "disagree." Finally, the validated 12-item FAME scale was administered (Sallam et al., 2024a), measuring Fear, Anxiety, Mistrust, and Ethics, with each construct represented by three items rated on a 5-point Likert scale from "agree" to "disagree." The full questionnaire is provided in Supplementary S1.

2.3 Statistical and data analysis

In the statistical and data analyses, IBM SPSS Statistics for Windows, Version 27.0, Armonk, NY: IBM Corp and JASP software (Version 0.19.0) were used (Jasp Team, 2024). Each construct score—Apprehension, Fear, Anxiety, Mistrust, and Ethics—was calculated by summing responses to the corresponding three items, where "agree" was assigned a score of 5, and "disagree" a score of 1, yielding higher scores for stronger agreement with each construct.

Data normality for these 5 scale variables was assessed via the Kolmogorov–Smirnov test, justifying subsequent use of the non-parametric tests (Mann Whitney U test [M-W] and Kruskal Wallis test [K-W]) for univariate associations based on non-normality of the five scales ($p < 0.001$ for all). Spearman's rank-order correlation was used to assess the correlation between two scale variables by measuring the Spearman's rank correlation coefficient (ρ).

In examining predictors of apprehension toward genAI, univariate analyses identified candidate variables for inclusion in multivariate analysis based on the p value threshold of 0.100. Analysis of Variance (ANOVA) was employed to confirm the linear regression model validity with multicollinearity diagnostics using the Variance Inflation Factor (VIF) to flag any potential multicollinearity issues, with VIF threshold of >5 (Kim, 2019). Statistical significance for all analyses was set at $p < 0.050$.

To validate the structure of the FAME scale, EFA was conducted with maximum likelihood estimation and Oblimin rotation and sampling adequacy checked through the Kaiser-Meyer-Olkin (KMO) measure, while the factorability was confirmed by Bartlett's test of sphericity. Subsequent CFA was performed to confirm the FAME scale latent factor structure. Fit indices, including the Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Goodness of Fit Index (GFI), and the Tucker-Lewis Index (TLI) were employed to evaluate model fit. Internal consistency across survey constructs was evaluated using Cronbach's α, with a threshold of $\alpha \geq 0.60$ considered acceptable for reliability (Tavakol and Dennick, 2011; Taber, 2018).

3 Results

3.1 Description of the study sample following quality checks

As indicated in Figure 1, the final study sample comprised 587 students representing 72.6% of the participants who consented to participate and met the quality check criteria.

The final sample primarily consisted of students under 25 years (92.7%) and females (72.9%). Medicine (35.8%) and Pharmacy/PharmD (34.2%) were the most represented faculties. The most common nationality was Jordanian (31.3%), and a slight majority of participants were studying in Jordan (51.3%), with most attending public universities (59.1%). A significant portion indicated high academic performance, with 67.1% reporting either excellent or very good latest GPAs. Generative AI use was widespread, with 80.4% indicating previous use of ChatGPT, although other genAI tools were used less frequently. Regular genAI engagement was common, and 55.9% of participants reported being either competent or very competent (Table 1).

3.2 Confirmatory factor analysis of the FAME scale

The CFA for the FAME scale showed a good model fit across several fit indices. The chi-square difference test revealed a statistically significant model fit improvement for the hypothesized factor structure ($\chi^2(48) = 194.455$, $p < 0.001$) compared to the baseline model ($\chi^2(66) = 4315.983$), which suggested that the four-factor model captured the structure of the data. The CFI was 0.966 and the TLI was 0.953, both of which indicated a good model fit while the RMSEA was 0.072 indicating an acceptable model fit.

Bartlett's test of sphericity ($\chi^2(66) = 4{,}273.092$, $p < 0.001$) and the KMO measure of sampling adequacy (0.872 overall) indicated that the data were appropriate for factor analysis (Table 2).

Figure 2 presents the CFA model for the FAME scale, evaluating constructs related to Fear, Anxiety, Mistrust, and Ethics as factors influencing health science students' perceptions of genAI in healthcare.

Each factor demonstrated strong factor loadings for its respective indicators, suggesting adequate construct validity within the model. Factor loadings ranged from 0.65 to 1.40 across items, indicating robust relationships between observed variables and their underlying latent constructs.

The inter-factor correlations revealed significant relationships between Fear and Anxiety (0.30), Fear and Mistrust (0.24), Anxiety and Mistrust (0.50), and Anxiety and Ethics (0.54), while Mistrust and Ethics showed a correlation of 0.59. The results highlighted the structural validity of the FAME scale, suggesting that Fear, Anxiety, Mistrust, and Ethics can be reliably measured as distinct yet related factors in understanding health students' attitude toward genAI role in healthcare.

3.3 Apprehension to genAI in the study sample

Apprehension toward genAI, as measured by a 3-item scale that showed an acceptable internal consistency with a Cronbach's α of 0.850, yielded a mean score of 9.23 ± 3.60, indicating a neutral attitude with a tendency toward agreement.

Significant variations in apprehension were observed across several study variables. Faculty showed the highest apprehension in Medical Laboratory (11.08 ± 3.29) and Pharmacy/Doctor of Pharmacy (10.11 ± 3.49) students, contrasting with lower scores in Medicine (8.00 ± 3.33; $p < 0.001$, Figure 3).

Kuwaiti students had the lowest apprehension (7.92 ± 3.46; $p = 0.006$), with students studying in Kuwait also reporting a lower apprehension (7.21 ± 3.48; $p = 0.004$). Public university students exhibited less apprehension (8.61 ± 3.55) than those in private universities (10.13 ± 3.47; $p < 0.001$).

Previous ChatGPT users reported lower apprehension (8.94 ± 3.5) than non-users (10.43 ± 3.75; $p < 0.001$), and daily users of genAI had lower apprehension (8.16 ± 3.49) compared to less frequent users ($p < 0.001$). Competency in genAI use was inversely related to apprehension, with "not competent" individuals scoring higher (10.9 ± 3.66) than those self-rated as "very competent" (8.63 ± 3.66; $p = 0.006$, Table 3).

3.4 The FAME scale scores in the study sample

The mean scores for the FAME constructs indicated varying distribution with Mistrust scoring the highest at 12.46 ± 2.54, followed

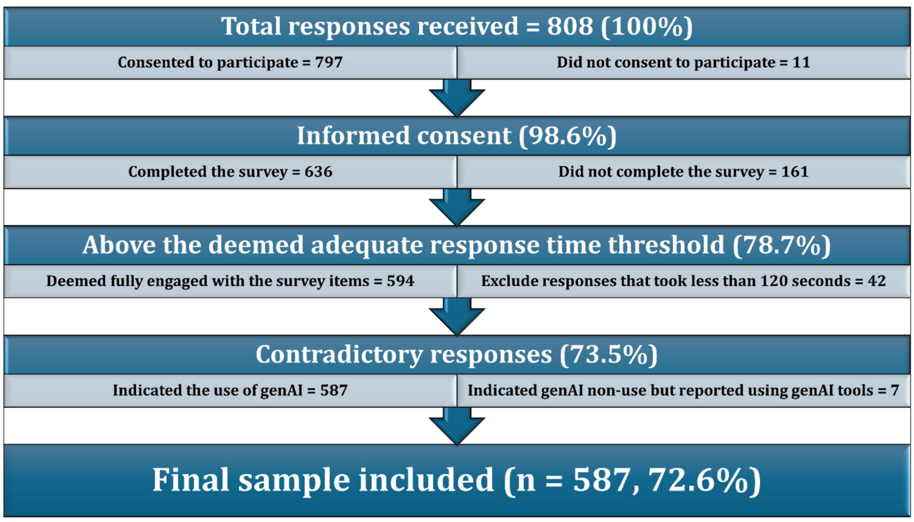

FIGURE 1
Flowchart of quality control for final study sample selection. genAI, generative artificial intelligence.

TABLE 1 General feature of the study sample (N = 587).

Variable	Category	N^2 (%)
Age	<25 years	544 (92.7)
	≥25 years	43 (7.3)
Sex	Male	159 (27.1)
	Female	428 (72.9)
Faculty	Medicine	210 (35.8)
	Dentistry	56 (9.5)
	Pharmacy/Doctor of Pharmacy	201 (34.2)
	Nursing	63 (10.7)
	Rehabilitation	20 (3.4)
	Medical Laboratory	37 (6.3)
Nationality	Jordan	184 (31.3)
	Kuwait	86 (14.7)
	Iraq	101 (17.2)
	Egypt	105 (17.9)
	Saudi Arabia	79 (13.5)
	Other country	32 (5.5)
In which country is your university?	Jordan	301 (51.3)
	Kuwait	48 (8.2)
	Iraq	69 (11.8)
	Egypt	95 (16.2)
	Saudi Arabia	63 (10.7)
	Other country	11 (1.9)
University type	Public	347 (59.1)
	Private	240 (40.9)
The latest Grade Point Average (GPA)	Excellent	171 (29.1)
	Very good	223 (38)
	Good	145 (24.7)
	Satisfactory	43 (7.3)
	Unsatisfactory	5 (0.9)
Number of generative AI[1] tools used	0	74 (12.6)
	1	322 (54.9)
	2	137 (23.3)
	3	33 (5.6)
	4	18 (3.1)
	5	1 (0.2)
	6	2 (0.3)
ChatGPT use before the study	No	115 (19.6)
	Yes	472 (80.4)
Copilot use before the study	No	511 (87.1)
	Yes	76 (12.9)

(Continued)

TABLE 1 (Continued)

Variable	Category	N^2 (%)
Gemini use before the study	No	525 (89.4)
	Yes	62 (10.6)
Llama use before the study	No	581 (99.0)
	Yes	6 (1.0)
My AI On Snapchat use before the study	No	491 (83.6)
	Yes	96 (16.4)
Other genAI tool use before the study	No	515 (87.7)
	Yes	72 (12.3)
How often do you use generative AI?	Daily	116 (19.8)
	Few times a week	178 (30.3)
	Weekly	71 (12.1)
	Less than weekly	222 (37.8)
Self-rated competency in using generative AI tools	Very competent	101 (17.2)
	Competent	227 (38.7)
	Somewhat competent	217 (37.0)
	Not competent	42 (7.2)

[1]AI, Artificial intelligence; [2]N, Number.

TABLE 2 Confirmatory factor analysis fit indices, reliability, and sampling adequacy of the FAME scale.

Measure	Value
Chi-square test	
Baseline model (df = 66)	χ^2 = 4,315.983
Factor model (df = 48)	χ^2 = 194.455, p < 0.001
Fit indices	
Comparative Fit Index (CFI)	0.966
Tucker-Lewis Index (TLI)	0.953
Root Mean Square Error of Approximation (RMSEA)	0.072
Standardized Root Mean Square Residual (SRMR)	0.047
Goodness of Fit Index (GFI)	0.991
Sampling adequacy tests	
Kaiser-Meyer-Olkin (KMO)	0.872
Bartlett's test of sphericity	χ^2 = 4,273.092, df = 66, p < 0.001
Reliability (Cronbach's α)	
Fear	0.879
Anxiety	0.881
Mistrust	0.657
Ethics	0.749
Overall FAME scale	0.877

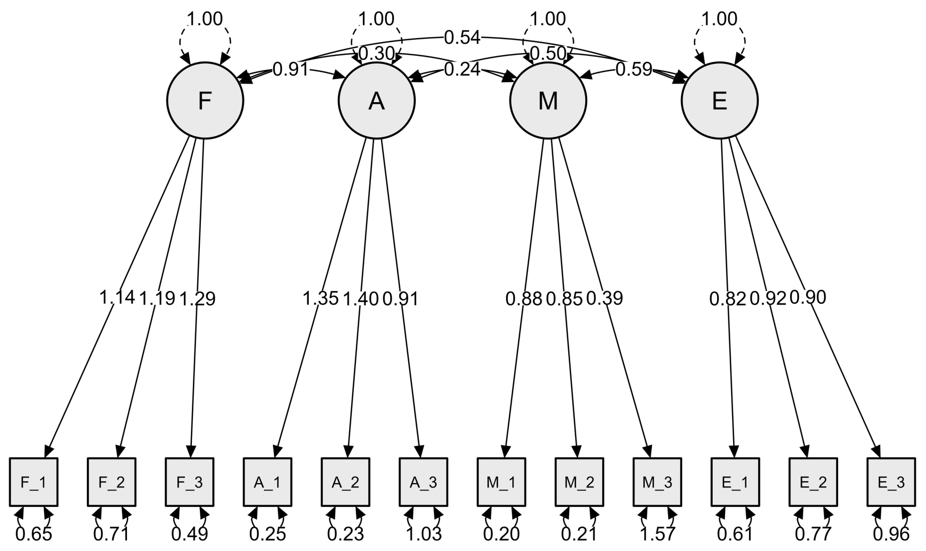

FIGURE 2
Confirmatory factor analysis (CFA) model of the FAME scale. F, Fear; A, Anxiety; M, Mistrust; E, Ethics.

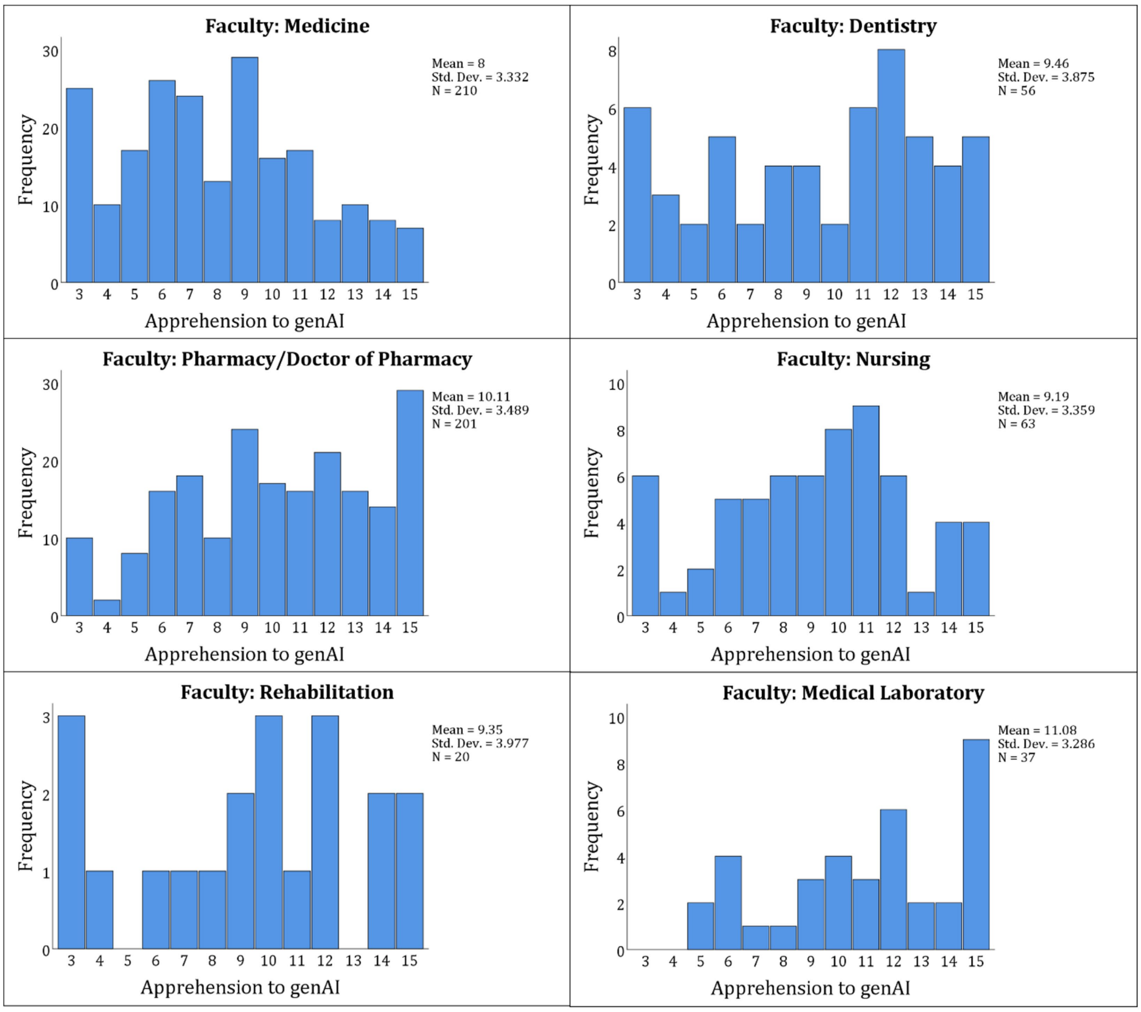

FIGURE 3
The distribution of apprehension to genAI in the study sample stratified per faculty. genAI, generative Artificial Intelligence.

by Ethics at 11.10 ± 3.06, Fear at 9.96 ± 3.88, and Anxiety at 9.18 ± 3.85 (Figure 4).

A Spearman's rank-order correlation was conducted to assess the relationship between apprehension toward genAI and the FEAR four constructs. The analysis revealed a statistically significant positive correlation between the Fear and apprehension constructs, $\rho = 0.653$, $p < 0.001$; the Anxiety and apprehension constructs, $\rho = 0.638$, $p < 0.001$; a weak yet statistically significant positive correlation with the Mistrust score, $\rho = 0.100$; $p = 0.016$, a moderate, statistically significant positive correlation with the Ethics construct, $\rho = 0.440$, <0.001 (Figure 5).

3.5 Multivariate analysis for the factors associated with apprehension to genAI

The regression analysis explained a substantial variance, with R^2 of 0.511, indicating that 51.1% of the variance in apprehension toward genAI was accounted for by the included predictors in the model. The regression model demonstrated statistical significance with an F-value of 54.720 and a $p < 0.001$ by ANOVA confirming that the whole model was a significant predictor of apprehension toward genAI.

The regression model examining predictors of apprehension toward genAI showed that faculty affiliation ($B = 0.209$, $p = 0.010$) and ChatGPT non-use prior to the study ($B = -0.635$, $p = 0.027$) were both significantly associated with apprehension, with faculty having a positive effect and non-ChatGPT use having a negative effect.

Nationality ($B = -0.180$, $p = 0.034$) and the country where the university is located ($B = 0.183$, $p = 0.036$) also demonstrated significant associations with apprehension levels. Among the psychological constructs, Fear ($B = 0.302$, $p < 0.001$), Anxiety ($B = 0.251$, $p < 0.001$), and Ethics ($B = 0.212$, $p < 0.001$) all showed strong positive associations with apprehension, suggesting that higher agreement with these constructs were linked with greater apprehension toward genAI (Table 4). In terms of multicollinearity, the VIF values indicated no severe multicollinearity concerns, as all are below 5. However, the Fear (VIF = 3.105) and Anxiety constructs (VIF = 3.118) were higher relative to other variables, suggesting moderate correlation with other predictors.

4 Discussion

In our study, we investigated the apprehension toward genAI models among health sciences students mainly in five Arab countries. The results pointed to a slight inclination toward apprehension about genAI, albeit the level of apprehension being close to neutral. Nevertheless, the level of genAI apprehension varied with notable disparities found in different demographic and educational contexts (e.g., nationality, faculty). The results suggested that while the participating students were not overwhelmingly apprehensive regarding genAI, they did harbor some apprehension about the implications of genAI in their future careers. This was manifested as a cautious acceptance of genAI rather than outright enthusiasm or rejection for this novel and inevitable technology.

TABLE 3 The association between apprehension to generative AI and different study variables.

Variable	Category	Apprehension to genAI Mean ± SD	p value
Age	<25 years	9.20 ± 3.56	0.393
	≥25 years	9.63 ± 4.07	
Sex	Male	8.96 ± 3.95	0.277
	Female	9.33 ± 3.46	
Faculty	Medicine	8.00 ± 3.33	<0.001
	Dentistry	9.46 ± 3.88	
	Pharmacy/ Doctor of Pharmacy	10.11 ± 3.49	
	Nursing	9.19 ± 3.36	
	Rehabilitation	9.35 ± 3.98	
	Medical Laboratory	11.08 ± 3.29	
Nationality	Jordan	9.55 ± 3.54	0.006
	Kuwait	7.92 ± 3.46	
	Iraq	9.89 ± 3.63	
	Egypt	9.36 ± 3.33	
	Saudi Arabia	9.03 ± 3.7	
	Other country	8.91 ± 4.08	
In which country is your university?	Jordan	9.28 ± 3.62	0.004
	Kuwait	7.21 ± 3.48	
	Iraq	9.86 ± 3.56	
	Egypt	9.54 ± 3.25	
	Saudi Arabia	9.37 ± 3.71	
	Other country	9.27 ± 3.8	
University type	Public	8.61 ± 3.55	<0.001
	Private	10.13 ± 3.47	
The latest Grade Point Average (GPA)	Excellent	9.13 ± 3.51	0.959
	Very good	9.36 ± 3.51	
	Good	9.23 ± 3.82	
	Satisfactory	9.09 ± 3.5	
	Unsatisfactory	8.20 ± 5.22	
The latest Grade Point Average (GPA)	Excellent/very good	9.26 ± 3.51	0.794
	Good/ satisfactory/ unsatisfactory	9.17 ± 3.77	
Number of genAI tools used	0	10.12 ± 4.06	0.120
	1	9.11 ± 3.52	

(Continued)

TABLE 3 (Continued)

Variable	Category	Apprehension to genAI	p value
		Mean ± SD	
	2	9.34 ± 3.4	
	3	8.00 ± 3.75	
	4	8.83 ± 3.49	
	5	13.00	
	6	9.50 ± 4.95	
ChatGPT use before the study	No	10.43 ± 3.75	<0.001
	Yes	8.94 ± 3.5	
Copilot use before the study	No	9.26 ± 3.6	0.632
	Yes	9.04 ± 3.57	
Gemini use before the study	No	9.30 ± 3.6	0.163
	Yes	8.60 ± 3.54	
Llama use before the study	No	9.22 ± 3.6	0.743
	Yes	9.83 ± 3.49	
My AI On Snapchat use before the study	No	9.2 ± 3.6	0.640
	Yes	9.36 ± 3.57	
Other genAI tool use before the study	No	9.16 ± 3.61	0.166
	Yes	9.76 ± 3.45	
How often do you use generative AI?	Daily	8.16 ± 3.49	<0.001
	Few times a week	9.06 ± 3.68	
	Weekly	9.62 ± 3.42	
	Less than weekly	9.81 ± 3.52	
Self-rated competency in using generative AI tools	Very competent	8.63 ± 3.66	0.006
	Competent	9.11 ± 3.46	
	Somewhat competent	9.31 ± 3.62	
	Not competent	10.9 ± 3.66	

p values were measured using the non-parametric Mann Whitney U and Kruskal Wallis tests; SD, Standard deviation.

The validity of our results is supported by the following factors. First, the rigorous quality check for responses received included ensuring the receipt of a single response per IP address, checking for contradictory responses, and setting a threshold for acceptable time to complete the survey to avoid common potential caveats in survey studies as listed by Nur et al. (2024). Second, the robust statistical analyses including EFA and CFA conducted helped to confirm the structural reliability of the FAME scale utilized in our assessment. Third, the diverse study sample primarily involving five different Arab countries provided acceptable credibility and generalizability to the study findings.

In this study, a substantial majority of the participants (87.4%) reported using at least one genAI tool, with a predominant use of ChatGPT by 80.4% of respondents. This result could highlight a trend hinting to the normalization of genAI tools' use among health sciences students in Arab countries. In turn, this could reflect a broader genAI acceptance and integration into the students' academic and potential professional careers.

The widespread use of ChatGPT specifically hints to its dominant presence and popularity compared to other genAI tools. As shown by the results of this study, lesser engagement with other genAI tools such as My AI On Snapchat (16.4%), Copilot (12.9%), and Gemini (10.6%) may indicate a disparity in functionality, user experience, or perhaps availability of different genAI tools, which suggests the ChatGPT position as the pioneering genAI tool. The pattern of genAI tool preference aligned with findings from other regional studies, such as that conducted by Sallam et al. (2024a), which also noted a variability of genAI use among medical students in Jordan, with ChatGPT leading significantly.

The dominant use of genAI tools, particularly ChatGPT, among university students, which was revealed in our study, hints to an emerging norm among university students in Arab countries as also shown in a recent study in the United Arab Emirates (Sallam et al., 2024b). This finding was reported internationally, as evidenced by Ibrahim et al. (2023) in a large multinational study that was conducted in Brazil, India, Japan, the United Kingdom, and the United States. The aforementioned study highlighted a strong tendency among students to employ ChatGPT in university assignments as shown in other studies as well (Ibrahim et al., 2023; Strzelecki, 2023; Mansour and Wong, 2024; Strzelecki, 2024). Taken together, the observed rise of genAI models' use in higher education demands an immediate and thorough examination by educational institutions and educators alike (Masters et al., 2025).

Specifically, this scrutiny must assess how genAI models could influence learning outcomes and academic integrity as reported in a recent scoping review by Xia et al. (2024). Such an evaluation is essential to ensure that the integration of genAI models in higher education does not compromise the foundational principles of educational fairness and integrity, but rather enhances them, maintaining a balance between innovation and traditional academic values (Yusuf et al., 2024).

The major finding of our study was the demonstration of a mean apprehension score of 9.23 regarding genAI among health sciences students in Arab countries. This result suggests a level of readiness among those future HCPs to engage with genAI tools, albeit with an underlying caution. Particularly pronounced was the Mistrust expressed in the FAME scale, where the Mistrust construct achieved the highest mean of 12.46 of the four constructs. This high score denoted an agreement among the participating students on the view of genAI inability to replicate essential human attributes required in healthcare such as empathy and personal insight. Such skepticism likely derives from concerns that genAI, for all its analytical capabilities, cannot fulfill the demands of empathetic patient care, which remains a cornerstone of high-quality healthcare and patients' satisfaction as shown by

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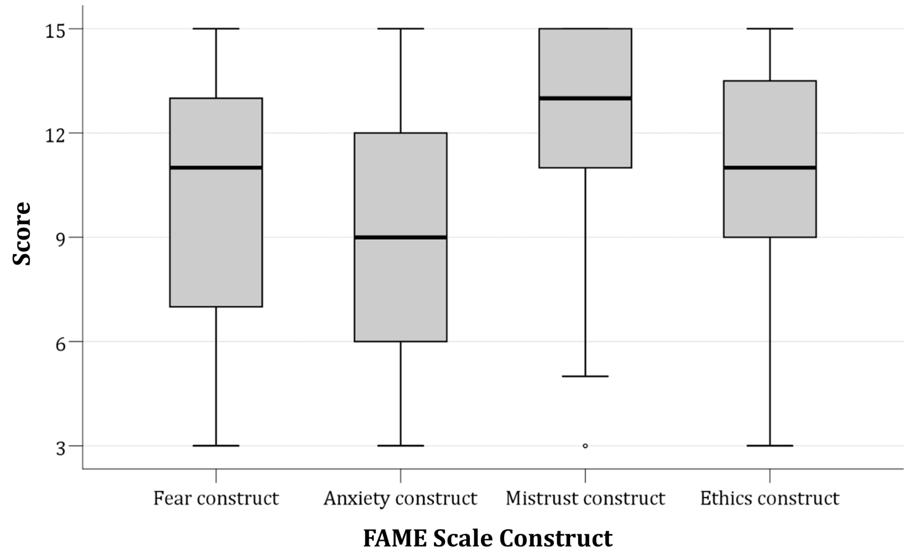

FIGURE 4
Box plots of the four FAME scale constructs.

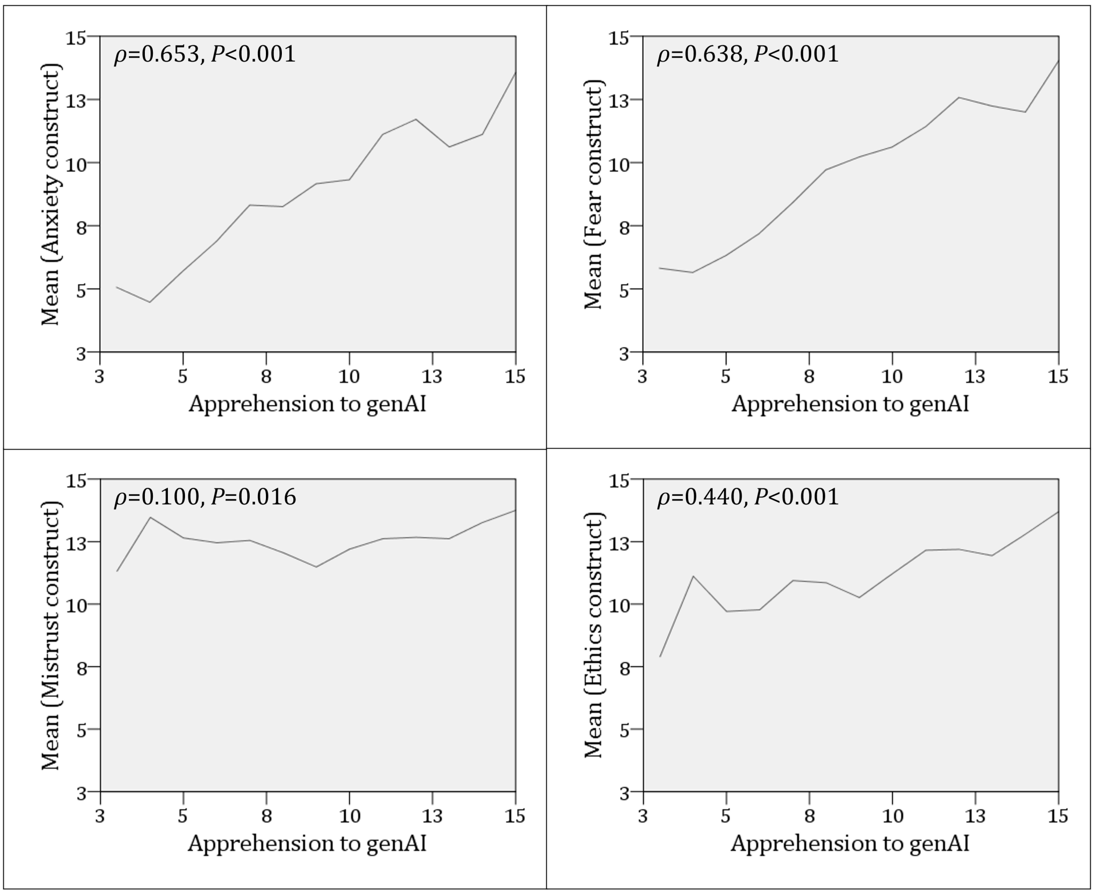

FIGURE 5
The correlation between the apprehension to genAI scores and the four FAME constructs scores. genAI, generative artificial intelligence; ρ, Spearman's rank correlation coefficient.

TABLE 4 Linear regression analysis of factors associated with apprehension toward generative AI.

Dependent variable: apprehension to genAI Independent variables	Unstandardized coefficients B	Standardized coefficients Beta	*t*	*p* value	VIF
Faculty	0.209	0.085	2.591	**0.010**	1.272
Nationality	−0.180	−0.080	−2.128	**0.034**	1.676
In which country is your university?	0.183	0.079	2.101	**0.036**	1.683
University type	0.258	0.035	1.072	0.284	1.280
ChatGPT use before the study	−0.635	−0.070	−2.215	**0.027**	1.179
How often do you use generative AI?	0.063	0.021	0.619	0.536	1.310
Self-rated competency in using generative AI tools	0.170	0.040	1.198	0.231	1.305
Fear construct	0.302	0.326	6.339	**<0.001**	3.105
Anxiety construct	0.251	0.269	5.223	**<0.001**	3.118
Mistrust construct	−0.050	−0.036	−1.078	0.281	1.276
Ethics construct	0.212	0.180	4.914	**<0.001**	1.583

Statistically significant *p* values are highlighted in bold style; VIF, Variance inflation factor.

Moya-Salazar et al. (2023). Nevertheless, this view has already been refuted in several studies that showed the empathetic capabilities of genAI at least to an acceptable extent (Ayers et al., 2023; Chen D. et al., 2024; Hindelang et al., 2024).

Additionally, ethical concerns among the participating students in this study were notable. This was illustrated by a mean score for the Ethics construct of 11.10, highlighting the anticipated ethical ramifications of genAI deployment in healthcare which were extensively investigated in recent literature (Oniani et al., 2023; Sallam, 2023; Wang et al., 2023; Haltaufderheide and Ranisch, 2024; Ning et al., 2024). In this study, the students voiced substantial concerns over potential ethical breaches, including fears of compromised patient privacy and exacerbated healthcare inequities which are among the most feared and anticipated concerns of genAI use in healthcare (Khan et al., 2023). Thus, there is a necessity for robust ethical guidelines and regulatory frameworks to ensure that genAI applications are deployed responsibly, safeguarding both equity and confidentiality in patient care (Wang et al., 2023; Ning et al., 2024).

In this study, the Fear construct showed a mean score of 9.96. This result could signal a cautiously neutral yet discernibly fearful stance among health science students about the implications of genAI for job security and the relevance of human roles in the future healthcare. Such fear likely stems from concerns that genAI efficiency and accuracy could overshadow the human roles in healthcare. Subsequently, this can lead to job redundancies and a transformative shift in the professional healthcare settings. This result was in line with fears expressed in a recent studies among HCPs in Bangladesh (Rony et al., 2024a; Rony et al., 2024b). Additionally, the Anxiety construct, with a score of 9.18, may suggest that the traditional healthcare curricula may not be fully preparing health science students for an AI-driven healthcare settings in the near future (Gantwerker et al., 2020). This suggests an urgent need to bridge the gap between current educational programs and the futuristic demands of a technology-driven healthcare sector as reviewed by Charow et al. (2021).

The nuanced patterns of genAI apprehension identified in this study should not be interpreted in isolation. Rather, these observations likely reflect a confluence of contextual and demographic factors. These factors include the students' academic backgrounds, levels of exposure to digital health technologies, and the broader socio-economic conditions surrounding healthcare education. The observed association between prior ChatGPT use and lower levels of genAI apprehension is particularly revealing. It suggests that familiarity with genAI tools can foster digital confidence, thereby reducing uncertainty and fear as shown in various contexts (Lambert et al., 2023; Abou Hashish and Alnajjar, 2024; Hur, 2025). In contrast, students with little or no exposure to such AI technologies may form their views based on unfamiliarity or secondhand perceptions, which can heighten skepticism as reported by García-Alonso et al. (2024). These insights highlight the importance of future research that moves beyond surface-level statistics to explore how educational, cultural, and psychological influences interact in shaping perceptions of genAI in healthcare education.

In regression analysis, the primary determinants of apprehension to genAI in this study included academic faculty, nationality, and the country in which the university is located. Additionally, statistically significant factors correlated with apprehension to genAI included the previous ChatGPT use and three out of the four constructs from the FAME scale namely Fear, Anxiety, and Ethics.

Specifically, the regression coefficients indicated distinct apprehension among pharmacy/doctor of pharmacy and medical laboratory students. This result could be seen as a rational response to the feared devaluation of the specialized skills and traditional roles of pharmacists and medical technologists by genAI (Chalasani et al., 2023). Additionally, the heightened apprehension toward genAI among pharmacy and medical laboratory students, relative to their peers in other health disciplines, can be attributed to the specific vulnerabilities of their fields to AI integration (Antonios et al., 2021; Hou et al., 2024). Pharmacy students may perceive a direct threat to their roles in medication management and patient counseling, as genAI promises to streamline treatment personalization, potentially diminishing the pharmacist involvement in direct patient care (Roosan et al., 2024).

Similarly, medical laboratory students face the prospect of AI automating complex diagnostic processes, potentially reducing their participation in critical decision-making and analytical reasoning (Dadzie Ephraim et al., 2024). On the other hand, medical students in this study showed a relatively lower apprehension toward genAI. This may stem from the perception that their roles involve a broader range of responsibilities and skills that are harder to automate and the many options of specialization they have. The practice of medicine involves complex decision-making, direct patient interactions, and nuanced clinical judgment, areas where AI is seen as a support tool rather than a replacement (Bragazzi and Garbarino, 2024). Nursing and dental students, like their medical counterparts in this study, exhibited relatively lower apprehension toward genAI likely due to the hands-on and interpersonal nature of their disciplines, which are perceived as less susceptible to automation.

An interesting result of the study was the variability in apprehension toward genAI among health sciences students from different Arab countries. Specifically, heightened apprehensions to genAI were found among student from Iraq, Jordan, and Egypt, contrasted with the significantly lower apprehension in Kuwait. This result can be explained through several socio-economic, educational, and cultural perspectives. Such an observation could potentially reflect a broader socio-economic uncertainties and disparities in technological integration within healthcare systems in Iraq, Jordan, and Egypt. These countries, while rich in educational history, face economic challenges that could affect the employment rates and resulting in healthcare resource constraints (Lai et al., 2016; Katoue et al., 2022). In such conditions, the introduction of genAI might be viewed more as a competitive threat than a supportive tool, exacerbating fears of job displacement amidst already competitive job markets (Kim et al., 2025).

The higher apprehension observed in these countries is likely compounded by concerns over the ethical use of AI in settings where regulatory frameworks might be perceived as underdeveloped or inadequately enforced. Conversely, Kuwaiti students' lower levels of apprehension can be attributed to several factors. Economically more stable and with substantial investments in healthcare and education, Kuwait among other Gulf Cooperation Council (GCC) countries offers a more optimistic outlook on technological advancements (Shamsuddinova et al., 2024). Subsequently, the integration of genAI into healthcare would be seen as an enhancement to professional capabilities rather than a threat. Nevertheless, these cross-group differences warrant cautious interpretation. The current study did not adjust for potential confounding factors such as variation in educational curricula, differential exposure to genAI models, or culturally embedded attitudes toward automation in healthcare. In addition, the lack of measurement invariance testing precluded reaching definitive conclusions regarding the FAME scale performance across sub-groups. Thus, the observed differences in genAI apprehension may, in part, reflect measurement bias rather than genuine underlying perceptual divergence. Future studies employing qualitative or mixed-method designs are needed to more precisely delineate the contextual and cognitive factors underlying these variations in genAI apprehension.

Finally, the pronounced apprehension toward genAI among students exhibiting higher scores in the Fear, Anxiety, and Ethics constructs of the FAME scale, as well as among those who had not previously used ChatGPT should be dissected through a psychological perspective. Students scoring higher in Fear and Anxiety constructs likely perceive genAI not merely as a technological tool, but as a profound disruption. Fear often stems from the perceived threat of job displacement which is a sentiment deeply in-built in the collective psyche of individuals entering competitive fields like healthcare (Reichert et al., 2015; Kurniasari et al., 2020; Zirar et al., 2023).

Anxiety, closely tied to fear as reveled in factor analysis, might be amplified by the uncertainty of coping with rapidly evolving genAI technologies that could alter the whole healthcare future settings (Zirar et al., 2023). On the other hand, the higher scores in Ethics construct in association with higher genAI apprehension suggested the role of ethical implications of integrating genAI in healthcare. Based on the items included in the Ethics construct, the students were likely worried about patient privacy, the integrity of data handling by genAI, and the equitable distribution of AI-enhanced healthcare services which are plausible issue as discussed extensively in recent literature (Oniani et al., 2023; Bala et al., 2024; Ning et al., 2024; Williamson and Prybutok, 2024). The heightened apprehension among students who had not previously used ChatGPT before the study can be attributed to a lack of familiarity and understanding of genAI capabilities and limitations.

The study findings highlight the need for a systematic revision of the current healthcare curricula to address apprehensions about genAI and prepare future HCPs for careers soon to be heavily influenced by AI technologies (Tursunbayeva and Renkema, 2023). To address genAI apprehension and enhance proficiency, curricular developments should include AI literacy courses to explore AI functionalities and ethical dimensions, tailored to each healthcare discipline given the current lack of such curricular as revealed by Busch et al. (2024).

Ethics modules in healthcare education, specifically dealing with AI, should dissect real-world scenarios and ethical dilemmas (Naik et al., 2022). Additionally, the curriculum can encourage research and critical analysis projects that assess genAI impact on healthcare outcomes and patient satisfaction. Workshops aimed at hands-on training in genAI tools can help diminish fear of redundancy by illustrating how genAI augments rather than replaces human expertise (Giannakos et al., 2024). These initiatives can collectively culminate in successful incorporation of AI into educational frameworks, fostering a generation of HCPs who are both technically confident and ethically prepared.

The current study methodological rigor and multinational scope provided a strong foundation for its findings; nevertheless, despite its strengths, our study was not without limitations. First, the use of a cross-sectional survey design precluded the ability to establish causal relationships between the study variables, and longitudinal future studies are recommended to assess the trends of changing attitude to genAI and causality. Second, recruitment of the potential participants was based on a convenience and snowball sampling approach, which could have introduced bias by over-representing certain groups within the network of the initial participants and under-representing others outside of these networks. Third, although the total sample size was adequate for psychometric analyses, the distribution across countries was uneven, which could limit the interpretability of country-specific comparisons and reduce the cross-national generalizability of findings. Fourth, while the FAME scale demonstrated strong psychometric properties in our overall Arab sample, we did not conduct formal measurement invariance testing across countries or academic sub-groups. Thus, the observed differences in this study may reflect potential measurement bias rather than true variation in apprehension toward genAI. This underscores the need for future studies to evaluate configural, metric, and scalar invariance to ensure cross-group comparability. Finally, the study relied on self-reported data (e.g., latest GPA, genAI use, etc.), which can be subject to response biases such as social desirability or recall biases. While self-reporting is a practical and widely used approach in survey research (Demetriou et al., 2015), these limitations may affect the accuracy and consistency of the responses (Brenner and DeLamater, 2016).

To enhance the generalizability and contextual depth of future research, we recommend the adoption of stratified or probability-based sampling methods to ensure more representative and balanced participant recruitment across diverse academic and national contexts. Additionally, while the FAME scale offers a robust framework for quantifying genAI-related apprehension, future studies should consider complementing it with qualitative approaches or expanded item sets that capture the more nuanced psychological and contextual dimensions of fear, anxiety, and mistrust toward genAI in healthcare. These strategies will support a more comprehensive understanding of how educational and cultural factors would shape attitudes toward emerging technologies among future healthcare professionals.

5 Conclusion

In this multinational survey, Arab health sciences students exhibited a predominantly neutral yet cautiously optimistic attitude toward genAI, as evidenced by a mean apprehension score that leaned slightly toward agreement. This perception varied notably by discipline and nationality as pharmacy and medical laboratory students expressed the highest apprehension, likely due to the perceived potential disruption of genAI in their specialized fields. On the other hand, Kuwaiti students showed the lowest genAI apprehension, potentially reflecting national policies favoring technological adoption and integration into educational systems or underlying job security. Significant associations were found between apprehension and three constructs of the FAME scale—fear, anxiety, and ethics—highlighting deep-seated concerns that call for targeted educational strategies to address genAI apprehension. However, given the limitations in sampling methods and lack of measurement invariance testing, these cross-national differences should be interpreted with caution and regarded as exploratory. As genAI tools advance, it is crucial for healthcare education to evolve accordingly, ensuring that future HCPs are not only technologically proficient but also well-prepared to address ethical issues introduced by genAI. Integrating genAI into healthcare curricula must be done strategically and ethically, to prepare the students to effectively manage both the technological and ethical challenges posed by AI, thereby enhancing their readiness to address fears of job displacement and ethical dilemmas.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary material.

Ethics statement

The studies involving humans were approved by The Institutional Review Board (IRB) of the Deanship of Scientific Research at Al-Ahliyya Amman University, Jordan. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

MaS: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. KA-M: Data curation, Investigation, Methodology, Writing – review & editing. HA: Data curation, Investigation, Methodology, Writing – review & editing. NAlb: Data curation, Investigation, Methodology, Writing – review & editing. ShA: Data curation, Investigation, Methodology, Writing – review & editing. FA: Data curation, Investigation, Methodology, Writing – review & editing. AA: Data curation, Investigation, Methodology, Writing – review & editing. SaA: Data curation, Investigation, Methodology, Writing – review & editing. NAlh: Data curation, Investigation, Methodology, Writing – review & editing. DA-Z: Data curation, Investigation, Methodology, Writing – review & editing. FS: Data curation, Investigation, Methodology, Writing – review & editing. MoS: Data curation, Investigation, Methodology, Writing – review & editing. AS: Data curation, Investigation, Methodology, Writing – review & editing. MM: Data curation, Investigation, Methodology, Writing – review & editing. DA: Data curation, Investigation, Methodology, Writing – review & editing. AA-A: Data curation, Investigation, Methodology, Supervision, Validation, Writing – review & editing.

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Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2025.1542769/full#supplementary-material

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Glossary

AI - Artificial intelligence

ANOVA - Analysis of Variance

CDA - Creative Displacement Anxiety

CFA - Confirmatory Factor Analysis

EFA - Exploratory Factor Analysis

EHRs - Electronic health records

FAME - Fear, Anxiety, Mistrust, and Ethics

GCC - Gulf Cooperation Council

genAI - Generative artificial intelligence

GFI - Goodness of Fit Index

GPA - Grade point average

HCPs - Healthcare professionals

HSSs - Health sciences students

KMO - Kaiser-Meyer-Olkin

K-W - Kruskal Wallis test

M-W - Mann Whitney U test

RMSEA - Root Mean Square Error of Approximation

SD - Standard deviation

SRMR - Standardized Root Mean Square Residual

STAI - State-Trait Anxiety Inventory

TAM - Technology Acceptance Model

TLI - Tucker-Lewis Index

VIF - Variance Inflation Factor

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Building responsible AI chatbot platforms in higher education: an evidence-based framework from design to implementation

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Generative AI presents opportunities and challenges for higher education stakeholders. While most campuses are encouraging the use of generative AI, frameworks for responsible integration and evidence-based implementation are still emerging. This Curriculum, Instruction, and Pedagogy article offers a use case of UT Austin's approach to this dilemma through an innovative generative AI teaching and learning chatbot platform called UT Sage. Based on the demonstrated benefits of chatbot technologies in education, we developed UT Sage as a generative AI platform that is both student- and faculty-facing. The platform has two distinct features, one a tutorbot interface for students and the other, an instructional design agent or builder bot designed to coach faculty to create custom tutors using the science of learning. We believe UT Sage offers a first-of-its-kind generative AI tool that supports responsible use and drives active, student-centered learning and evidence-based instructional design at scale. Our findings include an overview of early lessons learned and future implications derived from the development and pilot testing of a campus-wide tutorbot platform at a major research university. We provide a comprehensive report on a single pedagogical innovation rather than an empirical study on generative AI. Our findings are limited by the constraints of autoethnographic approaches (all authors were involved in the project) and user-testing research. The practical implications of this work include two frameworks, derived from autoethnographic analysis, that we used to guide the responsible and pedagogically efficacious implementation of generative AI tutorbots in higher education.

KEYWORDS

generative AI (GenAI), chatbots, responsible AI, instructional design (ID), educational technology, higher education, science of learning, teaching and learning

Introduction

Background

In the 1970s, inexpensive, hand-held calculators sparked a revolution in math education (Ellington, 2003; Raymond, 2024). After learning basic arithmetic, students could relegate tedious paper and pencil calculations to machines, opening up the opportunity to work on more interesting problems. Educators, however, faced a sea of ambiguity. Would students use

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these tools to cheat? Would they lose computational skills by offloading too much to a piece of hardware? Could the calculator help advance student learning and solve long-standing problems, such as student motivation, in math education?

At present, the higher education discourse on generative AI parallels much of the early 1970s viewpoints on calculators (see Science News, 1975). Technically, generative AI and calculators represent radically different academic technologies. Lodge et al. (2023) emphasize that even though it is tempting (and popular) to do so, comparing the two oversimplifies the complexity of generative AI. For example, "generative AI could be described more as a technological infrastructure, like electricity, and not a single tool" (Lodge et al., 2023, para 4). That said, higher education faculty, administrators, and students today face a pedagogical dilemma analogous to the 1970s. Should we adopt generative AI without clear empirical evidence of how the tool might help, hinder, or harm student learning? How can we do so when so many unresolved questions about ethics, privacy, environmental impacts, bias, and career impacts relative to generative AI abound?

The existing situation: generative AI adoption and the teaching and learning landscape

Empirical research is a slow process, and so it can take years (or decades) to build up an evidence base about the efficacy of a new technology. Generative AI is not just "here" in that it is widely available throughout society, it is also solidly here and freely available on campuses worldwide. A study of 116 major research institutions in the United States found that most campuses are encouraging generative AI use (McDonald et al., 2025). Not only that, most of those same campuses also provide guidance to support generative AI adoption. Higher education leaders who are AI forward are aware of the importance of minimizing the digital divide and preparing students for a future where AI is ubiquitous. Students, moreover, want (and need) more than just access: They want generative AI lessons, especially concerning ethical adoption, incorporated into classroom learning (Cengage Group, 2024). Most faculty want to support student learning, but they may be unclear about how to do so with generative AI since it is so new. In addition, while some empirical studies correlate the use of generative AI with improved student learning outcomes (see Lo et al., 2025, Yilmaz, et al., 2023, Zhu, et al., 2025), generalizability and statistical effects vary widely. As such, institutions find themselves in a position whereby they need to lead their campuses toward the responsible adoption of generative AI in a rapidly shifting landscape of highly unresolved, high-stakes questions related to student learning.

While the impact of generative AI on student learning is evolving, general principles of responsible adoption of AI in teaching and learning do exist (U.S. Department of Education, Office of Educational Technology, 2023; WEF, 2024; McDonald et al., 2025). So too does firmly established, long-standing evidence of how students learn best (National Research Council, 2000; Ambrose et al., 2010; Hattie, 2015; National Academies of Sciences, Engineering, and Medicine, 2018). For example, drawing on the science of learning, it is clear that student learning is optimized when educators design their courses using student-centered, active learning approaches (Ambrose et al., 2010; Schell and Butler, 2018). However, the large majority of higher education faculty are disciplinary specialists rather than pedagogical experts, so they may be unfamiliar with the scholarship of teaching and learning and how to apply it within an AI context. Moreover, faculty gaps in pedagogical knowledge may lead to inadvertent replication of teacher-centered designs in college classrooms.

Learning science research is both extensive and dense, which has led to a number of publications aiming to translate findings to practice (see National Academies of Sciences, Engineering, and Medicine, 2018; National Research Council, 2000). Improving one's teaching using principles from the science of learning takes time and effort, both of which are in short supply among research-active faculty. While information on how people learn best is plentiful, the realities of the faculty workload present a challenge for educators and institutional leaders who aim to advance the academic mission. Some institutions offer instructional design services to bridge these gaps.

With backgrounds in both learning theory and technology-enhanced pedagogy (Kumar and Ritzhaupt, 2017; Pollard and Kumar, 2022), instructional designers offer a valuable resource to faculty who want to build technological pedagogical content knowledge—or that special knowledge base for teaching specific content with technology (Voogt et al., 2013). Not all faculty are open to working with instructional designers, however (see Pollard and Kumar), and at major research universities, the need for quality instructional design consultation far exceeds available resources.

Advancing high-quality pedagogical practices by blending generative AI and learning science in a chatbot

The Office of Academic Technology Team at the University of Texas at Austin launched a generative AI development project to explore whether responsible adoption of emergent technology could help scale the use of learning science-driven instructional design at a major public research university. The purpose of this Curriculum, Instruction, and Pedagogy article is to offer a use case of an innovative generative AI chatbot designed from the ground up called UT Sage. For context, this paper focuses on the process of locally developing and alpha and beta testing an AI chatbot in higher education and is not an empirical study. We describe our conceptual approach to chatbot design and deployment, and detail two evidence-based frameworks that guided our design decisions. These frameworks represent replicable elements that higher education stakeholders can adapt to guide chatbot or other generative AI development efforts in their own instructional contexts.

UT Sage is a generative AI chatbot that is both student- and faculty-facing. AI chatbots are not new in education. In two separate meta-analyses covering AI chatbots, Okonkwo and Ade-Ibijola (2021) and Winkler and Soellner (2018) identified a host of potential benefits aligned with chatbot technology when educators deploy them for teaching and learning purposes, including student engagement, memory retention, access, metacognition, and self-regulation. Although these studies precede the influx of generative AI in education, established literature on AI chatbots in teaching and learning along with newer works (see Lo et al., 2025, Yilmaz, et al., 2023, Zhu, et al., 2025), form a solid foundation from which to begin generative AI adoption initiatives on university campuses.

The UT Sage user experience for students is similar to other chat or tutorbot interfaces. Where UT Sage differs from other generative AI chatbot experiences is within its faculty-facing "builder bot" or custom-GPT features. Behind the scenes of the student-facing tutorbot, UT Sage functions as an always available, learning-science-driven, virtual instructional design coach or agent. The builder bot is a helper agent intentionally programmed to promote virtual instructional design coaching rooted in learning science research. With its dual nature feature of student tutorbot and instructional design agent, we believe UT Sage is a first-of-its kind application to integrate the science of learning with generative AI custom GPT technologies for classroom use.

This article begins with a broad overview of UT Sage as an educational innovation activity. We detail the key features that support the use case of UT Sage as a scalable, virtual instructional design agent. We include a methodology section to situate the project, while acknowledging the limitations of a non-experimental study. Then, we provide an overview of results from our assessments of UT Sage so far. Finally, we close with a discussion of the practical implications and lessons learned from our effort to scale learning-science driven instructional design coaching using a generative AI agent. After reading this case study, we expect higher education faculty and leaders to have an example for how to navigate the dilemma-laden landscape that broad, open-access to generative AI has brought to higher education. We offer two evidence-based frameworks we used to guide the local development of a generative AI chatbot. UT Sage serves as one early effort to adopt generative AI in higher education by integrating responsible AI and learning science principles with emergent technologies.

We want to be clear from the outset that our aim is not to replace or limit the role of instructional designers in higher-education institutions or to reduce faculty autonomy in course design. Teaching is an inherently human task, and what we offer through Sage is only a small part of what an instructional designer can do when engaging with faculty. Instead, the goal of this project is to improve teaching practice by scaling introductory elements of instructional design through the use of generative AI to bridge the gap between the supply of and demand for instructional resources on our campus. Without administrative intention and adherence to responsible AI principles, automation of course design will lead to deleterious effects on student, faculty, and designer roles. Automating basic elements of instructional design may also require designers and faculty to develop new competencies in the ethical and responsible implementation of generative AI in the classroom that aligns with the academic mission. When implemented with clear intention and responsible adoption principles, however, tutors like Sage may also open opportunities for instructional designers, technologists, and faculty to create innovative approaches to learning experiences that support transferable knowledge and skills.

Educational innovation activity: UT Sage

UT Sage overview

UT Sage is a platform that provides a scalable, virtual instructional design agent (the builder bot) to aid instructors in creating their own tutorbots for students. Our vision was to enable instructors to conceive of an idea for a student-facing chatbot tutor, have a conversation with the Sage agent to refine their vision, upload resources, and deploy their tutorbot to students in a few hours or less. As an agent, Sage is built to provide instructional design coaching with faculty to help them build effective tutorbots based on established learning science principles. Sage asks instructors the questions found in Table 1 to gather information about the learners and the desired learning experience. Once an instructor's tutorbot is created and shared, students can start a conversation with the tutor to supplement their knowledge of a topic. Tutorbots in Sage offer the experience of using chatbots to learn using generative AI tools, but with the assurance that the content knowledge loaded into those tools has been vetted by their instructors and adheres to the University's information security policies. Another unique aspect of Sage compared to other generative AI chatbots is that it is designed to operate at the topic or lesson plan level, rather than a full-course level. This decision was made to align Sage with a more typical tutor experience and to reduce the learning curve for a faculty member who may want to build a tutor bot.

TABLE 1 A list of the attributes that UT Sage uses to configure tutors for instructors and the related inquiries used by the instructional design agent as part of the conversational builder bot.

Tutor attribute	Instructional design coach inquiry
Topic	What topic would you like to create a tutor for today?
Learner Description	Who are your learners? Describe things like their likely academic year, majors, and minors. How large is their class and how is it delivered? What prior knowledge might they have about this topic, or what prior knowledge gaps might they experience. What is their motivation like for the topic?
Learning Outcomes	What are your learning outcomes for this tutor? What would you like your students to know about the topic? What would you like them to be able to achieve? What kinds of attitudes would you like them to gain or develop?
Topic Importance	Why is this topic important to learning in your class? Why is this topic important, generally, for students to learn?
Common Misconceptions	List common difficulties, misconceptions, inaccurate knowledge, or challenges that your students have with this topic. How have you helped your students work around these in the past?
Learning Activities	What kinds of activities would you like students to do when they engage with this tutor? For example, would you like them to quiz themselves or practice in some other way?
Training Documents	What kinds of resources would you like to upload to configure this tutor?

UT Sage as AI-tutor and instructional design agent

The UT Sage platform is made up of two distinct elements:

(1) The builder bot instructor interface is where instructors can create tutors according to their own instructional needs. Instructors can chat with an instructional design

agent that asks them about what topic they'd like to build a tutorbot for, who their learners are, and how they'd like to define their learning outcomes as detailed in Table 1 and illustrated in Figure 1. The builder chatbot will make suggestions or pose questions to help guide the faculty in creating their tutor. In addition, the agent prompts instructors to document common misconceptions or difficulties students might have and any unique ways the faculty member has found for addressing those misconceptions. If instructors would like to adjust their tutor, they can also make changes to all of its parameters using a configuration form (see Figure 2). Additionally, faculty can upload and categorize three different text-based resources to train the tutor on the tutor topic. For example, a user can upload an administrative document, an assignment, or notes, and UT Sage will incorporate the information into conversations appropriately. For example, information parsed from assignment documents is handled with less literal transcription and more directed inquiry. Content from administrative and notes documents is more directly integrated into tutor responses. As instructors build their tutors, they can also test the student experience in the Student Preview window on the right. The builder bot and training interface are illustrated in Figures 2,3.

(2) Students can access and use UT Sage tutors after their instructors have created, shared, and published them. The student-facing interface is illustrated in Figure 4. Tutorbot-student facing conversations are programmed to be helpful and to encourage students to engage in Socratic dialogue by asking questions at the end of appropriate interactions. Tutorbots use training documents uploaded by instructors as the first and best source of information. They do not engage in conversations about unrelated subjects. The tutor maintains a memory of what it has discussed with students previously, but a new session can also be created if students wish to start a new line of inquiry. A history of these conversations is maintained for students and accessible in the chat interface.

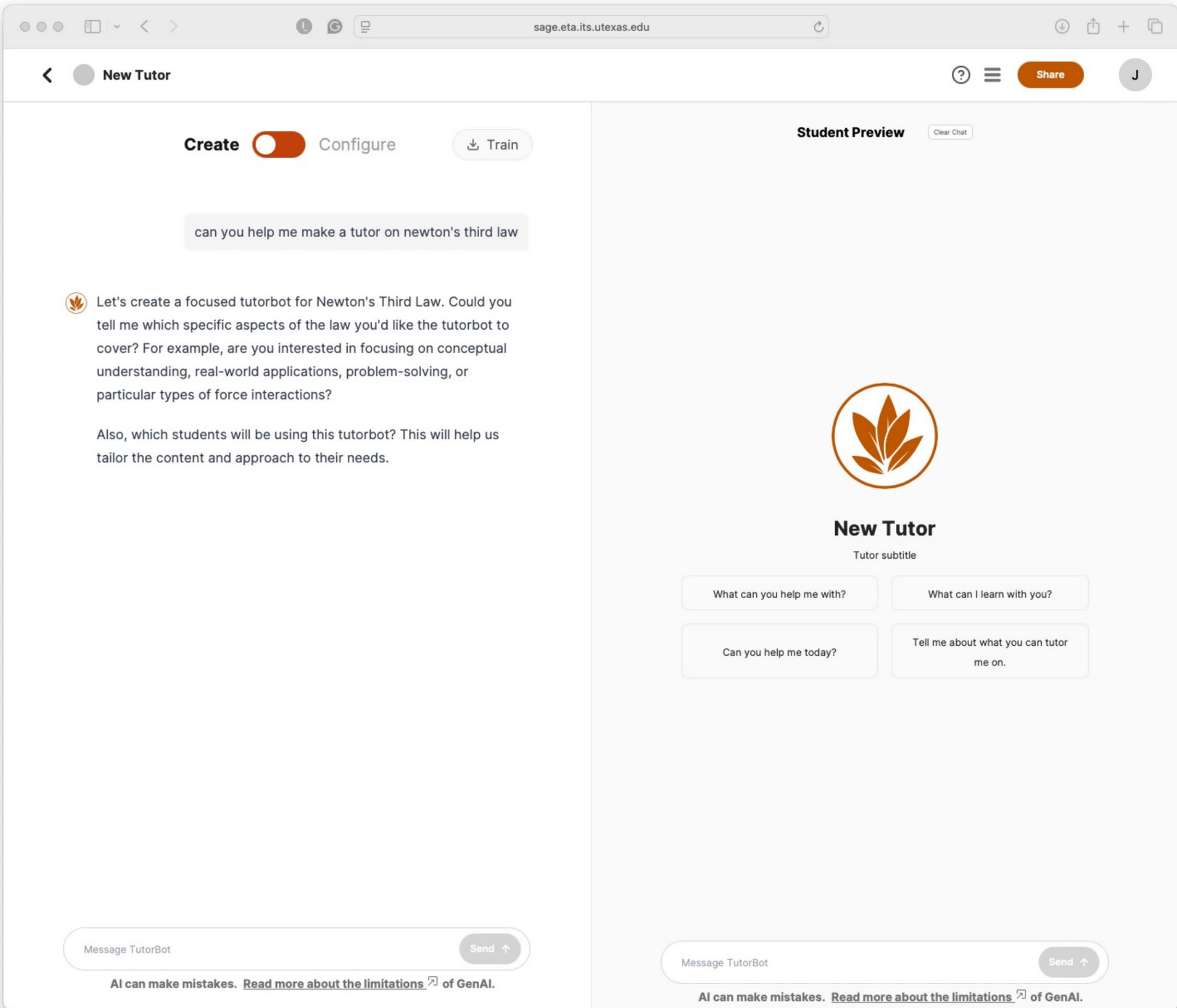

FIGURE 1
UT Sage's instructor-facing instructional design agent (Left) with student view test window (Right).

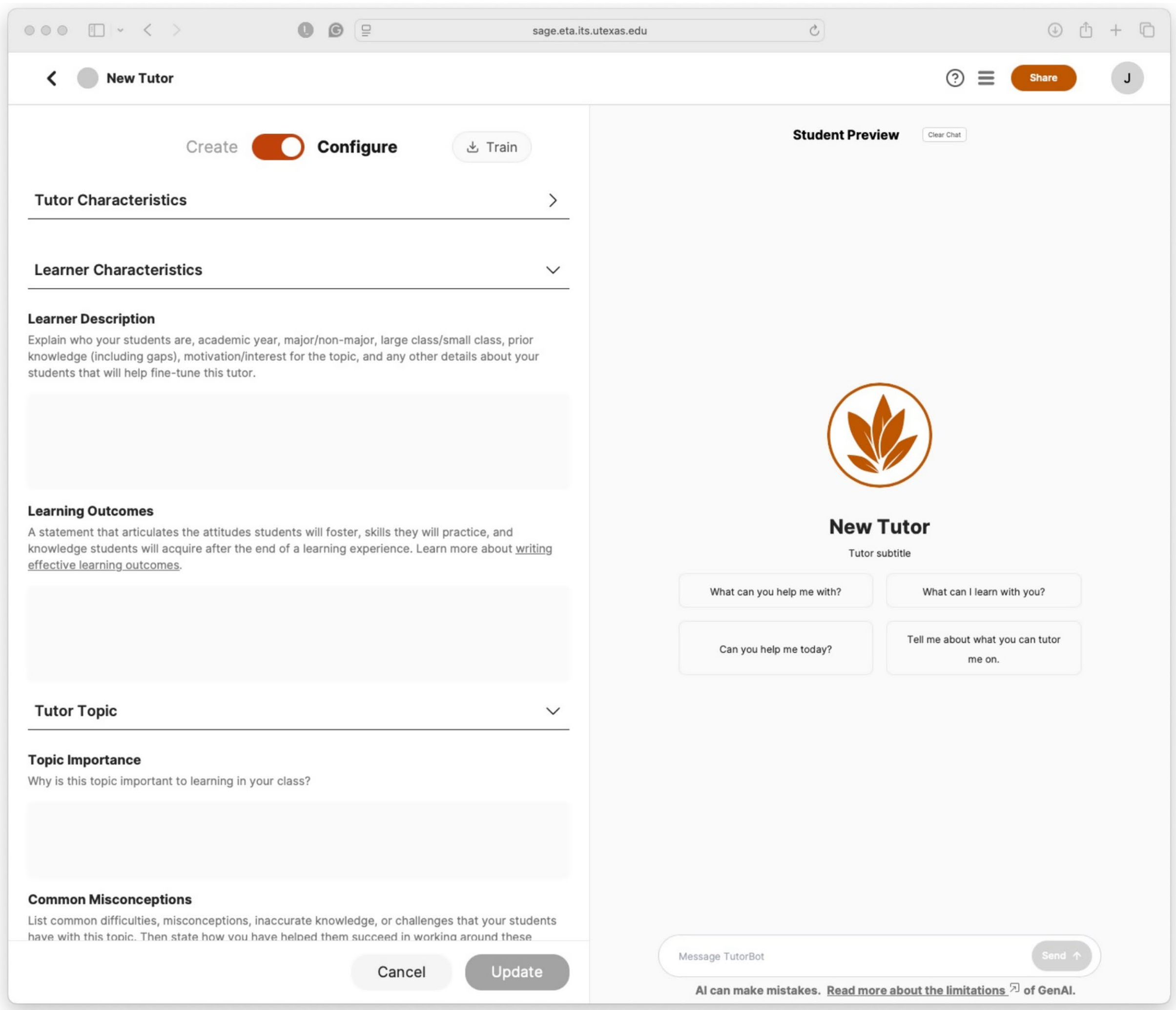

FIGURE 2
UT Sage's instructor-facing instructional design configuration form (Left) with student view test window (Right).

Each of these functions, builder bot and tutorbots, can be accessed via the platform homepage, which features all of the tutors that the user has access to. Students can see their tutors organized according to term, and instructors can edit or test any of their tutors from this page.

Figure 1 illustrates the instructor-facing experience with the instructional design agent on the left, with a preview window that instructors can use to test out the student-facing tutorbot they are building. Instructors use the configuration (Figure 2) and training (Figure 3) interfaces to refine and assess their tutors. The remainder of the configuration form includes the categories outlined in Table 1: learning outcomes, topic importance, common misconceptions and workarounds, learning activities, and "conversation starters" to help guide students who may not know how to begin. Figure 4 illustrates the student-facing experience with a tutorbot. In Figure 4, the instructor has created a tutorbot to help students with logistic regression. Students can get started with one of the conversation starters or type in their own text.

Technical details

Sage uses, at time of writing, the Claude 3.5 Haiku and Claude 3 Sonnet large language models (LLMs) to understand what students are asking and answer with context from topic-specific information using a retrieval-augmented generation (RAG) pipeline. Access to learn with Sage is free and available to students 24/7. Because this platform is owned by the University and students and faculty engage after logging in with their university ID, their input and output is protected by the University's highest data security and privacy standards.

Sage is a collaboration between the UT Austin's Office of Academic Technology and Enterprise Technology group, with the former offering product requirements and design and the latter developing institutional infrastructure, the user interface, and connecting underlying technologies. The prompts that power Sage's tutors were developed in partnership with AWS, which approached UT Austin about finding applications for generative AI technologies in higher education.

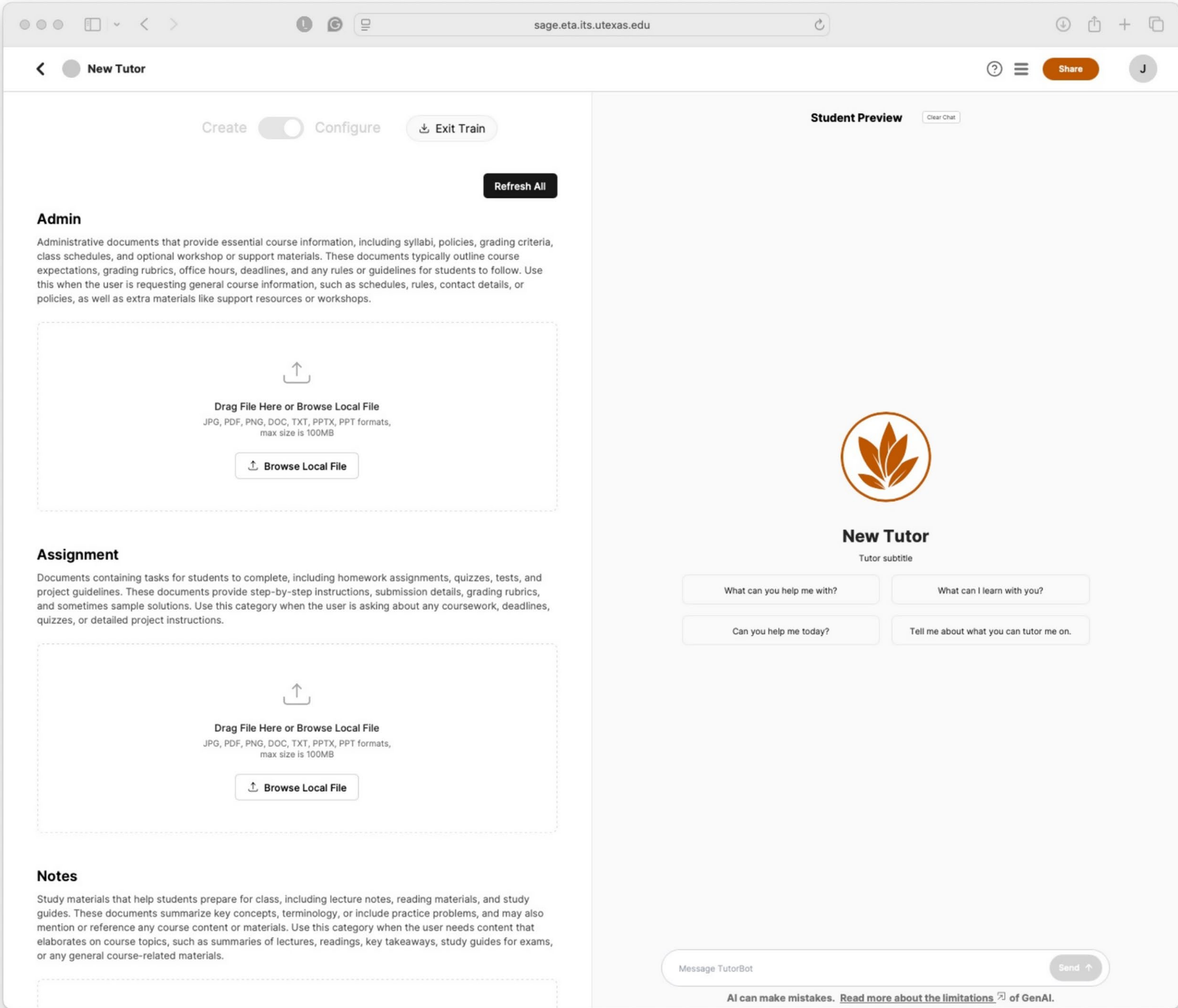

FIGURE 3
UT Sage's instructor-facing instructional design resource interface (Left) with student view test window (Right).

Learning environment

UT Austin is a large, public, R1 university with 19 colleges and schools. 51,913 individuals were enrolled as students in Fall 2023. Of those students, 56.3% are federally identified as women and 43.8% as men. 80.1% or 42,444 are undergraduate students, and 19.9% or 9,469 are seeking graduate degrees. These students are distributed among 156 undergraduate degrees and 237 graduate programs. 3,917 faculty were employed by the university for the 24–25 academic year and about 48.7% are tenure or tenure-track and 51.3% were professional or non-tenured (University of Texas at Austin, 2024).

Given the size of the student body and the breadth of available educational programs, the instructional needs and circumstances of these students and faculty are highly varied. A small handful of schools and departments have dedicated instructional designers, educational developers, and educational technologists on staff to address the needs of faculty, but the availability of these services across campus is inconsistent. While centralized offices offering support for course design and technology implementation, such as the Office of Academic Technology and Center for Teaching and Learning, are available for consultation, the need for flexible access to personalized learning experience design advice has been recognized by central administrators.

Principles and frameworks underlying UT Sage

Responsible adoption of generative AI

The literature on the responsible adoption of generative AI in education—both in K12 and higher ed—calls for balancing its transformative potential of the new technology with active efforts to address its limitations and potential dangers (Saaida, 2023; WEF, 2024; McDonald et al., 2025). The UT Sage initiative involved a number of design decisions aimed at maintaining such balance. Prior to

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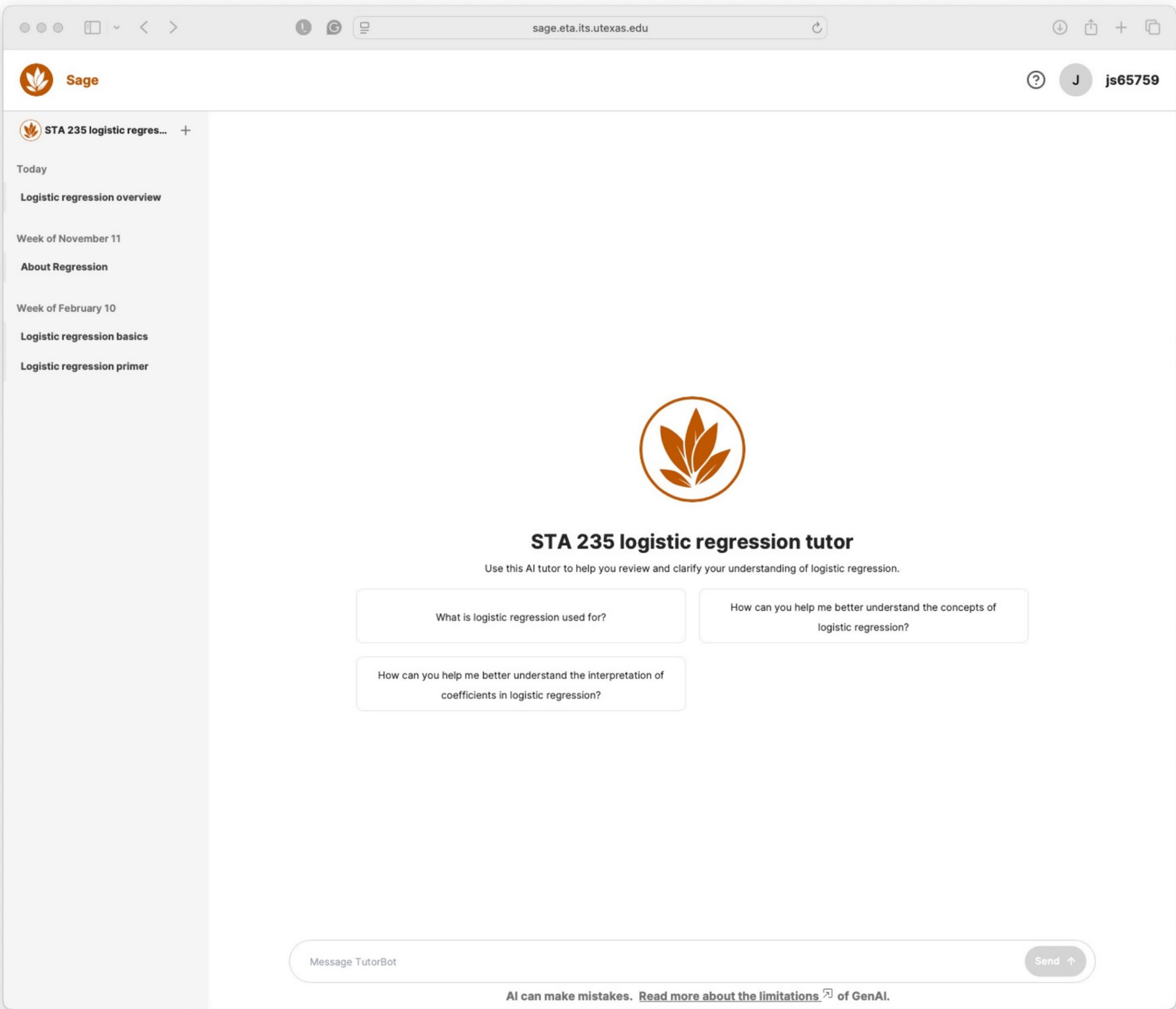

FIGURE 4
An example of a student-facing tutorbot chat interface in UT Sage called 'Statistics 235 logistic regression tutor".

conceptualizing Sage, we developed the AI-Forward - AI-Responsible Framework (Office of Academic Technology, UT Austin, 2024) to guide campus to engage in responsible adoption of generative AI for academic use.

AI-Responsible/AI-Forward framework

Our AI-Responsible/AI-Forward framework calls for embracing generative AI for teaching and learning while also acknowledging that the technology also has significant limitations. The framework defines responsible use of generative AI tools for teaching and learning as using generative AI in ways that foster the achievement of learning outcomes and not using it in ways that would negate or inhibit the realization of those outcomes (Office of Academic Technology, UT Austin, 2022). We drew on the "human-in-the-loop" concept to develop this framework (U.S. Department of Education, Office of Educational Technology, 2023). Human-in-the-loop generative AI emphasizes that students and teachers must always be involved and have agency when it comes to the adoption of AI tools. Our definition aims to empower educators to decide for themselves (1) how generative AI might improve student learning of specific topics and (2) to be transparent with students about why and how generative AI might help them achieve specific learning outcomes, or on the other hand, inhibit or harm their learning. We encourage faculty to foster a climate where students can become the architects of their own ethical frameworks in light of such transparency.

To help support AI literacy and bolster the responsible side of the balance needed for effective adoption, we also developed what we refer to as the "Big 6," which detail six limitations of using generative AI for learning in particular (Office of Academic Technology, UT Austin, 2024) as follows: Data privacy and security, hallucinations, misalignment, bias, ethics, and cognitive offloading. The limitations of generative AI become even more complex at scale. Efforts to adopt generative AI across contexts require higher education leaders to engage in consistent grappling with issues such as the digital divide, training and algorithmic biases, risks of exposing student data, and over-reliance on AI tools in ways that short-circuit the academic honor code and productive struggle (Bjork and Bjork, 2020).

While the University now provides enterprise-level access to Microsoft Copilot, at the time we began developing Sage, the campus did not have an open-access, approved generative AI tool for educational use. We used the AI-Responsible/AI-Forward framework to determine a set of four design strategies and related design principles to build Sage highlighted in Table 2.

This documentation provides an overview of principles of responsible AI that we used to guide the need to balance embracing new and rapid diffusion of a new technology in teaching and learning, with the need to ensure transparency and education related to its hazards. Institutional leaders, faculty, and other stakeholders can use or adapt these principles to help guide their responsible AI efforts.

The Tetrahedral Model of Classroom Learning

Educational technology scholars emphasize that the killer app feature inherent in an AI chatbot is tied to such tools' abilities to personalize or customize student learning experiences (Bii, 2013; Winkler and Soellner, 2018). We adopted this perspective by conceptualizing UT Sage as an AI tutorbot that could be trained by faculty through an instructional design agent programmed specifically to elicit an educator's pedagogical content knowledge (PCK; Shulman, 1986). PCK is a special blend of disciplinary expertise and depth of understanding around how students best learn content within a discipline. Faculty build PCK throughout their careers and develop an intuition for what makes learning a particular topic difficult and how to help students overcome those challenges. Because it is complex knowledge (Shing et al., 2015), PCK is often deeply internalized, but not externalized in one's teaching practice beyond typical artifacts, such as a syllabus. UT Sage was conceptualized to allow educators to capture intuitions like this and document them through custom training a tutorbot using their own PCK.

Principles of learning

How do students learn best? One answer to this question is that students learn best when educators design learning experiences that center on the learner and their needs relative to the content (Ambrose et al., 2010; Hattie, 2015; National Academies of Sciences, Engineering, and Medicine, 2018; Schell and Butler, 2018). Learner-centered approaches contrast with topic-centered or instructor-centered teaching, where delivering the content alone is the central point of focus. Learner-centered teaching is generally guided by PCK, where topic-centered teaching often bifurcates content and pedagogy. While learner-centered teaching has caught on in some sectors of higher education and empirical evidence supports its use (Shing et al., 2015), it remains that most faculty are trained to be disciplinary versus pedagogical experts, and as such, their teaching approaches replicate the topic-centered instruction they themselves received. Learning-science-trained instructional designers are aware of the benefits of learner-centered teaching and can help instructors transition their approaches. The problem we worked to address with UT Sage is supply versus need for instructional design at a R1 campus.

Morever, Chen et al. (2025) recently documented that, while generative AI provides support for teachers in building lesson plans, AI-generated content predominantly promotes teacher-centered approaches, "with limited opportunities for student choice, goal-setting, and meaningful dialogue" (p1). Ensuring generative AI's promise for teaching and learning requires leaders to intentionally guard against building systems or chatbots that replicate ineffective teaching. Chen et al. also demonstrated how appropriate prompt engineering can help mitigate inherent teacher-centered biases in generative AI.

Sage was designed from the ground up to drive student-centered tutoring with a generative AI chatbot. The Tetrahedral Model of Classroom Learning (TMCL) (Schell and Butler, 2018) depicted in Figure 5 is a student-centered model that highlights four key components that any educator must consider to facilitate effective learning in their classroom. We used these four components to define a set of additional design strategies and principles to help faculty train their tutorbots in Sage. It is worth noting that instructional design is an established field that cannot nor should be replaced by a tool like Sage. Teaching is an inherently human task, and what we offer through Sage only touches the surface of what can and should be accomplished through a strong instructional design relationship. We hope that by initiating ways to surface and interact with one's own PCK, we will help promote effective lesson plan design to those who do not practice or are not aware of learner-centered teaching and spark interest in developing deeper learner-centered teaching practices.

We designed the Sage's instructional design agent depicted in Figures 1–3 above to align directly with TMCL principles. For example, the scholarship of teaching and learning has established that prior knowledge strongly influences new learning (Ambrose et al., 2010; Hattie, 2015). This literature informed our decision to require instructors to document students' prior knowledge gaps during bot configuration. Similarly, Sage will coach a faculty member through the development of learning outcomes, which reflects longstanding research that demonstrates student achievement is correlated with clearly articulated goals and expectations. Finally, self-regulated learning theories (Ambrose et al., 2010; National Academies of Sciences, Engineering, and Medicine, 2018; Schell and Butler, 2018) bolstered our efforts to ensure the tutor posed questions to spark metacognition (the act of thinking about or assessing one's learning state).

Table 3 outlines each of the key learning science principles we used and how those principles were built into design requirements for Sage.

In summary, by carefully conversing with the instructional design agent within UT Sage (i.e., the builderbot), we designed and implemented a novel way for instructors to (1) begin engaging in learner-centered design following established principles; (2) customize their students' learning experiences with generative AI based on their own individual PCK in ways that are only possible through generative AI; and (3) surface, interact with, and incorporate their own PCK into customized, generative AI tutor bots for their students.

Methods

UT Sage pilot release life cycle and sampling

The primary purpose of this project was to develop software. As such, methodologically, we followed a standard, user-centered software lifecycle approach to developing, releasing, testing, and refining UT Sage with evaluation measures, data collection, and participant selection procedures that aligned with our production

TABLE 2 Design principles framework for responsible adoption of generative AI, illustrating the strategies and design principles used to build UT Sage to ensure responsible AI adoption.

Strategy	Principle	Description
Provide all responsible access to generative AI for teaching and learning	Equitable Access	To ensure equitable access to University resources to all learners, UT Sage was designed to be freely accessible to all faculty and students.
Offer generative AI tools that ensure information security resources are protected and accessible	Data Privacy and Security	Since UT Sage is designed to create and collect educational records, Data Security and Privacy were driving concerns. Moreover, students at The University of Texas at Austin maintain the intellectual property rights of materials they create or produce in their coursework. UT Sage was designed to align directly with the University's Information Resources and Security Resources and to provide data security, intellectual property and FERPA protections. In addition, our team is partnering with the University's Digital Accessibility Center to follow best practices and accessibility requirements.
Infuse learning science into the adoption of generative AI	Focus on prior knowledge and learning outcomes	To configure a tutor on any topic Sage, instructors must think about their students' characteristics, including the state of their prior knowledge acquisition on the topic. They must also document their learning outcomes or what they hope students will know, be able to do, or the attitudes they might develop as a result of using the tutor.
Practice transparency and support AI literacy	Balance	While using UT Sage, Students see an always-on display above the chat interface (see bottom of Figure 2) that reads: "AI can make mistakes. Read more about the limitations of Gen AI" which directs to our Big 6 limitations page (Office of Academic Technology, UT Austin, 2024): Data security and privacy, hallucinations, misalignment, bias, ethics, and cognitive offloading.

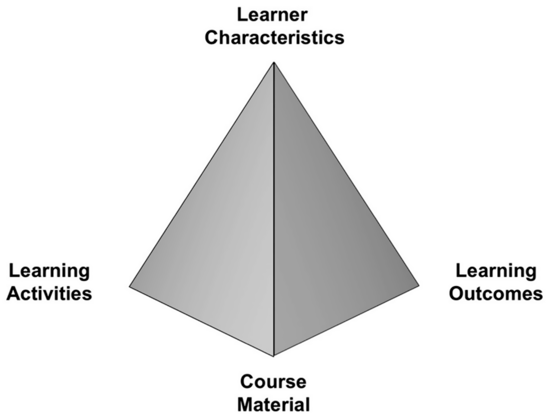

FIGURE 5
The tetrahedral model of classroom learning (adapted from Jenkins, 1979; Schell and Butler, 2018).

goals. We designed the project to align with the following phases: pre-alpha, alpha, closed-beta, open-beta, and general availability. For the purposes of this article, we employed autoethnographic methods by systematically analyzing and describing a teaching and learning innovation that all three authors were involved in (see the Acknowledgements section). Below we provide details on pilot participant sampling and limitations, data analysis, and each phase of the pilot implementation.

Pilot participant selection

For the pre-alpha through the closed-beta phases of the project, faculty participants were recruited using convenience sampling via University-wide announcements and programming events. During the open-beta phase, both convenience and snowball sampling – where faculty heard about UT Sage from other users, were employed. Student participants were recruited through convenience sampling and limited by their enrollment in courses taught by the faculty participating in the pilot. The first author participated in the Alpha testing with students to assess the alignment of the tutor with the original concept. The second and third authors participated pre-alpha through beta testing with the builder bot.

An important limitation of our alpha and beta testing was that we prioritized convenience sampling for the purposes of eliciting feedback on bugs, functionality, and general user experience. User-centered software development can prioritize the needs of immediate user preferences and may lead to solutions that are biased and do not generalize well across all users. The open-beta phase will address some of these risks by broadening participation beyond a convenience sample to the full instructor and student population at the University. This larger sample should enable more differentiated feedback that will better reflect a fuller range of user needs and contexts.

Pilot data collection and analysis

Using an issue tracking process, the Sage team collected quantitative and qualitative data documented from surveys, narrative feedback, and observational feedback in each phase of testing. Data was thematically coded as a bug or as a feature enhancement and translated into design requirements.

Pre-alpha testing proof of concept

We began developing a proof of concept for the vision of UT Sage as an instructional design agent and student-facing tutorbot in the Summer of 2024. During the pre-alpha phase, we wrote narrative scripts for how the instructional design agent should interact and function with the users, as well as created wireframes for the interface. As is standard practice, pre-alpha iteration was completed internally with key stakeholders and project team members only.

TABLE 3 Design principles framework for learning science-driven adoption of generative AI, illustrating the strategies and design principles used to build Sage to ensure established learning science drove the generative AI tutorbot experience.

Strategy	Principle	Description
Consider your learner characteristics and how they might influence their learning experiences	Learner Characteristics	There few influences that have more power to determine student learning than their specific learning characteristics, especially their prior knowledge and previous exposure to the topics (Ambrose et al., 2010). Learning is influenced when teachers based their teaching on "what students bring to the subject" (Hattie, 2015, p. 81). As such, one of the first requirements for building a bot within UT Sage is to document learners' characteristics relative to the course context and topic.
Clearly articulate learning outcomes	Learning Outcomes	Student learning outcomes are the things students should know, be able to do, and the attitudes they should hold after completing a learning experience (Allan, 1996; Wiggins and McTighe, 2005; Tyler, 1949; Schell and Butler, 2018). Large meta analyses focused on higher education indicate that when educators clearly articulate learning outcomes, student learning is heightened (Hattie, 2015). One reason for this finding is that when students can identify what success might look like they can more easily self-regulate their learning to achieve those outcomes. Moreover, with clearly articulate learning outcomes instructors can more easily evaluate their impact on learning (see Hattie). However, effective learning outcomes can be both elusive and difficult to develop, especially for higher education who have had limited or no pedagogical training. UT Sage provides an interface for instructors to develop effective learning outcomes to guide their tutor bots.
Develop learning activities that promote active versus passive learning	Active Learning	Active learning is variously defined in the literature; we define active learning as acquiring knowledge, skills or attitudes through intentionally self-directing one's learning activities and constructing rather than "receiving" content knowledge (Schell and Butler, 2018). UT Sage was conceptualized to support instructors training tutors to promote active learning heavy hitters such as metacognition, retrieval-enhanced-learning, and corrective as well as evaluative feedback. For example, instructors can configure their bots to nudge students to start off a session by quizzing themselves or analyzing a piece of text. In addition, there is a dedicated section in the bot-builder to encourage instructors to describe these activities but as of the publication date, a technical barrier has prevented implementation.
Optimize faculty time by leveraging course materials you have pre-built and found effective	Course Materials	Most instructors have spent extensive time developing and curating course artifacts to support student learning, including readings, documents, slides, images, videos, audio and more. Knowing when and how to deploy such artifacts is a key component of PCK. Our Beta version of Sage supports uploading of text-based documents that the technology then incorporates into training tutorbots. If additional releases of Sage are deployed, we expect additional media types to be included in future versions.

Alpha testing

Alpha testing was staged in early Fall of 2024 and included testing of the proof of concept and internal functioning with minimal features and known errors. Issue tracking was implemented at this stage. The team was tasked with creating a user interface and engineering a prompt that integrated the learning principles identified in the initial design process with the LLM and RAG pipeline.

Among the fifteen faculty enrolled in the closed-beta testing phase, which focused on the creation and tuning of tutors, five colleges (College of Natural Sciences, College of Education, McCombs School of Business, College of Fine Arts, and the College of Liberal Arts) and 11 fields and disciplines (chemistry, statistics, computer architecture, information studies, information management, business management, entrepreneurship, marketing, design, higher education leadership, classics) were represented. A total of six of the tutors proposed were created and tested by instructors and their colleagues as part of the phase 1 alpha. Of these, two were shared with students for testing. One tutor was provided to a group of fifteen graduate students during a face-to-face class. The other was provided as a resource to a class of sixty undergraduate students for use during preparations for the course final exam.

Once the student-facing tutorbot interface (Figure 4) was functional, faculty worked with a human instructional designer specializing in AI (this paper's second author) to provide specifications for their tutors in a design document similar to what one might use as part of an instructional design consultation and following the TMCL in Figure 5 above. Sage used faculty responses to the prompts in Table 1 to define and create six tutors for closed-beta testing. These tutors addressed varied pedagogical needs in diverse fields of study. Examples of tutors conceptualized and created by instructors and the Sage team include the following cases.

- Case 1: A tutor focused on aiding undergraduate business students in a Statistics course in understanding concepts related to logistic regression. Resources were provided to train the tutor to advise students on how to determine when to use logistic versus linear regression and their underlying mathematical distinctions.
- Case 2: A tutor designed to coach senior-level chemistry majors in the application of analytical chemistry techniques. The tutorbot was designed as a study aid and bridging activity for students who are learning concepts in their lecture-based instruction and performing them in the lab.
- Case 3: A tutor whose primary purpose is to coach graduate students in design and education in the creation of learning outcomes. Depending on their background, these students might have congruent gaps in knowledge in design and learning theory, respectively. This tutor can evaluate outcomes provided by the student and advise them on improvements using the resource Bloom's Taxonomy.

Alpha testing results

The purpose of the Alpha user testing was to get initial feedback on the usability and perceptions of the chatbot. Data collection methods included two surveys (included in the Supplemental materials) and an option for faculty and students to give open, narrative feedback via e-mail, and one, autoethnographic live observation conducted by the first author.

Faculty feedback

The faculty reported an overall positive experience using their tutors and unanimously agreed that it could aid students in meeting their stated learning outcomes, however, we did not test this perception. They also noted that the information provided was accurate and the answers were clear. They also provided suggestions for interface features (such as removing in-text citations and automatically naming chat sessions) and changes to the way the tutor interacts with students. Specifically, they requested that the length of responses be reduced; that the tutors determine when it should use Socractic questioning to engage students with topic concepts; and to avoid being apologetic when it could not retrieve additional information for the user.

Student feedback

Of the seventy five users that were given access to beta tutors, 14 provided feedback in live observations and surveys. Student reactions to the tutors were mixed with many experiencing authentication, display, and other technical errors. Most acknowledged that the tutorbot helped them learn the topic at hand and met or exceeded their expectations for such a tool. Some also noted lengthy responses and numerous questions that the faculty had also pointed out to the team. One user provided in-depth feedback about the lack of customization in tutorbot responses for students who have reading disorders and other needs related to processing text, suggesting that they be able to have text read to them by the tool or adjust response output to their particular needs.

Many of the suggestions made during phase 1 alpha testing were implemented for the phase 2 beta and integrated into the interface shown in Figures 1–3.

Closed beta

Phase 2 of testing began in January of 2025 and was structured as a closed beta with a pool of invited testers of more than 40. In this phase, the instructor-facing builder tools were partially available with instructors being granted the ability to configure tutors through a form and to upload text resources to be ingested into the tutor's knowledge base. Additionally, tutors were shareable with anyone within the University or assigned to existing course rosters, so that student testing could be expanded. As of this writing, faculty can train tutors using the interface illustrated in Figures 1–3 instead of working directly with the designer.

Open beta

The next phase of testing is an open-beta where any staff or faculty member with an active University ID can designed a tutor and share it with their students. Key milestones for this phase include the addition of the following features.

- Conversational configuration where faculty can create new tutors by having a two-way conversation with the agent versus configuring the form in Table 1 and Figure 2. In addition to enabling an organic design experience, the agent will make suggestions about how to effectively tune and scope the tutor based on the learning characteristics and learning outcomes that the instructor has identified;
- Summary of student insights about common student questions and misconceptions about a topic. Sage will produce output for instructors to use for just-in-time teaching based on analysis of common student questions, misconceptions or other input and output.
- Integration of more input and output data processing tools that allow for Sage to ingest and properly respond with images, LaTeX, formatted code, and audio.
- Outcomes research planning to organize the assessment of the Sage platform across disciplines and implementations. Institutional Review Board processed studies will examine questions related to the effect of generative tutors on student learning outcomes, how to effectively train, test, and introduce tutors into course design, and student attitudes toward instructor-trained course topic tutors. Methodologies will be chosen to best fit each question, course, and field of study.

Along with these new features, we will continue to expand the scope of our testing, making use of the influx of data that new users will provide.

Discussion and implications

Our experience testing UT Sage has supported our motivations for developing a tutor-based chatbot, while also providing us with important feedback about how to improve platforms of this type in the future. Our aim was to provide a learning technology platform that leads faculty through the process of identifying the core elements of the tetrahedral model of classroom learning (i.e., learner characteristics, learning outcomes, learning activities, and course materials) using a conversational interface that would be comfortable for faculty to engage with ease. In this way, a simple instructional design task can be automated and we can mitigate the teacher-centered biases that may be inherent in current generative AI platforms (see Chen et al., 2025).

With the development of the builderbot, we were able to validate that a learner-centered process can be implemented in a way that supports student engagement across a variety of topic areas and levels of student expertise. Once implemented, the platform is relatively easy for faculty to use, so that they can quickly answer the instructional design questions and construct a bot for their course.

In addition to embedding principles of learner-centered design in the tutorbots, UT Sage has the benefit that it is always available to students, thereby increasing the amount of time that a proxy for the instructor can be accessed. Students frequently get stuck when reading complex material or working on difficult assignments at times when instructors and teaching assistants are not available. The tutorbot enables students to continue working on potentially frustrating assignments at a time convenient for them rather than just when human instructors are available.

That said, there are challenges that we have encountered as well. A human instructor can often sense levels of student frustration and can calibrate the degree to which they can lead students through a Socratic dialog when the student is asking for the answer to a question they are struggling with. The tutorbot is not sensitive to these aspects of student motivation, and so it may provide answers that are too long and may engage students in dialog longer than the student is comfortable with.

Planned enhancements to Sage include summaries of common themes and misconceptions that instructors can use to enhance direct instructional efforts. When instructors have insight into what tutors are helping students with, they can further refine learning outcomes for class sessions. In a similar fashion, information about what kinds of topics and learning activities are being selected for tutors by instructors can give instructional support staff in departments and colleges more insight into learning challenges.

In this way, we hope that UT Sage ultimately increases engagement between faculty, good instructional design, and instructional designers on campus. At present, many faculty do not have a deep understanding of the benefits of working with an instructional designer. By highlighting the instructional design capacities baked into the design of the builderbot, we give faculty a chance to get a first experience with instructional design and effective pedagogy. We hope that positive experiences with UT Sage increases faculty interest and willingness to work with generative AI and instructional designers to further improve their courses using evidence-based practices. These efforts may lead to additional ideas for builderbots to solve frequently encountered education problems in our courses.

While we did not empirically evaluate the relationship between UT Sage and the achievement of learning outcomes, we believe it is the most important direction for future research and practice in line with recent scholarship on the topic (Lo et al., 2025; Yilmaz and Yilmaz, 2023; Zhu et al., 2025). Research questions for future study of Sage include but are not limited to: How does the use of the learner-centered UT Sage tutor relate to student performance on assessments? What is the relationship between student self-efficacy on specific topics and use of UT Sage tutors tailored to those topics? How does performance on assessments or self-efficacy differ when we compare UT Sage with other generative AI tools that may have teacher-centered biases? In addition, we expect to explore a research agenda related to the adoption of generative AI by designing studies that investigate the relationship between the use of the UT Sage tutor and faculty self-efficacy with using generative AI and/or science of learning principles.

Finally, this article provides two frameworks in Tables 2, 3 to guide structured approaches to responsible adoption of generative AI in higher education. Specifically, higher education leaders can apply the design strategies and principles offered in this case study to integrate generative AI tools into teaching and learning in ways that are secure, pedagogically effective, responsible, transparent, accessible, and support AI literacy.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and the institutional requirements.

Author contributions

JS: Conceptualization, Funding acquisition, Investigation, Project administration, Supervision, Writing – original draft, Writing – review & editing. KF: Project administration, Resources, Writing – original draft, Writing – review & editing. AM: Funding acquisition, Supervision, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2025.1604934/full#supplementary-material

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Student engagement with artificial intelligence tools in academia: a survey of Jordanian universities

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The rapid advancement of artificial intelligence (AI) has led to its increasing integration into academic environments, raising critical questions about its educational implications. This study investigates the use of AI tools among university students in Jordan, focusing on platforms such as ChatGPT, Google Bard, Microsoft Bing, and Meta AI. A convergent-parallel mixed-methods design was employed, with quantitative (closed-ended) and qualitative (open-ended) data collected concurrently through an online survey distributed over two months. A total of 337 valid responses were obtained from students across 27 universities. The survey explored demographic characteristics, chatbot awareness and use, perceived benefits and challenges, ethical concerns, and future intentions. Results indicate that ChatGPT is the most recognized (94.3%) and widely used (90.4%) tool, while Meta AI is the least utilized (7.8%). Approximately 89% of students reported using AI tools for academic tasks, and 86.6% perceived them as educationally beneficial. However, only 39.7% believed these tools significantly improved their understanding, while 57.6% reported a positive impact on academic performance. These findings reveal a growing trend of AI integration into student study practices in Jordan, highlighting both its practical advantages and the need for further inquiry into its pedagogical value and ethical use.

KEYWORDS

artificial intelligence in education (AIeD), learning analytics, large language models (LLMs), chatbots, higher education

1 Introduction

1.1 Motivation

Artificial Intelligence (AI) has become an integral part of modern society, influencing various industries and transforming traditional practices. In recent years, AI technologies have made significant strides in the field of education, reshaping the way institutions approach teaching, learning, and research. Scholars studied how AI technologies improve teaching and research based on reinforcing and balancing feedback loops (Katsamakas et al., 2024; Tomaskinova et al., 2024). The findings underscore the significant role of AI in higher education institutions HEIs. AI-powered tools such as intelligent tutoring systems, learning analytics, and AI-driven assessments have provided new opportunities to personalize learning experiences, automate administrative tasks, and improve educational outcomes (Popenici and Kerr, 2017; Crompton and Burke, 2023; Zawacki-Richter et al., 2019). These innovations have the potential to streamline operations and improve the quality of education, making AI a critical component of modern educational practices.

One of the most notable developments in the application of AI to education is the emergence of conversational AI tools like ChatGPT. Such tools can significantly alter the way students interact with educational content and engage in academic activities. ChatGPT, in particular, has been praised for its versatility in helping students with tasks such as writing essays, providing instant feedback, and supporting research efforts (Ariyaratne et al., 2023; Pallivathukal et al., 2024; Salvagno et al., 2023). However, while the advantages of these tools are evident, their widespread adoption has sparked a range of ethical concerns, especially regarding data privacy, academic integrity, and the role of AI in promoting or diminishing critical thinking skills (Holmes et al., 2022; Mahrishi et al., 2024; Irfan et al., 2023a).

In the context of higher education, the introduction of AI offers both opportunities and challenges. AI enables institutions to track student progress in real-time and personalize learning on a large scale. For example, convolutional neural networks (CNNs) and classification models–such as support vector machines (SVM), Random Forest, and KNN–have been applied to predict student success (Shoaib et al., 2024). In parallel, artificial intelligence-enabled intelligent assistants (AIIAs) support students through adaptive instructional pathways that respond to individual needs (Sajja et al., 2024). On the other hand, concerns about algorithmic bias, unequal access to technology, and potential misuse of AI by students pose significant risks to academic integrity and equity in education (Tsai et al., 2020; El Alfy et al., 2019; Crawford et al., 2023). These developments also prompt deeper inquiry into how AI shapes students' critical engagement with academic content and learning behaviors (Mapletoft et al., 2024; Mujtaba et al., 2024).

While there is a growing body of global research on the role of AI in education, gaps remain in understanding how these technologies are being adopted in specific regional contexts. In countries like Jordan, where educational institutions face challenges related to infrastructure, digital literacy, and equitable access to technology, the integration of AI tools brings both new opportunities and obstacles (Al-Qerem et al., 2023; Mosleh et al., 2023). Addressing these issues is essential for ensuring that the benefits of AI are equitably distributed and that potential drawbacks are mitigated.

1.2 Study aim

Building on the above motivation, the present work investigates the uptake and educational impact of AI-powered chatbots–principally ChatGPT–in Jordanian universities. Employing a *convergent-parallel mixed-methods design* (Creswell and Plano Clark, 2018), quantitative (closed-ended) and qualitative (open-ended) data were gathered simultaneously via one survey instrument and integrated during interpretation. The study is guided by three research questions:

1. **RQ1:** To what extent, and for which academic tasks, do Jordanian university students use generative-AI chatbots?
2. **RQ2:** What benefits, challenges, and ethical concerns do students perceive when engaging with these tools?
3. **RQ3:** How do usage patterns and perceptions vary across demographic variables such as gender, academic level, and college type?

Clarifying these aims helps situate the subsequent methodology and ensures that the mixed-methods design is explicitly linked to concrete, answerable research questions.

2 Background

Artificial Intelligence (AI) has grown significantly, evolving from theoretical frameworks to practical applications across multiple fields. Since its inception, AI has permeated industries like healthcare, finance, software development, and, most recently, education, transforming traditional methodologies (Beganovic et al., 2023; Rahmaniar, 2024; Tabone and De Winter, 2023). In education, AI tools like ChatGPT, learning analytics, and automated assessments have been applied to transform instructional delivery and assessment models. For example, AI is used to provide instant feedback, adapt content in real time to individual learner progress, automate formative assessment, and generate personalized learning materials that cater to students' specific strengths and weaknesses (Yadav, 2025). AI also offers numerous opportunities to transform traditional teaching and learning methodologies. For instance, in translation pedagogy, AI technologies have been used to reduce assessment time and automate grading systems (Khasawneh and Shawaqfeh, 2024). Another example is the integration of AI in natural language processing (NLP) education, enhancing both instruction and learner engagement (Mishra, 2024).

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2.1 AI in higher education

Recent research underscores the growing significance of chatbots in education, noting their scalability and potential to provide personalized support. Key findings indicate that chatbots play important roles in mentoring students, offering tailored feedback, and increasing student engagement through adaptive interactions. Current challenges identified include ensuring chatbot evaluations align with educational goals, effectively utilizing chatbots for mentoring roles, and enhancing their adaptability to individual learner needs (Wollny et al., 2021). AI is increasingly transforming higher education by enhancing instruction, administration, and research productivity. Studies indicate that its integration improves personalized and adaptive learning experiences, as well as overall educational outcomes (Ke Zhang, 2021; Jiahong Su, 2023). Generative AI tools such as ChatGPT have attracted significant attention, particularly in engineering education, with benefits noted for both students and instructors (Qadir, 2023; Eman A. Alasadi, 2023).

AI-powered systems such as intelligent tutoring platforms and adaptive learning environments provide dynamic, real-time feedback and personalized instruction by analyzing student performance data (Crompton and Burke, 2023; Kamalov et al., 2023; Wang et al., 2023; Celik, 2023). These tools support mastery of complex topics, early identification of at-risk students, and tailored intervention strategies (Chaudhry et al., 2023; Mackney and Shields, 2019; Embarak and Hawarna, 2024; Sunandar et al., 2024).

In addition to instruction, AI is increasingly used in grading, administrative functions, and student support systems. Learning analytics enables data-driven decision-making by offering insights into student engagement and institutional performance (Ojha et al., 2023; El Alfy et al., 2019; Jones et al., 2020; Shaik et al., 2022; Schönberger, 2023).

Global trends reflect growing scholarly interest in AI's role in higher education. Most publications are concentrated in the United States and China, with a marked increase in output between 2021 and 2022 (Crompton and Burke, 2023). A survey of 311 educators found that using AI in classrooms positively influenced both their perceptions of ease of use and their attitudes toward AI-enhanced instruction (Youmei Wang, 2021).

Beyond teaching and learning, AI tools also support university administration and student care functions (Hannan and Liu, 2023). As AI continues to evolve, its integration into academic processes is expected to expand further, raising important questions around pedagogy, equity, and data ethics (Selwyn, 2022).

2.2 AI in scientific research and writing

In addition to transforming education, AI has significant applications in scientific research. AI tools, such as ChatGPT, assist researchers in drafting, editing, and summarizing academic articles, thus streamlining the scientific writing process (Castillo-Martínez et al., 2024). This automation can reduce the time and effort required to produce research content, potentially enhancing productivity. AI-generated content has been found useful for tasks such as literature reviews, data synthesis, and report generation (Uhlig et al., 2023). However, these benefits come with notable limitations. Concerns around academic integrity, including the risk of plagiarism and overreliance on AI, remain significant (Pallivathukal et al., 2024; Mosleh et al., 2023). Moreover, AI-generated texts may lack the depth, critical analysis, and domain-specific insight expected in scholarly work. As such, while AI can be a supportive tool, its outputs should be carefully reviewed and supplemented by human expertise to maintain academic standards.

In healthcare education, AI-driven tools are used to support decision-making processes, diagnostic simulations, and personalized learning experiences for students in medical and pharmacy disciplines (Al-Qerem et al., 2023; Ajlouni et al., 2023). While these tools show promise in enhancing educational outcomes, they also bring ethical dilemmas related to fairness, data security, and transparency (Dergaa et al., 2023; Crawford et al., 2023).

2.3 Ethical concerns and challenges in AI integration

AI's growing presence in education and research brings several ethical considerations, particularly related to data privacy, algorithmic bias, and academic integrity (Kooli, 2023). The rapid integration of AI technologies into academic environments demands robust frameworks that address these concerns and ensure that AI systems are used responsibly. For instance, the "privacy paradox" in learning analytics, where students are concerned about their data privacy yet benefit from AI systems that rely on personal data, poses an ethical dilemma.

Researchers argue that institutions must develop transparent policies and guidelines to manage the ethical use of AI tools in academia. This includes creating frameworks to ensure that AI-generated content does not hinder critical thinking and creativity (Arman, 2023; Elbanna and Armstrong, 2024). Moreover, the potential bias in AI algorithms and the risk of over-reliance on AI technologies require careful consideration by educators and policymakers (Irfan et al., 2023b; Zeb et al., 2024).

2.4 Challenges and future directions for AI in education

Despite the promising benefits of AI in education, several challenges remain. The technological infrastructure required to support AI-based tools is often lacking in many institutions, particularly in underserved regions. This digital divide limits the potential of AI to deliver equitable learning outcomes across different educational environments (Mahrishi et al., 2024; Dare, 2024). Additionally, educators need to be trained in AI literacy to leverage the benefits of these tools fully (Mapletoft et al., 2024; Mujtaba et al., 2024).

Future research should focus on developing more inclusive AI tools that account for diverse student populations and creating ethical frameworks that guide the responsible use of AI in education and research. As AI continues to evolve, its role in enhancing collaboration, critical thinking, and interactive learning experiences will become increasingly important.

Educators and scholars are calling for a discussion about the future of AI in higher education (Schön, 2023; K.F.Chiu, 2024). The rapid change in the learning attitude of modern students, together with the implementation of AI in higher education, is prompting lecturers and professors to adapt their pedagogical approaches (Shrivastava et al., 2024). Modern students from Generation Z often apply AI tools in higher education and prefer a personalized approach to learning (Bennett and Abusalem, 2024).

2.5 Identifying gaps in the literature

While existing research has addressed AI applications in healthcare education in Jordan, (Al-Qerem et al., 2023; Mosleh et al., 2023) there remains a need to understand how AI tools–particularly generative chatbots–are used across other academic domains. A recent systematic review identified 69 studies on ChatGPT in education, including work in general higher education, engineering, social sciences, and health sciences. However, most of these studies originate from North America, Europe, or Asia, and none examine usage in Jordan or the Arab region more broadly (Ansari et al., 2024).

This study seeks to address that gap by providing one of the first empirical, survey-based investigations into the use of AI-powered chatbots by university students in Jordan. The Jordanian context introduces distinct variables–such as a strong emphasis on academic integrity, varying levels of digital infrastructure, and differing cultural attitudes toward AI-generated content–that may shape usage patterns in ways not captured by existing literature. For example, concerns about plagiarism and mistrust in chatbot-generated information may be more pronounced due to institutional codes of conduct and students' limited exposure to AI-integrated pedagogies.

Although our findings confirm global trends–such as ChatGPT being the most recognized tool and ethical concerns being widely shared–they also suggest that sociocultural and institutional contexts may mediate student experiences. This research thus contributes new insights by grounding AI adoption in a specific underrepresented context and demonstrating how global technological trends intersect with local academic ecosystems.

3 Methodology

This section outlines the research methodology used to investigate the integration and impact of AI-powered chatbots on university students in Jordan. The study uses a mixed methods approach, combining quantitative and qualitative data collection to gain a comprehensive understanding of students' perceptions, experiences, and attitudes toward chatbot technologies, such as ChatGPT, Microsoft Bing AI, Google Bard, and Meta AI, in their academic practices. Using a cross-sectional survey design, this research aims to capture diverse insights from students from various academic disciplines at Jordanian universities. The methodology ensures robust data collection and analysis, allowing the identification of trends, challenges, and opportunities associated with AI integration in education.

3.1 Survey design

This study used a cross-sectional survey to assess the impact of AI-powered chatbots on university students in Jordan. The survey, titled "Survey on the Impact of Using Chatbots in the Educational Process in Jordan", was designed to gather data on students' experiences, perceptions, and attitudes toward chatbot technologies, such as ChatGPT, Microsoft Bing AI, Google Bard, and Meta AI, in their academic practices. The survey comprised both closed and open-ended questions, divided into sections covering demographic information, knowledge and usage of chatbots, perceived benefits, ethical considerations, and future intentions to use AI tools in both academic and non-academic contexts.

This study employed a convergent-parallel mixed-methods design, in which quantitative (closed-ended) and qualitative (open-ended) data were collected concurrently using the same survey instrument. Each strand was analyzed independently and later integrated during interpretation to enable triangulation of findings (Creswell and Plano Clark, 2018).

3.2 Target population and sampling

The target population consisted of undergraduate and graduate students enrolled in all faculties (scientific, humanities, and health) at Jordanian universities, including public and private institutions. A random sampling method was used to ensure a broad representation of students from various academic disciplines. The survey was distributed electronically using social media platforms (e.g., university student groups) and group emails sent to student bodies. This approach facilitated access to a diverse sample of students representing a wide range of educational backgrounds and experiences with AI technologies.

3.3 Survey instrument

The survey instrument was structured to capture both quantitative and qualitative data and included the following sections:

- **Demographic information**: participants provided details on their gender, university affiliation, degree level, faculty (scientific, humanities, or health), and year of study.
- **Knowledge and usage of chatbots**: this section assessed participants' awareness of various AI-powered chatbots, including ChatGPT, and their extent of use for academic purposes. Specific tasks such as finishing homework, coding, writing reports and email drafting were also addressed.
- **Perceptions and benefits**: participants rated the perceived benefits of using chatbots in their education, including saving time, improving comprehension, and accessing diverse resources. They also rated how these tools affected student-teacher interaction, academic performance, and overall learning.

- **Ethical and practical considerations**: questions focused on privacy concerns, trust in AI-generated content, and the extent to which students cross-checked the information produced by chatbots. Participants were also asked to rate their level of reliance on these tools for academic tasks.
- **Future use and challenges**: this section captured participants' intentions regarding the continued use of chatbots in both academic and non-academic settings, as well as an open-ended question about the challenges they faced while using these tools.

3.4 Data collection

Data collection was carried out over a two-month period, during which the survey was distributed via Google Forms to students at Jordanian universities. Participants were recruited through social media platforms (e.g., university Facebook and WhatsApp groups) and group email distributions. The random sampling approach ensured diverse participation, with students from different faculties and academic levels represented in the dataset. To encourage a higher response rate, reminders were sent periodically during the data collection window.

3.5 Data analysis

The data collected were analyzed using both quantitative and qualitative methods to fully understand the students' perceptions and experiences.

3.5.1 Quantitative analysis

Quantitative data from closed-ended questions were analyzed using descriptive statistics, including frequencies, percentages, and means. Likert scale responses, ranging from "strongly disagree" to "strongly agree", were used to assess student attitudes and perceptions toward chatbot technologies. These data were further analyzed by demographic variables such as faculty type (scientific, humanities, or health), degree level (undergraduate or graduate) and year of study to examine variations in chatbot usage and perceptions between student groups.

3.5.2 Qualitative analysis

The open-ended responses were subjected to thematic analysis to identify common challenges, benefits, and concerns raised by participants regarding the use of chatbots. The responses were coded into themes such as perceived benefits, ethical concerns (e.g., privacy), and challenges faced while using AI technologies. This qualitative analysis provided deeper insights into students' nuanced experiences and the barriers they encountered when integrating chatbot tools into their academic routines.

3.6 Ethical considerations

The survey followed strict ethical guidelines to protect the rights and privacy of the participants. Informed consent was obtained from all participants, who were informed of the purpose of the study, how their data would be used, and the voluntary nature of their participation. No personally identifiable information was collected, and all responses were anonymized to ensure confidentiality. Data privacy measures were adhered to, ensuring that participant data was securely stored and accessed only by the research team for analysis purposes.

3.7 Limitations

Although the survey used random sampling and reached a broad audience through social media and university channels, reliance on online distribution may have excluded students who are less active on digital platforms or lack consistent internet access. Furthermore, self-reported data may be subject to biases, such as social desirability bias, where participants may provide responses that they perceive as favorable.

4 Results

The survey revealed a nearly even gender distribution among participants, with 49% identifying as female and 51% as male. A substantial proportion of respondents, 25.1%, were affiliated with the University of Jordan, the country's oldest public institution, while 16.1% came from Al-Hussein Technical University, Jordan's newest private university. Overall, the participants represented 27 out of the 30 registered universities in the country.

The overwhelming majority of participants, an impressive 94.3%, reported familiarity with ChatGPT, making it by far the most recognized AI tool in the survey. Google Bard (Gemini) followed with 36.7%, while 34.9% of respondents were aware of Microsoft's Bing AI chatbot. Meta AI was also known to 33.1% of participants. A handful of other AI tools, including Microsoft CoPilot, Quillbot, and Plusfinity AI, were recognized by a smaller percentage of the respondents, highlighting the dominance of a few key platforms in the AI landscape. A graph representing these results is shown in Figure 1. Based on these results, it is clear that ChatGPT can be considered the most widely used tool by students due to its ability to understand and generate human-like text, which is consistent with other findings in the literature (Beganovic et al., 2023; Rahmaniar, 2024).

The scientific faculties demonstrate strong recognition of multiple AI tools beyond just ChatGPT. In addition to the near-universal familiarity with ChatGPT (96.6%), a significant proportion of participants are aware of other AI tools such as Google Bard (40.2%), Meta AI (31.4%), and Microsoft Bing AI Chatbot (39.8%). This suggests that students in scientific disciplines are exposed to a wider range of AI technologies, likely due to the technical nature of their studies, which often integrate cutting-edge tools. In contrast, humanities and health faculties exhibit a narrower scope of familiarity with AI tools, with their recognition primarily centered around ChatGPT.

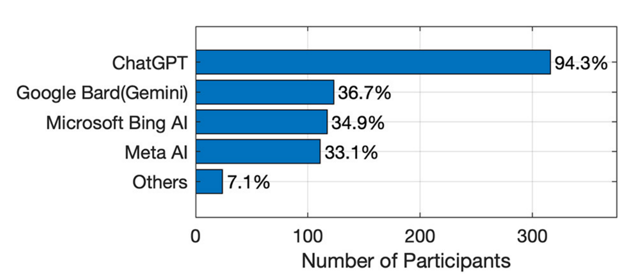

FIGURE 1
Participants' familiarity with various AI tools.

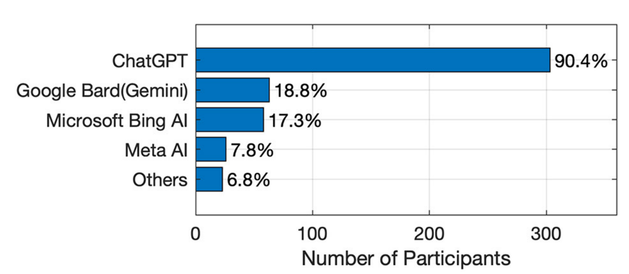

FIGURE 2
The distribution of AI tools used by students for task completion.

The usage of AI tools reveals that the majority of participants, 90.4%, used on ChatGPT to complete their tasks, making it the most dominant tool in academic settings. This strong preference highlights ChatGPT's versatility and effectiveness in generating human-like text to meet student needs. In contrast, 18.8% used Google Bard (Gemini), 17.3% utilized Microsoft's Bing AI chatbot, and 7.8% employed Meta AI. The limited usage of these alternatives suggests that students find ChatGPT more suitable for their tasks. Other AI tools were used by only a small fraction of participants, indicating that the AI landscape in education remains largely concentrated around a few key platforms, as shown in Figure 2.

A comparison of Figures 1, 2 reveals that although many participants are aware of other prominent AI tools, such as Microsoft Bing AI chatbot, Google Bard (Gemini), and Meta AI, they do not rely on them as heavily as they do on ChatGPT for completing tasks. Several factors may explain this preference: ChatGPT's earlier introduction, which has led to greater familiarity among students; its superior performance and capabilities (Al Mashagbeh et al., 2024); and its more user-friendly interface, which makes it more accessible compared to other tools (Tabone and De Winter, 2023).

When asked whether they had used any AI tools during their studies to solve homework, assignments, or other tasks, 89% of participants responded positively, while only 11% indicated they had not. This high level of usage reflects a major shift in how students approach their academic responsibilities, leveraging AI tools to enhance productivity and optimize learning outcomes. The widespread adoption of these tools signals a transformation in study habits as technology becomes increasingly embedded in the educational experience.

The increasing use of AI tools presents both opportunities and challenges for educators. On the one hand, these technologies can create more personalized, adaptive, and engaging learning experiences that cater to diverse student needs. By integrating AI, educators can make learning more dynamic and accessible. However, there are concerns that excessive reliance on AI could hinder students' ability to think critically and solve problems independently. If students rely on these tools to complete tasks without fully understanding underlying concepts, it may result in superficial learning. Thus, educators face the challenge of incorporating AI in a way that enhances learning while ensuring students continue to develop essential cognitive and problem-solving skills.

The results highlight notable trends in how students integrate AI tools into various tasks. With 73.9% of students using these tools for homework and assignments, it can be inferred that AI tools may support students in improving efficiency and understanding, based on their self-reported usage patterns. Studies such as Bin-Nashwan et al. (2023) have highlighted similar motivations driving the use of AI tools like ChatGPT, including time-saving and academic self-efficacy. The fact that 59.6% use AI for writing projects shows its growing role in complex tasks like essays and reports, suggesting a significant change in traditional academic processes.

The 45% of students utilizing AI for coding highlights its growing role in technical education, where real-time assistance can enhance skill-based learning, as supported by Rohm et al. (2021). However, the 31% of students using AI for online quizzes raises concerns about academic integrity, underscoring the need for careful monitoring of assessments. Additionally, 31.6% of students using AI for writing emails demonstrates the broader application of these tools beyond academic tasks, signaling their expanding influence in everyday communication. The remaining participants, accounting for less than 5%, used these tools for a variety of other tasks including paraphrasing content, translating text, simplifying complex concepts, providing explanations, and verifying solutions. This illustrates the versatility of AI tools, as students are leveraging them not only for traditional academic tasks but also for support in more specialized areas of their studies.

When students were asked about the most useful features of AI tools for educational purposes, responses varied. The majority, 86.6%, indicated that these tools help save time and effort when searching for information. This finding suggests that many students may prioritize efficiency and convenience, potentially focusing more on achieving high grades with minimal time investment rather than deeply engaging in the learning process itself. While AI tools offer significant benefits in streamlining academic tasks, this trend raises questions about whether students are fully exploring the educational value these technologies can offer.

Although AI tools provide access to a vast range of information, there is a risk that the information may be inaccurate or misleading. Additionally, the convenience of these tools may discourage students from using more traditional learning methods, such as studying textbooks or conducting independent research. These methods are essential for developing a stronger knowledge base and fostering a deeper understanding of core concepts. As students increasingly rely on AI, there is a concern that the depth of their learning may be compromised in favor of speed and convenience.

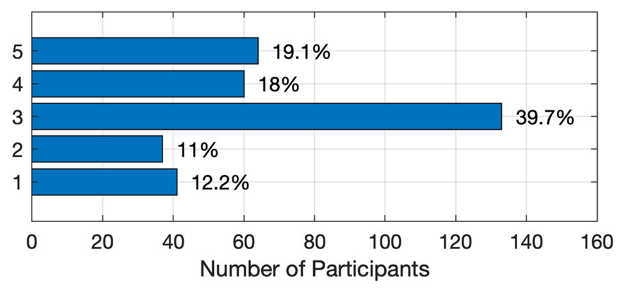

FIGURE 3
Students' perceptions of the extent to which AI tools have improved their understanding of academic concepts.

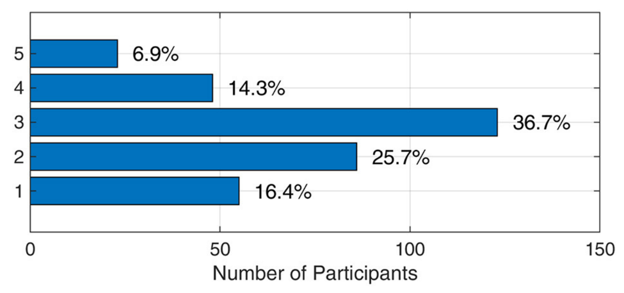

FIGURE 5
Distribution of students' reliance on AI tools, indicating varying levels of dependence from low to high.

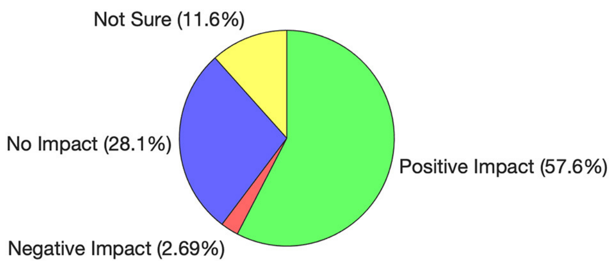

FIGURE 4
Impact of using AI tools on students' academic performance.

Students were asked, "To what extent do you believe that using AI tools has improved your understanding?" The response scale ranged from 1, representing very low improvement, to 5, representing very high improvement. The results, presented in Figure 3, show that only 19.1% of students felt these AI tools significantly enhanced their understanding of concepts. This suggests that while AI tools may offer convenience and efficiency, their impact on deep learning and conceptual comprehension may be more limited than anticipated.

The encouraging news is that when participants were asked whether the use of AI tools had impacted their academic performance, 57.6% responded positively, as shown in Figure 4. Only 2.7% believed these tools had a negative effect, while 28.1% indicated that AI had no impact on their performance. The remaining participants were unsure. While these results are promising, further investigation is needed to determine whether students perceive this positive impact due to an actual improvement in understanding or because AI tools enable them to complete homework and assignments more efficiently, with minimal time investment and potentially without deep comprehension.

Another positive sign emerged when students were asked whether they verified the answers obtained from AI tools. A majority, 78.2%, reported that they checked the accuracy of the answers, a practice essential for meaningful learning. However, 21.8% accepted the AI-provided answers without verification, which raises concerns about potential over-reliance on these tools. This minority may risk diminishing their analytical skills and deep understanding. To mitigate this, educators should encourage cross-verification of AI-generated information and promote a more reflective use of these tools, ensuring that they enhance learning rather than hinder students' educational development.

When asked whether they plan to continue using AI tools in their future education, 86.3% of participants indicated they would, while 13.7% stated they would not. This strong inclination toward continued use suggests that students derive significant benefits from these tools, whether through enhanced productivity, comprehension, or academic performance. Understanding the reasons behind the minority's reluctance to use these tools could provide valuable insights for developers, helping to address any limitations or challenges that may be inhibiting wider adoption. Additionally, as AI becomes more integrated into education, laws and regulations must evolve accordingly, ensuring that these tools are used ethically and effectively in shaping the future of learning.

Figure 5 illustrates the distribution of students' responses regarding their reliance on AI tools, with "1" representing low reliance and "5" representing high reliance. As shown, 42.1% of students reported low reliance on these tools, while 21.2% fell into the high-reliance category. The remaining 36.7% selected "3," indicating moderate reliance. These results suggest that while a considerable number of students find AI tools somewhat helpful, they do not view them as essential for their academic success.

Figure 6 shows the distribution of students' confidence in the accuracy of answers provided by AI tools, where "1" represents low confidence and "5" represents high confidence. The survey results reveal a range of opinions: 26% of students reported low confidence, indicating caution or skepticism, while 29.2% expressed high confidence, suggesting trust in AI-generated results without further validation. The majority, 44.8%, selected "3", reflecting a moderate level of confidence. These findings suggest that although many students find AI tools useful, they often feel the need to verify the information provided. The distribution highlights both the strengths and perceived limitations of AI tools in delivering accurate information.

The students were also asked whether they believed that the answers obtained from the AI tools could be better than their own. While 23.3% of students felt that the AI-generated answers could surpass their own, only 16.7% disagreed, expressing confidence in their abilities. Interestingly, 60% of the students were uncertain, indicating uncertainty about the reliability or effectiveness of these tools. This hesitation may arise from a lack of familiarity or

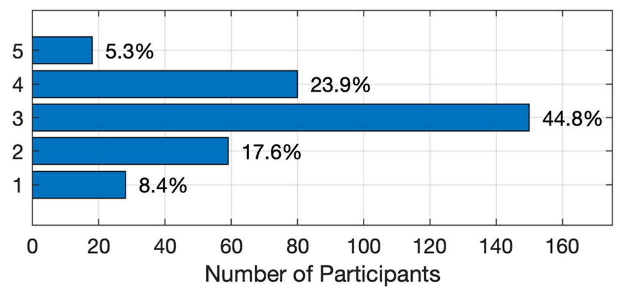

FIGURE 6
Distribution of students' confidence in the accuracy of answers provided by AI tools, ranging from low to high confidence.

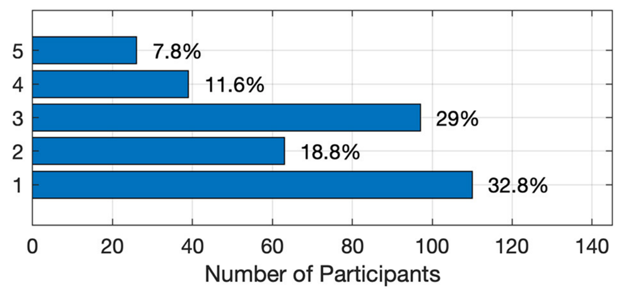

FIGURE 7
Student responses about their level of concern regarding security and privacy issues when using AI tools.

trust in AI tools, which aligns with the confidence levels shown in Figure 6.

The majority of students, 77.6%, believe that the use of AI tools positively contributes to the educational process, indicating strong confidence in the role of digital technologies in enhancing learning. This suggests that most students recognize the benefits these tools offer, such as increased efficiency and improved access to information. However, 11.6% of the students expressed skepticism, potentially due to concerns about the risks of overreliance on technology, which could undermine critical thinking and independent problem-solving. The remaining students, who were uncertain, may not have enough experience with these tools to evaluate their impact fully. This uncertainty points to the need for further research to understand whether these tools foster deeper learning or provide surface-level convenience in academic tasks.

Figure 7 presents students' responses regarding their level of concern about security and privacy when using AI tools, with 1 representing low concern and 5 representing very high concern. As indicated, most students exhibit relatively low levels of concern about the security and privacy risks associated with AI tools, with only 19.4% selecting 4 or 5, signaling significant concern. This suggests that most students do not prioritize these risks or may not fully grasp the potential implications of security and privacy when using such technologies. The low level of concern could be attributed to the convenience and perceived usefulness of AI tools, overshadowing their potential risks. Alternatively, it may reflect a lack of awareness about how personal data is collected, stored, and used by AI platforms. This points to the need for greater education on digital security and privacy, ensuring that students are more informed and cautious in their use of these tools. Understanding these risks is essential as AI becomes more integrated into academic and personal activities.

The results show that 59.1% of the students use AI tools to assist with non-academic tasks, highlighting their broader role in personal productivity beyond education. Meanwhile, 40.9% limit their use of these tools to academic purposes, suggesting varying levels of adoption for everyday activities. This indicates that AI tools are becoming integral to both academic and personal domains for a majority of students.

4.1 Qualitative findings: thematic analysis of challenges

To analyze the open-ended responses regarding challenges faced when using AI tools, we applied Braun and Clarke's (2006) thematic analysis method. Out of 337 participants, 93 provided valid qualitative input. Five major themes emerged:

- **Theme 1: accuracy and relevance issues**–many students reported receiving vague, inaccurate, or unhelpful responses from AI tools. Several emphasized that the information provided was either off-topic or confusing.
- **Theme 2: difficulty in framing questions**–respondents noted that how a question is phrased significantly affects the quality of the AI's answer. Some expressed frustration with having to reword their questions multiple times.
- **Theme 3: ethical concerns and academic misconduct**–a number of students raised concerns about plagiarism and the potential for duplicate responses among peers using the same tools.
- **Theme 4: lack of source credibility**—several students indicated that AI-generated content often lacked verifiable sources or citations, making it difficult to trust or reference in academic work.
- **Theme 5: technical and language limitations**—some participants experienced technical issues, such as delayed responses, language mismatches, or the inability to upload images or complex input formats.

These themes provide deeper insight into the practical, ethical, and pedagogical limitations students encounter when using AI tools for academic purposes. Addressing these challenges through institutional policy and digital literacy training may help improve outcomes.

5 Discussion

The results indicate a high rate of adoption and recognition of AI tools–especially ChatGPT–among Jordanian university students. This finding aligns with global patterns observed in prior research (Beganovic et al., 2023; Rahmaniar, 2024), which document ChatGPT's wide popularity due to its accessibility, effectiveness, and human-like response generation. The significant reliance on ChatGPT over other platforms may reflect not only its usability but also a lack of awareness or institutional promotion of alternative tools.

The findings also suggest that students perceive AI tools as beneficial for enhancing academic performance and managing their workload efficiently. This corroborates prior literature (Ke Zhang, 2021; Celik, 2023), which emphasizes the productivity gains and engagement benefits of integrating AI into higher education.

However, the limited proportion of students (only 19.1%) who reported that AI tools significantly enhanced their understanding points to a critical limitation. This aligns with studies that question the depth of learning supported by AI tools (Tabone and De Winter, 2023), indicating that while such technologies can facilitate task completion, they may not necessarily promote conceptual mastery.

Moreover, qualitative findings revealed concerns about the accuracy, ethical implications, and technical constraints of AI tools. These are consistent with challenges noted in previous studies (Jiahong Su, 2023; Hannan and Liu, 2023), especially in relation to academic misconduct, the lack of source credibility, and difficulties in generating contextually accurate outputs. The issue of framing questions effectively was also prominent–underscoring the importance of digital literacy and prompting skills, which should be integrated into university curricula.

Interestingly, while most students reported verifying AI-generated content (78.2%), a significant minority did not, highlighting the risk of over-reliance and the potential erosion of critical thinking skills. This concern has been echoed in literature addressing the unintended consequences of unchecked AI use in academic environments (El Alfy et al., 2019).

These findings illustrate the dual-edged nature of AI in education: its potential to democratize access and enhance efficiency, and its risk of diminishing deep learning and academic integrity. As AI tools become increasingly embedded in student practices, institutions should develop structured guidelines for ethical use and offer support mechanisms that encourage thoughtful, critical engagement with AI technologies.

Ultimately, this study offers valuable insights into student experiences with AI in a developing country context, contributing to the broader discourse on global educational transformation. Future work should consider longitudinal analyses to capture evolving perceptions and learning outcomes, and investigate the differential impacts of AI use across disciplines and demographic segments.

6 Conclusions and future research

6.1 Conclusions

This study provides valuable insights into the adoption of AI tools among university students in Jordan, based on responses from 337 participants. The survey highlights the majority of chatbot technologies, particularly ChatGPT, which emerged as the most recognized and widely used tool for academic tasks. With 90.4% of respondents utilizing ChatGPT, the findings demonstrate its pivotal role in enhancing task efficiency and academic performance. Our finding is aligned with other research in the field. For instance, a study conducted across Germany found that nearly two-thirds of students used AI-based tools in their studies, with ChatGPT or GPT-4 being commonly mentioned by students in engineering, mathematics, and natural sciences, which aligns with our findings on the increasing reliance on AI tools for understanding and explaining subject-specific concepts (Von Garrel and Mayer, 2023). However, only 19.1% of students reported significant improvements in their understanding of academic concepts, suggesting that while AI tools are beneficial for productivity, their contribution to deeper learning remains limited. As noted in the study by Fošner (2024), while AI tools are increasingly recognized for their efficiency in education, there are concerns about their impact on learning quality and academic integrity, which align with the findings indicated above.

The analysis also revealed differences in AI tool usage across academic disciplines, with students from scientific fields displaying greater familiarity with multiple platforms compared to those in humanities and health disciplines. Additionally, ethical considerations surfaced, as only 19.4% of students expressed significant concern about privacy and data security. This lack of awareness highlights the need to address the potential risks associated with AI technologies and encourage responsible usage practices.

6.2 Future research directions

Future research should investigate the long-term impacts of AI tools on students' academic performance, focusing on critical thinking, problem-solving skills, and conceptual understanding. Studies could explore how AI tools influence diverse learning outcomes across disciplines, addressing the unique needs and challenges of fields such as humanities, sciences, and health education. Additionally, research should examine strategies for effectively integrating AI into curriculum design, ensuring these tools enhance learning processes without fostering over-reliance.

The development of ethical frameworks is another key area for future work, particularly with regard to data privacy, academic integrity, and equitable access to AI technologies. Investigating how AI can address gaps in digital literacy and technology infrastructure, especially in under-resourced regions, remains a crucial focus.

Furthermore, new evaluation models should be developed to assess the benefits of AI adoption in higher education. Such models, incorporating multidimensional criteria, could streamline the analysis of AI's effectiveness in teaching and learning. They would also enable educators to design consistent surveys and compare data across studies, facilitating deeper insights into AI's impact on education.

In addition, future research should explore how sociocultural and institutional factors mediate student engagement with AI tools in diverse regional contexts. Comparative studies between Jordanian and non-Arab university cohorts may reveal how academic norms, technological readiness, and cultural attitudes shape the perceived benefits and ethical concerns associated with AI use. Qualitative investigations–such as interviews or focus groups–could deepen our understanding of how students and educators interpret the role of AI in learning and assessment. Moreover, policy-oriented studies could examine how institutional guidelines on academic integrity and digital conduct influence AI adoption in Middle Eastern education systems.

By extending this line of inquiry, future research can help build a more globally inclusive evidence base and ensure that AI-supported learning is responsive to both universal and context-specific educational needs.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Ethics statement

Ethical approval was not required for the studies involving humans in accordance with the local legislation and institutional requirements. The participants provided their informed consent to participate in this study.

Author contributions

MAM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. MA: Conceptualization, Data curation, Software, Writing – review & editing. UT: Formal analysis, Validation, Writing – review & editing. HK: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

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