Artificial Intelligence (AI) Tools among University Students: A Structured Literature Review of Current Trends and Future Research

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ABSTRACT

Artificial Intelligence (AI) tools like ChatGPT, Gemini, Microsoft Copilot, NotebookLM, and DeepSeek have transformed higher education. AI tools are becoming commonplace among university students for academic writing, problem-solving, information retrieval, and self-directed learning. There has been an increase in research on these technologies, but current empirical studies remain scattered, using a variety of theoretical lenses, research variables, and methodological approaches. This makes it difficult to deepen the understanding of the usage of AI by university students. Relevant articles published from 2022 to 2026 were identified exclusively from the Scopus database and systematically analysed using the Literature Review Matrix, resulting in 35 empirical studies. The review synthesised evidence on theories, research variables, methodologies, and research gaps in the literature. The findings show that the most used theories are the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Although studies on technology acceptance, student perceptions, and learning outcomes have received attention, the focus on AI literacy, responsible use of AI, and organisational aspects remains under-researched. This review offers a detailed summary of the existing research and suggests future directions for the effective and ethical use of AI technologies in higher education.

Keywords:
Artificial intelligence; Generative AI; Higher education; University students; Technology acceptance

Introduction

In recent years, one of the most important technological developments has been artificial intelligence (AI), which has greatly impacted higher education. Generative AI's advancements in information generation, analysis, and sharing have revolutionised the process of producing text, graphics, computer code, and other digital information (Kumar et al., 2025). As a result, AI is increasingly defining the teaching and learning process, the academic research process, and the academic decision-making process, prompting universities around the world to rethink and reconsider traditional academic practices and to prepare students to learn in a technologically advanced learning environment.

Whilst many AI tools are being adopted, the use of generative AI tools such as ChatGPT, Google Gemini, Microsoft Copilot, NotebookLM, Claude, and DeepSeek has had a significant impact. They are used for a wide range of academic tasks, including literature searching, academic writing, programming, data analysis, idea generation, and collaborative learning. Their user-friendly platforms have contributed to the swift adoption by university and college students, making AI a regular part of their academic experience. While these technologies offer opportunities for improved productivity and individualised learning experiences, they have also raised many issues about academic integrity, information reliability, ethical use, and the development of critical thinking (Matos et al., 2025).

The use of AI has accelerated research in higher education. AI has created a lot of interest in scholarship (Malik et al., 2023; Lachheb et al., 2025). Empirical studies have investigated issues of technology acceptance, AI literacy, learning outcomes, trust, academic integrity, and behavioural intention, among others, under different theoretical frameworks such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Planned Behaviour (TPB), and Social Cognitive Theory (SCT). The results of these studies, however, are scattered across diverse teaching contexts, AI platforms, and research methodologies, making it difficult to build a clear picture of the state of the knowledge landscape.

While the relevance of AI in higher education has been reviewed in the past, there are differences in the topics covered and the focus. For instance, Baig and Yadegaridehkordi (2024) summarized 57 studies exploring the use and applications of ChatGPT in higher education, and reviewed the theoretical perspectives and research gaps. Qian (2025) examined the pedagogical use of Generative AI and its emerging place in education and learning. Likewise, Abdallah et al. (2025) gathered evidence relating to ChatGPT and its impact across various domains, including academic outcomes, mental health, second language acquisition, social impact, and ethical implications. Later, Xu and Thien (2026) discuss the overall advancement of AI studies in higher education, such as the methodologies used, gaps in research, and ethical issues. All of these reviews have helped to shape the knowledge about the applications, educational outcomes, challenges, and general development of AI in higher education. However, a more targeted integration of empirical work across several AI tools with university students is needed. Specifically, it could be useful to present the theoretical frameworks, research variables, methodological approach, main results, and needs for future research in a shared analytical framework in order to gain a clearer understanding of the state of empirical studies. Based on this, the current study conducts a systematic review of empirical research on university students and AI tools, based on the PRISMA 2020 guidelines.

Literature Review

Artificial Intelligence (AI) is the ability of computer systems to learn, think and reason, solve problems, understand language and make decisions, all of which are traditionally human activities (Kaplan, 2022). Research focused on early breakthroughs in AI systems that included knowledge-based systems and machine learning algorithms designed to automate repetitive tasks and enhance decision-making across different industries. In the last 10 years, however, the capabilities of AI have greatly increased with the development of deep learning, natural language processing, and large language models (LLMs), which allow computer systems to produce human text, images, programming code and multimedia content (Raieni, 2025).

ChatGPT by OpenAI's public launch in late 2022 brought a significant leap in AI technology that has paved the way for generative AI's adoption in the education, business, healthcare, and government sectors. As opposed to earlier uses of AI, which concentrated mostly on automation, generative AI empowers individuals to produce new material, address tough challenges, and participate in conversational interfaces (Storey et al., 2025). This has enabled a more seamless embedding of generative AI in the realm of teaching and learning, academic research, and academic writing in higher education, which has led to changes in how students and teachers interact with information and knowledge creation (Jin et al., 2025; Wang et al., 2024).

AI Tools in Higher Education

The increasing availability of generative AI has sped up the adoption of AI-powered tools that support teaching and learning in higher education. Among these, ChatGPT has become one of the most widely used conversational AI applications, helping students to generate ideas, explain concepts, summarise information, support academic writing, assist with coding, and analyse complex problems (Deng et al., 2024). Similarly, Google Gemini offers multimodal capabilities that enable users to analyse text, images, and documents, facilitating research, collaborative learning, and information retrieval.

There are also a number of other AI-powered resources that have gained recognition in the higher education sector. By integrating with Microsoft Office applications, Microsoft Copilot improves productivity, document preparation, document analysis with spreadsheets, and programming. Google's NotebookLM allows users to engage directly with uploaded academic sources, enabling them to conduct literature reviews, organise their notes, summarise documents, and learn from the literature. While Claude is being more widely known for its capabilities in generating coherent academic content and conducting advanced document analysis, DeepSeek has recently become an alternative LLM that can be used for tasks like academic writing, coding, and analytical reasoning. Canva AI is also capable of helping users design presentations, communicate visually, and create educational materials, which is helpful for creating interesting learning materials through the use of multimedia.

Collectively, these AI tools have altered learning processes by improving access to information, improving productivity, supporting independent learning, and assisting collaborative knowledge construction. Despite those

benefits, their rapid adoption has also elicited crucial concerns regarding responsible AI use, academic integrity, information accuracy, and the development of students' critical-thinking skills (Papagiannidis et al., 2025).

AI in Teaching and Learning

Benefits of AI Tools

With an increasing volume of empirical evidence, it is becoming clear that AI tools offer a range of educational benefits to university students (Chen & Cheung, 2025; Archana et al., 2025). These technologies serve to improve personalised learning through the delivery of instant feedback, creation of learning materials, academic writing, and facilitating cross-disciplinary problem-solving. They also enhance study efficiency in the sense of the time they can save in searching for information, summarising academic literature, writing code, and organising study materials. This allows learners to focus more on higher-order thinking skills such as analysis, evaluation, and creativity (Kasneci et al., 2023; Dwivedi et al., 2023).

Furthermore, AI technologies facilitate students' independent learning by allowing them to study on their own, receive personalised explanations, and rehearse skills beyond the classroom. Empirical studies additionally point out the potential of improving the learning experience in higher education through the effective utilisation of AI-driven educational technologies, which positively impact students' learning engagement, motivation, creativity, and perceived learning performance (Yang et al., 2023; Mohamed et al., 2024; Dong et al., 2025).

AI Tools Present Challenges

As AI adoption expands, however, it also presents challenges. The credibility and veracity of AI-produced material is one of the primary issues. If they are not used with appropriate verification, large language models can also produce false or fabricated information, or "hallucinations" that can negatively affect student learning (Anh-Hoang et al., 2025). Moreover, excessive dependence on AI tools can also result in a loss of students' ability to think critically, solve problems independently, and be creative (Abubakar et al., 2025). The other challenges are data privacy, algorithmic bias, access to AI technologies, and lack of AI literacy for students. The concerns underscore the importance of teaching students the skills necessary to critically interpret AI-generated information, as well as the need to teach them how to engage in responsible and ethical use of these technologies.

Ethical Issues

As AI tools become more prevalent in higher education, ethical considerations have come to the forefront. Academic integrity is still a common concern, especially in terms of plagiarism, improper authorship, the use of AI tools, and the fairness of the student evaluation process (Balalle & Pannilage, 2025). In response, universities around the world have continued to adapt institutional policies and assessment practices to make sure that they use AI tools responsibly, while maintaining academic standards (Guidance for Generative AI in Education and Research, 2023). Moreover, being transparent, accountable, and responsible about the use of AI by both students and teachers is essential to its ethical application. However, rather than banning the use of AI, some researchers argue that greater emphasis should be placed on developing students' AI literacy and ethical awareness. This would help students use AI as a learning tool while continuing to think critically and learn independently (Funa & Gabay, 2024).

Learning Outcomes

Existing research suggests that, when applied correctly, AI can boost learning outcomes. Research findings indicate that students' learning engagement, academic productivity, writing skills, creativity, and perceived learning effectiveness are consistently positively correlated with the use of AI writing tools (Alam et al., 2026; Grājeda et al., 2024). The outcomes, however, are constrained by various factors such as students' digital competencies, AI literacy, motivation, trust in AI, and educational context, among others. Hence, the factors that affect the effective use of AI among University students are still a topic of interest in future research.

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Existing Reviews of AI in Higher Education

Existing research indicates that the use of AI in higher education has developed around several interconnected areas. AI tools are increasingly being utilized in academic contexts to assist with tasks like information retrieval, academic writing, problem-solving, content creation, and self-directed study. One major trend is the use of AI tools to enhance academic tasks like information retrieval, academic writing, problem-solving, content generation, and independent learning. Secondly, the literature confirms the possibility of enhancing learning efficiency, engagement, personalisation, and access to academic support via the use of AI. Meanwhile, concerns are raised about the accuracy of information, overreliance on AI, academic honesty, privacy, and responsible use of AI-generated information (Baig & Yadegaridehkordi, 2024; Abdallah et al., 2025; Qian, 2025).

The current knowledge further indicates that research is shifting from the question of student acceptance of AI technologies to understanding how students are using them and what factors influence their learning value. Consequently, the importance of AI literacy, trust, SRL, critical thinking, ethics, and institutional support has become more pertinent. The field of AI research in higher education is also evolving, with significant variations in theory and methodology as highlighted by recent reviews (Xu & Thien, 2026). However, no clear consensus exists on the current state of AI use among university students. Comparing empirical studies is difficult because of differences in methodological and theoretical approaches, research variables, and educational contexts. This forms the groundwork for more in-depth analysis of the theoretical and methodological underpinnings of the literature, which is to be discussed in the next section.

Theoretical Foundations

The technology acceptance and adoption behaviour of university students and the Learning Outcomes (LOs) of university students towards the use of Artificial Intelligence (AI) tools have been examined using various theoretical frameworks. Numerous theoretical models have been applied in the study of students' acceptance and use of AI tools and learning outcomes in universities. There are several theoretical frameworks that have been explored in studying how students respond to and utilize AI tools and their resulting learning outcomes in university settings. These include technology acceptance perspectives (TAM and UTAUT) in addition to TPB, SCT, and TTF. These theories can be complementary to gain insights into students' behaviours in the context of AI-supported learning, such as their behavioural intention and technology acceptance.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a popular model that seeks to understand how users accept and use new technologies. According to TAM, attitudes toward a technology and behavioural intentions to use a technology has two main determinants: perceived usefulness and perceived ease of use (Davis, 1989). Perceived usefulness is a belief that using a specific technology will enhance performance, whereas perceived ease of use is a belief that little effort is needed to use a specific technology. From a higher education perspective, the findings from TAM offer valuable insights into students' acceptance of AI tools. When students think that AI tools like ChatGPT can be helpful for their academic work and that they're easy to use, they're more likely to embrace them and make them part of their lives. The literature also shows that TAM has been expanded by adding other elements to better capture students' acceptance and use of emerging technologies involving AI. It shows the ongoing importance of TAM, acknowledging that students' engagement with AI might include aspects that extend beyond the original constructs of the model.

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) extends coverage of technology adoption by combining constructs from previous technology acceptance models. UTAUT introduces four critical factors of technology acceptance and use: performance expectancy, effort expectancy, social influence, and facilitating

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conditions (Xue et al., 2024). Performance expectancy is the degree to which a user feels that a technology will facilitate performance, and effort expectancy is the ease of use of the technology. Social influence is defined as how much others value and see as important, and say that they should use the technology, and facilitating conditions as the availability of organizational and technical resources that facilitate the use of the technology. In the context of higher education AI research, UTAUT has been applied to the study of students' adoption and maintenance of AI technologies. Table 4 depicts several studies that extend UTAUT by adding factors such as AI literacy, self-regulated learning, and self-empowerment. The extensions show that students' experiences of using AI are shaped not just by their experiences of the technology, but by their skills, social setting and learning context as well.

Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) posits that attitude, subjective norms and perceived behavioural control (Ajzen, 1991) are the key factors that determine behavioural intention to act. For students to be responsible in their use of AI tools, we need to understand their intentions, taking into account both ethical considerations and social expectations. As indicated in Table 4, TPB has been used to study students' intentions to use AI tools responsibly, while taking into account ethical issues and social expectations. A few studies also integrated TPB with technology acceptance components to gain a deeper understanding of students' AI adoption behaviour.

Social Cognitive Theory (SCT)

Social Cognitive Theory (SCT) emphasises the interaction between personal factors, behaviour, and environmental factors (Schunk & DiBenedetto, 2022). In the field of educational research related to AI, SCT has served to illustrate how students' self-efficacy and their experiences and confidence in learning relate to their effective use of AI technologies. The literature search also revealed studies that studied SCT coupled with AI literacy or information literacy. There were studies that explored students' responsible and independent learning behaviours in using AI tools.

Task-Technology Fit (TTF)

According to the Task-Technology Fit (TTF) model, technology will be more likely to enhance performance if it has the ability to meet the user's task requirements (Bazine & Salahddine, 2025). To improve academic writing, problem-solving, programming, and information retrieval in higher education, TTF has been used to identify how the functionalities of AI tools align with the learning activities of students. Research mostly finds a positive relationship between TTF and learning outcomes, and technology usage typically suggests that the higher the alignment of AI use in academic tasks, the more these tools are used and the better the results.

The literature reviewed shows that technology acceptance theories remain the main basis for the understanding of the adoption of AI among university students. Newer studies, however, are adopting an educational, behavioural, and psychological perspective in conjunction with the traditional technology acceptance models in order to more closely reflect the complexity of the students' interactions with the generative AI tools. The findings of this trend indicate that future research may profit from multi-theoretical frameworks that will account for the adoption of technology and educational outcomes.

Research Objectives

The research objectives of this research are:

1. To examine the current trends in empirical research on AI tools among university students.
2. To identify the theoretical perspectives and research variables commonly employed in studies on AI tools among university students.
3. To examine the methodological approaches used in existing empirical studies on AI tools among university students.
4. To identify research gaps and propose directions for future research on the use of AI tools in higher education.

Methods

Review Design

The research design used in this study was the structured literature review method, which is used to synthesise empirical data regarding the use of Artificial Intelligence (AI) tools by university students. A literature review is conducted in a structured way that is transparent and systematic, as opposed to a narrative review, which involves identifying, selecting, evaluating, and synthesising published studies, while enhancing the reliability and reproducibility of the review process (Snyder, 2019). The study adhered to the PRISMA 2020 reporting guidelines in identifying, screening, and selecting relevant articles to ensure transparency throughout the review (Page et al., 2021). Relevant studies were sourced from the Scopus database and filtered for the inclusion and exclusion criteria. The articles that were eligible were then analysed, and a Literature Review Matrix was used to collate their theoretical underpinning, research variables, methodologies, key findings and research gaps. The overall study selection process is presented using the PRISMA 2020 flow diagram in Figure 1.

The main data extraction and synthesis tool used was the Literature Review Matrix to facilitate a systematic comparison across the selected studies. The matrix allowed information from each article to be organised in a consistent manner to identify similarities, differences, and patterns in the research in the articles selected for review.

Search Strategy

The review was narrowed to studies published between 2022 and 2026 to reflect the recent developments in the use of AI in higher education. The year 2022 was chosen as the beginning year since it was a significant change in the availability and the use of generative AI, especially since the launch of ChatGPT in late 2022. Although AI had been developed after this time period, the selected time frame represents the swift emergence of generative AI tools that have been created after this period and have increasingly influenced university students' learning and academic practices.

A literature search was conducted only in the Scopus database because it contains a broad range of high-quality peer-reviewed journals covering education, information systems, business, psychology, and related fields. Scopus was selected for the above reasons, as it offers such wide coverage as well as being one of the most reliable databases for structured literature searches. The search terms consisted of different permutations and combinations of artificial intelligence, students at universities, and higher education. Boolean operators (AND and OR) were used to expand and narrow the search and ensure complete coverage of relevant studies. The predominant search term employed was:

> TITLE-ABS-KEY(("artificial intelligence" OR "generative AI") AND ("higher education" OR "student")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO(LANGUAGE, "English")) AND (LIMIT-TO(SUBJAREA,"SOCI") OR LIMIT-TO (SUBJAREA,"BUSI")) AND PUBYEAR > 2021 AND PUBYEAR < 2027

The term “student” was retained as a broad search term during the identification stage to minimise the possibility of excluding potentially relevant studies. However, as this term could also retrieve studies involving students outside higher education, population relevance was further assessed during the title and abstract screening stage. Studies that clearly focused on primary or secondary school students or other non-university populations were excluded. Where the educational level of the participants could not be determined from the title and abstract, the article was retained for full-text eligibility assessment. At this stage, only empirical studies involving university or higher education students and relevant to the use of AI tools in higher education were retained for the final review.

Additional keyword combinations were used as needed to capture relevant studies on emerging AI tools and educational applications. The complete screening and eligibility process is further described in the next section and presented in the PRISMA 2020 flow diagram in Figure 1.

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Inclusion and Exclusion Criteria

In order to guarantee the relevance and quality of the studies selected, a set of inclusion and exclusion criteria was determined prior to the screening process. Only empirical journal articles written in English and published from 2022 to 2026 were selected. The review was limited to peer-reviewed journal articles to maintain a consistent and comparable evidence base across the selected studies. The reasons for excluding conference papers and book chapters were not necessarily because of the quality of the research, but because of different publication formats for conference papers versus book chapters, the different reporting requirements, the different review processes, and the extent to which methodological details are provided. Limiting the review to journal articles also ensured greater uniformity in extracting and comparing theoretical backgrounds, research methodology, variables, and findings across studies. The selection is based on the scope of the review, not the academic standards of conference papers or book chapters.

Table 1
Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Publication year	2022-2026	Before 2022
Language	English	Non-English
Publication type	Peer-reviewed journal articles	Conference papers, book chapters, reviews, editorials
Research design	Empirical studies	Conceptual or opinion papers
Population	University students	School students, lecturers only, non-educational contexts
Topic	AI tools in higher education	AI unrelated to higher education on student learning

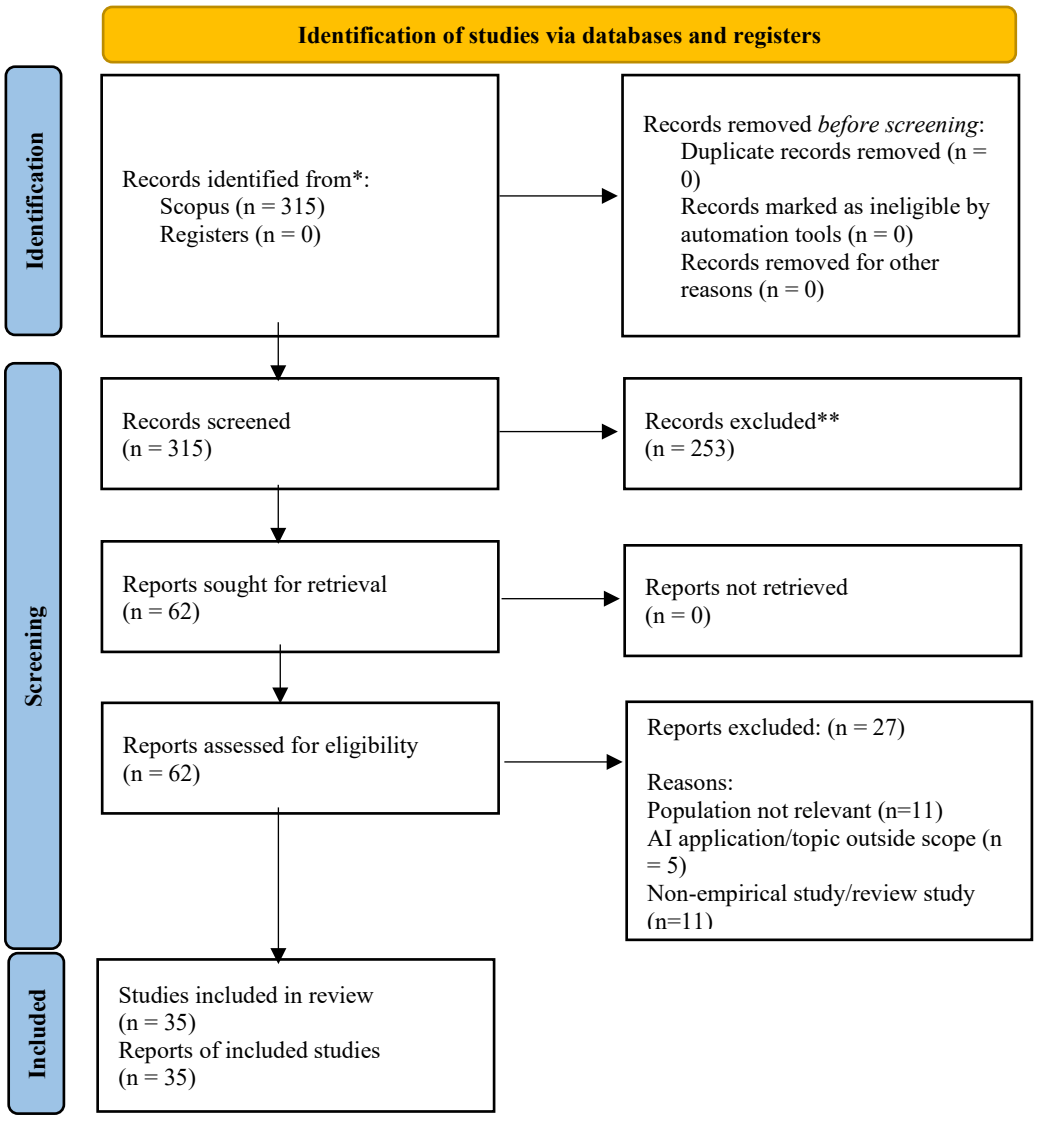
Screening Process

The screening process consisted of four stages: identification, screening, eligibility, and inclusion, following the PRISMA 2020 criteria. In the identification phase, 315 records were identified in the Scopus database. Duplicate records were not removed prior to screening. The titles and abstracts of 315 records were then pre-screened using the pre-established inclusion and exclusion criteria. There were 62 articles for full-text evaluation, and 253 were excluded at this stage.

The remaining 62 articles were assessed for eligibility using the full text. Twenty-seven articles were excluded due to failure to fulfil our predetermined inclusion criteria. The primary reasons for exclusion were: The study population was not relevant, the AI application or topic was outside the scope of the review, or the article was not empirical or a review. After full-text assessment, 35 empirical studies fulfilled the inclusion criteria and were included in the final analysis. The entire study selection process is shown in the PRISMA 2020 flow diagram in Figure 1.

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Figure 1.
PRISMA 2020 Flow Diagram of the Study Selection Process



Data Extraction and Synthesis

Following the screening process, information from the 35 selected empirical studies was extracted and organised using a structured Literature Review Matrix. The matrix was used to record information consistently across the selected studies and to facilitate comparison during the synthesis process. The data obtained comprised author(s) and year, country, type of AI tool studied, theoretical framework, research methodology and design, key variables, key findings, and research gaps. The Literature Review Matrix that was used for data extraction is a sample and is shown in Table 2.

The information extracted was then compared between the studies to see what similarities, differences, and trends were found in the literature. The theoretical views, research variables, methodological approaches, and research gaps were given special attention. The AI tools related to similar concept variables were consolidated under the same themes to help understand the state of the research in relation to AI tools among university students. A narrative and thematic synthesis was used to integrate the evidence across the selected studies. Rather than discussing each study separately,

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findings addressing similar concepts and research areas were brought together to identify common patterns and emerging research directions. The resulting themes provided the basis for the findings and discussion section.

Table 2

Sample of the Literature Review Matrix Used for Data Extraction

Author(s) & Year	Country	AI Tool Investigated	Theoretical Base	Methodology & Design	Key Variables/Dimensions Examined	Identified Research Gap
Bera et al. (2026)	India	General AI tools (ChatGPT, Gemini, Grammarly, QuillBot)	Extended UTAUT (with Self-Empowerment	Quantitative survey using SEM & MIMIC modelling (n=305)	Performance Expectancy, Effort Expectancy, Self-Empowerment, Social Influence, Facilitating Conditions, AI Adoption	Dearth of empirical evidence on independent, unmandated AI adoption among university students in developing economies.
Tenakwah et al. (2025)	Australia	ChatGPT (v3.0)	Competence-Based Learning (CBL) Theory	Multidisciplinary team-based content analysis & peer debriefing across 5 institutions	Evaluates three dimensions of ChatGPT competency. The paper itself identifies these as language proficiency, critical thinking and reasoning, and structure and relevance of response	Limited understanding of ChatGPT's competency in responding to university-level assessment tasks across different academic disciplines.
Khurramov et al. (2025)	Uzbekistan	Hybrid DNN, BOTler, SmartGrading	Grounded Theory, Bloom's Taxonomy, Toulmin Argumentation Model	Mixed-methods: Structured questionnaires (n=402) & focus groups (n=49)	Prior AI exposure, academic year, grading accuracy, precision, evaluation time efficiency	Limited discussion about the legal and educational role of AI and its ethical considerations in the context of higher education in Central Asia.
Ranjan et al. (2024)	India	AI-enhanced Knowledge Management (AI-KM) systems	Knowledge-Based View (KBV); Absorptive Capacity Theory; Responsible AI Paradigm	Quantitative survey; 401 student responses; PLS-SEM using SmartPLS 4	Knowledge creation, knowledge capture, knowledge storage, knowledge discovery, knowledge prediction, knowledge delivery, ethical AI-KM integration, sustainable learning	Limited empirical research on the integration of AI-enhanced knowledge management practices and sustainable learning in higher education, particularly in developing countries

Note: This is a sample of the literature review matrix used for extracting data from the literature. The full matrix contained 35 empirical studies and other data, including country, sample characteristics, research gaps, suggestions for future research and source references.

Results

Overview of the Selected Studies

Thirty-five empirical studies between 2022 and 2026 were included and met the inclusion criteria. The studies were carried out in various geographical areas, such as Asia, Europe, Australia, and North America, which reflects the spread of interest in incorporating Artificial Intelligence (AI) in higher education institutions around the globe. The studies reviewed included different AI tools like ChatGPT, Gemini, Microsoft Copilot, Claude, Perplexity AI, and other generative AI tools. The majority of the research papers were of quantitative survey designs based on the theory of technology acceptance, specifically the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), but some research papers used mixed methods and qualitative designs. The information gained from the chosen articles was systematically organised into the Literature Review Matrix, which was used to develop the thematic synthesis that is presented in the next section.

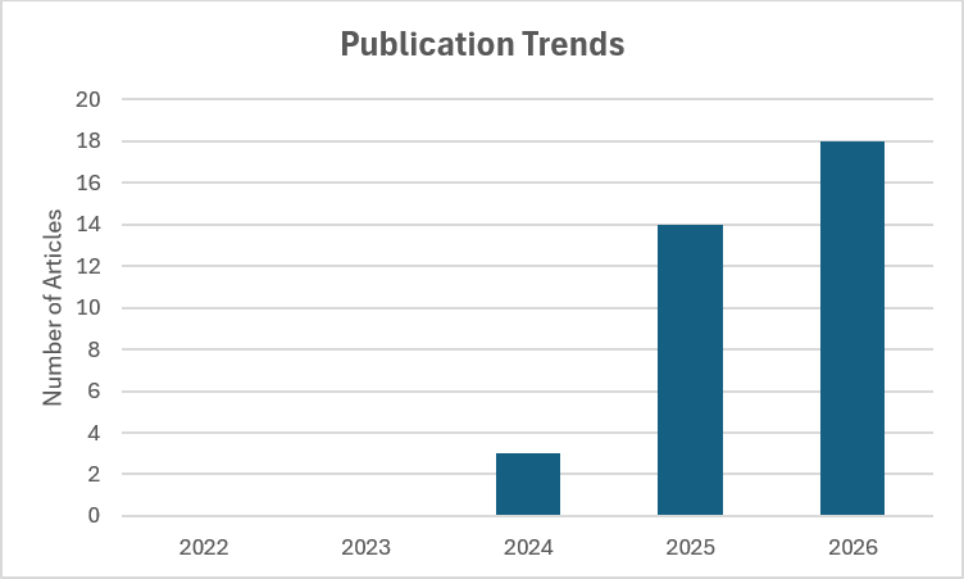
Publication Trends

Table 3 and Figure 2 present the publication trends of the 35 empirical studies included in this review over the period from 2022 to 2026.

Table 3
Publication Distribution of the Selected Studies (2022-2026)

Year	Number of Articles	Percentage (%)
2022	0	0.0
2023	0	0.0
2024	3	8.6
2025	14	40.0
2026	18	51.4

Figure 2
Publication Trends of the Selected Studies (2022-2026)



As can be seen in Table 3 and Figure 2, the number of studies on AI tools among university students has substantially increased in recent years. Of the 35 selected studies, three (8.6%) were published in 2024, followed by 14 studies (40.0%) in 2025 and 18 studies (51.4%) in 2026. In 2022 and 2023, no studies were published that fulfilled the inclusion criteria previously outlined in the protocol. This trend is a reflection of the rise of empirical studies since the public

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release of ChatGPT at the end of 2022, which has sparked further research interest in the field of generative AI in higher education.

The publication trend indicates a substantial increase in empirical research on AI tools among university students, particularly from 2024 onwards. The majority of the studies selected were published in 2026 or later, indicating a trend of increased research interest in the use and implications of AI tools within higher education. This pattern, however, must be viewed as a descriptive publication trend, and not necessarily as a statistically significant rise in publications.

Theoretical Perspectives

Table 4 summarizes the major theoretical perspectives discussed in the 35 empirical studies reviewed.

Table 4
Major Theoretical Perspectives in the Selected Studies

Theoretical Perspective	Representative Theories	Frequency
Technology Acceptance	• Technology Acceptance Model (TAM) • Unified Theory of Acceptance and Use of Technology (UTAUT) • Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) • Technology Readiness and Acceptance Model (TRAM)	14
Behavioural	• Theory of Planned Behavior (TPB) • Social Cognitive Theory (SCT)	5
Learning	• Constructivism • Experiential Learning Theory (ELT) • Scaffolding • Competence-Based Learning (CBL) Theory	7
Innovation & Knowledge	• Knowledge-based view (KBV) • Disruptive Innovation Theory (DIT) • Diffusion of Innovations Theory	3
Digital/Educational Framework	• Digital Competence • AI Literacy • Technology-Organization-Environment (TOE)	3
Others	• Activity Theory • Creativity Theory • Critical Theory • AI Agent Perspective	3

The results indicate that the most common theoretical categories represented were technology acceptance with a frequency of 14, which included the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the Technology Readiness and Acceptance Model (TRAM). These frameworks indicate that current research has been mainly concerned with understanding the factors affecting university students' acceptance, intention to use, and continued use of AI tools. Another category of theories that were commonly used was behavioural theories, which consisted mainly of the Theory of Planned Behaviour (TPB) (frequency = 5) and Social Cognitive Theory (SCT). The theories deepen the knowledge of the adoption of AI by incorporating behavioral intention, self-efficacy, and social factors that may influence students' interactions with AI technologies.

The review also included studies that presented learning-oriented perspectives (frequency = 7). To understand how AI tools can assist students in building knowledge, accessing learning content, and becoming more independent learners, the theories of Constructivism, Experiential Learning Theory (ELT), Scaffolding, and Competence-Based Learning

(CBL) Theory were used. Other perspectives, such as innovation and knowledge-based theories, digital and educational frameworks, and emerging perspectives, were less represented, indicating increasing theoretical diversity in research on the use of AI in higher education.

Overall, the results suggest that the technology acceptance theories still have an influential role in the literature, but the studies reviewed also include education, behaviour, psychology, and other viewpoints to offer a comprehensive view of AI-supported learning. The diversity implies that while early studies centered on the adoption of AI, we are now seeing a shift towards exploring its broader pedagogical and educational impacts.

Research Variable Matrix

Beyond identifying which AI tools have been implemented in higher education, it is crucial to examine the variables measured in previous studies. These variables describe the primary fields of interest within the scholarly community and the theoretical directions which inform research into AI. These variables are explored in detail, offering a systematic insight into the research on AI tools within the context of university students, covering technological, educational, behavioural, psychological, and ethical aspects.

The research variables identified in the 35 selected empirical studies were grouped into broader conceptual categories based on the underlying constructs and their overall research focus. This thematic classification identifies not only the predominant variables examined in the literature but also less frequently studied areas that may require further investigation. Table 4 presents the synthesis of the research variables identified across the selected studies.

Table 5
Synthesis of Research Variables in the Selected Studies

Variable Category	Representative Variables	No. of Studies
Student Perceptions & User Experience	Student Perceptions, Satisfaction, Awareness, Trust, Motivation, Confidence, Engagement, Usage Experience	15
Technology Acceptance & Adoption	Perceived Usefulness, Perceived Ease of Use, Performance Expectancy, Behavioural Intention, Attitude, Actual Use, Social Influence, Facilitating Conditions	13
Learning Outcomes & Academic Performance	Learning Performance, Learning Effectiveness, Knowledge Acquisition, Educational Quality, Student Outcomes, Academic Performance, Competency Development	10
Ethics & Responsible AI	Ethical Concerns, AI Ethics, Trust in AI, Transparency, Verification Behaviour, Responsible AI	9
AI Literacy & Digital Competence	AI Literacy, Digital Literacy, GenAI Literacy, Programming Skills, AI Knowledge	8
Behavioural & Psychological Factors	Self-efficacy, AI Readiness, Career Adaptability, Personality, Learning Motivation	8
Creativity & Higher Order Thinking	Creativity, Critical Analysis, Reasoning Ability, Cognitive Development, Problem Solving	6
Institutional & Environmental Factors	HEI Support, Organisational Support, Environmental Fit, Institutional Guidelines	5

Note: Several studies investigated more than one category of variables; therefore, the total frequency exceeds the number of reviewed studies.

Table 5 presents the key research variables analysed in the 35 empirical studies included in this review. The literature is not limited to focusing on a single construct, but rather shows that researchers have investigated a diverse range of technological, educational, behaviour and ethical factors to gain a better understanding of the adoption and educational impact of AI tools amongst university students.

Student perceptions and user experience were the most studied category (15 studies), followed by technology acceptance and adoption variables (13 studies). Many constructs were measured repeatedly, such as perceived usefulness, perceived ease of use, performance expectancy, behavioural intention, social influence and facilitating conditions, which are still influenced by the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). The results suggest that many studies published so far have aimed to understand students' attitudes towards the acceptance and continued use of learning technology with AI. Beyond technology acceptance, the reviewed studies also examined students' experiences of AI-assisted learning. Variables related to perceptions, satisfaction, awareness, trust, motivation, confidence, and engagement indicate that researchers are also interested in how students experience and interact with AI technologies within educational contexts, rather than focusing solely on their intention to adopt them.

The review also mentions the increasing focus on "AI literacy" and "digital competence". Recent studies began to integrate more variables such as AI literacy, digital literacy, programming skills, and AI knowledge, reflecting the recognition that students' abilities are key factors in their ability to effectively use AI. Similarly, as learning outcomes, educational quality, competency development, knowledge acquisition, and academic performance were common areas of study, the focus remained on the pedagogical impact of AI-based learning.

Another major research focus is on ethical issues. The studies were distributed across a variety of variables related to ethical issues, responsible AI use, transparency, verification behaviour, and trust in AI-driven content, indicating a growing awareness of the challenges posed by generative AI in higher education. Self-efficacy, AI readiness, career adaptability, and learning motivation were among the behavioural and psychological factors that were also commonly studied as potential factors to account for individual differences in AI adoption and utilization. The results provide a general picture of the evolution of research from the technology acceptance paradigm to a more holistic and integrated perspective of AI in higher education, encompassing educational, behavioural, psychological, and ethical dimensions.

Methodological Trends

A review of the methodological strategies used in past research will give insights into the evolution of research on AI tools in higher education. The research design, analysis, and data collection methods used in the selected studies are examined to determine the methodological maturity of the field as well as to identify opportunities for future study. For the purpose of this analysis, the methodological approaches of the 35 empirical studies were classified into higher-order categories that were based on their general methodological research design and analytical work. The methodological trends identified from the literature reviewed are summarised in Table 6.

Table 6
Methodological Trends in the Selected Studies

Methodological category	Typical Methods	No. of Studies
Quantitative Research	Online surveys, questionnaires, SEM, regression analysis, correlation analysis, MANCOVA	15
Mixed Methods Research	Surveys combined with interviews, focus groups, thematic analysis, sequential explanatory design	9
Experimental/Quasi-Experimental Research	Control group experiments, pre-test, post-test, classroom interventions, comparative experiments	7
Qualitative Research	Interviews, focus groups, thematic analysis, content analysis	3
Design-based/Educational Design Research	Engineering cycle, educational design, Research (EDR), Project-based learning design	1

Note: Studies were classified according to their primary methodological approach. Three studies employed exclusively qualitative approaches using focus groups and/or interviews (N = 35).

Table 6 shows that quantitative research was the predominant methodological approach. Quantitative research was the most common methodological approach, accounting for 15 of the 35 studies (Table 5). Most of the quantitative studies used online questionnaires or surveys that were analysed using structural equation modelling (SEM), regression analysis, correlation analysis, and other multivariate statistical methods.
Mixed methods represented the second most common methodological approach, comprising nine studies that combined quantitative methods, such as surveys, with qualitative methods, including interviews, focus groups, and thematic analysis. Integrating these approaches enabled researchers to complement statistical findings with more context-specific insights into students' experiences with AI tools. Experimental and quasi-experimental designs were also included and made up seven studies. Typical studies compared pre-test and post-test results, interventions in the classroom, or control group studies to assess the effectiveness of the AI-supported learning interventions. This helped to demonstrate the role of AI tools in enhancing learning outcomes, including student engagement, creativity, and performance.

In comparison, only three studies adopted exclusively qualitative approaches. These studies primarily used interviews, focus groups, thematic analysis, or content analysis to explore students' perceptions, ethical concerns, and learning experiences. Only one study adopted a design-based or educational design research approach, indicating that this methodological approach remains comparatively underrepresented in the reviewed literature.

Figure 3 provides a graphical overview of the methodological approaches adopted across the 35 selected studies. Quantitative research was the most frequently employed approach (n = 15), followed by mixed methods (n = 9) and experimental or quasi-experimental designs (n = 7). Qualitative research accounted for three studies, while only one study employed a design-based or educational design approach. This distribution shows the literature's strong quantitative orientation while also indicating the presence of mixed and experimental approaches.

Figure 3
Methodological Trends of the Selected Studies (2022-2026)



Overall, methodological trends show that research on the use of AI tools in higher education is becoming more diverse. While quantitative methods remain prevalent in the literature, mixed methods and experimental designs are also being used to provide a more comprehensive and in-depth understanding of AI-supported learning. Longitudinal, multi-institutional, and mixed-methods research designs would be good next steps to further enhance the robustness, contextual depth, and generalisability of future research.

Research Gaps and Future Directions

The aim of a structured literature review is not only to review and synthesize the existing body of knowledge, but also to pinpoint areas of research that are lacking in the field and may inspire subsequent research. The theoretical approaches, research variables, AI tools, and methodological techniques used in the 35 empirical studies selected were

analysed to see if there were any recurring limitations and underexplored areas. These gaps offer some great opportunities to enhance the theoretical underpinning, methodological sophistication, and knowledge of AI adoption and utilisation among university students, as summarised in Table 7.

Table 7
Research Gaps and Future Research Directions

Research Gap	Evidence from the Literature	Future Research Directions
Dominance of technology acceptance perspectives	Most studies adopted technology acceptance models such as TAM and UTAUT and its related technology adoption models, with the emphasis on behavioural intention and system use.	Implement pedagogical, psychological, ethical and organisational theories into more holistic models of explaining the use of AI in higher education.
Overreliance on ChatGPT	With ChatGPT being the main AI tool studied, and a few studies examining other emerging AI tools such as NotebookLM, Claude, DeepSeek, and Microsoft Copilot.	Make comparative studies of different AI tools and their differential effects on learning, collaboration, creativity and academic performance.
Limited examination of long-term educational outcomes	Many studies focused on perceptions, intention to use, or short-term learning outcomes rather than sustained educational impact	Examine long-term educational outcomes of AI use, not just immediate learning outcomes or intentions to use.
The lack of attention to ethical elements in the use of AI	The use of ethical considerations (academic integrity, bias, transparency, privacy, responsible AI practices) was discussed in relatively few studies.	Create AI adoption research frameworks that incorporate ethical AI literacy, responsible AI use, and academic honesty/institutional governance.
Methodological imbalance	The majority of literature was conducted in a cross-sectional quantitative survey design, with limited literature from other designs that were either longitudinal or experimental or qualitative.	Use longitudinal, mixed-methods, experimental and multi-case study designs to gain in-depth knowledge on the processes of AI adoption and AI learning over time.
The lack of geographical and institutional variation in studies	Many studies were carried out in just one university or a specific country, which makes the results less generalizable.	Increase the number of institutions, countries and cultural contexts in which research is conducted, to allow for cross-cultural comparisons and enhance external validity.
Lack of integrated conceptual models	The lack of integrated conceptual models, indicative of most studies, was the case where only one particular aspect of technological, educational, behavioural and ethical factors was focused on.	Create seamless conceptual schemes which take into account the attributes of the learners, the educational results, the characteristics of the technology and the institutional support.

Discussion

The findings of this review are broadly consistent with previous reviews of artificial intelligence in higher education, while also providing a more focused picture of empirical research involving university students. One of the findings is the continued prominence of technology acceptance perspectives, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). This finding aligns with Baig and Yadegaridehkordi (2024), who identified technology adoption and usage as important areas in the higher education literature on ChatGPT. However, the present review also shows that researchers are increasingly drawing on behavioural and learning-oriented perspectives, including the Theory of Planned Behaviour, Social Cognitive Theory,

Constructivism, and Experiential Learning Theory. This theoretical diversity is important because Xu and Thien (2026) similarly identified theoretical fragmentation as an ongoing characteristic of AI research in higher education.

The research focus on ChatGPT also aligns with past reviews. Baig and Yadegaridehkordi (2024) reported that the use of ChatGPT is growing rapidly in the higher education sector, and even with the rise of multimodal applications, text-based ones are still quite popular, as Qian (2025) noted. The current review echoes these insights and further explores the topic through empirical research with university students across various AI tools. While tools like Gemini, Microsoft Copilot, Claude, DeepSeek, and NotebookLM are gaining traction, they are not as prevalent in the reviewed empirical literature. This imbalance indicates that the evidence base for the use of AI by students is still heavily dependent on evidence produced by ChatGPT and other AI-based text generation tools.

The research variable matrix also shows this focus on technology adoption and students' experiences. The most commonly explored was that of student perceptions and user experience, followed by technology acceptance and adoption. This is similar to previous research that explored students' acceptance, perception, and experience of generative AI. Simultaneously, significant focus on learning outcomes, ethical and responsible use of AI, AI literacy, and behavioural and psychological aspects was found in the present review. This is a wider range of variables, which reflects Qian's (2025) finding that the study has started to include pedagogical variables like creativity, critical thinking, autonomous learning, and digital literacy. Likewise, Abdallah et al. (2025) showed that research with ChatGPT extends beyond adoption to include academic achievement, learning, well-being, collaboration, and ethical issues.

Methodologically, the overwhelming weight of quantitative research in the present review also reflects issues found in the broader literature. There were 15 quantitative, nine mixed-methods, seven experimental/quasi-experimental, three qualitative and one design-based study. There was a strong representation of survey-based and multivariate methods, suggesting much of the empirical literature continues to focus on measuring relationships between constructs related to acceptance, behavioural and learning constructs. This is significant given Xu and Thien (2026) who noted methodological homogeneity as an ongoing challenge in higher education AI research. However, the number of mixed-methods and experimental studies reviewed here suggests that the study of AI-supported learning has also started to explore beyond the cross-sectional perceptions and behavioural intentions.

The comparison with the earlier reviews indicates continuity and one might argue an incremental extension of scope across the field. The literature still predominantly focuses on technology acceptance, ChatGPT, student perceptions, and quantitative approaches. Meanwhile, the evidence examined here shows a greater focus on learning outcomes, AI literacy, responsible AI use, psychological factors, and other methodological approaches. The review does not offer anything new, as many have previously pointed out, but rather a mix of ChatGPT, pedagogical use of generative AI, or the wider education sector of AI. The present review builds on this literature by focusing on empirical research with university students and by considering theoretical approaches, research variables, and methodologies within a common analytical framework. The synthesis suggests that researchers should not only create more studies on AI acceptance but also expand the theoretical, technological, and methodological perspectives to comprehend students' use of AI in higher education.

Next, the synthesis shows that much of the research on AI tools in higher education has followed two technology acceptance theories: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). While these models have made significant strides in understanding students' intentions to use AI technologies, they offer only a partial picture of AI's educational implications. Pedagogical, behavioural, psychological, ethical, and organisational approaches should thus be combined in future research to create more explanatory models. Another significant shortcoming is the focus on ChatGPT alone. The other generative AI platforms, such as Gemini, Microsoft Copilot, Claude, DeepSeek, or NotebookLM, have received less scrutiny than ChatGPT. Comparative studies on a variety of AI platforms would offer a more comprehensive perspective of their strengths, weaknesses, and potential uses in education, considering how quickly generative AI technologies are changing.

The review also shows that the existing literature has concentrated on students' perceptions, behavioural intentions and short-term learning outcomes. Fewer studies focus on the long-term educational impact of AI, such as its effects on critical thinking, creativity, academic integrity, employability, and lifelong learning skills. Longitudinal studies could

help to better understand the impact of AI on students' learning over time and their educational growth. In terms of methodology, cross-sectional quantitative survey designs are still predominant in the literature. While these methods provide valuable analysis of relationships between variables, they do not provide a deep understanding of students' interactions with AI technologies in real educational environments. More evidence could be collected using longitudinal, mixed-methods, experimental, and multi-case study designs, which would provide more depth to the evidence, merging measurable outcome evidence with the context of AI-supported learning.

The review further highlights the need for greater geographical and institutional diversity. Many studies were limited to a single university or nation, so their findings were not generalizable. To better capture how context shapes AI adoption in diverse learning settings, cross-cultural and multi-institutional studies would help establish external validity and contribute to a fuller understanding of this issue.

Conclusion

The objective of the present structured literature review was to provide an overview of the available literature regarding the use of artificial intelligence (AI) tools among university students, and to synthesise 35 empirical research papers published from 2022 to 2026. The results show that there is a substantial increase in scholarly interest in the adoption of AI in higher education, with ChatGPT being the most studied platform. Prior studies have mainly explored the acceptance of technology, learning outcomes, and students' perceptions using mostly quantitative, cross-sectional research designs, and theories like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

The review also revealed a number of gaps in research, such as the lack of use of various theories in the application, weak consideration of factors like AI literacy and responsible use of AI, and the continued use of cross-sectional quantitative designs in single institutional and national contexts. This review offers a holistic view of the present state of AI research in higher education by summarizing the trends in publications, theoretical frameworks, research variables, methodological strategies, and potential areas for future research into AI in education. The findings are relevant to those who work with AI technologies in higher education teaching and learning, including both teachers and researchers, as well as policymakers who aim to promote effective, responsible, and sustainable use of AI in such work and learning.

Limitations

Several limitations constrain the interpretation of this review's results. One drawback of the literature search is that only the Scopus database was used. While Scopus covers a wide range of peer-reviewed academic literature, some relevant studies might not have been indexed in the database. These 35 studies are therefore not necessarily representative of all research on AI tools with university students. Second, only English-language publications were considered. This criterion may have made it difficult to include empirical research in other languages, especially research in contexts outside of the English-speaking world. Therefore, the geographical and cultural diversity reflected in the review might be less rich than the wider international literature.

Third, the search was limited to selected Scopus subject areas, particularly Social Sciences and Business, Management and Accounting. While these subject areas were consistent with the educational and behavioural focus of the review, relevant studies indexed under other disciplines, such as Computer Science, Engineering, Psychology, or Health Sciences, may not have been included. These limitations may affect the completeness and generalisability of the findings. Future reviews could therefore expand the search across multiple databases, include a broader range of subject areas, and consider publications in languages other than English to provide a more comprehensive understanding of AI use among university students.

Conflict of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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