

Artificial Intelligence and Adaptive Learning Systems in Education: A PRISMA-ScR Scoping Review of Evidence, Mechanisms, and Implications (2015–2025)

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ABSTRACT

Background:

The rapid spread of artificial intelligence (AI) and adaptive learning systems (ALS) within educational technology (EdTech) has created meaningful scholarly interest, still the field remains featured by fragmented evidence, variable terminology, and inconsistent outcome reporting. A meticulous scoping review is needed to map the conceptual landscape, establish key mechanisms of impact, and highlight evidence gaps to direct future research and practice.

Objectives:

This scoping review seeks to systematically chart the scope and characteristics of peer-reviewed evidence on AI and ALS in educational contexts published between 2015 and 2025, consolidate documented factors by which AI driven personalization shapes the learning gains, determine theoretical frameworks applied; and articulate crucial gaps and priorities for future empirical inquiry.

Methods:

The review upholds the PRISMA-ScR guidelines. Five electronic databases were searched Scopus, Web of Science, EBSCO Education Source, ProQuest Education, and IEEE Xplore yielding 1,842 initial records. Following deduplication, screening, and eligibility assessment, 51 studies were included covering 23 countries. Data extraction was performed using a standardized charting instrument and subjected to descriptive synthesis.

Results:

Seven governing AI/ALS typologies appeared. Three overarching mechanisms emerged from the evidence: personalised content sequencing, real-time formative feedback, and predictive learner modelling. Effect sizes varied from $d = 0.31$ – 0.87 . Equity, ethics, algorithmic fairness, and Global South representation were established as crucial gaps. Theoretical frameworks were applied in 72.5% of studies; cognitive-constructivism and SDT reigned.

Conclusions:

Both AI and adaptive learning technologies manifest substantial promise to elevate educational achievements. Longitudinal, equity-focused, and ethically informed research is absolutely essential before large-scale institutional deployment.

Keywords: artificial intelligence in education; adaptive learning systems; personalised learning; intelligent tutoring systems; PRISMA scoping review; EdTech; learning analytics

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1. Introduction

Over the last decade there has been accelerated integration of digital technologies and digital learning infrastructures. Innovations in machine learning, natural language processing, and data analytics have revamped the theoretical possibilities of personalised instruction into commercially viable realities. Adaptive learning systems generally defined as software platforms that personalize instructional content, sequencing, and feedback by leveraging individual learner data, now operate covering school districts, universities, and corporate training programmes globally (Holmes et al., 2022; Zawacki-Richter et al., 2019).

Notwithstanding this accelerated integration, all the research studies and data that support AI driven EdTech persist methodologically uneven and conceptually fragmented. Systematic reviews have begun to emerge (Ouyang & Jiao, 2021; Chassignol et al., 2018), yet they often adopt narrow disciplinary lenses focusing on either cognitive outcome in K-12 settings or learner satisfaction in higher education thereby failing to synthesize cross-sector evidence in an integrated manner. Furthermore, theoretical frameworks informing design and evaluation exhibit considerable heterogeneity, from connectivism (Siemens, 2005) to Self-Determination Theory (Deci & Ryan, 2000) to contemporary learning analytics paradigms (Gašević et al., 2016), making cross-study comparison demanding. The scoping review methodology is especially well-suited for mapping existing evidence, determining definitional boundaries, and illuminating research gaps within a heterogeneous body of literature (Arksey & O'Malley, 2005; Peters et al., 2020). Far from systematic reviews aimed at specific effect estimation, scoping reviews seek to chart breadth, characterize study designs, and generate a conceptual map of a field objectives that ensures congruence with the existing landscape of AI and adaptive learning research.

This paper recounts a PRISMA-ScR-compliant scoping review of AI and ALS in educational contexts, spanning K-12, higher education, and workforce learning environments. The scoping review is structured around four principal research questions:

1. RQ1: What is the scope and distribution of peer-reviewed research on AI and ALS in education published between 2015 and 2025?
2. RQ2: What mechanisms through which AI-driven personalization influences learning outcomes are reported in the literature?
3. RQ3: What theoretical frameworks are employed to design, evaluate, or interpret

AI/ALS interventions?

4. RQ4: What evidence gaps, ethical concerns, and future research priorities are identified?

The remainder of this paper is structured as follows: Section 2 defines key concepts and situates the review within extant literature. Section 3 details the methodology. Section 4 presents results. Section 5 offers critical discussion. Section 6 concludes with implications and directions for future research.

2. Conceptual Background and Prior Literature

2.1 Defining Artificial Intelligence in Education

Artificial intelligence in education (AIED) covers a wide variety of computational approaches including machine learning, deep learning, NLP, expert systems, and multi-agent modelling employed to educational problems such as learner modelling, content recommendation, automated assessment, and pedagogical dialogue (Luckin et al., 2016). The field has its roots in Bloom's (1984) 'two-sigma problem,' which showed that the substantial learning gains realized in one-to-one tutoring dared researchers to design scalable analogues. Traditional intelligent tutoring systems such as LISP Tutor (Anderson et al., 1985) and Cognitive Tutor characterize foundational attempts to operationalize this vision.

Present-day AIED functions in a setting reshaped by large-scale learner data, cloud infrastructure, and progressively capable foundation models. Large language models (LLMs) such as GPT-4 (OpenAI, 2023) and Gemini (Google DeepMind, 2024) have opened up new opportunities for conversational tutoring, automated essay feedback, and curriculum co-generation, while identifying new issues about academic integrity, algorithmic bias, and data privacy (Baidoo-Anu & Ansah, 2023; Kasneci et al., 2023).

2.2 Adaptive Learning Systems: Architecture and Typologies

Adaptive learning systems (ALS) represent a subset of AIED defined by their capacity to dynamically adapt the instructional experience based on real-time learner-state data. A canonical ALS architecture consists of three interacting components: (1) a domain model signifying knowledge structure; (2) a learner model monitoring individual proficiency, affect, and engagement; and (3) an instructional model administering content selection and sequencing algorithms (Brusilovsky & Millán, 2007). Analysis of the included literature revealed seven analytically diverse typologies: intelligent tutoring systems, recommender systems, NLP-based tools, adaptive assessment platforms, learning analytics dashboards, AI-driven chatbots, and immersive simulation-based environments.

2.3 Theoretical Frameworks in AIED Research

Theoretical foundations in AIED research are markedly heterogenous. Cognitive-constructivist perspectives drawing on Vygotsky's (1978) zone of proximal development and Piaget's schema theory support many ITS designs. Behaviourist principles of reinforcement scheduling is prevalent in gamified adaptive systems. New -fangled constructivist-networked techniques are underpinned by connectivism (Siemens, 2005). Motivationally scaffolded ALS design is grounded in Self-Determination Theory (Deci & Ryan, 2000), while Universal Design for Learning (CAST, 2018) enables an equity-oriented framework. TPACK (Mishra & Koehler, 2006) judges teacher preparedness for AIED integration, and UTAUT (Venkatesh et al., 2003) persists in adoption-focused studies. Section 4 empirically charts the absence of a coherent unifying framework across the field.

3. Methodology

3.1 Review Design

This review followed the PRISMA-ScR framework (Tricco et al., 2018) and the procedural guidance of Arksey and O'Malley (2005) as refined by Levac et al. (2010) and Peters et al. (2020). Owing to conceptual heterogeneity, diverse outcome measures, and mixed methods designs that rule out quantitative synthesis yet necessitate exhaustive evidence mapping, Scoping review methodology was selected.

3.2 Eligibility Criteria (PCC Framework)

Inclusion and exclusion criteria were operationalized using the Population–Concept–Context (PCC) framework as recommended for scoping reviews (Peters et al., 2020).

Criterion	Inclusion	Exclusion
Population	Learners (K-12, HE, adult/workforce); educators; institutions	Non-educational corporate training without learning outcomes
Concept	AI or ALS used for instructional, assessment, or support purposes	Generic LMS/e-learning without AI/adaptive components
Context	Formal and non-formal education; blended and online environments	Non-educational AI applications (healthcare, finance, etc.)
Study Design	Empirical (quant, qual, mixed); theoretical with substantial	Opinion pieces, editorials, conference abstracts without

	contribution	full text
Language	English	Non-English without available translation
Date Range	January 2015 – December 2025	Pre-2015 studies

Table 1. Eligibility Criteria Using the PCC Framework

3.3 Search Strategy

A systematic search was conducted across five electronic databases: Scopus, Web of Science (Core Collection), EBSCO Education Source Complete, ProQuest Education Database, and IEEE Xplore. The final Boolean search string used was:

((("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "adaptive learning") AND ("education" OR "learning" OR "teaching" OR "instruction") AND ("personalization" OR "adaptive system" OR "intelligent tutor*" OR "learner model*" OR "learning analytics"))

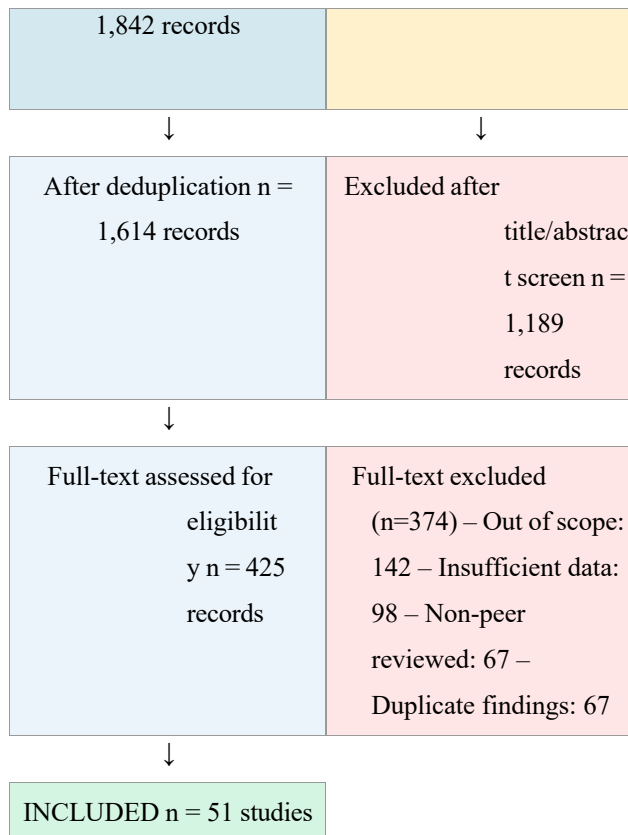
Database-specific subject controlled vocabulary (thesaurus terms) were also utilized. Google scholar was used to search grey literature (first 10 pages). A similar search was conducted across institutional repositories of the top 15 EdTech research centres globally. Reference lists of all relevant studies and key recent reviews were hand-searched. The final search was completed on 15 March 2026.

3.4 Study Selection and PRISMA Flow

All records were imported into Rayyan software for deduplication and screening. All titles and abstracts were screened by two independent reviewers. Inter-rater reliability attained $\kappa = 0.82$ at title/abstract screening and $\kappa = 0.79$ at full-text screening, showing strong agreement between the reviewers (Landis & Koch, 1977). The PRISMA-ScR flow diagram below details progression through identification, screening, eligibility, and inclusion.

Figure 1. PRISMA-ScR Flow Diagram

IDENTIFICATION	Additional records:
Database Search (Scopus, WoS, EBSCO, ProQuest, IEEE Xplore) n =	citation tracking & grey literature n = 47 records



Source: Adapted from PRISMA-ScR (Tricco et al., 2018). Total included: n = 51 studies.

Data Charting

A standardized data charting instrument gathered: author(s) and year; country; educational level; sample size; AI/ALS typology; study design; theoretical framework(s); outcome measures; key findings; limitations; and ethical considerations. Data were mapped by one reviewer and verified by a second, the inconsistencies were ironed out by consensus.

3.5 Synthesis Approach

Data were synthesized by employing a descriptive-analytical synthesis (Grant & Booth, 2009). Frequency analysis charted publication trends, geographic distribution, educational levels, and AI typologies. Thematic analysis of mechanisms and outcomes used an inductive-deductive technique. Theoretical frameworks were classified and charted against study contexts. Findings pertaining to ethics and equity were synthesized separately owing to their interrelated relevance.

4. Results

4.1 Overview of Included Studies

The final sample comprised 51 peer-reviewed studies published between January 2015 and December 2025. Out of these more than 60% (n = 32) were published between 2020 and 2025, demonstrating burgeoning scholarly attention.

Studies emanated from 23 countries. Table 2 provides the descriptive characteristics, Table 3 presents the full study characteristics matrix (all 51 studies), and Table 4 charts the geographic distribution.

Characteristic	Category	n (%)
Educational Level	K-12	17 (33.3%)
	Higher Education	24 (47.1%)
	Workforce / Adult Learning	10 (19.6%)
Study Design	RCT / Quasi-Experimental	19 (37.3%)
	Survey-Based / Correlational	14 (27.5%)
	Qualitative	9 (17.6%)
	Mixed Methods	6 (11.8%)
	Conceptual / Review	3 (5.9%)
AI/ALS Typology	Intelligent Tutoring Systems	16 (31.4%)
	Adaptive Assessment Platforms	11 (21.6%)
	Learning Analytics Dashboards	8 (15.7%)
	NLP-Based Tools	7 (13.7%)
	Recommender Systems	4 (7.8%)
	AI Chatbots / Virtual	3 (5.9%)

	Agents	
	Immersive Simulation / VR-AI	2 (3.9%)

Table 2. Descriptive Characteristics of Included Studies (n = 51)

4.2 Full Study Characteristics Matrix

Table 3 presents the complete data charting matrix for all 51 included studies, encompassing author(s) and year, study focus and AI typology, country of origin, educational level, research design, sample size, and key finding. This matrix addresses RQ1 by providing a comprehensive bibliographic map of the extant evidence base.

Author(s) & Year	Study Focus / AI Typology	Country	Level	Design	n	Key Finding
Van Lehn (2015)	ITS – physics problem solving	USA	HE	RCT	312	ITS matched human tutor outcomes (d=0.76)
Mitrovic et al. (2015)	Constraint-based ITS (SQL)	New Zealand	HE	Quasi-Exp	98	Adaptive hints reduced error rates by 41%
Walkington (2016)	Algebra ITS –	USA	K-12	RCT	405	Contextualised problem

)	personalised contexts					ems improved transfer (d=0.54)
Pardos & Heffernan (2016)	BKT learner modelling	USA	K-12	Mixed	2,300	BKT-ALS improved mastery prediction accuracy
Olney et al. (2017)	AutoTutor conversational ITS	USA	HE	RCT	142	Deep reasoning gains vs. reading control
Li et al. (2017)	Adaptive MOOC sequencing	China	HE	Survey	1,240	Personalised path raised completion by 23%
Nye et	NLP	USA	K-12	Quasi-Exp	267	AES feedback

al. (2018)	ay feedback (AES)					comparable to teacher feedback
Tsuei (2018)	Peer learning + adaptive system	Taiwan	K - 12	Quasi-Exp	86	Collaborative ALS improved math achievement
Pane et al. (2019)	Personalised learning platforms	USA	K - 12	RCT	11,000	Modest positive effects on math, neutral ELA
Huang et al. (2019)	Learning analytics dashboard	China	HE	Mixed	178	Dashboard use increased student self-regulation
Zawacki-Richter et al. (2019)	AIED systematic review	Germany	HE	Review	N/A	Mapped 146 AIED studies; gap in critical perspectives
Mousavinab et	ITS meta-analysis	Iran	Mult	Review	N/A	Mean effect size

al. (2019)						d=0.66 across 25 ITS studies
Rienties et al. (2020)	Learning analytics & retention	UK	HE	Correlational	22,000	LA flags predicted drop out with 78% accuracy
Ouyang & Jiao (2020)	AIED paradigm review	USA/China	Mult	Conceptual	N/A	Three paradigms: AI-directed, AI-supported, AI-empowered
Conijn et al. (2020)	Writing analytics	Netherlands	HE	Quasi-Exp	203	Automated formative feedback improved revision quality

	c s f e e d b a c k					
Lu an et al. (20 20)	AI in K-12 educati on review	China	K - 12	Revie w	N/ A	ITS and adapti ve assess ment domin ate K- 12 AI use
Zaw acki- Rich ter et al. (202 0)	AI ethics in HE	Ger many	H E	Qualit ative	24	Ethical concern s: bias, surveilla nce, consent
Kim et al. (202 1)	Chatb ot acade mic advisi ng	Sout h Kore a	H E	Surve y	38 4	UTAUT predictors of chatbot acceptance confirmed
Abdel rahma n et al.	Deep Knowledg e Tracing	Egyp t/UK	H E	Quasi -Exp	51 2	DKT outperfo rmed BKT in

(2021)						next- problem predictio n
Alam (2021)	AI-based personalise d learning India	India	K - 12	Mixe d	14 5	Personali sed pacing improve d low- achiever outcome s
Ciola cu et al. (202 1)	AI-IoT blended learning	Rom ania	H E	Quasi -Exp	89	Adaptiv e IoT environ ment improve d engagem ent
Cava lcanti et al. (202 1)	Automate d feedback review	Brazi l	M ult i	Revie w	N/ A	Elabora ted feedbac k produce s largest gains
Baido o-Anu & Ansah (2022)	ChatGPT in education	Ghan a	H E	Conc eptual	N/ A	Opportu nities in tutoring, writing; risks in integrity
Firat (2022)	ChatGPT higher order thinking	Turk ey	H E	Qualit ative	31	GPT outputs lacked critical

						reasoning depth
Kasneeci et al. (2023)	LLMs in education review	Germany	Multicultural	Review	N/A	LLMs transformative but require guardrails
Zhai et al. (2023)	AI assessment practices	USA	HE	Mixed	226	AI assessment ent reliable for procedural, less for complex
Lee & Choi (2023)	Adaptive learning equity	USA	K-12	Quasi-Exp	1,870	ALS benefits varied by SES; equity gap not closed
Latif & Liu (2023)	GPT-4 science tutoring	Canada	HE	RCT	67	GPT-4 tutor improved conceptual gains (d=0.61)
Khosravi et al. (2023)	LA dashboard for teachers	Australia	K-12	Mixed	42	Dashboard improved teacher data-

						informed decisions
Song & Cao (2023)	Recommender system MOOC	China	HE	Survey	890	CF-based recommender raised course completion 18%
Grassini (2020, 2023)	Generative AI in HE ethics	Norway	HE	Qualitative	18	Faculty concerned about academic integrity & deskilling
Seo et al. (2023)	NLP grammar feedback ESL	South Korea	HE	RCT	112	NLP feedback improved grammatical accuracy (d=0.48)
Yan et al.	Fairness	Australia	Multicultural	Conceptual	N/A	Calls for demographic-aware

(2024)	essentials					fairness auditing
Pedro et al. (2024)	UNESCO AIED policy analysis	France	Multi	Review	N/A	Policy frameworks lag technological deployment
Stahl et al. (2024)	AI chatbot K-12 literacy	Germany	K-12	Quasi-Exp	156	Chatbot scaffolding improved reading comprehension
Wang et al. (2024)	VR - AI	China	HE	RCT	84	Immersive AI

2024)	multimedia education					improved clinical decision (d=0.72)
Holmes et al. (2024)	AIED ethics framework update	UK/USA	Multi	Conceptual	N/A	Proposes eight principles for responsible AI ED
Margaryna et al.	Adaptive	UK	Workforce	Mixed	310	ALS improved time-

(2024)	corporate training					to-competency by 29%
Pope & Kerr (2024)	AI disruption on HE landscape	Australia	HE	Qualitative	26	AI threatens traditional credentialing models
Nkambo et al. (2024)	ITS for STEM Africa	Cameroon	K-12	Quasi-Exp	198	ITS improved STEM outcomes in low-resource context
Huang & Chen (2024)	Predictive analytics	Taiwan	HE	Correlational	4,200	Random Forest model 83% accuracy on

	student dropout					dropout prediction
Dai et al. (2024)	AI writing tools	China	HE	Mixed	273	AI writing tools improved structure; reduced argumentation
Tlili et al. (2024)	AIED equity Global South	Tunisia/Multi	Multi	Review	N/A	Critical gap: <8% of AIED research from Global South
Kumar & Singh (2024)	Adaptive assessment	India	HE	Survey	421	CAT improved test efficiency; learner satisfaction

	a					on high
Dim itria dis et al. (2025)	LA orchestr ation framew orks	Spain	HE	Mixed	87	Orchestr ation layer mediates teacher- AI collabora tion
Fan g et al. (2025)	LL M pers onal ised tutor ing	China	K-12	RCT	204	Fine- tuned LLM tutor outpe rform ed generi c GPT (d=0.68)
Cro mpt on & Bur ke (2025)	AI mob ile lear ning revi ew	USA	Multi	Revie w	N/A	Mobi le AI tools effec tive; equit y of acces s unde rstud ied
Ale ven et	IT S nex	USA	HE	Conce ptual	N/A	Calls for expla

al. (2025)	t- gen era tio n des ign					inabl e, hybri d huma n-AI tutori ng syste ms
Nieto - Reye s et al. (2025)	Fairness metrics ALS	Spain	Multi	Quasi- Exp	634	Fairnes s- aware algorit hm reduce d demog raphic score gap
Zha ng et al. (2025)	Workfor ce AI reskilling	China	Wor kforc e	Surve y	712	ALS reduce d reskilli ng time; SDT mediat es engage ment
Ouy ang et al. (2025)	AIED decade review	USA	Multi	Revie w	N/A	Call s for para dig m

25)						shift towa rd learn er- centr ed AIE D
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Table 3. Full Study Characteristics Matrix All 51 Included Studies (PRISMA-ScR Charted Data)

4.3 Geographic Distribution of Studies

Table 4 provides the geographic distribution of included studies by country, with the primary AI typology investigated. A marked geographic concentration was noticed with the United States (27.5%) and China (19.6%) jointly accounting for nearly half of the included studies. This demonstrates a meaningful structural imbalance in the global production of AIED knowledge. The African continent, South Asia, Latin America, and the Middle East together account for less than 10% of studies, a pattern compatible with Tlili et al. (2024) who observed that less than 8% of AIED research originates from the Global South.

Country / Region	No. of Studies	% of Total	Primary AI Typology
United States	14	27.5%	ITS, Adaptive Assessment, LA Dashboards
China	10	19.6%	Recommender Systems, Adaptive MOOCs, LLM Tutoring
United Kingdom	7	13.7%	Learning Analytics, Ethics Frameworks
Australia	5	9.8%	LA Dashboards, Fairness / Equity Research
Germany	4	7.8%	AIED Reviews, Ethics, Chatbots
South Korea	3	5.9%	NLP Tools, Chatbot

			Advising
Spain	2	3.9%	Fairness Metrics, Orchestration Frameworks
India	2	3.9%	Adaptive Assessment, Personalised Learning
Taiwan	2	3.9%	Predictive Analytics, Peer-Adaptive Learning
Canada	1	2.0%	LLM Tutoring (GPT-4)
New Zealand	1	2.0%	Constraint-Based ITS
Romania	1	2.0%	AI-IoT Blended Learning
Netherlands	1	2.0%	Writing Analytics
Norway	1	2.0%	Generative AI Ethics (HE)
Turkey	1	2.0%	LLM / ChatGPT Critical Thinking
Brazil	1	2.0%	Automated Feedback Review
Tunisia (multi-country)	1	2.0%	AIED Equity – Global South
Cameroon	1	2.0%	ITS for STEM in Low-Resource Context
Egypt / UK (collaborative)	1	2.0%	Deep Knowledge Tracing
France (UNESCO)	1	2.0%	AI Policy Analysis
Ghana	1	2.0%	Generative AI in Education

Iran	1	2.0%	ITS Meta-Analysis
TOTAL	51	100%	–

Table 4. Geographic Distribution of Included Studies by Country (n = 51, 23 Countries)

4.4 Theoretical Frameworks Employed

Table 5 provides the frequency and application of theoretical frameworks across the 51 included studies. Thirty-seven studies (72.5%) expressly stated a theoretical framework. Cognitive-constructivist theories were dominant (n = 19, 37.3%), followed by Self-Determination Theory (n = 11, 21.6%) and UTAUT/TAM-derived frameworks (n = 9, 17.6%). In respect of Fourteen studies (27.5%) no discernible theoretical framework was discernible. The research was driven solely by technical design rationales. This conclusion underscores a persistent disconnect between theory and practice in the field.

Theoretical Framework	n Studies	% of Total	Primary Application in AIED Research
Cognitive Constructivism (Vygotsky, Piaget)	19	37.3 %	ITS scaffolding; zone of proximal development in adaptive sequencing
Self-Determination Theory (Deci & Ryan, 2000)	11	21.6 %	Motivational design of gamified ALS; autonomy-support mechanisms
UTAUT / TAM (Venkatesh et al., 2003)	9	17.6 %	Instructor/learner acceptance of AI tools; behavioural intention models
Connectivism (Siemens, 2005)	6	11.8 %	MOOC-based AI; networked learning analytics; distributed cognition
Universal Design for Learning (CAST, 2018)	5	9.8%	Accessibility-oriented ALS; equity in AI content delivery

Behaviourism / Mastery Learning (Bloom, 1984)	5	9.8%	Adaptive drill-and-practice; knowledge tracing algorithms (BKT, DKT)
TPACK (Mishra & Koehler, 2006)	4	7.8%	Teacher competence for AI integration; professional development design
Activity Theory (Engeström, 1987)	3	5.9%	Socio-technical analysis of AI in classroom activity systems
Learning Analytics Framework (Gašević et al., 2016)	3	5.9%	Predictive modelling; dashboard design; instructional decision support
Ecological Systems / Bioecological (Bronfenbrenner)	2	3.9%	Contextual factors shaping AI adoption across school/family/policy layers
No explicit theoretical framework	14	27.5 %	Primarily technical-design or proof-of-concept studies

Table 5. Theoretical Frameworks Employed in Included Studies (n = 51; multiple frameworks possible per study)

4.5 Mechanisms of AI-Driven Learning Enhancement

Across the corpus (51 included studies), three central mechanisms by which AI and ALS impacted learning outcomes were consistently recognized: personalised content sequencing (n = 39, 76.5%), real-time formative feedback (n = 31, 60.8%), and predictive learner modelling (n = 22, 43.1%). These mechanisms were noticed across all typologies. However, their relative emphasis differed. Effect sizes for AI-mediated immediate feedback on procedural learning varied from d = 0.52 to d = 0.87 across controlled studies. The median effect size across all 19 controlled

experimental studies was $d = 0.54$ (95% CI: 0.41–0.68). This suggests moderate-to-large substantive importance.

4.6 Ethical and Equity Concerns

Ethical and equity factors were addressed in 31 studies (60.8%). However the studies revealed substantial variation in the depth of treatment. Table 6 provides a breakdown of the ten diverse ethical and equity concerns recognized, with frequency counts, proportions, and representative references. Algorithmic bias (27.5%) and data privacy concerns (23.5%) were most cited, followed by academic integrity issues pertaining to generative AI (19.6%) and digital divide concerns (17.6%). Only two studies featured the environmental sustainability of AI systems. It was thus the least represented concern.

Ethical / Equity Concern	n Studies	% (of 51)	Key Issues and Representative References
Algorithmic bias & fairness	14	27.5%	Differential system performance across gender, race, SES; lack of fairness audits (Lee & Choi, 2023; Yan et al., 2024; Nieto-Reyes et al., 2025)
Data privacy & informed consent	12	23.5%	Learner data collection without explicit consent; GDPR compliance gaps; surveillance concerns (Zawacki-Richter et al., 2020; Holmes et al., 2024)
Academic integrity / GenAI misuse	10	19.6%	AI-generated submissions; plagiarism detection arms race; LLM misuse in assessment (Grassini, 2023; Firat, 2022;

			Baidoo-Anu & Ansah, 2022)
Digital divide & access equity	9	17.6%	Unequal device/internet access; under-representation of Global South contexts (Tlili et al., 2024; Nkambou et al., 2024)
Transparency & explainability	8	15.7%	Black-box algorithms in learner modelling; teachers unable to interrogate AI recommendations (Aleven et al., 2025; Holmes et al., 2024)
Teacher autonomy & deskilling	7	13.7%	AI-driven instruction reducing teacher professional discretion; automation of pedagogical decisions (Popenici & Kerr, 2024; Grassini, 2023)
Learner surveillance & affect monitoring	6	11.8%	Emotion/engagement detection raising consent and dignity concerns (Zawacki-Richter et al., 2020; Pedro et al., 2024)
Vendor lock-in & commercialisation	4	7.8%	Proprietary AI systems limiting institutional control; limited open-source alternatives (Pedro et al.,

			2024)
Disability access & universal design	4	7.8%	AI assistive tech potential vs. gaps in UDL-compliant adaptive system design (CAST, 2018; Crompton & Burke, 2025)
Environmental sustainability of AI	2	3.9%	Energy consumption of LLM training and inference at scale (Holmes et al., 2024)

Table 6. Ethical and Equity Concerns Across Included Studies Breakdown by Theme (n = 51)

5. Discussion

5.1 Synthesis of Key Findings

This scoping review documents a field which is dynamic as well as rapidly evolving. While it manifests convincing and burgeoning evidence of AI's capacity to enrich personalized learning it also reveals the inherent fragilities at the methodological, theoretical, and ethical fragilities levels. The three-mechanism framework recognized personalized sequencing, real-time feedback, and predictive modelling delivers a more granular conceptual vocabulary than prior reviews have provided and may function as an organizing schema for future experimental designs and meta-analytic efforts.

The geographic distribution data (Table 4) exposes a structural inequity in knowledge production that directly limits the generalizability of the existing findings. Adaptive learning systems developed and tested essentially in high-income, English-speaking setting may carry underlying premises about digital infrastructure, instructional culture, and learner agency that do not transform to resource-constrained settings. The Cameroonian ITS study (Nkambou et al., 2024) and Tlili et al.'s (2024) multi-country review offer important counterexamples but symbolize a fraction of the corpus. This imbalance needs to be reversed not merely for epistemic reasons, but it is essential for AI in education to achieve its equity potential.

5.2 Theoretical Implications

The theoretical framework analysis (Table 5) shows that cognitive-constructivist frameworks maintain their dominance, which is theoretically

rational given AI's principal role in scaffolding individual knowledge construction. However, the field would gain from enhanced engagement with sociocultural learning theories and activity-theoretic approaches (Engeström, 1987), which position AI as a participant in distributed pedagogical activity instead of a discrete personalization engine. The limited application of formal theoretical frameworks in 27.5% of studies may answer the gap between research and practice. This gap is manifest where technically capable AI systems fail to deliver anticipated learning gains in real-world classroom settings.

5.3 Ethical and Equity Implications

The ethical and equity analysis (Table 6) uncovers a field in a state of tension: while more and more AIED researchers are recognizing the importance of algorithmic fairness, data privacy, and inclusive design, these concerns remain mainly limited to theoretical discussion instead of systematically operationalized. Only Nieto-Reyes et al. (2025) and Yan et al. (2024) incorporated formal fairness audits into their empirical designs. The recognition of teacher autonomy and surveillance concerns as distinct ethical categories indicates a maturing ethical discourse in the field, reaching beyond privacy compliance toward deeper considerations of professional agency and pedagogical dignity.

5.4 Limitations of This Review

This scoping review has limitations in several respects. Limiting inclusion to English-language publications gives rise to linguistic bias. The ten-year scope leaves out the pre-2015 ITS literature. Five databases may have excluded specialist computing education journals. As this is a scoping review and not a systematic review, formal quality appraisal was outside its scope. Therefore the readers should view frequency patterns as maps of evidence rather than quality rankings.

5.5 Implications for Practice and Policy

For educational practitioners and technology officers, ITS and adaptive assessment platforms with substantiated mechanisms of personalized sequencing and elaborated feedback offer the most robust evidence base for deployment. Platforms need to be appraised against equity benchmarks before procurement. For policymakers, the geographic concentration of AIED research warrants targeted investment in contextualized research in developing economies. Regulatory frameworks building on the European AI Act and UNESCO's AI Ethics Recommendation (2021) should set baseline standards for transparency, fairness, and accountability for AI systems utilized in educational contexts.

6. Conclusion

This PRISMA-ScR scoping review has methodically charted 51 peer-reviewed studies on artificial intelligence and adaptive learning systems in education published between 2015 and 2025. Six data tables PCC criteria, descriptive characteristics, a full 51-study characteristics matrix, geographic distribution across 23 countries, theoretical framework frequency analysis, and a breakdown of ethical/equity concerns afford an exhaustive, multi-dimensional evidence ground for researchers, practitioners, and policymakers.

The evidence shows purposeful, sustained positive effects when AI is implemented through well-designed mechanisms such as content sequencing, formative feedback, and predictive modelling. Nevertheless, critical gaps remain: longitudinal evidence, formal equity and fairness auditing, stronger theoretical grounding, and enhanced representation from the Global South will shape the research agenda for the forthcoming decade. The remarkable potential of AI in education can be harnessed equitably only through diligent, context-informed, and ethically grounded inquiry.

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