Dahri & Al-Rahmi *Research and Practice in Technology Enhanced Learning* (2027) 22:28
https://doi.org/10.58459/rptel.2027.22028

Research and Practice in Technology Enhanced Learning

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Artificial intelligence adoption in education: A systematic review of trends, theoretical models, and influencing factors (2021-2025)

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Abstract

The integration of Artificial Intelligence (AI) in education is rapidly transforming teaching and learning practices; however, its adoption remains challenging and is influenced by multiple technological, behavioral, and contextual factors. This study conducts a systematic literature review (SLR) following the PRISMA 2020 framework to synthesize empirical research on AI adoption in educational settings. A total of 153 peer-reviewed journal articles published between 2021 and 2025 were analyzed to examine research trends, theoretical foundations, key influencing factors, applications, and emerging directions in the field. The findings reveal a substantial growth in AI adoption research, particularly after 2023, driven by the emergence of generative AI technologies such as ChatGPT. The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) dominate the theoretical landscape, collectively underpinning the majority of studies. Core determinants of AI adoption include perceived usefulness, perceived ease of use, performance expectancy, trust, and behavioral intention, highlighting the continued reliance on established information systems (IS) frameworks. The results also show that research is heavily concentrated in higher education contexts, with students as the primary participants and a strong dominance of quantitative methodologies. In terms of applications, generative AI tools, particularly ChatGPT, represent the most widely studied technologies, reflecting a shift toward interactive and content-generating systems in education. Despite these advancements, significant gaps remain, including limited geographical diversity, underrepresentation of educators and institutional stakeholders, and insufficient focus on qualitative insights, ethical considerations, and long-term learning outcomes.

Keywords: artificial intelligence in education, AI adoption, technology acceptance model (TAM), UTAUT, generative AI, ChatGPT, systematic literature review

Introduction

Artificial intelligence in education (AIE) has recently emerged as a prominent and influential field, playing a transformative role across diverse sectors and industries, including education (Khan & Alamäki, 2023). Artificial intelligence (AI) has potentially addressed various global challenges and opportunities within the field of education (Ahmad et al., 2021; Khan, 2023). It can enhance access, quality, equity, personalization, and lifelong learning while creating more effective, personalized and inclusive learning environments (Ahmad et al., 2021). Several applications of AI in education are currently being explored, such as adaptive(K. Li, 2023), personalized learning (Zacharis & Nikolopoulou, 2022), teaching metacognitive skills (Khan & Alamäki, 2023), critical thinking and problem-solving skills (Khan & Alamäki, 2023), curriculum development (ChengmingZhang et al., 2023), Instructional Planning, Assessment, and evaluation (Khan & Alamäki, 2023). Many scholars are searching for how AI generative tools can teach students and teachers metacognitive skills (Khan & Alamäki, 2023). Metacognitive skills help learners to become lifelong learners(Mahdavi, 2014). AI applications in education also support and meet the various needs and diverse skills required by students and help overcome the different learning disabilities; However, a comprehensive educational framework capable of fully addressing diverse learner needs across all levels is still lacking(Bilquise et al., 2023; Ragheb et al., 2022). This is where generative AI becomes very helpful; generative AI generates multiple representations of teaching content and creates alternative assessment methods (Salas-Pilco et al., 2022). For example, some students want to learn through visual aids or audio, and several AI applications can transform text-based content into visuals or illustrations; AI applications also provide automatic captioning and sign language interpretations for auditory learners(Khan & Alamäki, 2023). AI also helps students convert text-based content into audiovisuals, lectures, and presentations(Chatterjee & Bhattacharjee, 2020). ChatGPT has emerged as a widely used AI tool supporting teaching and learning activities, a scaffolding that students and teachers use nowadays in education. It works for teachers as mentors and supports the development of lesson plans, activities, and worksheets (Foroughi et al., 2023).

Numerous applications are being used for educational purposes; another application of AI-driven search engines is widely used to find more precise and accurate information for preparing lectures, assignments, and research projects (Zawacki-Richter et al., 2019). These tools facilitate the identification and synthesis of relevant literature, more connected studies, and compare studies with authentic and reliable sources. Likewise, numerous other AI applications are used to summarize long articles, research studies, books, and teaching content materials into more precise and informative forms (Khan, 2023).

Another important application of AI technology in education is for assessment and feedback; for example, ChatGPT can be trained and provided with sufficient information about students, course level, course learning outcomes, course content, and other relevant materials, and asked to create several course projects, assignments, and quizzes based on different groups of students and course objectives (Lai et al., 2023; Rahim et al., 2022). Then, students can also get help from AI applications to get the proper solution for these projects, assignments, and quizzes with the support of a real-time AI-based assistance guide (Bilquise et al., 2023). AI has empowered students to learn at their own pace by providing personalized and adaptive courses, AI-based support, and feedback(Bilquise et al., 2023). For example, learners can choose the most suitable course, content, and learning methods for their desired skill set (Pan et al., 2023). AI applications can also support learners via AI-based mentoring and coaching solutions. It helps the learners to develop 21st-century skills(Al-Abdullatif, 2023; Pan et al., 2023).

There are various other applications of AI in education currently being designed by many countries for education purposes, such as Singapore, Malaysia, and South Korea (Ahmad et al., 2021). Singaporean companies have developed education-specific agents that target learners of various groups, providing answers to education questions for that age group. Likewise, a Chinese company also developed an LLM specific to education, providing teaching courses, various career counseling support, and emotional support to students; another company developed a large mathematics GPT for solving significant mathematical problems (K. Li, 2023). AI has dramatically changed classrooms and labs. Teachers, students, parents, and AI experts can work together. We must design more specific platforms based on institutional needs(Chang et al., 2023).

Furthermore, the adoption of generative AI in education has gained significant attention in recent years, supported by the application of established theoretical frameworks. Models such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) have laid the conceptual foundation for understanding users' acceptance and adoption of emerging technologies. In the context of education, these models have been widely employed to examine factors influencing the adoption of AI tools, particularly in relation to user perceptions, behavioral intention, and system usability (Chen et al., 2023; Choudhury & Shamszare, 2023). In addition to TAM and UTAUT, other theoretical perspectives, including the Theory of Planned Behavior (TPB), Social Cognitive Theory (SCT), Task–Technology Fit (TTF), and motivation-based models, have been applied to explore specific aspects of AI adoption in educational settings. However, the application of these frameworks remains fragmented, and there is a lack of comprehensive synthesis that integrates these theoretical approaches within the rapidly evolving landscape of generative AI in education.

While existing reviews have contributed significantly to our understanding of AI in educational research, their scope remains limited. Previous studies have predominantly focused on areas such as academics' interaction with AI tools, AI-driven learning outcomes, and learners' self-regulation in AI-supported environments. Additionally, a substantial portion of the literature emphasizes technical aspects of AI, addressing system-level challenges and solutions. However, the adoption of AI technologies in education has emerged as a critical area of research in recent years, requiring a more comprehensive synthesis of influencing factors. In this context, this study incorporates a thematic and bibliometric analysis of constructs to provide deeper insights into the evolving structure and focus of AI adoption research in education.

In contrast, this study distinguishes itself by aiming to systematically examine AI research studies in the education domain through the lens of IS theories/models. The main objective is to provide an extensive resource that enables researchers to conduct additional studies on adopting AI technologies in education. By examining AI technology adoption from both an organizational and an individual standpoint, this study seeks to provide a comprehensive overview of the research conducted from 2021 to 2025.

To address these gaps, the present study systematically reviews and synthesizes articles on AI in education, focusing on IS theoretical models. The scope of this research extends beyond the analysis of IS theories or models, including examining countries actively engaged in the field, various categories of samples, efficient technologies, and research approaches. The formulation of specific investigation questions has provided direction for the study's objective:

- RQ1: What are the latest trends in published articles on AI in education across different years, in journals, countries, and education levels?
- RQ2: How is the distribution of AI in educational studies characterized in terms of sample types and significant research methods?
- RQ3: What are the various applications of AIE settings, and what AI tools are used for education purposes?
- RQ4: What models or theories are commonly employed, and what measures are taken to assess the acceptance or adoption of AI technologies in education, and what key factors influence their adoption and categorical significance?
- RQ5: What are the limitations of new research on AI in education, and what are the future research directions?

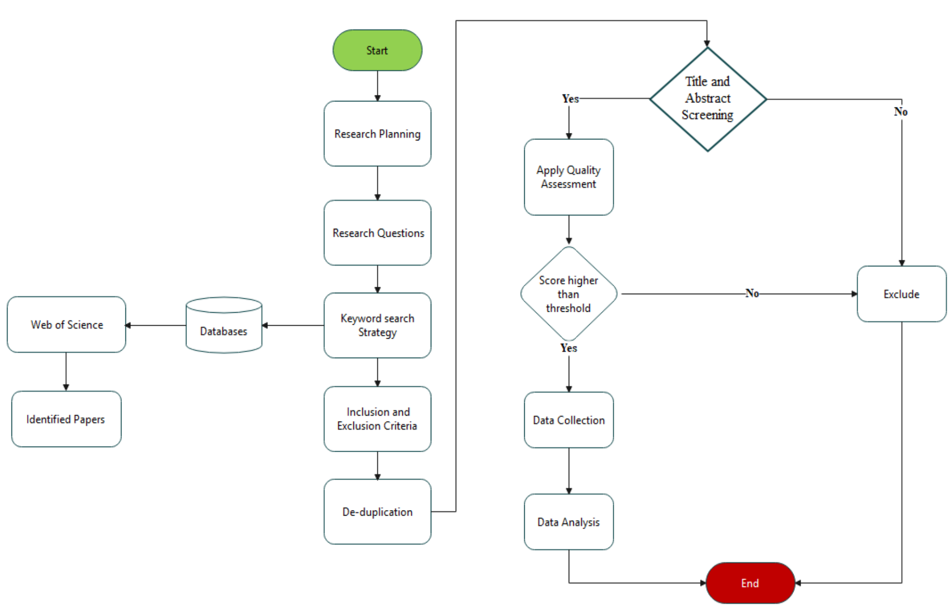
By addressing these research questions, this study aims to comprehensively analyze the state of AI in education technologies, providing insights into publication trends, global distribution, methodological approaches, and overarching research objectives. The findings will offer valuable perspectives for educational stakeholders seeking to navigate the dynamic landscape of AI integration in educational settings.

Methodology

This study employed a systematic literature review (SLR) approach to synthesize empirical research on the adoption and acceptance of artificial intelligence (AI) technologies in educational settings. The review followed established guidance for conducting systematic reviews, particularly the recommendations of Keele (2007), and adopted the PRISMA 2020 framework to ensure transparency and reproducibility in study identification, screening, eligibility assessment, and inclusion. The review process was designed to be methodical and protocol-driven, using predefined criteria to identify relevant studies and minimize selection bias. The methodology followed a systematic literature review (SLR) approach consisting of six structured stages, as illustrated in Figure 1. These stages include: (1) review protocol development, encompassing research planning and formulation of research questions; (2) definition of inclusion and exclusion criteria; (3) database search and keyword search strategy using the Web of Science database; (4) study screening and selection, including de-duplication and title and abstract screening; (5) quality assessment of eligible studies based on predefined criteria; and (6) data extraction and synthesis, involving data collection and analysis. This structured process ensured a rigorous and transparent selection of studies, allowing for a comprehensive examination of empirical research on AI adoption in education. Particular attention was given to studies grounded in information systems (IS) and technology acceptance theories, ensuring consistency with the theoretical focus of the review.

Figure 1

Systematic literature review approach



Inclusion/exclusion criteria

Explicit inclusion and exclusion criteria were developed to ensure that only studies directly relevant to the review objective were retained. The criteria were designed to capture empirical studies that examined the adoption or acceptance of AI technologies in educational contexts and that employed an IS-related theoretical model or framework.

Table 1

Inclusion and exclusion criteria for AI in education context

Inclusion criteria	Exclusion criteria
a. The study examines the acceptance, adoption, use intention, actual use, or continuance intention of AI technologies in education.	a. Dissertations, theses, and other unpublished academic work.
b. The study uses an information systems (IS), technology acceptance, or related theoretical model/framework (e.g., TAM, UTAUT, UTAUT2, TPB, DOI, SCT, TTF).	b. Preprints, unpublished manuscripts, and non-peer-reviewed studies.
c. The study is conducted in an educational context, including schools, colleges, universities, or other formal educational institutions.	c. Book chapters, editorials, commentaries, conference abstracts, and opinion papers.
d. The study is a peer-reviewed journal article.	d. Studies not focused on AI adoption/acceptance in education.
e. The study is published in English.	e. Studies that do not apply a relevant theoretical model or framework.
f. The study was published between 2020 and 2025.	f. non-English studies.

These criteria helped maintain methodological consistency and ensured that the selected studies aligned with the review scope, namely, AI adoption and acceptance in education through the lens of IS and technology acceptance research.

Sources of data and search methods

To address the rapid growth of AI-related research in education, the search was updated to include studies published between 2020 and 2025. The primary database used for this review was the Web of Science (WoS) Core Collection, selected because of its multidisciplinary coverage, strong indexing standards, and suitability for transparent and reproducible systematic review procedures. The search strategy was derived from the review questions and the conceptual scope of the study. Specifically, the search terms were organized around four concept blocks: (1) AI technologies, (2) educational context, (3) adoption and acceptance behavior, and (4) IS and technology acceptance theories. The final Boolean search string was as follows:

("artificial intelligence" OR AI OR "generative AI" OR "GenAI" OR ChatGPT OR chatbot* OR "intelligent tutoring system*" OR "AI-based system*" OR "AI tool*" OR "AI application*" OR "large language model*" OR LLM*) AND (education OR "higher education" OR university* OR college* OR school* OR "secondary education" OR "primary education" OR classroom* OR learning OR teaching) AND (adoption OR acceptance OR "behavioral intention" OR "intention to use" OR use OR usage OR "actual use" OR "continuance intention" OR readiness) AND ("Technology Acceptance Model" OR TAM OR UTAUT OR UTAUT2 OR "Unified Theory of Acceptance and Use of Technology" OR "Theory of Planned Behavior" OR TPB OR "Diffusion of Innovation" OR DOI OR "Social Cognitive Theory" OR SCT OR "Task-Technology Fit" OR TTF OR "acceptance model*" OR "adoption model*" OR "Information Systems model*")

The initial search returned 2,082 records. After restricting the time span to 2021–2025, 1,691 records remained. Filtering by document type (articles) reduced the results to 1,479, and restricting the language to English reduced the dataset to 1,466 records. Applying filters relevant to the educational domain resulted in 302 records. These records were exported in RIS format for screening. One retracted article was identified and removed during data cleaning, leaving 301 records for title and abstract screening. In addition to the database search, a backward reference check was conducted on the full-text articles selected for eligibility assessment to identify any potentially relevant studies not retrieved in the initial search. Any additional records identified through manual checking were screened using the same inclusion, exclusion, and quality assessment criteria.

Selection process

The study selection process followed the PRISMA 2020 guidelines. Figure 2 presents the PRISMA flow diagram summarizing the identification, screening, eligibility, and inclusion stages. The WoS search and filtering process resulted in 301 records for title and abstract screening after the removal of one retracted article. In the first screening stage, records were excluded if they did not focus on AI adoption or acceptance in education, were not conducted in educational settings, were not published as peer-reviewed journal articles, or did not employ a relevant theoretical model. The remaining studies were then assessed in full text against the predefined inclusion and exclusion criteria shown in Table 1. During this eligibility stage, studies were excluded for reasons such as lack of theoretical grounding, absence of an AI adoption focus, non-educational context, insufficient methodological detail, or failure to meet the review’s publication criteria. After full-text screening, the eligible studies underwent quality assessment. The final number of studies included for synthesis was 153.

Assessment of quality

The methodological quality of the eligible studies was assessed using criteria adapted from Kitchenham (2004). The purpose of this step was to ensure that only studies with sufficient conceptual clarity and methodological rigor were included in the final synthesis. Each study was assessed using four quality questions:

1 Does the article clearly identify or explain the AI technology examined?

2 Does the study explicitly address AI use, adoption, or acceptance in an educational context?

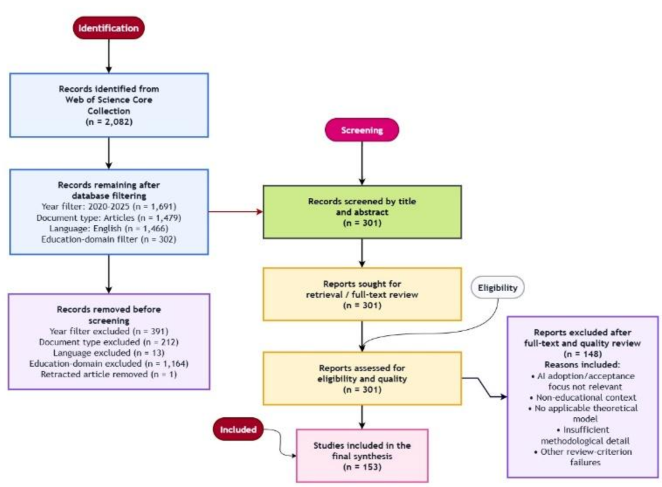
3 Is the study an empirical peer-reviewed research article?

4 Does the study clearly report its research method?

Each criterion was scored as 2 for full compliance, 1 for partial compliance, and 0 for non-compliance. The quality scores were then used to classify studies as high, medium, or low quality. Studies that did not meet the minimum quality threshold were excluded from the final synthesis. One retracted article identified during screening was removed before quality assessment to preserve the integrity of the evidence base.

Figure 2

Research studies selection Process via PRISMA



Data extraction and synthesis (coding and analysis of data)

A structured coding framework was developed to systematically extract and synthesize data from the included studies. The coding scheme captured the following dimensions: (i) year of publication, (ii) journal name, (iii) country or region of the study, (iv) sample size, (v) participant type (e.g., students, teachers, faculty, or mixed groups), (vi) research method (quantitative, qualitative, experimental, or mixed methods), (vii) theoretical model or framework applied, (viii) constructs or factors examined, (ix) AI technology investigated (e.g., ChatGPT, generative AI tools, chatbots, or AI-based systems), (x) research purpose (e.g., adoption, teaching and learning, assessment, or outcomes), and (xi) application domain (e.g., higher education, school education, medical education, or STEM). The extracted data were analyzed using descriptive and comparative techniques to identify patterns in publication trends, geographical distribution, methodological approaches, theoretical foundations, participant characteristics, AI technologies, and research purposes. This process facilitated a comprehensive understanding of the factors influencing AI adoption in education and supported the identification of research gaps, methodological limitations, and future research directions.

Data analysis techniques and tools

The analytical framework was designed to systematically address the study's research questions. A combination of a descriptive statistical technique, bibliometric, and thematic mapping techniques is used to analyse the overall AI adoption research in education. All data preprocessing and data organization were performed with the help of Ms. Excel where studied information was decoded. Statistical analysis which consists of frequency distribution and percentage was done to (specifically) observe the trends in publication year, country of publication, method used, theory used. Also, bibliometric and thematic analysis was performed using VOSviewer (Version 1.6.18). to identify dominant research themes, relationships among constructs, and emerging trends in AI adoption literature researcher used keyword co-occurrence, thematic mapping and network visualization techniques.

Results

This section presents the findings derived from the systematic analysis of 153 peer-reviewed studies on artificial intelligence in education published between 2021 and 2025. The results are organized according to the specific research questions mentioned earlier. This analysis examines empirical studies that use IS theories or technology acceptance models and sees a number of facets including but not limited to trend in publications, geography of authorship, methodology, participant description, AI technology used, theory, and key factors in the adoption of AI in education.

RQ1: What are the latest trends in published work on AI in education across different years, journals, countries, and education levels?

Research study distribution by year of publication

The distribution of studies by publication year demonstrates a rapid and significant growth in research on artificial intelligence in education, as shown in Table 2 and Figure 3. Out of the 153 included studies, only a minimal number were published in the early years, with 2 studies (1.3%) each in 2021 and 2022. The number of publications increased notably in 2023 to 16 studies (10.5%), followed by a substantial rise in 2024 with 37 studies (24.2%). The highest concentration of studies was observed in 2025, accounting for 96 studies (61.4%). This sharp upward trend highlights the accelerating scholarly interest in AI adoption in education, particularly driven by the emergence and widespread use of generative AI technologies in recent years.

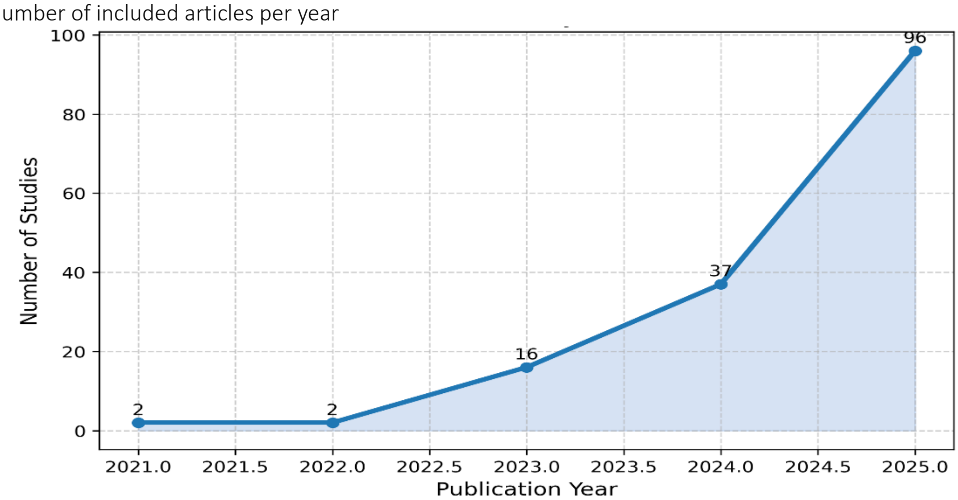
Table 2

Distribution of included studies by publication year (N = 153)

Publication Year	Number of Studies (N)	Percentage (%)
2021	2	1.3%
2022	2	1.3%
2023	16	10.5%
2024	37	24.2%
2025	96	61.4%
Total	153	100%

Figure 3

Number of included articles per year



Research Study Distribution by Journal

The distribution of studies across journals highlights the interdisciplinary nature of AI in education research, as details are summarized in Table 3. The highest number of publications appeared in Computers & Education: Artificial Intelligence (n = 25, 16.3%), followed by Frontiers in Education (n = 17, 11.1%). Journals such as Cogent Education and Education and Information Technologies each contributed 13 studies (8.5%), while Education Sciences accounted for 12 studies (7.8%). Other notable contributions came from BMC Medical Education and the International Journal of Educational Technology in

Higher Education, each with 5 studies (3.3%). A large proportion of studies (36.6%) were distributed across a wide range of other journals, indicating the broad and interdisciplinary interest in AI applications within education. This dispersion reflects the expanding scope of the field across multiple academic domains.

Table 3

Top publishing journals in AI in education research (N = 153)

Rank	Journal Name	Number of Studies (N)	Percentage (%)
1	Computers & Education: Artificial Intelligence	25	16.3%
2	Frontiers in Education	17	11.1%
3	Cogent Education	13	8.5%
4	Education and Information Technologies	13	8.5%
5	Education Sciences	12	7.8%
6	BMC Medical Education	5	3.3%
7	International Journal of Educational Technology in Higher Education	5	3.3%
8	Australasian Journal of Educational Technology	4	2.6%
9	JMIR Medical Education	3	2.0%
—	Other Journals (combined)	56	36.6%

Geographical dispersion of research studies

Table 4 presents the geographical distribution of studies, revealing that the majority of research on AI in education is conducted within single-country contexts, accounting for 104 studies (68.0%). A smaller proportion of studies (5.2%) involve multi-country collaborations, reflecting limited cross-national research efforts. Notably, a substantial number of studies (29.4%) did not clearly specify their geographical context or were categorized as not applicable or unclear. This indicates a significant reporting gap in the literature, which may limit the generalizability and contextual interpretation of findings across different educational systems.

Table 4

Summary of geographical distribution of studies (N = 153)

Category	Number of Studies (N)	Percentage (%)
Single-country studies	104	68.0%
Multi-country studies	8	5.2%
Unspecified / Not reported	45	29.4%

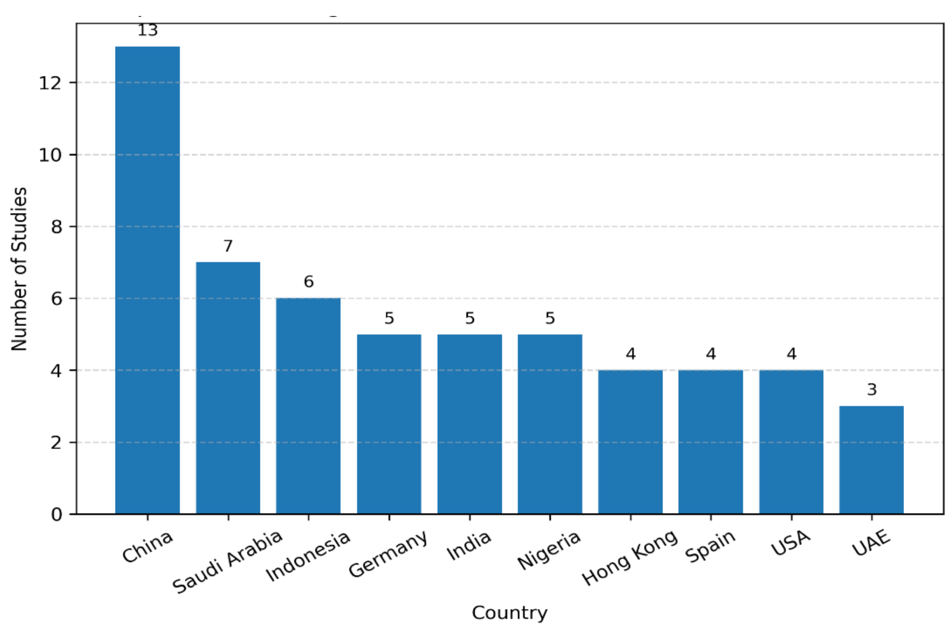
In a major geographical analysis, the top contributors were analysed distinctly as shown in Table 5 and Figure 4. Results show with 13 studies (8.5%) China dominates the research output, followed by Saudi Arabia with 7 studies (4.6%) and Indonesia with 6 studies (3.9%). Germany, India, and Nigeria each accounted for 5 publications (3.3%) whereas Hong Kong, Spain, and the USA contributed 4 publications (2.6%). The UAE made 3 contributions (2.0%). The study suggests that educational data-based research is concentrated in limited countries with a large part contribution from developed and developing world. Educational institutions across the world are showing increased interest in AI implementation and adoption, more so in Asia and Middle East.

Table 5

Top 10 contributing countries in AI in education research (N = 153)

Rank	Country	Number of Studies (N)	Percentage (%)
1	China	13	8.5%
2	Saudi Arabia	7	4.6%
3	Indonesia	6	3.9%
4	Germany	5	3.3%
5	India	5	3.3%
6	Nigeria	5	3.3%
7	Hong Kong	4	2.6%
8	Spain	4	2.6%
9	USA	4	2.6%
10	UAE	3	2.0%

Figure 4
Top 10 contributing countries in AI in education research



Research studies distributed by education level

Table 6 presents the distribution of studies across educational domains, showing a strong concentration in higher education. The majority of studies (n = 94, 61.4%) were conducted in higher education settings, indicating that universities are the primary context for AI adoption research. School-level education accounted for 13.1% of studies, while teacher education contributed 8.5%. Medical and healthcare education represented 6.5% of the studies, reflecting the growing integration of AI in specialized professional training. Language education and learning contexts accounted for 5.2%, while STEM education was relatively underrepresented at 2.0%. A small proportion of studies focused on other specialized domains such as arts, design, and computing education. These findings suggest that AI research in education is heavily concentrated in higher education, with comparatively limited exploration in primary, secondary, and specialized educational domains.

Table 6

Distribution of studies by educational domain (N = 153)

Educational Domain	Number of Studies (N)	Percentage (%)
Higher Education	94	61.4%
School Education	20	13.1%
Teacher Education	13	8.5%
Medical / Healthcare Education	10	6.5%
Language Education / Learning	8	5.2%
STEM Education	3	2.0%
Other Specialized Domains	5	3.3%

RQ2: How is the distribution of AI in education studies characterized in terms of sample types and significant research methods?

Research studies distributed by sample type

Table 7 shows the different types of participants in this research. Most of the research focused on students. Most of the studies (n 91, 59.5%) were with students which implies there is ample of emphasis placed on learners perspective toward AI issues. Out of the total studies undertaken, the largest share was based on teachers, educators, and faculty comprising 52 studies (34.0%). It shows that there is increasing interest in this area with extensive literature emerging about the involvement of educators in the adoption of AI. A smaller proportion of studies (4.6%) included mixed participants, i.e., students and students, to capture a wider perspective. Few studies (2.0%) focused on stakeholders or other specific professional context experts. The findings indicate that current research is strongly student-centred while much less consideration is provided for institutional actors and other stakeholders.

Table 7

Distribution of participant types in AI in education studies (N = 153)

Participant Category	Number of Studies (N)	Percentage (%)
Students	91	59.5%
Teachers / Educators / Faculty	52	34.0%
Mixed Participants	7	4.6%
Other / Specific Groups	3	2.0%

Research studies distributed according to research methods

The findings of research techniques indicate heavy prevalence of quantitative studies in AI in education research (Table 8). Out of 153 studies, most of them employed quantitative studies (n = 126, 82.4%) which made heavy use of statistical modelling techniques including SEM, PLS-SEM, and survey-based analyses. Fourteen studies (9.2%) employed mixed-methods approaches, combining quantitative and qualitative methods to enhance the breadth of the research outcomes. In contrast, the qualitative studies were limited (n = 6, 3.9%) indicating an underrepresentation of in-depth exploratory research. Of the total studies, 5 studies (3.3%) were experimental studies (randomised controlled trials), while 2 studies (1.3%) were conceptual or unclear methodology. To sum up, this study find that quantitative research designs are used comparatively more than qualitative research designs and experimental research designs.

Table 8

Distribution of research methods (N = 153)

Research Method Category	Number of Studies (N)	Percentage (%)
Quantitative	126	82.4%
Mixed Methods	14	9.2%
Qualitative	6	3.9%
Experimental	5	3.3%
Conceptual / Unclear	2	1.3%

RQ3: What are the various applications of Artificial Intelligence in Education environments, and which AI applications are utilized for learning?

Research studies distributed by type of AI technology used

Table 9 presents the analysis of AI technologies used in education, which reveals a strong dominance of generative AI tools. ChatGPT and related generative AI technologies accounted for the majority of studies (n = 86, 56.2%), highlighting their rapid adoption in educational contexts as depicted in Figure 5. General AI tools represented 27 studies (17.6%), while AI chatbot technologies accounted for 14 studies (9.2%). AI applications and system-based implementations contributed 11 studies (7.2%), reflecting broader system-level integration of AI in education. Additionally, specialized AI tools such as coding assistants, writing tools, and feedback systems accounted for 5.2% of studies. A smaller proportion of studies explored emerging or niche AI technologies (4.6%). These findings demonstrate that recent research is heavily concentrated on generative AI, particularly ChatGPT, indicating a significant shift toward conversational and content-generating technologies in educational environments.

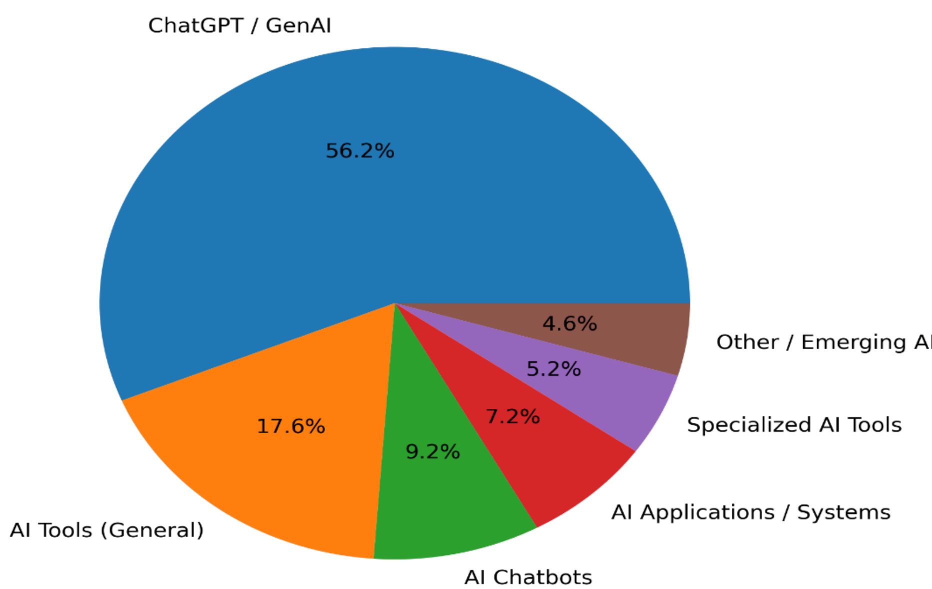
Table 9

Distribution of AI technologies in education studies (N = 153)

AI Technology Category	Number of Studies (N)	Percentage (%)
ChatGPT / Generative AI	86	56.2%
AI Tools (General)	27	17.6%
AI Chatbots	14	9.2%
AI Applications / Systems	11	7.2%
Specialized AI Tools	8	5.2%
Other / Emerging AI	7	4.6%

Figure 5

AI technologies in education studies



Research studies distributed by application of AI in education

As shown in Table 10, most studies assess artificial intelligence (AI) adoption and acceptance in an educational context. Of the 153 studies, 96 studies (62.7%) examined the factors that influenced the adoption, acceptance and/or use of AI technologies, confirming that the area with the most concentration is technology acceptance research. Further, 11.8% of studies were based on behavioral intention and usage patterns like continuance intention and actual use. Of the studies which made it to the sampling frame, 10.5% were on the Teaching and Learning applications of AI. A smaller number of studies looked at assessment & evaluation (5.2%), and the effects of AI on learning (3.9%). Only 3.3% of studies dealt with ethical matters, such as trust, risk, and integrity. Overall, the findings show that the bulk of the existing research focuses on adoption-related factors while learning outcomes, ethics, and classroom-based use are relatively neglected.

Table 10

Distribution of research purposes in AI in education studies (N = 153)

Research Purpose Category	Number of Studies (N)	Percentage (%)
AI Adoption & Acceptance	96	62.7%
Behavioral Intention & Usage	18	11.8%
Teaching & Learning Applications	16	10.5%
Assessment & Evaluation	8	5.2%
AI Impact on Learning Outcomes	6	3.9%
Ethics, Trust & Risk	5	3.3%
Other / Emerging Purposes	4	2.6%

RQ4: What models or theories are commonly employed, and what measures are taken to assess the acceptance or adoption of AI technologies in education, and what key factors influence their adoption and their categorical significance?

Commonly used models/theories to assess the acceptance or adoption of AI

The distribution of theoretical models used in AI in education research demonstrates a strong reliance on established technology acceptance frameworks. As illustrated in Figure 6, the major theoretical models include the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Planned Behavior (TPB), and their respective extensions. These models provide the conceptual foundation for examining user acceptance and behavioral intention toward AI technologies in educational contexts. As summarized in Table 11, among the 153 studies analyzed, the TAM family represents the most dominant theoretical foundation, accounting for 73 studies (47.7%), followed by the UTAUT family with 53 studies (34.6%). Together, these two model families account for more than 80% of the theoretical approaches used in the literature, highlighting the central role of user acceptance frameworks in AI adoption research. Other theoretical perspectives are used less frequently. The Theory of Planned Behavior (TPB) is applied in 6 studies (3.9%), while Social Cognitive Theory (SCT)-based models appear in 5 studies (3.3%). Additionally, models such as Diffusion of Innovation (DOI), Task-Technology Fit (TTF), and Expectancy-Value theory are each employed in a small proportion of studies (1.3% each). A small number of studies utilize other or hybrid models (3.9%), while 2.6% do not specify a theoretical framework.

Figure 6

Conceptual overview of major theoretical models used to examine AI adoption in education, including TAM, UTAUT, TPB, and their extensions

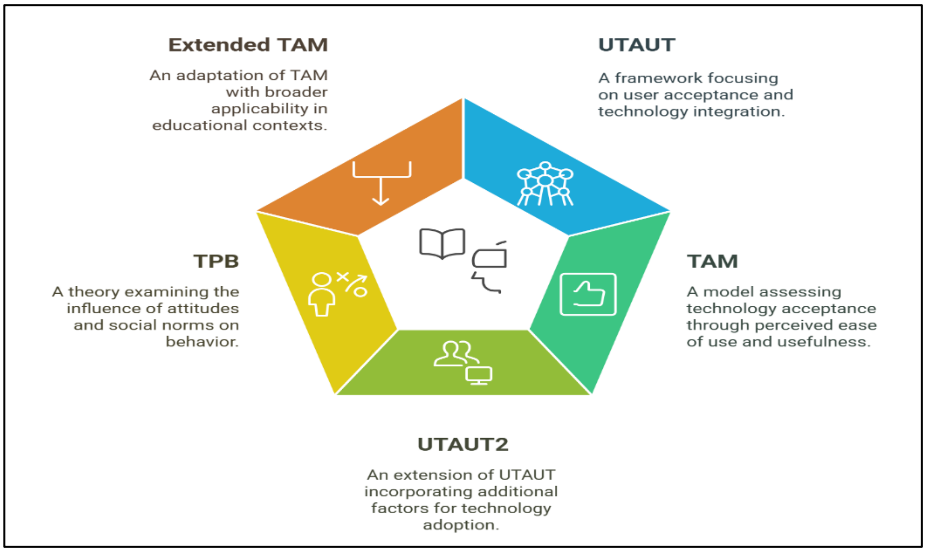


Table 11

Distribution of theoretical models used in AI in education studies (N = 153)

Category	Number of Studies (N)	Percentage (%)
TAM family	73	47.7%
UTAUT family	53	34.6%
TPB family	6	3.9%
SCT-based models	5	3.3%
DOI	2	1.3%
TTF	2	1.3%
Expectancy-Value models	2	1.3%
Other models	6	3.9%
None / Unspecified	4	2.6%

Understanding the factors driving the adoption and use of AI technologies like ChatGPT, AI bots, and other AI tools is important for enhancing their effectiveness in education (Foroughi et al., 2023). Identifying common needs and user behaviors helps refine these technologies and ensures their long-term value(Romero Rodríguez et al., 2023). Studying the theories and models used to evaluate AI adoption is essential for continuous improvement. The post-adoption stage of AI in higher education examines its usage and continuous intention. Studies using frameworks like UTAUT and TTF reveal factors such as performance expectancy and task-technology fit, influencing students' engagement with AI (Chatterjee & Bhattacharjee, 2020; Chen et al., 2023). Behavioral intention studies highlight willingness to adopt AI, with models like TAM, TPB, and SCT showing how perceptions and intentions drive AI adoption in education (AlGerafi et al., 2023; Foroughi et al., 2023; Maheshwari, 2023). Data collection often involves surveys or mixed methods, and analyses use tools like PLS-SEM, fsQCA, and AMOS (Romero Rodríguez et al., 2023; Strzelecki, 2023). Research also emphasizes technology acceptance, exploring attitudes and impacts of AI on learning outcomes using TAM and UTAUT (Al Shamsi et al., 2022; Bilquise et al., 2023; Huang et al., 2022) . These insights underline AI's potential to transform higher education through informed adoption and usage.

Factors are identified in studies on AI technology adoption in education?

The analysis of constructs extracted from the included studies provides a comprehensive overview of the key factors influencing the adoption of artificial intelligence (AI) in educational contexts. A total of 153 studies were examined, and their reported constructs were systematically synthesized and grouped into meaningful categories, as presented in Table 12. The findings reveal that constructs derived from established information systems (IS) models dominate the literature. In particular, core constructs from the Technology Acceptance Model (TAM), such as perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention (BI), are the most frequently examined factors. These constructs emphasize the importance of users' perceptions regarding the utility and ease of interaction with AI systems in shaping their adoption decisions.

Likewise, the constructs from the unified theory of acceptance and use of technology (UTAUT), including performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and hedonic motivation (HM), are common in the studies. The results suggest that performance-related expectations and system usability significantly impact the behaviour of individuals adopting AI in education. Along with the aforementioned major theoretical constructs, a myriad of psychological and emotional concepts like motivation, trust, anxiety, and enjoyment were commonly mentioned. Trust is a particularly critical factor that reflects users' concerns regarding the reliability, transparency, and ethics of AI systems. On the contrary, anxiety and perceived risk are barriers to adoption. Moreover, technology-related factors like AI literacy, system quality, compatibility, and perceived accuracy showcase users' technical capability and the system performance for adoption. Many studies have also compiled educational factors, including learning outcomes, engagement and academic performance, displaying rising trend for assessing AI technologies on pedagogical practice.

Various ethical and contextual considerations like privacy, academic misconduct, and institutional backing were also seen, indicating the need for responsible and context-aware integration of AI. Recently, continued use and long-term engagement with AI systems has become the focus of research adopting post-adoption constructs such as satisfaction and continuance intention. The results show that the use of AI in education is influenced by a multi-faceted and multi-dimensional set of technological, psychological, pedagogical and ethical factors. This emphasizes the need for a holistic approach in the design and implementation of AI-based education systems.

Table 12

Key Constructs Identified in AI Adoption Studies (N = 153)

Category	Construct	Frequency
Core Acceptance (TAM)	Perceived Usefulness (PU)	52
	Perceived Ease of Use (PEOU)	49
	Behavioral Intention (BI)	41
	Attitude	34
	Social Influence (SI / SN)	32
UTAUT-Based Factors	Performance Expectancy (PE)	36
	Effort Expectancy (EE)	30
	Facilitating Conditions (FC)	22
	Hedonic Motivation (HM)	18
	Habit	14
Psychological Factors	Motivation	21
	Trust	28
	Anxiety	17
	Enjoyment	15
	Self-efficacy	19
	Risk	14
Technology Factors	AI Literacy / Knowledge	12
	Compatibility	6
	Relative Advantage	5
	Complexity	3
	Accuracy / Information Quality	6
Educational Factors	Learning Outcomes / Performance	8
	Academic Performance	5
	Engagement	7
	Critical Thinking	3
Ethical & Contextual	Ethics	12
	Privacy	4
	Academic Integrity	3
	Institutional Support	6
Usage & Continuance	Satisfaction	14
	Continuance Intention	11
	Actual Use	9
	Expectation Confirmation	3

Thematic analysis of constructs in AI adoption research

A bibliometric and thematic analysis using visualisation techniques, as depicted in Figures 7–11, was performed to enhance the grasp of construct distribution and thematic coverage among the studies reviewed. The visualizations provide an overview of the various themes, their relationships and how they evolved with time. The treemap visualization in Figure 7 represents the major themes in the literature according to their frequency. The findings explicitly reveal that the Technology Acceptance Model (TAM) constitutes the most significant theme, followed by information technology and artificial intelligence. The prevalence of TAM and related concepts in AI adoption literature indicates strong theoretical support (from established streams of IS research). These findings suggest a continued tendency among researchers to employ acceptance models for examining user behavior toward AI technologies in education. The literature on users' positive perception of AI and/or their willingness to accept AI systems is mostly concentrated on user acceptance, adoption and behavioural intention constructs, among others. This illustrates the fact that most of the studies are focusing on the impact of different factors that are affecting the intention to adopt and use AI technologies rather than their use and effectiveness. The rise of ChatGPT and generative AI as major themes marks a recent shift in research focus. This trend shows that more people are interested in advanced AI technologies such as large language models for educational purposes. The trend of higher education being the dominant theme, suggest that universities remain the most common context for studying AI adoption, with comparatively less attention to primary and secondary education. In addition, the treemap depicts the interconnectedness of themes like technology, model, adoption, among others, showing that AI research in education is highly intertwined. The coexistence of technological, behavioral, and contextual themes underscores the complexity of AI adoption, which is influenced by a combination of system-related, psychological, and educational factors. Overall, the treemap analysis provides strong evidence that AI adoption research is heavily centered on acceptance models and user-focused constructs, while emerging themes such as generative AI are gaining increasing attention. This shift suggests a transition in the field from traditional technology adoption studies toward more application-oriented and innovation-driven research.

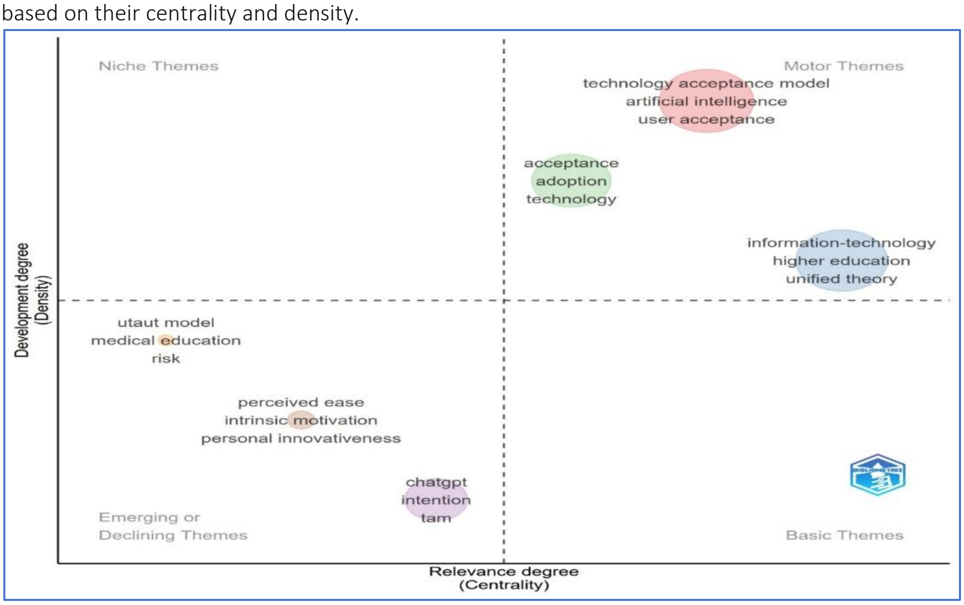
Figure 7

Treemap visualization of the most frequent themes in AI adoption research

The thematic map (Figure 8) provides an organized overview of the intellectual structure of AI adoption research by grouping the themes according to their centrality and density. According to the findings, the themes of the technology acceptance model (TAM), artificial intelligence and user acceptance are motor themes due to their high importance and high development. This implies that research on AI adoption primarily draws upon established theories as well as user-centered perspectives. Conversely, chatgpt and intention are among the emerging themes in the upper left quadrant which are the themes that are gathering attention but yet in their infant stage. There's been a recent shift towards generative AI and changing paradigms of user interaction in education. In addition, the presence of information technology and higher education in the basic quadrant shows that these topics are fundamental ones that are widely researched, but are not as conceptually rich. The thematic map demonstrates that while the field is strongly anchored in traditional acceptance models, it is simultaneously evolving toward new research directions driven by generative AI technologies and emerging user behaviors.

Figure 8

Illustrates the thematic structure of the field, identifying motor, basic, niche, and emerging themes based on their centrality and density.



The word cloud analysis (Figure 9) further reinforces the dominance of key themes identified in the study by visually highlighting the most frequently occurring terms in the literature. Prominent keywords such as technology acceptance model, artificial intelligence, information technology, and ChatGPT appear with greater emphasis, indicating their central role in shaping AI adoption research in education. This visualization confirms that the field is highly concentrated around acceptance-related constructs and AI-driven technologies, particularly those grounded in established theoretical frameworks. The noticeable presence of ChatGPT also reflects the growing influence of generative AI in recent studies, signaling a shift toward more advanced and application-oriented research. The word cloud provides a clear and intuitive representation of the thematic focus of the literature, supporting the findings derived from the tabular and thematic analyses.

Figure 9
Displays the most frequently occurring keywords

The co-occurrence network analysis (Figure 10) provides insight into the structural relationships among key constructs in AI adoption research. The visualization reveals that central nodes such as the technology acceptance model, artificial intelligence, and user acceptance occupy dominant positions within the network, indicating their strong influence across the literature. These core themes are highly interconnected with constructs such as trust, perceived usefulness, and behavioral intention, highlighting the integrated and interdependent nature of factors influencing AI adoption. This pattern suggests that adoption behavior is not driven by isolated variables but rather by a complex relationship of technological, psychological, and contextual elements. The network structure demonstrates a well-connected research landscape, where established theoretical constructs remain central while simultaneously linking with emerging factors, reinforcing the multidimensional nature of AI adoption in education.

Figure 10
Shows the co-occurrence network of constructs, demonstrating the interrelationships among key factors influencing AI adoption

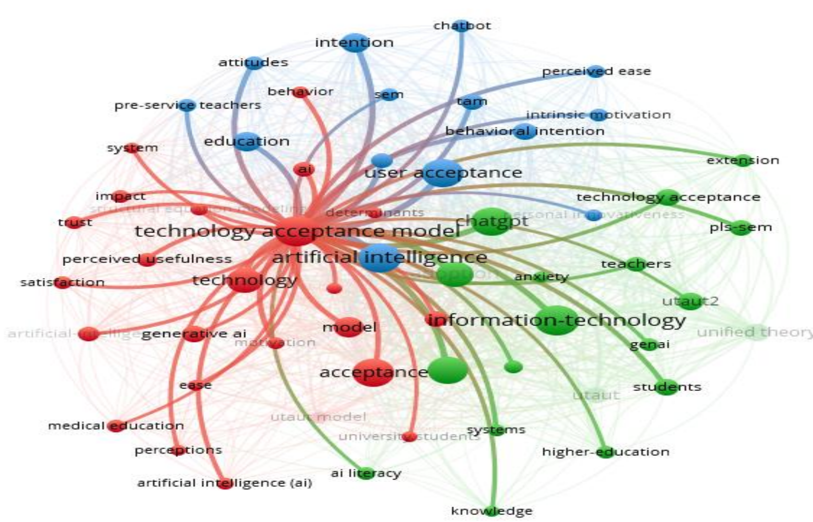
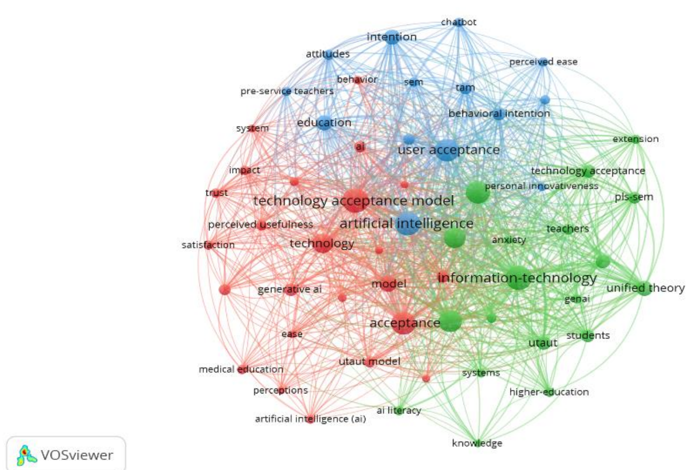


Figure 11. provides a more detailed representation of the clustering structure among key constructs. The figure reveals distinct clusters that group related themes, highlighting the multidimensional nature of AI adoption research. The red cluster primarily represents core acceptance-related constructs, including technology acceptance model, perceived usefulness, and trust, indicating the central role of traditional acceptance theories. The green cluster focuses on information technology, UTAUT-related constructs, and educational contexts, reflecting system-level and contextual influences. Meanwhile, the blue cluster emphasizes behavioral intention, attitudes, and user acceptance, capturing the psychological and behavioral dimensions of adoption. Additionally, emerging elements such as ChatGPT, generative AI, and AI literacy are integrated within these clusters, suggesting that new technological developments are being incorporated into existing theoretical frameworks rather than forming entirely separate research streams. This clustered network reinforces the findings of the previous network analysis by demonstrating that AI adoption research is both highly interconnected and structured around well-established theoretical foundations, while simultaneously evolving to include emerging AI technologies.

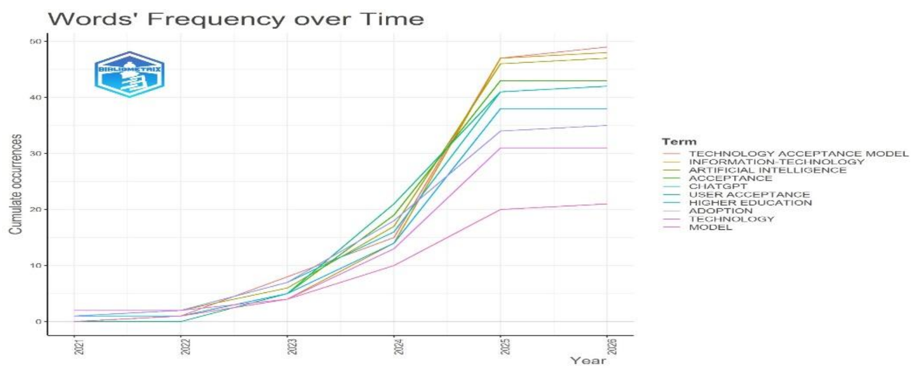
Figure 11

Keyword co-occurrence network showing clustered relationships among key constructs in AI adoption research



The temporal analysis of keyword trends (Figure 12) reveals a clear and significant increase in the prominence of key terms over time. Notably, terms such as ChatGPT, generative AI, and technology acceptance model show a sharp upward trajectory in recent years, particularly after 2023. This trend reflects the rapid emergence and growing influence of generative AI technologies within the educational domain. The increasing frequency of these keywords indicates a shift in research focus from traditional AI adoption studies toward more advanced, application-driven investigations centered on generative AI tools. At the same time, the continued presence of the technology acceptance model highlights that established theoretical frameworks remain relevant in explaining user behavior in this evolving landscape.

Figure 12
Trend analysis of the most frequent keywords illustrating their growth over time



The temporal trends demonstrate that AI adoption research in education is transitioning from theory-driven studies toward innovation-oriented and practice-focused research, with generative AI playing a central role in shaping future directions.

RQ5: What are the limitations of current research on AI in education, and what are the future research directions?

This section synthesizes the key limitations identified across the 153 studies included in this review and outlines important directions for future research. Understanding these limitations is essential for improving the effectiveness, scalability, and ethical integration of AI technologies in education. The findings highlight several critical gaps related to geographical coverage, theoretical diversity, participant representation, methodological approaches, and long-term impact. Addressing these limitations will support the development of more robust, inclusive, and context-sensitive AI adoption frameworks in educational settings.

Geographical and contextual constraints

Many studies focus on specific countries, such as China, Malaysia, and the United Arab Emirates, which may limit the generalizability of the findings to other contexts geographically and culturally. For instance, Foroughi et al. (2023) and Alhumaid et al. (2023) focus on the adoption of AI in Malaysia and the United Arab Emirates, respectively. Focusing on specific countries may overlook different challenges and opportunities in other countries. Future research should expand into diverse geographical settings and educational contexts to gain an international perspective on AI adoption.

Conceptual framework and theoretical models

Current studies mostly base their assessment of AI in education on TAM, UTAUT, and UTAUT2 models (e.g., Wang et al., 2021; Strzelecki, 2023). These are the models widely used, but not necessary to account for all aspects of AI. The Technology Acceptance Model has been widely applied and well-proven. As seen in the study from Zhang et al. (2023) and Li (2023), other frameworks may be implemented, such as the Theory of Planned Behavior (TPB) or Social Cognitive Theory (SCT), to gather more insight. Further research studies must apply various theoretical models to make a better understanding of AI adoption-related behaviors and consequences possible.

Participant diversity

Many studies focus more on students and involve fewer stakeholders, such as faculty, administrative staff, and educational researchers (An et al., 2023; Chaoning Zhang et al., 2023). This limited focus might limit the understanding of AI's effects on different parts of the education system. Future studies must include a broader set of participants, including faculty and administrative staff, to better understand the effect of AI and the challenges in implementing AI.

Data collection and methodological approaches

Much of the research uses quantitative methods, especially surveys (Bilquise et al., 2023, 2024). Although these methods give valuable information about trends and general perceptions, they may not fully capture the complexity of user experiences with AI. Qualitative methods, such as interviews and case studies, as well as mixed-method approaches, may be able to reveal more depth about the challenges and benefits of AI adoption (Almogren et al., 2024a, 2024b; Menon & Shilpa, 2023; Uzumcu & Acilmis, 2023). Future studies should include qualitative and mixed methods to study more subtle experiences and contextual factors.

Application areas and domain-specific research

Investigations are often tailored to specific applications of artificial intelligence, such as chatbots and intelligent tutoring systems (Dahri et al. 2024a; Dahri et al., 2024b; Huang et al., 2022). These questions are very useful in giving insight into specific technology, but the scale of AI use across a range of educational contexts, from STEM to the arts and humanities, would be more relevant. Research studies like those of (Abdalla et al., 2024; Bahadur et al., 2024; Kiyak & Emekli, 2024; Rojas et al., 2024; Singh et al., 2025) can be useful in finding the customization of different AI applications for a variety of educational needs. Future research should pursue this study by examining current applications of AI for understanding their effectiveness and potential.

Ethical and privacy considerations

Very few studies address ethical considerations and issues related to privacy surrounding AI in education (AI Shamsi et al., 2022; Rahim et al., 2022; Soomro et al., 2024) . As technology in AI evolves, data security and privacy, along with ethics, become very vital issues. Future research, therefore, needs to revolve around such issues to provide a basis for ethical AI adoption. For instance, how institutes deal with AI-generated data and handle the privacy issues of the students will be worthwhile.

Long-term impact and scalability:

Many studies focus on short-term effects and immediate responses of the user (Dahri, et al. 2024c; Omrani et al., 2022; Romero Rodríguez et al., 2023). Longitudinal studies are required to assess the long-term effects of artificial intelligence on learning outcomes and its adoption scalability across different institutions. Future research could explore how AI tools influence learning outcomes in the long term and their scalability.

Impact on education results

While many studies examine user perceptions and behavioral intentions regarding adoption (Alhwaiti, 2023; Y. Li et al., 2024; Ngo, 2023) To name a few, abound very few that focus specifically on the direct impact of artificial intelligence on tangible learning outcomes. Future studies should thus look at how AI tools and educational tools influence students' scores, participation, and attainment of skills. For example, it may examine how an AI-based tool improves specified outcomes or enhances educational outcomes.

Integration with traditional teaching approaches

Another area for future research is the integration of AI with traditional approaches to pedagogy. While most studies focus on the study of AI in isolation (Chai et al., 2021; Damerji & Salimi, 2021), Limited research has examined how AI can complement traditional teaching approaches and enhance existing pedagogies. Future studies should, therefore, investigate ways through which AI technologies can best be integrated into traditional curricula and teaching practices that will maximize their effectiveness and fulfill diverse learning needs. By addressing such constraints and exploring potential areas of research, scholars can nurture a deeper understanding of how artificial intelligence works in educational settings and its potential to enhance learning and teaching experiences in varied contexts.

These limitations highlight the need for more comprehensive and balanced research approaches in the study of AI adoption in education. Future research should move beyond traditional acceptance models and short-term analyses by incorporating diverse theoretical perspectives, broader participant groups, and longitudinal designs. Addressing these gaps will enable a more holistic understanding of AI integration and its long-term implications for teaching, learning, and educational systems.

Conclusion

This study presents a comprehensive systematic literature review of 153 peer-reviewed articles on AI adoption in education, following a rigorous PRISMA-based methodology. Although the search covered studies published between 2020 and 2025, only studies from 2021 to 2025 met the inclusion criteria. The findings demonstrate a significant increase in research activity in recent years, particularly driven by the emergence of generative AI technologies such as ChatGPT. The review reveals that AI adoption research is strongly grounded in established information systems theories, with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) dominating the theoretical landscape. The results further indicate that key determinants of AI adoption include perceived usefulness, perceived ease of use, performance expectancy, trust, and behavioral intention. Research is predominantly concentrated in higher education contexts, with students as the primary participants and a strong reliance on quantitative methodologies. Despite the growing body of research, important gaps remain, including limited geographical diversity, underrepresentation of educators and institutional stakeholders, and insufficient attention to qualitative insights and long-term educational outcomes. This study contributes to the literature by providing a structured and comprehensive synthesis of AI adoption research in education, consolidating fragmented findings into a unified perspective grounded in information systems theories. The findings offer valuable implications for educators. AI tools can support personalized instruction, assessment design, and student engagement. Policymakers should focus on developing ethical guidelines, infrastructure, and training programs to facilitate responsible AI integration in education. Ultimately, this review provides a foundation for advancing future research and supporting more effective and inclusive integration of AI in educational environments.

Abbreviations

AI: Artificial Intelligence; AIE: Artificial Intelligence in Education; SLR: Systematic Literature Review; PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses; TAM: Technology Acceptance Model; UTAUT: Unified Theory of Acceptance and Use of Technology; UTAUT2: Unified Theory of Acceptance and Use of Technology 2; TPB: Theory of Planned Behavior; SCT: Social Cognitive Theory; TTF: Task–Technology Fit; DOI: Diffusion of Innovation; IS: Information Systems; LLM: Large Language Model; MOOCs: Massive Open Online Courses; SEM: Structural Equation Modeling; PLS-SEM: Partial Least Squares Structural Equation Modeling.

Acknowledgements

The authors would like to express their sincere appreciation to the researchers whose work contributed to this systematic literature review. The authors also acknowledge the valuable support provided by their respective institutions throughout the preparation of this manuscript.

Author's contributions

NAD conceived the study, designed the review protocol, developed the research questions, performed the systematic literature review, screened and analyzed the selected studies, conducted the statistical and thematic analyses, interpreted the findings, and drafted the manuscript.

WMAR contributed to the conceptualization of the study, supervised the research process, validated the methodology, critically reviewed the manuscript, refined the theoretical discussion, and approved the final version of the manuscript.

Both authors read and approved the final manuscript.

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Funding

The authors received no specific funding for this research from any funding agency in the public, commercial, or not-for-profit sectors.

Availability of data and materials

The data supporting the findings of this systematic literature review are available in the supplementary materials accompanying this manuscript. The supplementary files include:

Table 1 for SLR Studies.docx

Supplementary File (Complete SLR Paper Information).xlsx

Declarations

Competing interests

The authors declare that they have no competing interests.

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Received: 14 July 2025 Accepted: 22 May 2026

Published online: 1 January 2027 (Online First: 27 July 2026)

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