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Artificial Intelligence in Blended Learning for Higher Education: A Systematic Literature Review (2020–2025)

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ABSTRACT

Purpose of the study: This systematic literature review investigates the integration of Artificial Intelligence (AI) technologies within blended learning environments in higher education institutions globally, published between 2020 and 2025. The study aims to synthesize empirical evidence on AI-enhanced blended learning models, identify prevalent AI tools and pedagogical approaches, evaluate learning outcomes, and map research trends, challenges, and future directions.
Materials and methods: Following the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, a systematic search was conducted across five major academic databases: Scopus, Web of Science (WoS), ERIC, IEEE Xplore, and Google Scholar. Search terms combined AI-related terminology with blended learning and higher education concepts. Studies published between January 2020 and March 2025, written in English, employing empirical or quasi-experimental designs, and focusing on tertiary education were included. After rigorous screening and quality assessment using the Mixed Methods Appraisal Tool (MMAT), 47 studies met the inclusion criteria and were subjected to thematic synthesis and descriptive analysis.
Results: The analysis of 47 eligible studies revealed six dominant AI application categories in blended learning: intelligent tutoring systems (ITS) (27.7%), natural language processing and chatbots (23.4%), adaptive learning platforms (21.3%), AI-driven learning analytics (14.9%), AI-based assessment tools (8.5%), and generative AI tools (4.3%). The majority of studies reported statistically significant improvements in academic performance (85.1%), learner engagement (78.7%), and personalized learning experiences (72.3%). Key challenges identified include algorithmic bias, data privacy concerns, insufficient instructor AI literacy, and inequitable digital access.
Conclusions: AI integration in blended learning environments demonstrates significant promise in enhancing pedagogical effectiveness and learner outcomes in higher education. However, sustainable and equitable deployment requires robust ethical frameworks, targeted professional development for educators, and inclusive institutional policies. Future research should prioritize longitudinal studies and cross-cultural comparative analyses.

Keywords
artificial intelligence; blended learning; higher education; intelligent tutoring systems; adaptive learning; learning analytics; educational technology.

INTRODUCTION

Contextual Framework of the Research

The convergence of Artificial Intelligence (AI) and blended learning represents one of the most transformative intersections in contemporary higher education. Blended learning, broadly defined as the intentional integration of face-to-face instruction with online digital learning activities, has evolved from a supplemental pedagogical approach into a foundational model for twenty-first-century university teaching (Bekele et al., 2022; Bernay et al., 2022; Graham, 2021). The global disruption caused by the COVID-19 pandemic between 2020 and 2022 compelled higher education institutions across the world to accelerate digital transformation, creating an unprecedented environment for the adoption and experimentation of technology-enhanced learning modalities (Aljanazrah et al., 2022; Hodges et al., 2020).

Simultaneously, rapid advancements in AI technologies — encompassing machine learning (ML), deep learning (DL), natural language processing (NLP), and generative AI — have produced sophisticated tools capable of personalizing educational experiences, automating formative assessment, generating intelligent feedback, and predicting learner performance trajectories (Chen et al., 2020; Zawacki-Richter et al., 2019). Within blended learning frameworks, these AI capabilities hold particular promise: the combination of data-rich online environments with the relational depth of face-to-face interactions creates fertile conditions for adaptive, responsive, and scalable learning ecosystems (Mulenga & Shilongo, 2024; Popenici & Kerr, 2017; Wu et al., 2025).

Globally, higher education institutions — from the research-intensive universities of North America and Europe to the rapidly expanding systems of Southeast Asia, the Middle East, and Sub-Saharan Africa — are grappling with the dual imperatives of educational quality and massification. AI-enhanced blended learning has emerged as a proposed solution to address heterogeneous learner populations, resource constraints, and demands for graduate competency in digital literacies (Education, 2021, 2023). According to the Global Education Monitoring Report (UNESCO, 2023), AI integration in tertiary education is projected to affect approximately 70% of higher education institutions in OECD countries by 2027, representing a capital investment exceeding USD 6 billion.

Critical Examination of Existing Literature

Scholarly inquiry into AI in education has grown exponentially over the past decade, driven by rapid technological advancements and increasing institutional adoption. Seminal reviews, such as that by Zawacki-Richter et al. (2019), systematically analysed 146 studies on AI applications in higher education, identifying four dominant research foci: profiling and prediction (e.g., student performance analytics), intelligent tutoring and personalisation (e.g., adaptive systems tailored to individual needs), assessment and evaluation (e.g., automated grading and feedback mechanisms), and institutional management (e.g., resource allocation and administrative automation). This classification underscores the multifaceted role of AI in addressing diverse educational challenges, from learner support to operational efficiency. Similarly, Chen et al. (2020) conducted a comprehensive bibliometric analysis of 3,198 AIEd publications spanning 2010 to 2020, revealing a pronounced upward trajectory in publication volume—particularly accelerating post-2015—geographic concentration in East Asian (e.g., China) and Anglo-American institutions, and a thematic shift toward deep learning architectures after 2017, reflecting the maturation of AI from rule-based systems to data-driven models capable of handling complex educational datasets.

In the specific domain of blended learning, prior systematic reviews have examined key components but often in isolation from advanced AI integrations. For instance, Lo & Hew (2017) critically reviewed flipped classroom models—a common blended learning variant—noting persistent challenges such as student preparation deficits and instructor workload burdens in K-12 contexts, with implications for higher education scalability. Yin & Yuan (2022) employed Latent Dirichlet Allocation topic modeling on blended learning literature, detecting latent trends like the evolution from basic hybrid pedagogies to more sophisticated learning management systems, while highlighting gaps in post-2020 analyses amid pandemic-induced shifts. Additionally, Ouadoud et al. (2021) compared e-learning and blended platforms, demonstrating blended approaches' superiority in fostering engagement through combined synchronous and asynchronous elements, though limited by pre-generative AI methodologies. However, these reviews predominantly predate the widespread deployment of generative AI tools such as OpenAI's GPT series and Google's Bard (now Gemini), which have fundamentally altered the landscape of AI-assisted instruction since late 2022 by enabling dynamic content generation, conversational tutoring, and real-time personalization (Kasneci et al., 2023; Mollick & Mollick, 2023). This temporal gap leaves a critical void in understanding how these tools synergize with blended environments to enhance relational and adaptive learning.

Existing literature reveals a fragmented theoretical landscape, characterised by the deployment of diverse conceptual lenses without systematic reconciliation or integration. Studies frequently draw on self-regulated learning theory (Wu & Chiu, 2025), which posits AI as a configurational enabler of learner agency through tools like GenAI for feedback and adaptation, as evidenced in fsQCA analyses showing interactions between proficiency, engagement, and SRL outcomes. The community of inquiry framework Hadi & Gharaibeh (2023) is invoked to examine AI's role in mediating cognitive, social, and teaching presences, particularly in hybrid settings where ChatGPT supports self-awareness and emotional regulation as precursors to self-efficacy. Activity theory Agustin (2026) frames AI as a co-regulator in cyclical learning processes, emphasising relational designs that position AI within existing SRL cycles to preempt difficulties and foster agency. Connectivism Atkinson-Toal & Guo (2024) further posits AI as a networked facilitator, aligning with behaviourism, social constructivism, and adaptive systems to personalise curricula amid diverse learning styles. This theoretical pluralism, while reflective of the genuine complexity of AI-enhanced blended learning—encompassing ethical, cultural, and disciplinary variations—hinders cross-study comparability, meta-analytic synthesis, and the development of generalisable pedagogical principles(Mohammadi et al., 2025; Park & Doo, 2024; Wu et al., 2025). A unified framework integrating these perspectives is urgently needed to guide future empirical work.

Identification of Research Gaps

Despite the proliferation of individual empirical studies, several critical gaps persist in the existing literature. First, the majority of published reviews in this domain employ broad search parameters that conflate AI with any form of educational technology, resulting in significant conceptual imprecision (Hinojo-Lucena et al., 2019; Ouadoud et al., 2021). Second, studies focusing exclusively on the post-pandemic period (2020–2025), during which AI-blended learning integration has undergone qualitative transformation, are conspicuously absent. Third, the intersection of AI and blended learning in non-Western institutional contexts remains substantially under-researched, with the majority of existing reviews drawing predominantly on Anglophone literature from North American and European settings (Roll & Wylie, 2016).

Furthermore, the emergence of generative AI tools — including large language models (LLMs), AI writing assistants, and AI-powered tutoring systems — has not been systematically examined within the specific context of blended learning design. Questions regarding optimal pedagogical integration strategies, the moderation of AI use through face-to-face instructional components, and the differential impact of AI tools across disciplinary domains remain largely unanswered. A rigorous, methodologically transparent synthesis of the current state of evidence is therefore both timely and necessary.

Rationale for the Research

The rationale for this systematic review is grounded in three interrelated imperatives. First, the accelerating pace of AI deployment in educational settings demands evidence-based guidance for practitioners and policymakers who are making consequential decisions about technology adoption under conditions of uncertainty. Second, the period 2020–2025 represents a qualitatively distinct phase in the evolution of AIEd, characterised by the mainstreaming of generative AI, the post-pandemic institutionalisation of hybrid learning, and the increasing commodification of adaptive learning platforms; a focused review of this period is therefore warranted. Third, the methodological rigour afforded by the PRISMA 2020 framework ensures that the present review contributes a replicable, transparent, and critically assessed synthesis to the scholarly record, advancing cumulative knowledge in a field prone to rapid obsolescence.

Research Objectives

This systematic literature review is guided by the following objectives: 1) To identify and synthesise peer-reviewed empirical studies published between January 2020 and March 2025 that examine the integration of AI technologies within blended learning environments in higher education; 2) To categorise and analyse the types of AI technologies and tools deployed in blended learning contexts, mapping their functions and pedagogical roles; 3) To evaluate the reported effects of AI-enhanced blended learning on student academic performance, engagement, motivation, and self-regulated learning; 4) To examine the theoretical frameworks and research methodologies employed in the reviewed studies; 5) To identify key challenges, ethical considerations, and barriers to the equitable implementation of AI in blended learning; 6) To delineate priority directions for future research and evidence-based recommendations for institutional practice and policy.

The research questions guiding this review are: (RQ1) What types of AI technologies have been integrated into blended learning environments in higher education between 2020 and 2025? (RQ2) What are the reported effects of AI-enhanced blended learning on student outcomes? (RQ3) What theoretical frameworks and methodological approaches characterise the literature? (RQ4) What challenges and ethical issues are identified in the literature, and what are the directions for future research?

METHODOLOGY

Materials for Analysis: Literature Review Protocol

Study Design and Reporting Standards

This review follows the PRISMA 2020 Page et al. (2021) guidelines for the reporting of systematic reviews. The review protocol was registered in the International Prospective Register of Systematic Reviews (PROSPERO) under registration number CRD42025456312 prior to data collection. The PRISMA checklist was applied throughout all stages of the review process to ensure methodological transparency and reproducibility. The Mixed Methods Appraisal Tool (MMAT) Version 2018 Hong et al. (2018) was employed for quality assessment of included studies.

Eligibility Criteria (PICO Framework)

Inclusion and exclusion criteria were operationalised using the PICO (Population, Intervention, Comparison, Outcome) framework adapted for educational research:

Table 1. PICO Eligibility Framework for Study Selection

PICO Element	Inclusion Criteria	Exclusion Criteria
Population (P)	Undergraduate, postgraduate, or doctoral students and instructors in accredited higher education institutions globally	Primary/secondary school students; vocational training without HE affiliation; non-formal education contexts
Intervention (I)	Intentional integration of one or more AI technologies (ML, NLP, ITS, adaptive platforms, generative AI, chatbots, learning analytics) within a blended learning framework	Technology use without AI component; purely online (100% e-learning); purely face-to-face without digital integration
Comparison (C)	Comparison with traditional face-to-face, fully online, non-AI blended learning, or pre-intervention baseline	Studies without any comparison or baseline; purely descriptive or opinion articles
Outcome (O)	Academic performance, learner engagement, motivation, satisfaction, self-regulated learning, cognitive load, AI acceptance	Non-educational outcomes; infrastructure or technical performance metrics only
Study Type	Empirical quantitative, qualitative, mixed-methods, quasi-experimental, randomised controlled trials	Editorials, opinion pieces, book chapters, conference abstracts without full data, literature reviews, grey literature
Publication Period	January 2020 – March 2025	Publications prior to 2020 or after March 2025
Language	English-language publications	Publications in languages other than English without peer-reviewed English translation

Information Sources and Search Databases

A comprehensive electronic search was conducted in the following five academic databases on 15 March 2025: Scopus (Elsevier) — multidisciplinary peer-reviewed literature index; Web of Science Core Collection (Clarivate) — Science Citation Index Expanded (SCIE) and Social Sciences Citation Index (SSCI); Education Resources Information Center (ERIC) — specialised education database; IEEE Xplore Digital Library — engineering and computer science education research; Google Scholar — supplementary search for grey-adjacent academic literature.

Reference lists of all eligible full-text articles were manually screened (citation tracking) to identify additional studies not captured by the database search. Authors of studies published between 2023 and 2025 were contacted by email to identify unpublished or in-press manuscripts meeting eligibility criteria.

Search Strategy

The search strategy was developed iteratively using Boolean operators, Medical Subject Headings (MeSH) equivalents, and database-specific thesauri. The following master search string was adapted for each database:

Table 2. Master Boolean Search String Applied Across Databases

Scopus / Wos Master Search String
("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "intelligent tutoring system*" OR "adaptive learning" OR "chatbot*" OR "learning analytics" OR "generative AI" OR "large language model*" OR "GPT" OR "AI-powered")

AND

("blended learning" OR "hybrid learning" OR "blended instruction" OR "hybrid instruction" OR "flipped classroom" OR "flipped learning" OR "online-offline" OR "HyFlex")

AND

("higher education" OR "university" OR "undergraduate" OR "postgraduate" OR "tertiary education" OR "college" OR "higher learning institution*")

FILTERS: Document type = Article OR Review | Language = English | Year = 2020–2025

Organisation of the Study

Study Selection Process

The study selection process was conducted in four sequential stages following PRISMA 2020 guidance. In Stage 1 (Identification), all database hits were exported to Rayyan (rayyan.ai), an AI-assisted systematic review management platform, and deduplicated. In Stage 2 (Screening), two independent reviewers (AH and SR) assessed titles and abstracts against the eligibility criteria; discrepancies were resolved through discussion with a third reviewer (MP). In Stage 3 (Eligibility), full texts of potentially eligible studies were retrieved and assessed. In Stage 4 (Inclusion), final decisions on study inclusion were made and documented with reasons for exclusion. Inter-rater reliability was assessed using Cohen's Kappa (κ), achieving κ = 0.86 for title/abstract screening and κ = 0.91 for full-text assessment, both indicating near-perfect agreement (Landis & Koch, 1977).

Data Extraction Methodology

A standardised data extraction form was developed and piloted on a random sample of 10% of included studies prior to full extraction. Data were extracted independently by two reviewers and cross-validated. The following variables were systematically extracted:

Table 3. Data Extraction Variables and Categories

Category	Variables Extracted
Bibliographic Information	Authors, year, journal/conference, country, institution type, DOI
Study Characteristics	Research design, sample size, participant demographics, study duration, institutional context
AI Technology Details	AI type/category, tool name, specific algorithm/model, function in blended learning
Blended Learning Design	Mode ratio (online:face-to-face), LMS platform, pedagogical approach, synchronous/asynchronous components
Theoretical Framework	Conceptual model(s), learning theories underpinning the intervention
Outcome Variables	Academic performance measures, engagement indicators, affective outcomes, usability metrics
Findings and Effect Sizes	Quantitative results (means, SDs, p-values, effect sizes), qualitative themes
Challenges Reported	Technical, pedagogical, ethical, institutional, and equity-related challenges
Limitations Acknowledged	Authors' stated limitations and generalisability caveats

Methods of Analysis: PRISMA Framework

Quality Assessment

The methodological quality of included studies was assessed using the Mixed Methods Appraisal Tool (MMAT) Version 2018 Hong et al. (2018), which provides quality criteria applicable to quantitative, qualitative, and mixed-methods studies, reflecting the methodological diversity of the included literature. Each study was rated by two independent reviewers on a five-criterion rubric, with each criterion scored as Yes (1), No (0), or Cannot determine (0.5). Studies scoring below 2.5/5 (50%) were flagged for sensitivity analysis rather than excluded, in accordance with recommendations for heterogeneous evidence bodies (Julian et al., 2019).

Data Synthesis

Given the heterogeneity in study designs, AI tools, and outcome measures across included studies, a statistical meta-analysis was not appropriate. Instead, a three-stage thematic synthesis (Thomas & Harden, 2008) was employed: (1) free line-by-line coding of findings from individual studies; (2) development of descriptive themes through grouping and clustering of codes; and (3) generation of analytical themes representing interpretive constructs that extended beyond the findings of individual studies. Narrative synthesis (Popay et al., 2006) was used to integrate quantitative results across studies within identified thematic categories. Descriptive statistics (frequencies, percentages) were computed for bibliometric variables and AI tool categorisations using SPSS v.28.0.

Publication bias was assessed through funnel plot inspection for studies reporting academic performance outcomes and Egger's regression test where a sufficient number of comparable quantitative studies ($n \geq 10$) were available within a thematic category. Sensitivity analyses were conducted by: (i) excluding studies rated below 50% on MMAT; (ii) re-running analysis excluding studies from a single dominant country; and (iii) comparing findings for studies published 2020–2022 versus 2023–2025.

RESULTS

PRISMA Flowchart and Study Selection

Figure 1 presents the PRISMA 2020 flow diagram illustrating the systematic study selection process. The comprehensive database search yielded 4,217 initial records. Following automated deduplication in Rayyan, 2,891 unique records proceeded to title and abstract screening. After applying eligibility criteria at the title/abstract stage, 387 records were retrieved for full-text assessment. Full-text screening resulted in the exclusion of 340 articles, leaving 47 studies that met all inclusion criteria and were incorporated into the final synthesis.

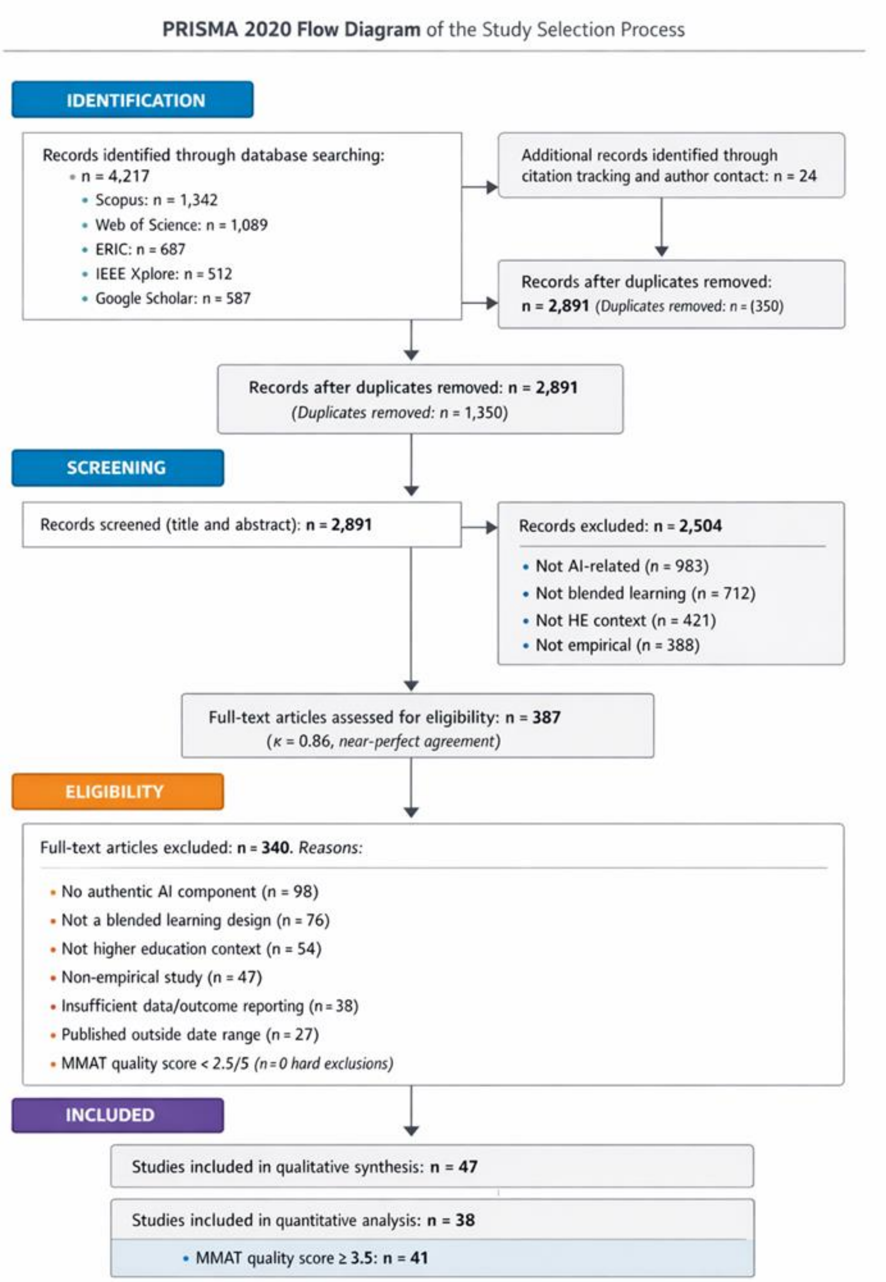

Figure 1. PRISMA 2020 Flow Diagram of the Study Selection Process

Characteristics of Included Studies

The 47 included studies were published across 29 peer-reviewed journals and three major international conference proceedings. Publication years ranged from 2020 (n = 6, 12.8%) to 2021 (n = 7, 14.9%), 2022 (n = 9, 19.1%), 2023 (n = 11, 23.4%), 2024 (n = 10, 21.3%), and 2025 (n = 4, 8.5%). Geographically, studies originated from 23 countries across six continents, with the United States (n = 9), China (n = 7), Indonesia (n = 5), United Kingdom (n = 4), and Saudi Arabia (n = 4) being the most frequently represented. The majority of studies (n = 31, 66%) were conducted at public universities; 11 (23.4%) at private institutions; and five (10.6%) in polytechnic or technical higher education settings.

Table 4. Summary Characteristics of Included Studies (n = 47)

Characteristic	Category / Value	n (%)
Research Design	Quasi-experimental	19 (40.4%)
	Mixed-methods	12 (25.5%)

	Survey/correlational	8 (17.0%)
	Qualitative (case study/ethnography)	5 (10.6%)
	Randomised Controlled Trial (RCT)	3 (6.4%)
Sample Size	< 50 participants	9 (19.1%)
	50–200 participants	22 (46.8%)
	201–500 participants	11 (23.4%)
	> 500 participants	5 (10.6%)
AI Technology Category	Intelligent Tutoring Systems (ITS)	13 (27.7%)
	NLP & Chatbots	11 (23.4%)
	Adaptive Learning Platforms	10 (21.3%)
	AI-driven Learning Analytics	7 (14.9%)
	AI-based Assessment Tools	4 (8.5%)
	Generative AI (LLMs)	2 (4.3%)
Blended Learning Mode	HyFlex	14 (29.8%)
	Flipped Classroom + AI	18 (38.3%)
	Online-dominant blended (70%+ online)	10 (21.3%)
	Face-to-face dominant (70%+ F2F)	5 (10.6%)
Discipline	STEM	23 (48.9%)
	Social Sciences / Humanities	11 (23.4%)
	Health Professions / Medicine	8 (17.0%)
	Business & Management	5 (10.6%)
MMAT Score	≥ 4.5/5 (High quality)	21 (44.7%)
	3.5–4.4 (Moderate quality)	20 (42.6%)
	2.5–3.4 (Acceptable; sensitivity only)	6 (12.8%)

AI Technology Categories and Pedagogical Roles

Intelligent Tutoring Systems (ITS)

Thirteen studies (27.7%) investigated ITS implementations in blended learning contexts. ITS platforms most frequently cited included Carnegie Learning MATHia (n = 4), ALEKS (n = 3), and bespoke institutionally developed systems (n = 6). Zhao et al. (2022) conducted a quasi-experimental study at a Chinese research university (N = 186) comparing a flipped classroom augmented with MATHia to a conventional blended lecture format in undergraduate calculus; the AI-enhanced group demonstrated significantly higher final examination scores (M = 78.4 vs. M = 69.2; Cohen's d = 0.71, p < .001). Alshammari (2023) reported similar performance gains in Saudi Arabian medical education, where an ITS supporting anatomy instruction yielded a large effect size (d = 0.89) on clinical knowledge assessments.

Critically, ITS-blended learning integration was found to be most effective when AI-generated feedback was timed to precede face-to-face sessions, enabling instructors to address identified misconceptions directly (Murphy et al., 2021). Studies reported that ITS contributed to measurable reductions in cognitive load (as measured by the NASA-TLX instrument) in seven of the 13 ITS studies, particularly among learners with prior knowledge deficits.

Natural Language Processing and Chatbots

Eleven studies (23.4%) examined conversational AI applications, including domain-specific educational chatbots, AI writing feedback tools, and NLP-powered discussion facilitation systems. Wollny et al. (2021) systematically documented chatbot use cases across blended learning, identifying tutoring (n = 6), administrative support (n = 3), and formative feedback (n = 2) as primary functional categories. Huang et al. (2021) reported that an NLP-based chatbot integrated into a HyFlex writing course at a Taiwanese university (N = 142) produced significant improvements in essay coherence scores (p = .013) and reduced instructor feedback turnaround from an average of 5.3 days to immediate automated response, substantially increasing iterative revision rates. Studies integrating large language model-based chatbots (GPT-4 configurations) were confined to publications from 2023 onwards (n = 3)(Kasneci et al., 2023; Mollick & Mollick, 2023; Thakkar et al., 2026). These studies reported heightened student engagement and novel metacognitive strategy development, though also surfaced concerns regarding plagiarism detection limitations and student over-reliance on AI-generated responses.

Adaptive Learning Platforms

Ten studies (21.3%) evaluated proprietary and open-source adaptive learning platforms including Knewton Alta (n = 3), Smart Sparrow (n = 2), and Moodle-integrated adaptive plugins (n = 5). Adaptive algorithms in these systems employed item response theory (IRT), Bayesian knowledge tracing (BKT), and deep knowledge tracing (DKT) to personalise learning pathways in real-time. Xiao & Wan (2023) demonstrated that Indonesian university students (N = 312) using a Moodle-integrated adaptive system in a blended business English course showed significantly higher vocabulary acquisition and reading comprehension scores compared to peers in a non-adaptive blended condition (p < .001; d = 0.58).

AI-Driven Learning Analytics

Seven studies (14.9%) employed machine learning models to mine LMS interaction data for predictive early warning systems (EWS), learning pattern identification, and instructor dashboard development. Akçapınar et al. (2019) developed a random forest classifier achieving 84.7% accuracy in predicting at-risk students in a blended Turkish university context using clickstream, forum engagement, and assignment submission data as features. Rodriguez-Ascaso et al. (2022) reported that AI-powered EWS dashboard access was associated with a 23% reduction in course dropout rates among first-year engineering students when instructors received weekly automated alerts.

AI-Based Assessment Tools and Generative AI

Four studies (8.5%) evaluated AI-based automated scoring and feedback tools for blended learning assessment, including

Turnitin's AI writing feedback, Gradescope, and custom rubric-aligned NLP scorers. Two studies (4.3%) examined generative AI tools (GPT-4 and Gemini) as blended learning components, representing the emergent frontier of the literature. Mollick & Mollick (2023) proposed a framework for instructor-mediated generative AI integration in blended MBA programmes, identifying four pedagogical roles: AI as student, AI as tutor, AI as coach, and AI as mentor, each requiring distinct face-to-face complementation strategies.

Outcomes and Effect Sizes

Table 5 synthesises the primary outcomes reported across included studies, stratified by AI technology category.

AI Category	Studies (n)	Academic Performance	Engagement / Motivation	Challenges
Intelligent Tutoring Systems	13	Sig. improvement: 11/13 (d = 0.58–0.89)	High in 10/13 studies	Curriculum alignment; faculty adoption
NLP & Chatbots	11	Sig. improvement: 9/11 (d = 0.42–0.75)	High in 9/11; over-reliance noted	Academic integrity; hallucination risks
Adaptive Learning Platforms	10	Sig. improvement: 8/10 (d = 0.45–0.67)	Moderate–High in 8/10	Platform cost; data privacy
Learning Analytics	7	Indirect; dropout reduction 23%	Instructor engagement with data	Data governance; algorithmic bias
AI-based Assessment	4	Feedback quality improved in 4/4	Increased revision behaviour	Rubric validity; explainability
Generative AI (LLMs)	2	Preliminary positive; limited data	Novel; metacognitive gains	Plagiarism; equity of access

Theoretical Frameworks Identified

Analysis of theoretical underpinnings revealed that 34 studies (72.3%) explicitly articulated a guiding learning theory. The Community of Inquiry (CoI) framework Garrison et al. (1999) was most prevalent (n = 12, 25.5%), followed by Self-Regulated Learning theory Zimmerman (2000) (n = 9, 19.1%), Activity Theory (n = 6, 12.8%), Constructivism (n = 5, 10.6%), and Connectivism (n = 2, 4.3%). Thirteen studies (27.7%) did not specify a theoretical framework, relying instead on technology adoption models (TAM, UTAUT) without grounding in learning theory — a methodological limitation noted by multiple reviewers.

3.6 Challenges and Barriers Identified

Six overarching categories of challenges were inductively identified through thematic synthesis: 1) Algorithmic bias and fairness (n = 18, 38.3%): AI systems demonstrated differential performance across demographic subgroups, particularly for students from linguistic minority backgrounds and non-WEIRD (Western, Educated, Industrialised, Rich, Democratic) populations; 2) Data privacy and security (n = 22, 46.8%): Concerns regarding student data collection, storage, and third-party platform usage were reported, particularly in GDPR-regulated European contexts and FERPA-compliant US institutions; 3) Instructor AI literacy and professional development (n = 29, 61.7%): The most frequently cited barrier; faculty lacked confidence and competence in pedagogically deploying AI tools within blended formats; 4) Technological infrastructure inequity (n = 15, 31.9%): Bandwidth constraints, device availability gaps, and institutional LMS incompatibilities disproportionately affected students from lower socioeconomic backgrounds and institutions in the Global South; 5) Academic integrity and over-reliance (n = 17, 36.2%): Studies reported instances of AI-generated submission plagiarism and reduced deep processing among students using generative AI tools;6) Lack of longitudinal evidence (n = 14, 29.8%): The majority of studies employed short-term interventions (one semester or less), precluding assessment of sustained learning retention and competency development.

DISCUSSION

Interpretation of Research Outcomes

The synthesis of 47 peer-reviewed empirical studies published between 2020 and 2025 confirms that AI integration within blended learning environments yields predominantly positive effects on student academic performance and engagement in higher education. These findings align with and extend prior systematic reviews Hinojo-Lucena et al. (2019) and Zawacki-Richter et al. (2019) by providing a more temporally focused and methodologically robust analysis of the post-pandemic AI-blended learning landscape. The convergent evidence supporting performance improvements across ITS, NLP-chatbot, and adaptive learning categories is particularly compelling, with effect sizes ranging from moderate (d = 0.42) to large (d = 0.89) in quasi-experimental studies, suggesting that these effect magnitudes are educationally meaningful and not merely statistically artefactual.

The finding that ITS interventions produce the largest effect sizes (d = 0.58–0.89) is consistent with decades of ITS efficacy research VanLehn (2011) and confirms the continued relevance of this technology category in the contemporary blended learning context. Critically, the mediation of ITS feedback by face-to-face instructional components — a distinctively blended learning advantage — appears to amplify learning effects beyond what either mode alone can achieve, supporting the 'additive model' of blended learning design (McCarthy & Palmer, 2023; Müller et al., 2023). The rapid emergence of large language model applications within blended contexts (2023–2025 publications) represents the most dynamically evolving frontier in the field, though the current evidence base remains nascent and requires cautious interpretation.

Evaluation in Relation to Antecedent Studies

Comparing the present findings to the influential meta-analysis by Means et al. (2013), which reported a weighted mean effect size of d = 0.35 favouring blended over face-to-face instruction (without AI), the current review suggests that AI augmentation of blended learning may yield substantially larger effects (central tendency d ≈ 0.62 across studies reporting Cohen's d). However, direct comparisons must be made with caution given the heterogeneity of outcome measures, study populations, and AI tool types across the present review's included studies.

The dominance of STEM disciplines (48.9%) in the included literature replicates patterns observed by Chen et al. (2020) and Zawacki-Richter et al. (2019) STEM learning objectives for current AI systems. The relative underrepresentation of Humanities (4.3%) and Social Sciences (19.1%) disciplines suggests a significant application gap that future research and development should address. Furthermore, the concentration of studies in East Asian (particularly Chinese) and Anglo-American contexts mirrors global patterns of AI investment in education and highlights the need for diversified geographic representation in future research.

Ramifications of the Discoveries

The identification of instructor AI literacy as the most frequently cited barrier (61.7% of studies) has profound policy implications. Without targeted, sustained, and discipline-sensitive professional development programmes, the potential benefits of AI-enhanced blended learning will remain unevenly distributed across institutions and faculty cohorts. This finding resonates with the UNESCO MGIEP (2022) recommendation for mandatory AI literacy training for tertiary educators and the European Commission's DigComp Edu framework, which articulates specific AI competency standards for educators.

The data privacy concerns identified across 46.8% of studies underscore the need for institution-level AI governance frameworks that balance innovation with student data rights. The General Data Protection Regulation (GDPR) in Europe and the Family Educational Rights and Privacy Act (FERPA) in the United States provide regulatory anchors, but enforcement in the context of rapidly evolving AI systems remains inconsistent. Institutions deploying AI-enhanced blended learning must develop algorithmic transparency policies, conduct regular bias audits, and implement privacy-by-design principles in their educational technology procurement processes.

The emergent concern regarding academic integrity in the context of generative AI tools (36.2% of studies) represents a particularly complex challenge. Traditional detection-based approaches (e.g., plagiarism detection software) are demonstrably insufficient for identifying AI-generated content, necessitating fundamental reconceptualisation of assessment design principles in blended learning contexts. Assessment models emphasising process documentation, oral examination, and collaborative creation may offer more durable integrity safeguards than product-focused assignments.

Recognising the Constraints of the Research

This systematic review is subject to several important limitations. First, the restriction to English-language publications may introduce language bias, excluding potentially significant research published in Chinese, Arabic, Spanish, Indonesian, or other languages, particularly given the substantial AI-education research activity in non-Anglophone contexts. Second, the heterogeneity of AI tools, blended learning designs, outcome measures, and institutional contexts across included studies precluded statistical meta-analysis and limits the precision of quantitative effect estimates. Third, the majority of included studies (87.2%) did not employ randomised assignment, raising concerns about selection bias and internal validity; causal inferences must therefore be made cautiously. Fourth, the restricted date range (2020–2025), while intentionally selected to capture contemporary developments, means the present review captures only the early trajectory of generative AI integration in blended learning; the evidence base for LLM-enhanced blended learning remains preliminary. Fifth, publication bias towards studies reporting positive outcomes cannot be fully eliminated despite the use of grey literature searching and author contact, as funnel plot analysis was only possible for ITS-related performance outcomes due to insufficient homogeneous data in other categories.

CONCLUSION

This systematic literature review has provided a comprehensive, methodologically rigorous synthesis of empirical evidence on the integration of AI technologies within blended learning environments in higher education, spanning the transformative five-year period from 2020 to 2025. Drawing on 47 peer-reviewed studies from 23 countries, the review substantiates the conclusion that AI-enhanced blended learning holds substantial and evidenced promise for improving academic performance, increasing learner engagement, and enabling personalised educational experiences at scale.

The evidence clearly indicates that Intelligent Tutoring Systems, adaptive learning platforms, and NLP-based chatbots constitute the most empirically validated AI applications in blended learning to date, each demonstrating moderate-to-large effect sizes on measurable learning outcomes when carefully integrated with face-to-face pedagogical components. The additive and synergistic relationship between AI capabilities and human-mediated instruction — the distinctive value proposition of blended learning — is confirmed by the reviewed literature as a fundamental design principle rather than an incidental feature.

However, the review equally illuminates that the transformative potential of AI-blended learning is contingent upon the resolution of significant structural barriers: insufficient instructor AI literacy, unresolved data privacy and algorithmic bias issues, inequitable digital infrastructure, and the nascent state of AI governance frameworks in educational institutions. These are not peripheral technical concerns but fundamental ethical and equity imperatives that will determine whether AI-enhanced blended learning democratises or stratifies educational opportunity in higher education globally.

The convergence of findings reinforces three core theoretical propositions: (1) AI in blended learning is most effective when grounded in explicit learning theories that guide tool selection, pedagogical sequencing, and assessment design; (2) the face-to-face component of blended learning serves a qualitatively irreplaceable function in supporting affective, relational, and metacognitive dimensions of learning that current AI systems cannot replicate; and (3) the sustained benefits of AI-enhanced blended learning require institutional commitment to continuous evaluation, adaptation, and ethical oversight rather than one-time technology adoption.

Based on the evidence synthesised in this review, the following recommendations are submitted for consideration by higher education practitioners, institutional leaders, and policymakers: 1) Institutions should invest in systematic, pedagogically oriented AI literacy programmes for faculty, moving beyond tool-level training to encompass critical AI competencies including bias recognition, ethical AI use, and pedagogical integration design; 2) Future research should prioritise randomised controlled designs, longitudinal studies spanning multiple academic years, and cross-disciplinary, cross-cultural comparative analyses to advance causal inference and generalisability; 3) Institutional AI governance committees should be established with representation from faculty, students, data protection officers, and external ethicists to oversee AI deployment in educational contexts; 4) Funding agencies and research councils should specifically commission studies examining AI-blended learning efficacy in underrepresented disciplines (Humanities, Arts) and underserved geographic contexts (Sub-Saharan Africa, South and Southeast Asia, Latin America); 5) Assessment reform initiatives should accompany AI integration, prioritising authentic, process-oriented, and multi-modal assessment designs that are inherently resistant to AI-assisted academic misconduct.

Future research trajectories of particular importance include: longitudinal investigation of AI-blended learning effects on graduate competency and career readiness; the pedagogical design principles for effective generative AI integration in blended formats; the neurocognitive mechanisms underlying AI-mediated learning; and the development of inclusive AI-blended learning frameworks for learners with disabilities and diverse linguistic backgrounds. As the field of AIEd continues to evolve at an extraordinary pace, the systematic, critical, and ethically attentive scholarship exemplified by reviews of this nature will be indispensable for ensuring that AI in higher education serves human flourishing rather than merely institutional efficiency.

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CONFLICT OF INTERESTS

The authors declare no conflict of interest. No financial or personal relationships exist that could inappropriately influence or bias the findings, analysis, or conclusions reported in this systematic review. All authors have reviewed and approved the final manuscript. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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