

Uneven But Accelerating: AI Adoption in Higher Education

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Abstract—Artificial Intelligence (AI) is increasingly recognized as a transformative force in higher education, yet adoption remains patchy and often confined to partial implementations. Using the PRISMA protocol, this study systematically reviews 74 Scopus-indexed articles published between 2015 and 2025. Publication activity rose sharply after 2020, led by contributions from China, the United States, and Saudi Arabia. Across the corpus, Perceived Usefulness and the Technology Acceptance Model (TAM) are the most frequently applied constructs, while ethical and policy dimensions remain underexamined. Thematic analysis delineates five clusters: adaptive learning and personalization; ethics and trust; digital literacy and readiness; AI in assessment and evaluation; and organizational transformation. Despite growing attention, regional gaps persist—especially in developing countries, where constrained infrastructure, funding, and digital literacy impede adoption. To address these challenges, the study proposes a multi-level conceptual framework integrating TAM, UTAUT, TPACK, and TOE to connect individual, institutional, and external factors for sustainable AI-driven education. Overall, the review underscores that AI adoption is not merely an efficiency tool but a strategic lever to advance the Sustainable Development Goals (SDGs), particularly by fostering inclusive, equitable, and innovative higher education systems.

Keywords—Artificial intelligence adoption; higher education; sustainable education; developing country

I. INTRODUCTION

Artificial Intelligence (AI) has advanced rapidly and is now deployed across multiple domains, including education [1]. It is widely regarded as a promising instrument for improving educational quality over the long term [2]. In educational settings, AI can generate strategic efficiencies by delivering personalized feedback, automating administrative tasks, forecasting student performance, enhancing learner engagement, and enabling adaptive assessment [3]. Accordingly, further development and careful integration of AI in education are needed to realize comprehensive, system-wide benefits.

AI-driven innovations are reshaping higher education at multiple levels [4]. Beyond streamlining administrative processes, AI enables adaptive learning, personalized curricula, and automation of academic services [5] [6] [7]. Its adoption has been linked to improvements in teachers' psychological well-being—through workload reduction, heightened motivation,

and strengthened assessment and evaluation skills [8]—while also promoting more personalized learning and richer student experiences [9]. Professional development has been shown to support effective integration of GenAI for enhancing student engagement in teaching practice [10] [11], an essential precursor to interaction and improved performance; accordingly, designing AI-enabled activities, including those using ChatGPT, is warranted. Evidence further suggests that AI can raise learning effectiveness by up to 30% via learning-style analytics and content-recommendation systems [12]. In the United States and China, AI-based chatbots already support interactive learning [13] [14]; in Serbia, artificial intelligence and machine learning have been used to cultivate collaborative learning environments, develop student skills, and provide accessible research opportunities [15]. In Australia, ChatGPT accounted for 17.3% of the variance in improved academic outcomes [16]. Overall, AI facilitates faster feedback for students and allows instructors to devote more attention to strategic, higher-order pedagogical work [17].

Adopting AI in higher education opens pathways to cultivate higher-quality student outcomes [18]. Implementation, however, remains uneven across countries. Hughes et. al. [19] report that GenAI uptake is hindered by heterogeneous knowledge of AI tools and processes and by underdeveloped GenAI regulation. In Nigeria, adoption is constrained by limited funding, scarce technical expertise, and inadequate infrastructure [20]. In China, low digital literacy and resistance to AI impede deeper integration [21]. Evidence from the Middle East and North Africa cites low State revenues and unclear policies as additional obstacles [22]. In Sri Lanka, the absence of university-level policies and guidelines further inhibits GenAI adoption [23]. Taken together, these findings underscore the diverse, context-specific challenges surrounding AI adoption in education. A fit-for-purpose development model is therefore critical as a strategic pathway to enable effective adoption across higher education institutions.

AI adoption models grounded in established frameworks such as UTAUT and TOE have been implemented in several countries [24] [25] [26]. However, these templates are not fully aligned with the realities of developing contexts marked by digital divides, institutional diversity, and distinct policy needs. Prior findings underscore the importance of determinants—government support, leadership, risk, strategy, system quality,

user satisfaction, and readiness—for information-system/technology adoption and the application of AI in learning [27] [30] [28] 29] [31] [32] [33] [34] 35] [36]. However, most studies remain confined to generic drivers of AI uptake and use. Recent evidence further indicates that ChatGPT adoption in higher education is shaped by Performance Expectancy, Effort Expectancy, Hedonic Motivation, and AI ethical issues (bias, privacy, transparency), which collectively call for educator training, AI literacy, critical-ethical competence, and practical learning (e.g., Moral Machine) to prepare an automation-ready workforce [37] [38] [39]. This stream of work, however, is limited to ChatGPT, lacks a holistic approach, and provides minimal discussion of AI adoption within local cultural and contextual settings.

Meanwhile, ChatGPT demonstrates fluency at the university level but falls short on critical, context-sensitive analysis. Teachers tend to view AI favorably, yet they often lack sufficient content knowledge [40] [41]. This study also has limitations in its analysis of student–lecturer readiness and in articulating an AI competency framework rooted in the local context. Mohd Rahim et. al. [42] propose a chatbot-based AI adoption model incorporating perceived trust, behavioral intention, and use among Malaysian graduate students; however, this study was constrained by a sample composed solely of university students. Alyousef et.al. [43] identify ease of use, usefulness, engagement, trust, familiarity, and behavioral intention as key drivers of AI adoption in higher education, but its reliance on a student-only sample limits generalizability beyond that context.

Celik [44] extends the TPACK framework by incorporating artificial intelligence and ethics, underscoring that teachers should master not only pedagogy, content, and technology but also ethical literacy in AI use. Its limitations include the lack of integration with other technology-adoption models and the omission of institutional and policy dimensions. Research [45] investigates factors influencing the adoption and use of AI-based voice assistants, but its household-only design yields a limited number of respondents. Rao and R. Prasad [46] examine the role of 5G technology as a leading enabler of Industry 4.0 and its integration with AI, the Internet of Things (IoT), big data, and cloud computing; however, it does not employ an adoption-theory framework, which is important for shaping AI acceptance at the institutional or individual level.

Okunlaya et. al. [47] examine how AI-enabled library services can catalyze digital transformation in higher education. Its principal limitation is the absence of a technology-adoption framework, leaving the determinants of AI acceptance unspecified. Huang and Lu [48] analyzes the implementation of AI in Intelligent Tutoring Systems (ITS) for continuing education but focus on developed-country contexts, leaving developing settings underexplored. More broadly, prior research has not integrated adoption models with institutional dimensions; consequently, AI acceptance—especially in developing countries—remains insufficiently understood.

Prior work has explored multiple facets of technology and AI adoption—government support, service quality, risk, strategy, system quality, user satisfaction, social capital, and readiness to adopt learning information technologies [27] [30]

[28] 29] [31] [32] 33] [34] [35]—alongside applications of AI in teaching and learning [36]. Taken together, these studies tend to emphasize individual-level elements such as chatbots for academic services, AI-based learning analytics, and assessment automation. Nevertheless, a holistic model that integrates technological, organizational, environmental, policy, and human-resource readiness factors is still absent [37] [38] [39]. Moreover, most prior research overlooks the distinctive characteristics of higher education institutions—including infrastructure constraints, regulatory conditions, and digital readiness—thereby limiting contextual applicability [49] [40] [41].

The literature still reveals a gap in AI adoption within higher education. This study addresses that gap by conducting a systematic literature review of AI adoption using a systematic approach within the higher education ecosystem [50]. The review considers technological, organizational, human, environmental, and ease-of-adoption factors [51] [52]. By analyzing prior research, the study maps research distribution, synthesizes theoretical models, performs cluster analysis, identifies research gaps, derives implications, and proposes a conceptual framework for AI adoption in higher education. The aim is to provide insights attuned to technological, organizational, environmental, cultural, and policy conditions. The results are intended to guide future researchers in enhancing higher-education quality through AI adoption and to encourage policymakers to support sustainable educational transformation.

This study undertakes a systematic literature review to map the field, identify research trajectories and opportunities for development, and synthesize the factors that shape artificial intelligence adoption in higher education, thereby consolidating the evidence base in this domain. It seeks to address the following research questions:

RQ1: What is the state of higher education’s readiness to adopt AI, and how is it related to continuing education?

RQ2: What is the potential of integrating cross-theoretical perspectives to build a conceptual framework of AI adoption for sustainable education?

RQ3: How can developing countries contribute to realizing AI-driven sustainable education?

RQ4: How does the conceptual framework of AI adoption support the goal of sustainable education?

The remainder of this article is organized as follows. Section II details the research methods, including the PRISMA protocol and the bibliometric and thematic procedures employed. Section III reports the analysis results on publication trends, dominant theoretical lenses, and the principal thematic clusters. Section IV concludes with the study’s conclusions. Finally, Section V discusses the study’s limitations, and recommendations for future research.

II. METHOD

A. Research Design

This study adopts a qualitative design employing a systematic literature review. A systematic literature review systematically identifies studies on a defined topic to answer

research questions transparently while incorporating evidence and assessing study quality [53] [54]. It synthesizes strengths, weaknesses, and patterns of divergence across prior work to produce a comprehensive account and reveal research gaps [55]. We applied the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol with Watase UAKE to identify systematic reviews [56], using PRISMA to ensure transparent reporting so that findings and procedures are fully described [57]. The review analyzes prior research on AI adoption models in higher education to provide a basis for developing adoption models aligned with educational conditions in Indonesia.

B. Identification

The literature search was conducted in Scopus using the keywords “AI Adoption,” “Artificial Intelligence,” and “Higher Education.” This initial sweep identified 126 articles.

C. Screening

The retrieved records were screened against inclusion and exclusion criteria to ensure alignment with the study’s aims. The inclusion criteria were: 1) publication in Scopus-indexed international journals (Q1–Q4), 2) a time window of 2015–2025, 4) empirical, developmental, or conceptual studies addressing AI adoption models in higher education, and 5) articles written in English. Applying these criteria led to the

removal of four articles that fell outside the publication years and eighteen that were not Scopus Q1–Q4, leaving 106 articles at the screening stage.

A second pass applied the exclusion criteria: 1) articles discussing AI outside an educational context, 2) duplicate records, and 3) non-peer-reviewed items. Five articles met these exclusion criteria, yielding 101 articles.

D. Eligibility

Titles, abstracts, and full texts were then assessed for eligibility using the same criteria to confirm topical relevance. Of the 101 articles entering this phase, 30 failed to meet the eligibility threshold, leaving 71 articles.

E. Appraisal of Quality

A quality appraisal ensured substantive relevance to AI adoption in higher education. The researcher examined methodologies associated with the adoption models TAM, UATUT, TOE, DOI, and AITAM, and verified that studies addressed organizational, technological, policy, cultural, and environmental factors. All 71 articles from the prior step were deemed eligible. At this point, three additional articles judged suitable were added, bringing the final corpus to 74 articles. The following Fig. 1 is a chart of the article selection process:

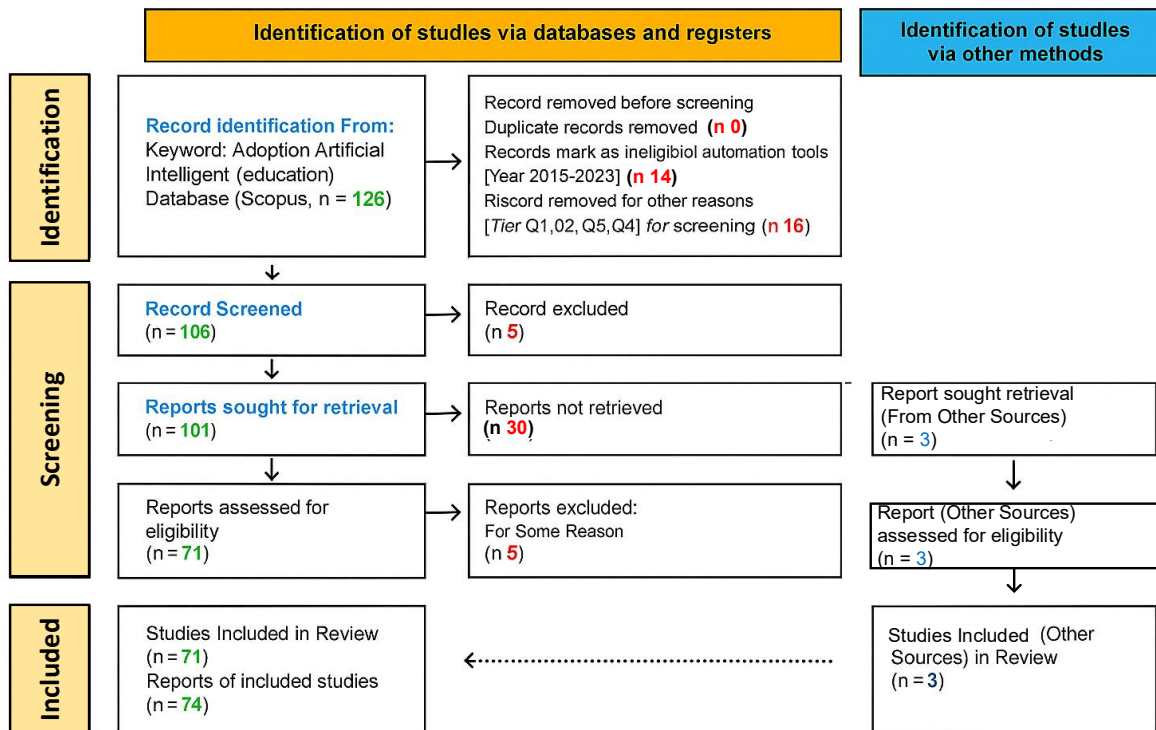


Fig. 1. Selection of articles in the PRISMA flow diagram.

III. RESULTS AND DISCUSSION

This section reports findings from the systematic literature review. The discussion is organized into three parts: descriptive statistics, thematic analysis, and theoretical and practical implications.

A. Overview of Study Selection

Using the Scopus database and the keyword Adoption Artificial Intelligence Education for the 2015–2025 period, 126 articles were initially identified. Of these, 20 did not meet the criteria (outside the year range, not in the education category, or published in journals below the quality standard), leaving 106

for screening. The screening phase yielded 101 records that advanced to the retrieval stage. Subsequently, 71 articles satisfied the inclusion criteria, and three additional articles were added from other sources, producing a final corpus of 74 articles. This process ensured coverage of recent developments published in reputable international journals (Q1–Q4) and relevance to AI adoption in higher education.

B. Geographical Distribution of Studies

The country-level distribution reveals pronounced disparities. China led with 14 publications, followed by the United States (7) and Saudi Arabia (5). Indonesia and Malaysia contributed three articles each, while Mexico, Spain, Morocco, South Africa, and Turkey produced two each. China's dominance situates East Asia as a hub of AI-in-education research, influenced by substantial ed-tech investment and assertive government policy. The United States contributes notably to evaluative, pedagogical, and ethical strands, whereas Saudi Arabia's output aligns with national digitization priorities (Saudi Vision 2030). Contributions from Southeast Asia—including Indonesia and Malaysia—and from Africa are emerging but remain limited, underscoring a regional research gap that scholars in developing countries can address with locally grounded perspectives. A graph of article distribution by country is provided in Fig. 2.

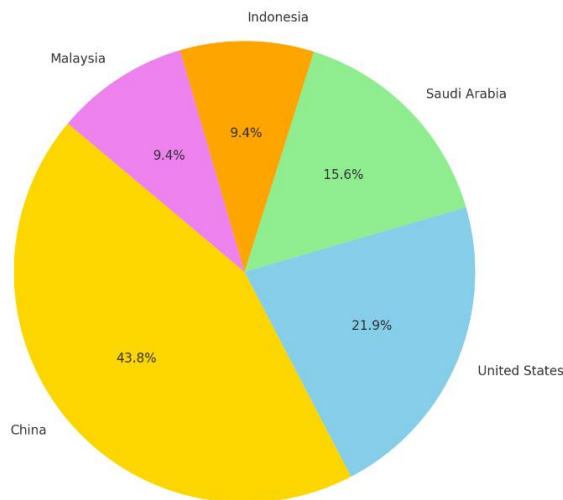


Fig. 2. Top 5 geographical distribution of studies.

C. Yearly Article Trends

Annual output shows a pronounced inflection after 2020. Between 2015 and 2020, publications were relatively flat at ≤ 2 articles per year. Starting in 2021, output rose sharply to 6 articles, followed by steady increases in 2022 and 2023 (11 articles each). The peak arrived in 2024 with 23 articles, signalling intensifying global attention to AI adoption in education. By mid-2025, 15 articles had already appeared, suggesting that the year's total may surpass prior records. This trajectory likely reflects exogenous drivers—most notably the COVID-19 pandemic's acceleration of educational digitization, policy support across countries, and expanded funding for AI-related research—pushing AI integration to the forefront of educational agendas in infrastructure, pedagogy, and ethics. A graph of article counts by year is presented in Fig. 3.

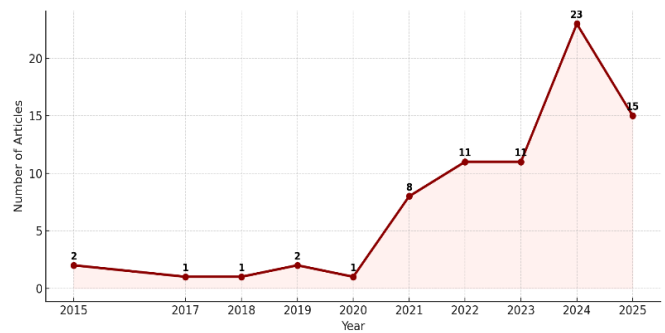


Fig. 3. Yearly article trends.

D. Variable Trends

The trend analysis indicates that Perceived Usefulness is the most frequently examined construct in AI - adoption research, appearing in 10 articles. This prominence suggests that the perceived benefits of technology are the dominant driver of readiness to adopt AI in higher education. Nine additional variables—Optimism, Perceived Privacy Risk, Social Influence, Artificial Intelligence, Effort Expectancy, Perceived Enjoyment, Trust, Perceived Ease of Use, and Perceived Ease—each appeared 2 times, underscoring the salience of social dimensions such as trust and usability in the adoption process. By contrast, Objective Useability, Insecurity, Relative Advantage, Compatibility, Expectation Confirmation, and Computer Playfulness appeared once each, signalling opportunities for deeper investigation of these factors in advancing sustainable education. The variable trends are presented in Fig. 4.

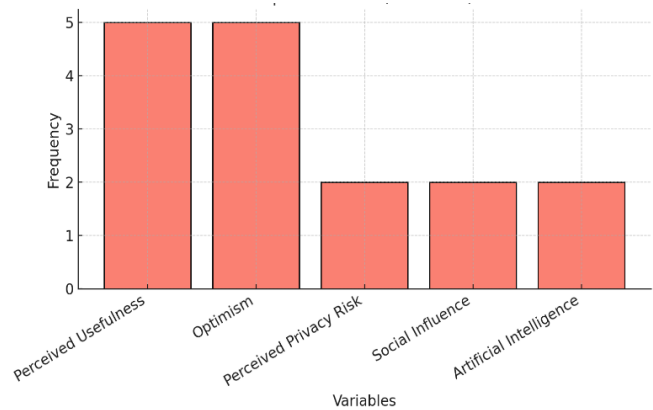


Fig. 4. Variable trends.

E. Theoretical Model of AI Adoption

Analysis of theoretical framing indicates that TAM (Technology Acceptance Model) is the most frequently employed approach, particularly for assessing faculty and student perceptions of AI's usefulness and ease of use. UTAUT/UTAUT2 appears in broader applications, incorporating performance expectancy, social influence, and facilitating conditions. At the institutional tier, TOE (Technology–Organization–Environment) is used to foreground organizational readiness, managerial support, and external pressures. At the same time, Diffusion of Innovation (DOI) is pertinent for explaining adoption dynamics across campus populations. Despite this range, most studies rely on a single

framework. The paucity of cross - model integration is a notable limitation, given that AI adoption in higher education is intrinsically multidimensional—encompassing individual, institutional, and policy dimensions.

F. Thematic Clusters from Network Analysis

Keyword network analysis identified five principal clusters: 1) Adaptive Learning & Personalization—centered on intelligent tutoring systems, intelligent-TPACK, and AI-based learning personalization; 2) Ethics & Trust—highlighting transparency, student data privacy, and potential algorithmic bias; 3) Digital Literacy & Readiness—emphasizing faculty/student technology literacy and AI integration; 4) AI in Assessment & Evaluation—covering automated assessment, learning analytics, and academic performance prediction; and 5) Organizational Transformation—focusing on institutional readiness, change-management strategies, and digital-infrastructure investment. These findings indicate a fragmented landscape: clusters largely operate in parallel, with limited cross-theme integration.

The analysis further shows that AI technology constitutes the largest node, influencing performance, trust, organizational capabilities, and sustainability—evidence of topic dominance within AI acceptance. Major concentrations also appear across the pedagogy and literacy, ethics and sustainability, organization and performance, and technology adoption and acceptance clusters. Overall, research on AI adoption in higher education remains broad yet dispersed rather than fully integrated. Thematic clusters are presented in Fig. 5.

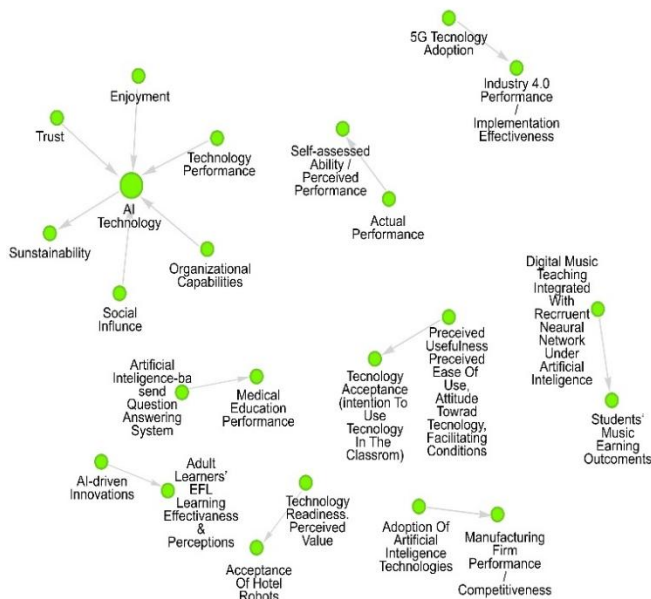


Fig. 5. Thematic clusters from network analysis.

G. Highly Cited Benchmark Articles

Citation analysis highlights several anchor studies. McLean & Osei-Frimpong (2019), with 536 citations, investigated determinants of adoption for AI-based virtual assistants (Alexa). Celik (2023), cited 330 times, advanced the concept of Intelligent (TPACK), embedding AI within teachers'

pedagogical-competency frameworks. Lin et al. (2023), with 184 citations, emphasized AI's role in intelligent tutoring systems, corroborating its effectiveness for personalized learning. Wang et al. (2024), with 121 citations, offered a systematic review of AI in education that serves as a key roadmap for subsequent inquiries. Collectively, these benchmark articles illustrate that work combining strong theoretical innovation with clear practical relevance tends to attract broad scholarly attention. Table I depicts citations from the SLR analysis.

TABLE I. HIGHLY CITED BENCHMARK ARTICLES

Rank	Journal	Tier	Author	Year	Cites	Title
1	Computers in Human Behavior	Q1	McLean, Graeme; Osei-Frimpong, Kofi	2019	536	Hey Alexa, examine the variables influencing the use of artificial intelligence in in-home voice assistants. Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education
2	Computers in Human Behavior	Q1	Celik, Ismail	2023	330	Impact of 5G Technologies on Industry 4.0 Artificial intelligence in intelligent tutoring systems towards sustainable education: a systematic review
3	Wireless Personal Communications	Q3	Rao, Sriganesh K.; Prasad, Ramjee	2018	278	Artificial intelligence (AI) library services provide an innovative conceptual framework for the digital transformation of university education.
4	Smart Learning Environments	Q1	Lin, Chien-Chang; Huang, Anna Y. Q.; Lu, Owen H. T.	2023	184	
5	Library Hi Tech	Q2	Okunlaya, Rifqah Olufunmilayo; Syed Abdullah, Norris; Alias, Rose Alinda	2022	178	

Rank	Journal	Tier	Author	YearCites	Title
6	Journal of Cases on Information Technology	Q4	Tahiru, Fati	2021 138	AI Education in
7	Expert Systems with Applications	Q1	Wang, Shan; Wang, Fang; Zhu, Zhen; Wang, Jingxuan; Tran, Tam; Du, Zhao Hernandez-de-Menendez, Marcela; Escobar Díaz, Carlos; Morales-Menendez, Ruben	2024 121	Artificial intelligence in education: A systematic literature review
8	International Journal on Interactive Design and Manufacturing (IJIDeM)	Q3	Marcela; Escobar Díaz, Carlos; Morales-Menendez, Ruben	2019 99	Technologies for the future of learning: state of the art
9	IEEE Access	Q2	Essa, Saadia Gutta; Celik, Turgay; Human-Hendricks, Nadia Emelia	2023 95	Personalized Adaptive Learning Technologies Based on Machine Learning Techniques to Identify Learning Styles: A Systematic Literature Review
10	Information	Q4	Sajja, Ramteja; Sermet, Yusuf; Cikmaz, Muhammed; Cwiertny, David; Demir, Ibrahim	2024 94	Artificial Intelligence-Enabled Intelligent Assistant for Personalized and Adaptive Learning in Higher Education

H. Research Gaps Identified

The synthesis reveals five persistent gaps. First, theoretical integration remains limited: studies continue to rely partially on TAM/UTAUT without adopting multi-level frameworks. Second, a regional skew persists, with East Asia dominating and developing countries contributing comparatively little. Third, longitudinal evidence is scarce; cross-sectional designs predominate, leaving long-term impacts largely unexamined. Fourth, ethical and policy dimensions—now increasingly salient in higher education—are underexplored. Fifth, links to academic outcomes are weak, as most research halts at adoption perceptions rather than connecting directly to student learning results.

I. Implications for Higher Education

Findings from this SLR carry multi-level implications. Academic: develop new conceptual frameworks that fuse technology-adoption theory with pedagogy (e.g., TAM + TPACK). Practical: universities should institute AI-literacy

training for lecturers and students and cultivate an AI-enabled learning ecosystem. Policy: regulations on the ethical use of AI, student-data protection, and evaluation standards require prompt development. Global-local: best practices from China and the United States can be adapted, but must be calibrated to Indonesia's infrastructural realities and learning culture.

J. Conceptual Framework

Building on the findings, the framework positions individual factors (digital literacy, attitude, motivation), institutional factors (management support, infrastructure, campus policy), and external factors (regulation, global trends) as primary determinants of AI adoption in higher education. AI adoption, in turn, affects learning outcomes—namely personalization, effectiveness, and 21st-century literacy. Innovation can trigger insecurity, thereby motivating the development of intelligent TPACK; simultaneously, optimism and AI literacy shape perceived ease, AI usability, and trust. When AI is perceived as valuable, beneficial, and safe, acceptance rises. These dynamics foster positive attitudes that lead to intention and, ultimately, actual use. The AI adoption model derived from this review is presented in Fig. 6.

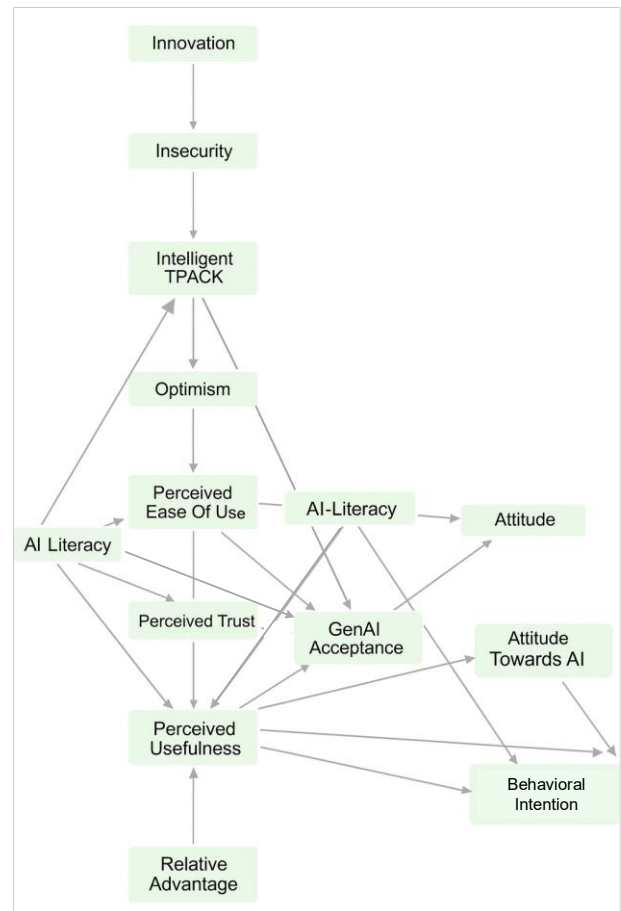


Fig. 6. AI adoption model.

1) RQ1: Readiness of Higher Education to Adopt AI and its Relevance to Continuing Education

Integrating AI into teaching through the Intelligent-TPACK lens presupposes pedagogical expertise, innovation readiness,

AI literacy, and robust teacher trust [44]. Because AI functions not merely as a tool but as a catalyst for pedagogical change, instructors must engage in reflective and ethical practice. In this view, the success of AI adoption hinges on educators' capacity to build Intelligent-TPACK. AI can also strengthen education by advancing civic responsibility, ethics, and character formation; realizing this potential requires AI-literate human resources and curricula that embed AI ethics [58]. To ensure students act as responsible, productive users rather than passive consumers, higher education institutions should elevate AI literacy—thereby supporting engagement and personalized learning. The upshot is that AI literacy is essential to cultivate ethical and critical AI use [59].

Within faculty recruitment, the use of GenAI renders AI literacy and Intelligent-TPACK foundational prerequisites. Framed this way, AI promotes data-driven, inclusive learning and supports the transition toward sustainable education. Institutions must therefore secure adequate digital infrastructure, ethical policies, and a supportive ecosystem—backed by AI training for lecturers [60].

SLR findings indicate heterogeneous readiness across systems. Universities in developed contexts (e.g., China, the United States, Australia) have integrated AI into adaptive learning, automated assessment, and academic chatbots, underwritten by mature infrastructure and regulation. These findings enable attention not only to adoption but also to sustainability dimensions such as energy efficiency, learning inclusion, and 21st-century literacies. By contrast, in many developing countries, readiness remains constrained by infrastructural gaps, limited funding, low digital literacy, and absent institutional policies, leaving the contribution of AI to sustainable education underrealized due to the digital divide. In Indonesia, despite government initiatives for educational digitalization, institutional readiness varies widely. Thus, AI readiness can serve as an accelerator of sustainable education—but only alongside deliberate strategies to build AI literacy, institute ethical governance, and secure national policy support.

2) RQ2: Potential for Cross-Theoretical Integration in the AI Adoption Conceptual Framework

UTAUT2 delineates determinants of behavioral intention for AI-based virtual assistants—performance expectancy, effort expectancy, social influence, and facilitating conditions—making it readily extensible to AI adoption in higher education. By contrast, TAM concentrates on perceived usefulness and related perception constructs while largely omitting social-infrastructure considerations. Treating these frameworks in isolation yields a piecemeal view of adoption; integrating TAM and UTAUT2 is therefore essential to capture AI's multidimensional uptake rather than privileging either technical or social facets alone [61]. Complementarily, TAM remains a primary predictor of technology acceptance, whereas TPB (Theory of Planned Behavior) enriches the socio-psychological layer. Together, TAM and TPB furnish a sustainable scaffold by combining technical, psychological, and social drivers, thereby strengthening inclusive science learning [62]. Because adoption in educational settings also hinges on pedagogy, TPACK serves as a gauge of teacher readiness; TPACK literacy tends to increase teachers' acceptance of AI's usefulness, particularly as

roles shift from information transmitters to facilitators of data-driven, personalized learning [44].

Most studies still deploy TAM to assess usefulness and ease, or UTAUT to add performance expectations and social influence; institution-level work commonly relies on TOE, and macro-level analyses sometimes invoke Diffusion of Innovation (DOI). This siloed use of frameworks fragments AI-adoption analysis. A cross-theoretical pathway is to combine TAM/UTAUT (individual level), TOE (organizational level), and TPACK (pedagogical level) within a single architecture. For instance, TAM can explain students' perceived usefulness of AI, TOE can capture organizational readiness (infrastructure, policies, external support), and TPACK can fortify lecturers' pedagogical and ethical literacy. Integrated in this way, the model becomes a holistic, multi-level framework suited not only to explaining adoption but also to designing implementation strategies aligned with sustainability goals—efficiency, inclusion, 21st-century literacy, and digital ethics.

3) RQ3: Contribution of Developing Countries in Realizing AI Adoption-Based Sustainable Education

AI is a powerful lever for improving learning quality, equitable access, and administrative efficiency. In developing contexts, however, success turns critically on the readiness of human resources and infrastructure; persistent challenges include infrastructural deficits, policy gaps, ethical risks, and limited AI literacy. These constraints can become opportunities when AI is positioned as an accelerator of educational transformation through policy support, capacity building, and targeted technology investment [63]. AI-based chatbots can also augment decision-making by enabling real-time interaction, personalized responses, and rapid data analysis, thereby elevating service quality and advancing continuing education as a transformational innovation [64]. Evidence further indicates that AI tools can raise academic performance by increasing learning efficiency, though concerns about personal-data misuse and algorithmic transparency—and the attendant risks of bias—underscore that safety and ethics are integral to sustainable education, not optional add-ons [65]. In the Middle East, university sustainability ratings have improved alongside AI adoption; beyond academic efficiency, AI has helped attract international students and spurred curricular shifts toward digitalization, AI ethics, and the green economy—together reinforcing AI's direct contribution to sustainability ratings in the region [66].

Developing countries such as Indonesia, Malaysia, and Sri Lanka are beginning to contribute empirical work on AI literacy, automated assessment, and generative AI ethics. Their studies provide essential local context to complement East Asia's dominant literature—for example, funding and infrastructure constraints in Nigeria and the absence of university-level regulation in Sri Lanka. To advance AI-enabled sustainable education, developing countries can:

Present local context-based models—for example, integrating AI with distance learning in remote areas.

Contribute policy perspectives—examining how governments, universities, and communities can narrow the digital divide.

Develop ethics and AI-literacy research—recognizing that the central challenge is not only technological but also human capacity and governance.

Pursued together, these strategies position developing countries not merely as consumers of global scholarship but as producers of contextually grounded knowledge that broadens and deepens the meaning of continuing education.

4) RQ4: Relationship of AI Adoption Conceptual Framework to Sustainable Education Goals

AI adoption for continuing education is multi-variable in nature. Perceived Usefulness and Optimism are pivotal because uptake in higher education hinges on users' confidence in the technology [67], and positive attitudes among students, institutions, and lecturers further reinforce acceptance. Conversely, inadequate AI literacy and concerns over data-security risks act as barriers. These conditions imply that successful adoption requires a coordinated blend of infrastructure readiness, policy support, and human-resource development. In this sense, AI is not merely a tool but a driver of continuing education when embedded within an integrated digital-transformation strategy. Related evidence indicates that trust, privacy, and perceived usefulness are necessary to encourage use, while enjoyment is important for cultivating student engagement; adoption also turns on psychological factors, since safe and positive user experiences shape success [45]. Accordingly, effective AI integration must address not only technical efficiencies but also social, ethical, and psychological dimensions [61].

The SLR-synthesized framework positions individual (digital literacy, trust, motivation), institutional (management support, infrastructure, campus policy), and external (regulation, global trends, ethics) factors as primary determinants of AI adoption. Their interplay forms an adoption ecosystem that contributes directly to sustainable-education targets: 1) SDG 4 (Quality Education): AI advances personalization, adaptive assessment, and inclusive access; 2) SDG 9 (Industry, Innovation, and Infrastructure): universities operate as AI innovation hubs that strengthen digital infrastructure; 3) SDG 10 (Reduced Inequalities): AI enables inclusion for remote learners via smart distance education; 4) SDG 17 (Partnerships for the Goals): cross-sector collaboration among universities, government, and industry in AI development. Thus, the conceptual framework not only maps determinants of adoption but also traces a causal pathway through which AI becomes an instrument for sustainable education—especially salient for developing countries working to narrow the digital divide.

IV. CONCLUSION

This study systematically reviewed AI adoption in higher education and its links to sustainable education. The evidence shows that perceived usefulness, ease of use, trust, optimism, and AI literacy strongly shape adoption behavior. However, the literature remains fragmented—dominated by single-theory applications (e.g., TAM or UTAUT) and concentrated in developed regions. To address these gaps, we propose an integrated, multi-level framework that combines TAM, UTAUT, TPACK, and TOE to capture individual, institutional, and policy dimensions. The synthesis indicates that AI adoption

enhances efficiency, personalization, and academic performance while directly advancing sustainability objectives, notably SDG 4 (Quality Education) and SDG 10 (Reduced Inequalities). Future research should prioritize longitudinal designs, ethics-policy integration, and context-sensitive models in developing countries. In sum, AI should be understood not only as a technological innovation but as a transformative lever for accelerating equitable and sustainable higher education.

V. LIMITATIONS AND FUTURE RESEARCH

This study acknowledges several limitations. First, the data were drawn exclusively from Scopus-indexed, English-language articles published between 2015 and 2025, and the chosen keyword strategy may have omitted relevant works that did not explicitly emphasize the term “adoption.” Second, technological developments—particularly the rapid evolution of GenAI after 2022—progress so swiftly that some findings may lag behind emerging practices. Third, the heavy theoretical reliance on individual-level frameworks such as TAM and UTAUT, coupled with regional imbalances, limits generalizability. To address these gaps, future studies should 1) test an integrated, multilevel TAM-UTAUT-TPACK-TOE model using hierarchical modelling, and 2) connect adoption measures to objective indicators through longitudinal designs while broadening contextual analyses.

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