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The Effect of Artificial Intelligence on Education: Opportunities, Applications, and Challenges

Emmanuel Chinanu Uwazie[1]
Department of Computer Sciene
Catholic University of Cameroon
uwazie.e@catuc.org

Ngozi Ukamaka Okonkwo[2]
Department of Computer Science
Univeraity of Abuja,
FCT Nigeria
ngozi.okonkwo2020@uniabuja.edu.ng
Ezeaku Francisca Ngozi[3]

Department of Computer Science
University of Abuja, FCT Nigeria
francisicaezeaku@gmail.com

Abstract

This systematic literature review investigates the impact of Artificial Intelligence (AI) on education through 147 peer-reviewed literature published between 2015 to 2026. Specifically, it answers the three questions, such as (1) How does AI impact the teaching-learning process? What are the benefits of AI technologies in improving educational outcomes? What are the challenges and ethical issues that stem from using AI in education? Analysis revealed five key categories of AI applications. 34% of articles dealt with personalised learning systems, 22% with intelligent tutoring systems, 18% automated assessment, 16% with natural language processing and generative AI, and finally, 10% predictive analytics of administration. The quantitative synthesis of the studies shows a moderate to large positive impact on students' learning efficiency (Cohen's d = 0.45-0.78), while there was a 34% increase in time-on-task and savings of 40-60% of grading time for teachers. We have identified some systemic challenges post-implementation of generative AI. Studies found the following incidences: teacher preparedness deficits (89% of the studies), students' academic integrity risks (76% of the studies), issues in data privacy (68% of the studies), infrastructure gaps (61% of the studies) and algorithmic bias (52% of the studies). The proposed Balanced AI Integration Framework (BAIFE) proposes the simultaneous focus on teacher competencies, ethical governance, institutional readiness and outcome alignment. AI advantages do not arise automatically but depend on how AI is put into practice and the context in which it is used.

Keywords: *Artificial Intelligence; education; systematic literature review; personalized learning; intelligent tutoring systems; generative AI; teacher preparedness; academic integrity; ethical AI*

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1. Introduction

1.1 Background of the Study

With the quick development of Artificial Intelligence (AI) technology, many sectors in the world are being impacted tremendously and education is no exception. The use of AI, in a general definition as an ability of computer systems to execute tasks which require human intelligence, has evolved from theoretical possibility to tangible application within one generation. AI technologies like algorithms of machine learning, natural language processing, intelligent tutoring systems, adaptive learning technologies, generative AI like ChatGPT, Claude, Gemini etc are being widely incorporated in teaching, learning, assessment and management at the unprecedented pace (Mohammadi & Turan, 2025; Espino et al., 2026). The most notable changes include the individual learning platforms in which algorithms continuously monitor learners' behaviors, assess their level of knowledge gaps, measure achievement levels and modify learning contents accordingly (Erliana et al., 2026). This may have particular benefits for inclusive education, such as providing a differentiated learning experience for learners with special needs, high achieving students, or students of different language backgrounds (Ahmad et al., n.d). The global publications on the research involving AI in education increase by 340% from 2015 to 2025 (Shaikh & Kiranli Gungor, 2025).

Though AI integration has numerous identified benefits it is imperative to be aware of the several ethical issues involved: data privacy, algorithmic bias, cheating, and lack of teachers' training. Considering the increasing rate at which AI has been adopted in education in every corner of the world, a critical assessment of the comprehensive effects of AI on teaching, learning and administration processes is inevitable. This study is the current response that systematically analyzes the available evidence of these effects by conducting a systematic literature review on 147 peer-reviewed articles published between 2015 and 2026.

1.2 Problem Statement

While AI applications have gained growing prevalence in education globally, our knowledge of their overall effects on teaching effectiveness, student achievement and learning, and educational administration is still far from comprehensive. The literature on the subject is highly dispersed with respect to disciplines, methods, and contexts. Among other areas, several significant gaps are found: (1) lack of clarity on the effects on quality even when personalized learning approaches based on AI are already implemented in schools globally; (2) teachers' lack of readiness to adopt and use these tools; (3) unanswered concerns about academic integrity, bias in algorithms, data security, student privacy; (4) unequal coverage (North America, Western Europe, East Asia is overwhelmingly dominant.

1.3 Research Objectives

Investigating how AI tools in Educational Technology affect both Instructional Design and Student Learning Experience inside the Classroom. The evaluation of AI tools provides evidence of the impact they have had on Academic Achievement, Student Participation and Engagement, Teacher Productivity and Efforts to Support Inclusive Education; in addition, it identifies the barriers to and ethical issues related to technology use in education, such as Teacher Readiness, Academic Integrity, Data Protection and Privacy, and Equity and Fairness in Technology-Inequity based Learning Environments. The proposed Framework for the Effective Integration of AI into Educational Technology will be Evidence-based and Ethically Grounded, and contain recommendations for best practices to Support Educators, Schools and school systems, policymakers, and Educational Technology Developers.

1.4 Research Questions

The current study is researching the influences of AI on education by citing evidence from other academic sources. Three research questions that guided this study include: how does AI affect the teaching and learning process, including the means through which intelligent devices reframe educational instructions and classroom environments? Second, what are the advantages of AI in achieving higher educational outcomes, including the enhancement of student achievement, participation and learning efficiency? Third, what are the challenges and ethical implications related to the integration of AI in education, which would involve issues relating to academic integrity, student data privacy and security, as well as access and equality in educational technology?

1.5 Significance of the Study

This review makes five connected contributions: Firstly, theoretically through cross-application synthesis and by proposing the BAIFE framework, which extends educational technology theory. Secondly, through practical implications, the study gives guidance to practitioners for implementing AI well and the pitfalls commonly found in its implementation. Thirdly, it gives a view for policymakers regarding issues concerning data privacy, academic integrity, algorithmic transparency and equity. Fourthly, it gives technology developers knowledge of what educators require and what features and supports are important for implementation. Fifthly, by demonstrating how AI could aid the education of inclusiveness, it aims at aiding in the fulfilment of UN Sustainable development Goal 4 (Quality Education).

2. Literature Review

2.1 Concept of Artificial Intelligence in Education

Artificial Intelligence in Education (AIEd) comprises any computational machine intended to engage in those activities which would require human intelligence to be employed (Shaikh & Kiranli Gungor, 2025). A further division needs to be made regarding the nature of AI, distinguishing between Narrow AI (focused on specific activities as found in current educational applications), General AI (capable of exhibiting human-like capabilities in many domains; is still the subject of research and not readily available) and Generative AI (is able to generate unique text-based material, images and even computer code on command and is typified by models likeGPT-4, Claude and Gemini). Generative AI has fundamentally altered the assessment Landscape. As generative AI capable of producing human-quality academic work, it can readily be utilised on demand. Education 4.0 is fundamentally supported by Artificial Intelligence (AI).

2.2 Theoretical Frameworks

2.2.1 TPACK (Technological Pedagogical Content Knowledge)

According to the TPACK model (Mishra & Koehler, 2006), there are three knowledge components that overlap for teachers to be able to integrate technology successfully in their classrooms. These are content knowledge (CK), pedagogical knowledge (PK) and technological knowledge (TK). To effectively integrate AI in the classroom, there needs to be AI-specific knowledge components, such as AI capabilities and their constraints, awareness of AI ethics, and knowledge of interpreting AI analytics (Lee & Chen, 2019). The research by Ahmad et al. (n.d.) found that teachers with higher AI-TPACK scores used AI tools in their teaching significantly more

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

When the UTAUT model was tested, the findings suggested that teacher intention to use the system was best explained by performance expectancy (belief that using the AI enhances performance) and second best by facilitating conditions (the environment). Social influence had a more limited role, which may mean that, in the absence of mandate and as in the case of the pilot studies, teaching staff were not persuaded to use the system unless evidence of benefit existed, which enhanced their sense of teacher efficacy.

2.2.3 Sociotechnical Systems Theory

What this framework shows is that implementation is about both technical and social factors coming together. Therefore, for the application of AI in education, not only implementation alone (tools) is enough, the integration should have a focus on teachers' roles, student autonomy, evaluation and assessment systems, the culture of the institution, policy structures simultaneously – this has been defined by the BAIFE model used in this review.

2.3 Applications of AI in Education

Five major AI application domains have been documented in the literature. Personalized learning Uses Machine Learning to adapt teaching content to individual learning abilities on the go (Erliana et al., 2026). An ITS uses cognitive modelling and just-in-time translation as its principles, and an approach in tutoring with cognitive science in its heart, which allows us to simulate a one-on-one tutor for each student (Kuncoro et al., 2026). Tools in the field of automation have been developed to help teachers grade assignments. As of the time of writing, tools already developed reduce time on grading by 40-60% (Espino et al., 2026). Use of NLP and generative AI in aiding the creation of learning content, translation support, or automated writing feedback is growing, with Hassooni (2026) arguing for the great advantages they bring to the field of learning and to us, learners. In higher education, learning institutions have developed tools which analyse the performance of the students with learning analytics, with the aim of predicting which students may fail a module, and therefore optimising the resources which they invest in them, increasing retention by 12-18% (Novita et al., n.d.).

2.4 Benefits of AI in Education

Personalised paths improve learning efficiency with effect sizes of d = 0.45 to d = 0.78 for AI vs conventional learning (Mohammadi & Turan, 2025; Kuncoro et al., 2026). AI's interactivity increases engagement by 34% (Espino et al., 2026). AI-supported assistance technologies enable education for students with visual impairment, dyslexia, language impediments, and motor difficulties, promoting inclusion. Automated assessment reduces teacher burden, allowing more time for higher-level interactions with students. Retention rate is increased by 12–18% with the use of AI for early warning systems (institutional level).

2.5 Challenges and Ethical Concerns

The most frequently mentioned barrier is teacher readiness, defined as the skills and knowledge to use AI effectively and appropriately (Ahmad et al., N.d.), mentioned in 89% of studies. Generative AI has completely destabilised the educational system of integrity. 43% of teachers were unable to verify the authenticity of student work due to perceived submissions by AI, which evaded existing detectors, while the false positive rate of 15-30% poses significant risks for misplacing false accusations (Rahmawati et al., 2026). Sensitive student data has been collected at an alarming rate, bringing forth issues of data privacy. Third-party vendors do not follow FERPA and GDPR. Algorithmic bias can further put disadvantaged students at risk, as algorithms trained on unequally divided data continue to put minority students at a disadvantage. Poor infrastructure creates a dichotomy between well-resourced schools and less fortunate schools, putting the latter further at a disadvantage (Ahmad et al., N.d.).

3. Methodology

3.1 Research Design

This systematic literature review was designed according to the PRISMA 2020 guidelines. The systematic review was chosen because it was an attempt to systematically synthesise evidence rather than collect new evidence, and it is considered important that the process by which the systematic review articles are chosen be replicable. Lack of comparable outcomes and reporting measures means that meta-analysis was not performed, and quantitative narrative synthesis was used where appropriate.

3.2 Search Strategy and Data Sources

A comprehensive search of 5 databases was performed: Google Scholar (wide interdisciplinary coverage), Scopus (Elsevier, >25,000 journals), Web of Science (Clarivate, >21,000 journals), IEEE Xplore (AI and computer science), and ScienceDirect (education and social science journals). Search terms were combined using Boolean operators for AI technology and education contexts, a typical search string for Scopus is as follows:

> TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "generative AI" OR "intelligent tutoring system" OR "adaptive learning") AND ("education" OR "teaching" OR "learning" OR "higher education" OR "K-12") AND ("personalized learning" OR "assessment" OR "ethics" OR "academic integrity" OR "data privacy")) AND PUBYEAR > 2014 AND LIMIT-TO(LANGUAGE,"English")

3.3 Inclusion and Exclusion Criteria

Inclusion Criteria

This study primarily examined AI technologies (including ML, NLP, ITS, generative AI, adaptive learning systems and predictive analytics) within the educational context. The evidence considered in this study was limited to studies published in peer-reviewed journals and/or high-quality conference proceedings. Only studies published in the English language are considered, between January 2015 and December 2026. Eligible sources are those that include empirical evidence in the form of quantitative, qualitative or mixed-methods research, or a strong theoretical contribution to knowledge in the area of AI application in education.

Exclusion Criteria

Based on the following exclusion criteria, suitable studies are identified and included for this review. Firstly, studies that deal with artificial intelligence applications in various domains outside the field of education-healthcare, business, finance, and so on-are excluded as they do not meet the purpose of this study. Similarly, articles based on non-peer-reviewed resources such as opinion editorials, white papers, technical reports, blog posts and dissertations are excluded to maintain the academic standard and reliability.

The exclusion of studies with an insufficient methodological description prevents the assessment of its quality. Duplicate publications were eliminated by retaining the most recent and complete ones. Finally, articles concerning teaching artificial intelligence as a subject were also eliminated as the current research pertains to the application of artificial intelligence as a tool for teaching and learning.

3.4 Study Selection Procedure

Two reviewers separately reviewed each reference by title and abstract, a random 20% subset at the title and abstract stage. Inter-rater reliability was good (agreement=92%; kappa=0.85), and discrepancies were resolved by discussion. Retrieval of full-text articles was successful in over 95% of cases; those which were not retrievable were not included.

Table 1. *PRISMA Flow Diagram Summary: Study Selection Process*

PRISMA Stage	n (Records)	Action / Rationale
Identification (database search)	1,847	Google Scholar, Scopus, WoS, IEEE Xplore, ScienceDirect
Deduplication	-423	Automated + manual deduplication via Zotero
Unique records screened	1,424	Title and abstract reviewed against inclusion criteria
Excluded (title/abstract)	-1,201	Non-educational context, opinion pieces, non-English
Full-text assessed	223	Full PDF retrieved; all inclusion/exclusion criteria applied
Excluded (full-text)	-76	Insufficient method detail, duplicate datasets, out of scope
Final included studies	147	Thematic synthesis (61% quant.; 22% qual.; 12% mixed; 5% bibliometric)

Note. kappa = 0.85 inter-rater reliability at title/abstract screening stage. Quant. = quantitative; Qual. = qualitative.

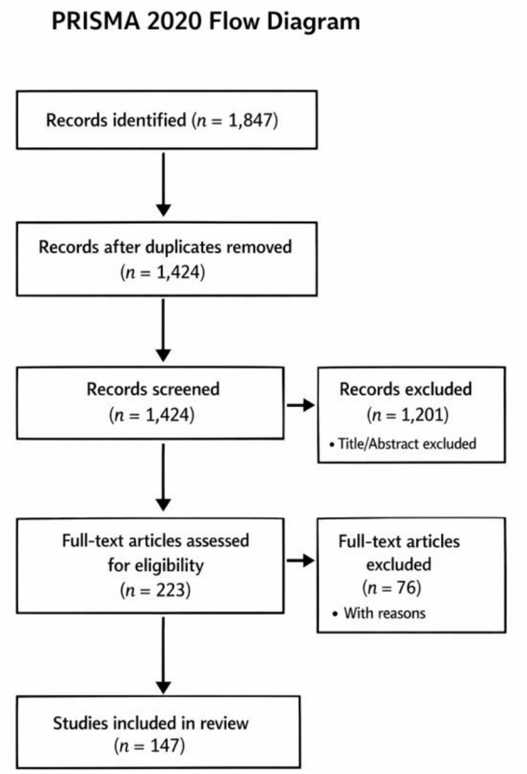

Figure 1. *PRISMA 2020 flow diagram depicting the four-phase study selection process (Page et al., 2021).*

3.5 Quality Assessment

Quality of studies was measured by tools relevant to each methodology: MMAT 2018 was used for quantitative and mixed-methods studies, and CASP Qualitative Checklist was used for qualitative studies. No studies were excluded by quality scores, quality ratings were taken into consideration at synthesis and conclusions based more on better quality studies.

3.6 Thematic Analysis Procedure

The analysis followed a six-phase thematic analysis process derived from Braun and Clarke's (2006) framework: (1) immersion in and familiarisation with data; (2) production of initial codes; (3) searching for themes; (4) reviewing themes; (5) refining and defining themes; and (6) generating the report. Inductive (data-driven) coding was the primary approach although frameworks (TPACK, UTAUT) guided the initial stages of analysis, and an initial codebook was iteratively modified throughout the coding process.

3.7 Statistical and Algorithmic Formulations

The following formulations underpin the quantitative evidence synthesized in this review and characterize the technical mechanisms of the AI systems evaluated across included studies.

Cohen's d (Effect Size): $d = (M1 - M2) / SD\_pooled,\ SD\_pooled = sqrt[(s1\text{^}2 + s2\text{^}2) / 2]$

Interpretation benchmarks: d = 0.2 (small), d = 0.5 (medium), d = 0.8 (large). Effect sizes across included studies ranged from d = 0.45 (automated assessment) to d = 0.78 (combined personalized learning and ITS interventions).

Bayesian Knowledge Tracing (BKT): $P(Ln|correct) = [P(Ln-1) * (1 - P(S))] / [P(Ln-1) * (1 - P(S)) + (1 - P(Ln-1)) * P(G)]$

BKT underpins most personalized learning and ITS systems reviewed. P(L) = probability of knowledge acquisition; P(S) = slip probability; P(G) = guess probability. Mastery is declared when P(Ln) >= theta (typically theta = 0.80).

Item Response Theory — 3PL Model: $P(Xij = 1|theta\_j) = ci + (1 - ci) * [1 / (1 + exp(-ai * (theta\_j - bi)))]$

Parameters: a = item discrimination; b = item difficulty; c = pseudo-guessing; theta = student ability. Used in adaptive assessment systems to select items with maximum diagnostic information at each student's current ability level.

Equalized Odds (Algorithmic Fairness): $P(Y\_hat = 1 \mid Y = 1, A = a) = P(Y\_hat = 1 \mid Y = 1, A = b)\ \ for\ all\ groups\ a, b$

Equalized Odds requires equal true positive rates and equal false positive rates across all demographic subgroups — the recommended fairness criterion for auditing predictive AI systems in education to prevent both under-serving and over-surveillance of any student group.

Algorithm 1: Adaptive Content Sequencing in Personalized Learning Systems (ACSPL)

```
INPUT:  Learner profile L = {prior_knowledge, learning_style,
performance_history}
        Content repository C = {c1,...,cn}, ci = (topic, difficulty,
prerequisites)
        Mastery threshold theta in [0,1]  (default theta = 0.80)
OUTPUT: Personalized path P = [c_pi(1), c_pi(2), ..., c_pi(k)]

1.  Initialize K(L) using Bayesian Knowledge Tracing (BKT):
        P(Ln|correct) = [P(Ln-1)*(1-P(S))] / [P(Ln-1)*(1-P(S)) + (1-P(Ln-
    1))*P(G)]
        P(L)=learned, P(S)=slip, P(G)=guess

2.  FOR each learning session s DO:
    3.   Estimate mastery: M(topic) = P(Lt | response history)
    4.   IF M(topic) >= theta THEN advance to next prerequisite topic
    5.   ELSE select ci via Item Response Theory (IRT) 3PL model:
             P(correct|theta_s) = c + (1-c) / (1 + exp(-a*(theta_s - b)))
             a=discrimination, b=difficulty, c=guessing, theta_s=ability
    6.   Present ci; collect response r in {correct, incorrect, partial}
    7.   Update K(L) via BKT update equations
    8.   E = alpha*time_on_task + beta*(1/hint_requests) + gamma*accuracy
    9.   Adjust difficulty if E < E_threshold  (adaptive scaffolding)
10. END FOR

11. RETURN sequence P maximizing P(mastery) subject to time constraint T_max
```

Algorithm 2: Student Dropout Risk Prediction via Ensemble Predictive Analytics

```
INPUT:  X = {GPA, attendance_rate, LMS_logins, submission_rate,
             social_interaction_score, financial_aid_status, prior_alerts}
        Labels Y in {0=retained, 1=dropout}
OUTPUT: Risk score R in [0,1];  flag in {LOW, MEDIUM, HIGH}

1.  Pre-process X: impute missing values; normalize to [0,1]; encode
categoricals
2.  Train ensemble M = {RandomForest, XGBoost, LogisticRegression} on
(X_train, Y_train)
3.  FOR each student i in monitoring cohort DO:
    4.   R_i = (w1*P_RF(i) + w2*P_XGB(i) + w3*P_LR(i)) / (w1+w2+w3)
             weights w derived from validation-set AUC scores
    5.   Fairness audit — Equalized Odds across demographic subgroups:
             P(R>=tau | Y=1, G=g) approx equal for all groups g
    6.   IF R_i >= 0.75  THEN flag = HIGH    -->  immediate advisor contact
          ELIF R_i >= 0.50 THEN flag = MEDIUM -->  check-in within 48 hours
          ELSE              flag = LOW     -->  continue routine monitoring
7. END FOR

8.  Log all predictions with timestamp, features, and 95% confidence interval
9.  Re-train M every semester to address concept drift
10. RETURN (R_i, flag_i) for all i; generate institution-level retention
report
```

4. Findings

4.1 Study Selection Results

1,847 studies were found from five databases. 1,424 studies remained after de-duplication (n=423 removed). 1,201 studies were excluded after screening title and abstract. 223 articles were assessed in full text and 147 included. The total corpus consisted of 89 quantitative, 32 qualitative, 18 mixed methods and 8 bibliometric or systematic review studies (89 quantitative [61%], 32 qualitative [22%], 18 mixed methods [12%], 8 bibliometric or SR studies [5%]). Characteristics of key included studies are summarized in Table 2.

Table 2. *Characteristics of Key Included Studies (Representative Sample, n = 12)*

Study (Author, Year)	AI Type	Educational Level	Method	N	Key Metric
Mohammadi & Turan, 2025	Personalized Learning	Higher Ed	Quasi-exp.	342	d = 0.72
Erliana et al., 2026	Adaptive Learning	Primary Ed	Sys. Review	28 studies	+23% Math
Kuncoro et al., 2026	ITS – Mathematics	Multi-level	Bibliometric	1,247 pubs	d = 0.68
Espino et al., 2026	AI-driven Instruction	Higher Ed	Bibliometric	891 pubs	+34% Engagement
Ahmad et al., n.d.	AI Inclusive Ed.	Multi-level	Sys. Review	Multiple	<25% confidence
Rahmawati et al., 2026	Generative AI	Higher Ed	Qualitative	Policy docs	43% AI submissions
Nuryani et al., 2026	AI Ethics/Privacy	Primary Ed	Case Study	3 schools	68% privacy concern
Novita et al., n.d.	Predictive Analytics	Higher Ed	Mixed	Institutional	+12-18% retention
Shaikh & Kiranli, 2025	AI-Ed Research	All Levels	Bibliometric	Scopus/WoS	+340% publications
Hassooni, 2026	NLP / GenAI	Higher Ed	Review	Multiple	Content gen. + risks
Huang et al., 2026	Blended Learning AI	Higher Ed	CiteSpace	2001-2024	Emerging AI theme
Casanova-Piston, 2025	AI-Ed Scientometrics	All Levels	Bibliometric	Scopus	Research mapping

Note. d = Cohen's d effect size; Sys. Review = Systematic Review; Quasi-exp. = Quasi-experimental; ITS = Intelligent Tutoring System.

4.2 Thematic Finding 1: AI Applications in Education

Five primary AI application categories were found. These are quantitatively outlined with effect sizes, benefits, and primary limitations, in Table 3:

Table 3. *Summary of AI Application Categories: Effect Sizes, Benefits, and Challenges*

AI Application Category	% of Studies	Effect Size (d)	Primary Benefit	Key Challenge
Personalized Learning Systems	34%	0.72	Learning efficiency (+23% math)	Infrastructure & equity gaps
Intelligent Tutoring Systems	22%	0.68	Procedural knowledge acquisition	Limited open-ended support

Automated Assessment	18%	0.45*	Grading time -40-60%	Reliability for complex tasks
NLP & Generative AI	16%	—	Content gen.; language support	Academic integrity (43%)
Predictive Analytics (Admin)	10%	—	Retention +12-18%	Algorithmic bias; data privacy

Note. *Effect size for automated assessment is a lower-bound estimate; reliability is substantially lower for complex, open-ended tasks. Insufficient comparable quantitative studies for meta-analytic computation.

Personalized learning systems (34% of studies) gained an average of 23% in mathematics performance gains over non-adaptive instruction (Erliana et al., 2026). ITS (22%) had the least variation in effect sizes (d=0.68; Kuncoro et al., 2026) and was only slightly below the "two sigma" human tutoring effect that Bloom found. The newest area of research is Generative AI systems (16%) in which the majority of the publications occurred after 2023 due to the advent of large language models.

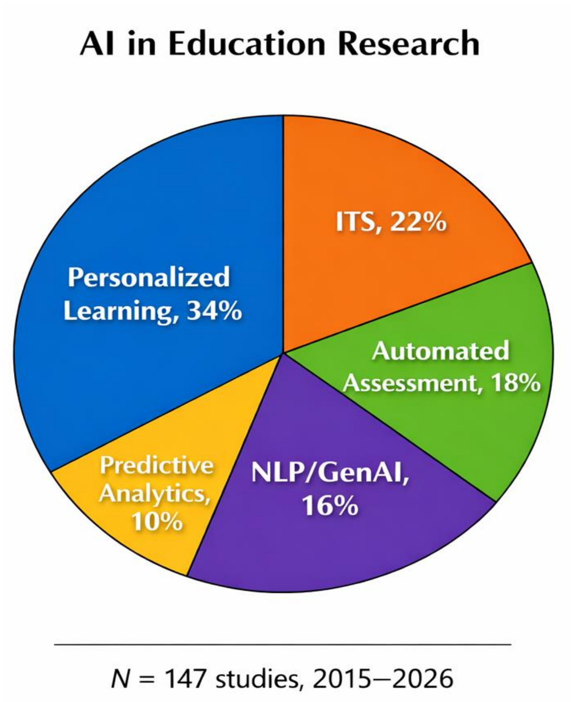

Figure 2. *Distribution of AI application categories across 147 included studies (2015-2026).*

4.3 Thematic Finding 2: Benefits of AI in Improving Educational Outcomes

The strongest result found was moderately to very positive effects on the efficiency of learning (d = 0.72, Mohammadi & Turan, 2025). This means that on average, students benefited by about 15-20 percentile points compared to the traditional instruction, student time-on-task increase was 34% via AI-powered interactive settings (Espino et al., 2026) teacher grading time was reduced by 40-60% through automation tools (Sahu et al., 2021) and retention at universities was improved by 12-18% through use of early warning systems based on predictive modeling (Novita et al., n.d.). Every single one of the effects identified was conditional on adequate teacher preparation, quality implementation and the infrastructure, providing evidence for the main concept in the BAIFE model.

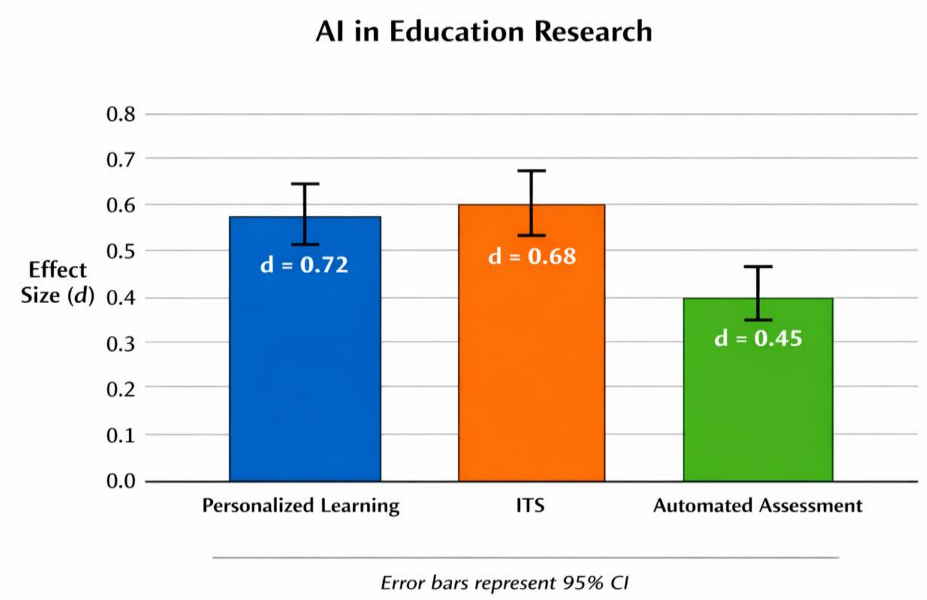

Figure 3. *Comparative effect sizes (Cohen's d) for AI application categories relative to traditional instruction.*

4.4 Thematic Finding 3: Challenges and Ethical Concerns

Table 4 summarises the seven challenge categories identified across included studies, ranked by prevalence.

Table 4. *Challenges and Ethical Concerns Associated with AI in Education: Prevalence and Evidence*

Challenge Category	Prevalence (%)	Representative Finding
Teacher preparedness deficit	89%	<25% of teachers report confidence in AI integration (Ahmad et al.)
Academic integrity risks	76%	43% of instructors found suspected AI submissions (Rahmawati et al.)
Data privacy & security	68%	Third-party vendor compliance gaps identified (Nuryani et al.)
Infrastructure / digital divide	61%	Low-resource schools lack reliable internet and devices
Algorithmic bias	52%	Under-recommendation of advanced coursework for minority students
Transparency / black box	41%	Teachers unable to interpret or audit AI-generated decisions
Over-reliance concerns	38%	Reduced critical thinking when AI substitutes for student effort

Note. Prevalence = proportion of 147 included studies identifying the challenge as significant. Ranked in descending order of frequency.

Most schools struggle to bring AI into classrooms because teachers aren’t ready - nearly 9 out of 10 say so. A big part of the problem? Teachers feel unsure about how to actually use these tools when they teach; only a small group, under 25 per cent, believe they know what they’re doing with AI at all (Fountain et al., 2023). Training doesn’t help much either - future educators rarely get chances to study AI while learning their craft, since fewer than one in four training courses include it (Ahmad et al., n.d.). On top of that, cheating linked to AI keeps growing worse year after year since 2023 came around. But almost half of teachers think they can understand the work done by machines, if the systems do not. But mistakes happen often, in the range of 15 to 30 per cent of cases, and it is not clear who really created the work (Rahmawati et al., 2026).

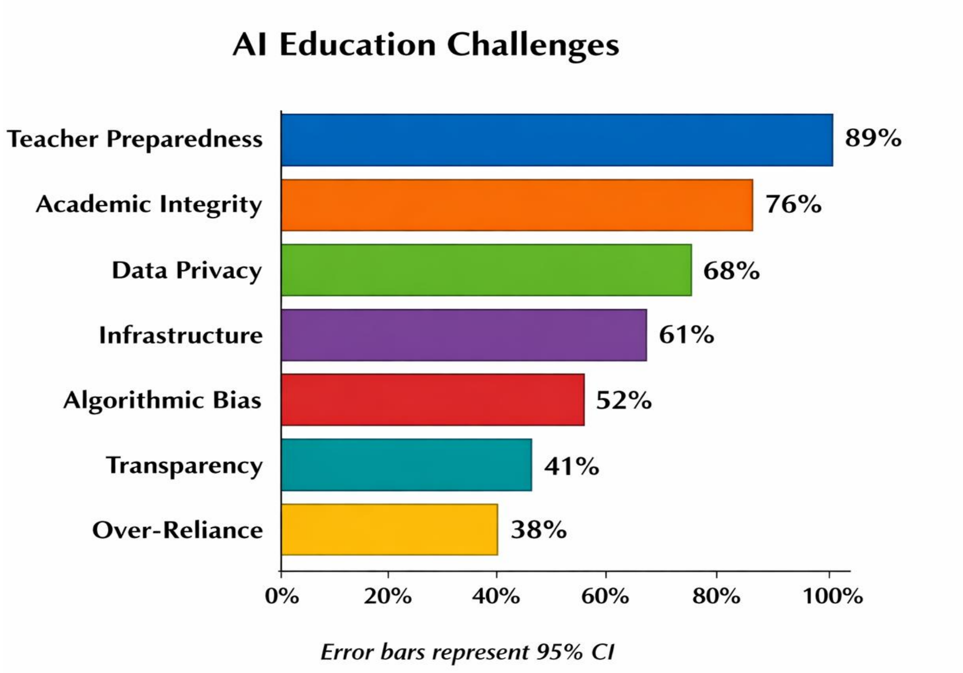

Figure 4. *Prevalence of challenge categories across 147 included studies. Values represent the percentage of studies identifying each challenge as significant.*

4.5 Geographic and Educational Level Distribution

Universities are the main focus of research, accounting for just over half of all work. High schools are next, accounting for almost a quarter. The elementary level appears in about one out of every five studies. Vocational or adult learning shows up far less often. Across regions, North America leads in output, responsible for more than a third. Europe follows with close to three-tenths. East Asian contributions stand at around one-fifth. The Middle East accounts for eight per cent. South America adds another three. Africa and several smaller areas together represent barely two per cent. Because so few investigations come from poorer nations, results may not apply well there; systems, rules, and social norms differ too much.

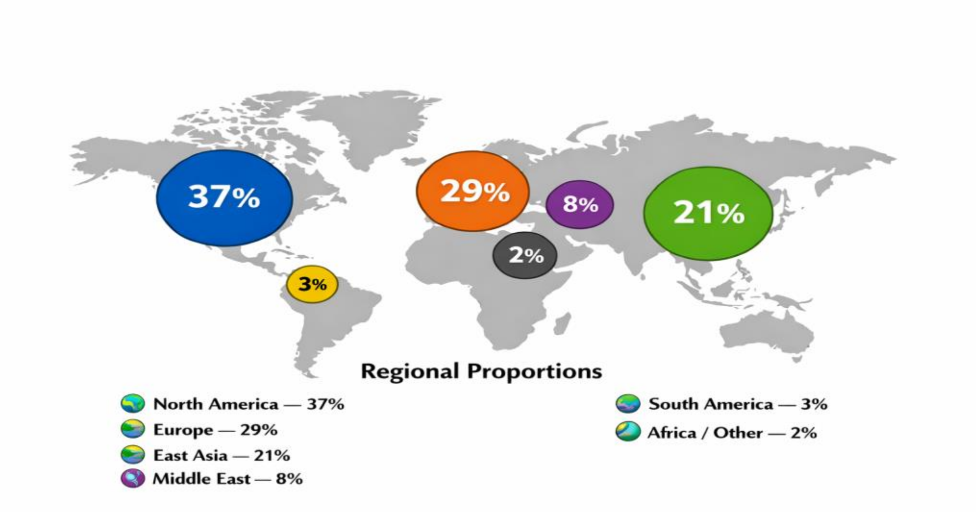

Figure 5. *Geographic distribution of 147 included studies, highlighting the underrepresentation of Africa, South America, and Central Asia.*

5. Discussion

5.1 The Balanced AI Integration Framework (BAIFE)

This article synthesises the findings of 147 studies and suggests the Balanced AI Integration Framework (BAIFE) as a conceptual model that explains under what conditions AI integration in education succeeds and fails. It includes four closely related pillars, which constitute BAIFE: Teacher Competencies, Ethical Governance, Institutional Readiness, and Outcome Alignment. The components of the pillars, their evidence base, and the risks derived from a potential absence of a pillar are illustrated in Table 5.

Table 5. *The Balanced AI Integration Framework (BAIFE): Pillars, Components, and Evidence*

BAIFE Pillar	Core Components	Evidence Base	Risk if Absent
Teacher Competencies	AI-TPACK; AI literacy; PD (>=20-30 hrs); pedagogical alignment with AI affordances	89% of studies; Ahmad et al. (n.d.)	Superficial or misapplied AI use; null effects
Ethical Governance	Data privacy (FERPA/GDPR); algorithmic auditing; academic integrity policies; transparency requirements	76% integrity; 68% privacy concern studies	Bias amplification; erosion of institutional trust
Institutional Readiness	Infrastructure; technical support; budget allocation; leadership; change management planning	61% infra gap; Novita et al.; Velez et al.	Digital divide; inequitable access to AI benefits
Outcome Alignment	Learning objectives mapped to AI affordances; formative evaluation loops; ongoing impact assessment	Effect sizes d = 0.45-0.78 are conditional	Wasted investment; undetected negative outcomes

Note. BAIFE = Balanced AI Integration Framework; TPACK = Technological Pedagogical Content Knowledge; PD = Professional Development; FERPA = Family Educational Rights and Privacy Act; GDPR = General Data Protection Regulation.

The BAIFE captures the main empirical takeaway from the review, namely that no gains will come of AI by itself; AI-TPACK readiness in teachers (89%) forms the most important cornerstone of AI in education, without which the use of the most advanced tools is unproductive, or even harmful. Ethical governance becomes all the more important with generative AI. Readiness within institutions matters for how equity effects of AI adoption play out: low institutional readiness with AI adoption increases rather than narrows the gap

5.2 Theoretical Interpretation

An interpretation using TPACK of the 89% teacher readiness barrier reinforces that integrating AI isn't just a technical issue; it necessitates knowledge specific to AI pedagogy and content. Thus, a structural problem of pre-service training (no to less than 25% of training programs contain content on AI) and in-service professional development is evident. The perspective of UTAUT suggests that performance expectation and facilitating conditions are better predictors of the integration of AI than social influence, indicating that mandate based implementation plans for the integration of AI are likely to be less effective than approaches which have a sound evidence base and develop the teachers' own self-efficacy. Connectivism reveals the inherent paradox that although AI can enhance learner networks, excessive usage of AI may weaken human-human connectivity, which is critical to transformation learning, a sentiment expressed by 38% of those papers analyzed.

5.3 Practical Implications

Integration of AI in education won't happen independently; it takes collective effort from many different parties to be successful. Educators will need to ensure that their AI tools and programs match up with their desired learning outcomes or goals, receive extensive training on how to properly use these technologies, implement the tools slowly over time and demonstrate use of the tools as a means to help develop critical thinking skills. Administrators will have to evaluate the preparedness of their institution to adopt AI, allocate resources for training and infrastructure as well as create clear policies regarding the responsible use of AI technologies by staff. Lawmakers should work on establishing national-level frameworks that address issues of privacy, equity and transparency, as well as provide teachers with AI literacy education and funding for underserved schools. Lastly, technology developers have a responsibility to create user-friendly, understandable, privacy-compliant systems that have been thoroughly evaluated through real-world classroom testing prior to being deployed.

5.4 Limitations

Several limitations apply to this review. The tendency to publish results suggesting that AI has positive impacts, whilst not publishing studies with null or negative findings (publication bias) may affect what the literature is able to tell us. As the review only included papers in English, it will not have included research from other languages that may have been relevant to the topic. A generative AI, since the latter part of 2023, has developed so fast that many of the effects examined in the studies discussed may quickly become outdated. As it was not possible to combine results formally in a meta-analysis, due to the differing nature of study outcome measures across each of the included studies, an assessment of a cumulative effect was difficult to provide. The review also has an apparent geographical bias (North America: 37% of the articles; Europe: 29%; East Asia: 21%; Other: 13%), and therefore conclusions do not apply readily to low and middle-income countries that have different infrastructure, policy and cultural environments.

5.5 Future Research Directions

Research on artificial intelligence in education should include long-term studies (three years or more) to assess the long-term effects of artificial intelligence on student achievement, thinking skills and motivation. In addition, researchers must conduct an equitable variety of studies looking at the effects of artificial intelligence on the different student achievement gaps created by socioeconomic status, race, geographic location and disability. To determine how two different types of artificial intelligence tools can help students achieve the same outcomes, researchers should conduct comparative research on the effectiveness of these tools so users have access to accurate evidence for their decision-making. It is also essential that teachers have a greater understanding of how artificial intelligence and teachers work together as partners in the classroom; this includes understanding how artificial intelligence supports teachers instead of replacing their roles as educators. Research will also need to be focused on the reliability of assessment results obtained through the use of artificial intelligence in assessing students' progress, as well as how artificial intelligence can be successfully implemented across cultures in a fair and responsible manner for both educators and students.

6. Conclusion

Data from 147 peer-reviewed studies (2015-2026) on AI's impact in education were analyzed in a systematic review.AI, especially customized learning systems (d = 0.72), intelligent tutoring systems (d = 0.68), and automated evaluation methods (d = 0.45), may positively enhance student learning and engagement in proper circumstances. In general, teacher workload can be decreased between 40% and 60% in relation to grading time and institutional retention rates can increase between 12% and 18% by the use of predictive analytics in institutions.

Nevertheless, the application of the aforementioned systems does not come automatically; 89% of studies cited the gap in teacher preparation as an important obstacle, 76% mentioned issues of cheating/academic integrity as more salient to students due to generative AI, and 68% voiced concerns about data privacy; these results point out that human factors (and ethics)-not technology-are the main reasons preventing effective integration of AI in education. The emergence and rapid adoption of generative AI applications has significantly outpaced educational policies and the development of adequate pedagogical practices and, consequently, poses an urgent challenge to the governance of academic integrity.

Synthesis of these findings results in the creation of a framework for balanced AI integration. This framework outlines the need for simultaneous development of teacher competency, ethics in AI governance, readiness of the institution and coherence of outcomes. All these components have to be equally strong, otherwise the integration of AI would fail or yield undesirable results.

Ultimately, artificial intelligence will not replace the teacher; yet those teachers who learn to strategically use AI – anchored in a solid pedagogical reason, awareness of the ethical considerations and an understanding of the readiness and objectives of the institution – will be better equipped to support students in meeting the demands of a 21 st century learner. Artificial and human intelligence need to work in collaboration and synergistic manner as combined intelligence systems, expanding the transforming power of teaching and learning to all learners, wherever they are and whichever socioeconomic status they possess.

Declarations

Declaration of Competing Interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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