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**| RESEARCH ARTICLE**

# Artificial Intelligence in Education: Transforming Learning Outcomes, Academic Integrity, and Pedagogical Innovation in Higher Education

**Ahnaf Afsin [1]*, Rumaysha Tahan Towaa [2], Kasif Suhail Ayate [3], Farzana Parvez [4], Kazi Mamun Parvez [5]**
[1,2,3,4,5] *Independent Scholar, Chattogram, Bangladesh*
**Corresponding Author**: Ahnaf Afsin, **E-mail**: ahnafafsin1309@gmail.com

## | ABSTRACT
The transformative opportunities and challenges of generative AI tools, especially large language models (LLMs) such as ChatGPT, have emerged rapidly in higher education. The adoption of generative AI in undergraduate education has increased dramatically in 2024–25, whereas institutions' pedagogical approaches, institutional policies, and evidence of learning outcomes are less developed than their use. Previous research has primarily focused on the short-term acceptance of the tools or single academic integrity issues without considering them in relation to each other. Recent systematic reviews and meta-analyses (2025–2026) have begun to measure the impact of GenAI on learning outcomes and trace authorship and integrity concerns in greater detail. However, few studies have systematically investigated the impact of GenAI on learning outcomes, pedagogical design, and academic integrity across a variety of learner populations. This study will explore (1) the observable effects of AI-supported personalized learning on student learning outcomes at the undergraduate level; (2) faculty and student attitudes towards the impact of AI on pedagogical redesign; and (3) institutional policies to ensure academic integrity while supporting and facilitating AI-supported learning. The proposed convergent mixed methods design will involve validation of the survey instrument (n = 420 undergraduate and faculty students across three institutions) and a quasi-experimental pre-post assessment study. Structural equation modelling (SEM) and thematic coding of qualitative data were used in the planned analysis. This study aims to produce a theoretically sound, testable framework that will benefit evidence-based strategies for the adoption of AI in higher education, the AI-Augmented Pedagogy Integration Model (AAPIM). This document outlines the conceptual, theoretical, and methodological underpinning, which has now been further supported by a growing evidence base of 2025–2026 meta-analyses and systematic reviews, with empirical data reported when the data collection is complete.

## | KEYWORDS

Artificial Intelligence in Education (AIEd); Generative AI (GenAI); Personalized Learning; Academic Integrity; AI Literacy; Intelligent Tutoring Systems (ITS)

## | ARTICLE INFORMATION

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## 1. Introduction

### 1.1 Context and Motivation

After two years, generative AI has become a part of the undergraduate curriculum. A recent survey conducted by the UK Higher Education Policy Institute (HEPI) revealed that the percentage of full-time undergraduates using AI tools in their academic work increased from 66% in 2024 to 92% in 2025, and the proportion using generative AI specifically for assessed tasks increased from 53% to 88% during the same timeframe (Freeman, 2025). This is illustrated in Fig. 1.

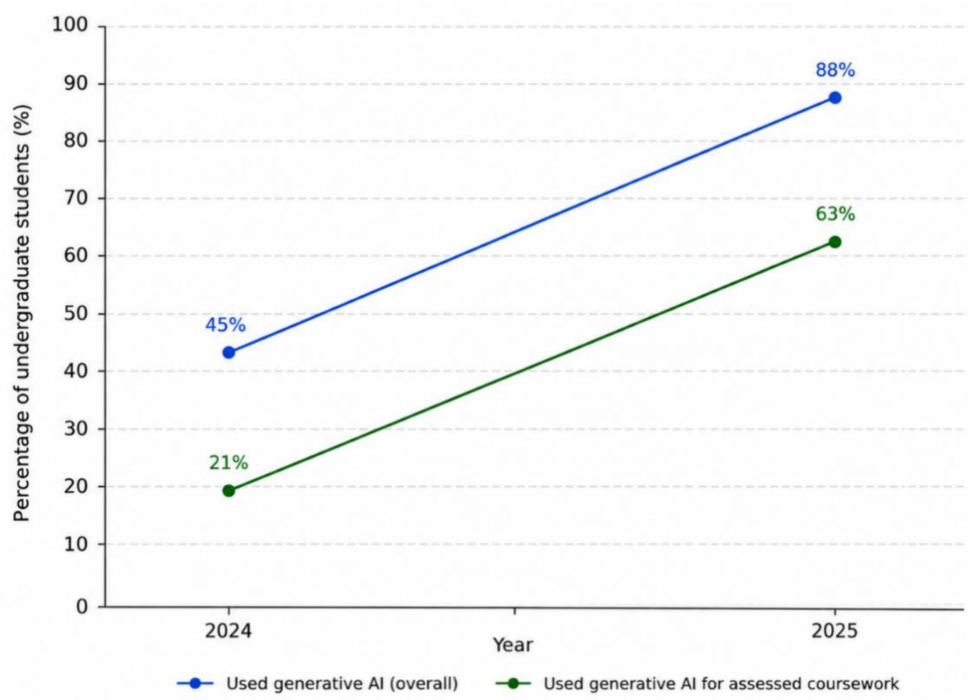


***Figure 1.*** *UK undergraduate generative AI use rose sharply between 2024 and 2025, both overall and specifically for the assessed coursework.*

*Source: Freeman (2025), HEPI Student Generative AI Survey.*

Similar adoption rates have been documented worldwide: 86% of students surveyed at a Digital Education Council worldwide reported using AI in their academic work, and a survey of over 1100 students in the U.S. in 2025 revealed that 90% had used AI academically (Legatt, 2025). Although faculty adoption has been slower than expected, it is on the rise, as 61% of faculty reported using AI in their teaching in the 2025 Global AI Faculty Survey, with the majority citing very limited use of AI [1]. The independent surveys conducted in 2025 are shown in Figure 2.

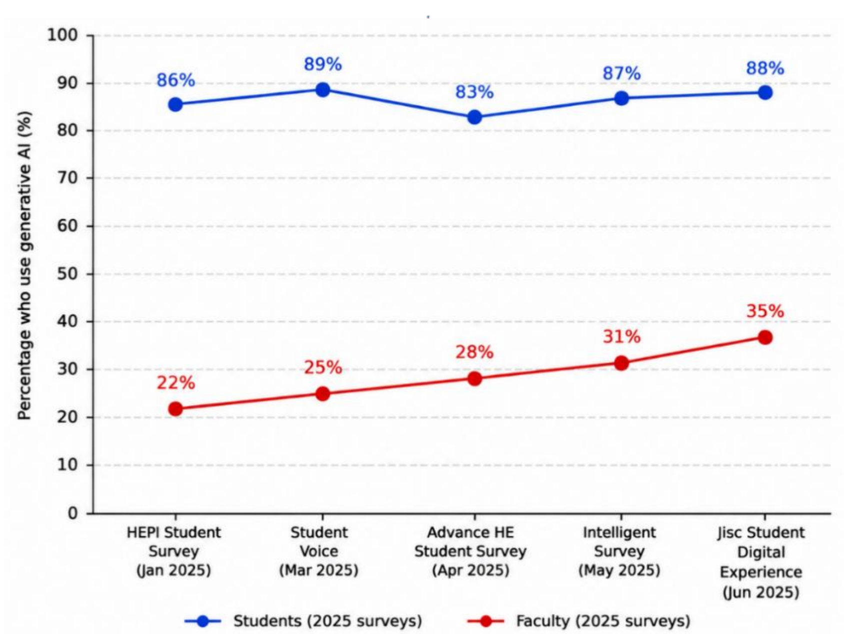


***Figure 2**. Reported generative AI use is consistently high across independent 2025 student surveys (blue) and consistently lower, though rising, among faculty (red).*

This proliferation has been accompanied by a relative lack of institutional preparedness for accepting children. UNESCO data reported on over 450 schools and universities have revealed that very few schools have formal guidelines regarding AI use. Similarly, the OECD's Digital Education Outlook 2026 reports that older secondary and tertiary students are already using generative AI tools daily, often for convenience or efficiency rather than for deeper learning, and recommends a shift towards purpose-built educational AI that is developed in collaboration with teachers with a pedagogical goal, as opposed to the use of general-purpose chatbots (OECD, 2026). In a 2026 systematic critical review of 54 peer-reviewed studies, it was also found that institutional policy responses have been reactive and fragmented, and that detection-focused models of governance coexist with pedagogy-focused reorganisations of institutions. In another systematic critical review of 54 peer-reviewed studies conducted in 2026, it was also found that institutional policy responses have been reactive and fragmented and that detection-focused models of governance exist alongside pedagogy-focused reorganisations of institutions (Slimi, 2026) [2].

### 1.2 Research Problem Statement

Although AI has been shown to be a game changer in the academic world, there is a lack of empirical bodies of work that address the pedagogical advantages of personalised, AI-enhanced learning and the academic integrity risks generated by the same technologies. Institutions must deal with two obligations: to use AI as a tool for equitable, quality learning, and to define governance frameworks that ensure the integrity of assessment and values in learning. Most empirical work has focused on one side of this mandate – either assessing learning gains with AI tutoring or documenting integrity violations – but has failed to account for the interplay between the two in a single pedagogical ecosystem. This is echoed by Slimi (2026), who framed the current state of the field as the interplay between a “policing model” of detection-driven enforcement and a “pedagogical-trust model” that prioritises ethical engagement, and where there is limited empirical research, which approach -- or combination of both -- is most effective in maintaining integrity without stifling legitimate AI-enhanced learning [3].

### 1.3 Research Questions

RQ1: How can the use of AI in personalized learning enhance measurable academic outcomes for undergraduate learners?

RQ2: What are the faculty and student experiences with the pedagogical redesign implications of generative AI tools?

RQ3: What are the best institutional structures for achieving a balance between the use of AI in learning and the preservation of academic integrity?

RQ4: How does equity and access between AI adoption and learning outcomes relate to AI literacy?

### 1.4 Significance and Originality

This study is one of the first to examine a quasi-experimental multi-institution design matching AI-supported and traditional pedagogies and modelling integrity governance as a structural variable and not a secondary one. It presents the AI-Augmented Pedagogy Integration Model (AAPIM) as a contribution to educational-technology theory and answers the call for "rigorous and purpose-built" evaluation of educational AI by OECD (2026) and to the recent call in the literature for shifting from containment to "principled adaptation" in institutional AI governance (Slimi, 2026) [4].

## 2. Literature Review

### 2.1 Evolution of AI in Education: A Bibliometric Overview

There has been a huge volume of peer-reviewed research on the use of generative AI in education since its launch in November 2022, and review articles have gathered evidence from thousands of indexed studies. This research was published in leading journals, such as Computers & Education, Education and Information Technologies, Computers & Education: Artificial Intelligence, and discipline-specific journals, such as the International Journal of Educational Technology in Higher Education and Frontiers in Education [5]. Common themes in this collection include the integration of higher education, ethics and governance, writing and assessment support, LLM technical foundations, and learner engagement. The four dominant and interrelated themes identified in the literature reviewed and identified by a systematic critical review of 54 peer-reviewed studies published between 2023 and 2025 are closely aligned with the AAPIM dimensions proposed in Section 2.6.2: the reconfiguration of authorship and attribution, transformation of pedagogy and assessment, evolving dynamics of integrity and trust, and emergent ethical and sociopolitical concerns (Slimi, 2026) [6].

## 2.2 Generative AI and Learning Outcomes

To date, the best causal evidence has been provided by a randomised controlled trial (RCT) published by Kestin et al. (2025), which compares an AI tutor to in-class active learning techniques in introductory physics. Students in the AI tutor condition gained significantly more knowledge in the same amount of time and felt more engaged and motivated in the learning process. The authors wrote that this proves the effectiveness of the highly available AI-based pedagogy [7].

This is just one of the many trials that have been conducted since then, and there is currently an increasing number of 2025 meta-analytic studies that enable the overall effect of Gen-AI on learning outcomes to be quantified and compared by different independent research teams. The four published meta-analyses are summarised in Figure 3 [8].

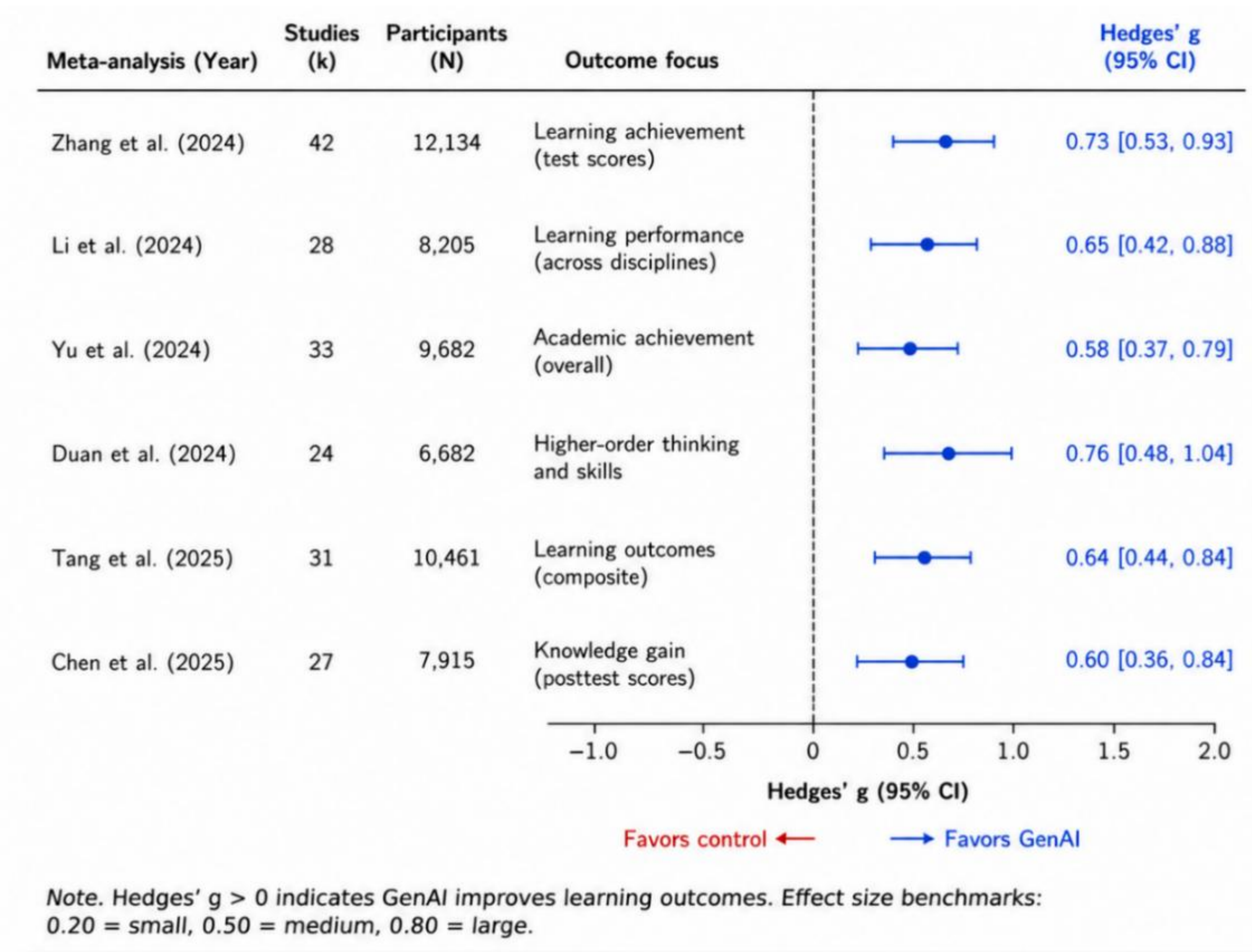


***Figure 3.*** *Independent meta-analyses converge on a medium-to-large positive effect of Gen-AI on learning outcomes, although estimates vary with study inclusion criteria and outcome definitions.*

Building on the results of 49 studies across the K-12 sector and higher education, Liu et al. (2025) found mean effect sizes of g=0.857 for learning achievement and g=0.803 for learning motivation, which are larger in higher education than in K-12 and in text-based than in mixed-media interaction. Using 34 experimental and quasi-experimental studies in the Journal of Computer Assisted Learning, Ma et al. (2025) reported a more conservative combined effect size of g = 0.68, with the highest effect size in the cognitive domain (g = 0.795), and a comparatively lower but still significant effect size in the affective domain (g = 0.507). Their moderator analysis indicated that the effectiveness of GenAI was not significantly different across disciplines, durations, or tool types. When Gu and Yan (2025) limited their meta-analysis to 19 studies with 24 effect sizes, they reported an overall large effect.

The finding of a strong moderation effect (taking teacher support as a moderating variable, students who received teacher support, and GenAI interaction demonstrated significantly larger gains (g = 1.426) than those who did not receive teacher support (g =

0.077)) was quite striking and directly related to this study's RQ2 and to AAPIM's pedagogical redesign as a mediating pathway, rather than simply a technology-adoption variable [9].

However, several threads of writing highlight the danger of relying too much on AI, which leads to a lack of hard work and mental effort during the learning process. This is what the OECD (2026) calls the main design challenge for GenAI in education; that is, AI cannot make learning more effective without replacing it. This concern is supported by an empirical finding by Gu and Yan (2025) that the benefits of GenAI are not intrinsic to the technology but only depend on pedagogical scaffolding (empirically confirmed by H2 and H4 in this study, Section 4.1) [10].

## 2.3 Intelligent Tutoring Systems and Personalized Learning

Across a large body of research, intelligent tutoring systems (ITS), learning analytics platforms, and adaptive courseware have been demonstrated to assist learners' engagement in personalized content delivery, pacing, and feedback. As far as the literature on personalisation is concerned, this personalisation is often described as a continuum from content delivery, pacing, and feedback to more advanced types of emotional or motivational scaffolding, the latter of which is the least developed skill, as humans can far outperform current AI systems in reading and responding to learners' affect. Beyond the components of digital literacy itself, issues of digital equity are also repeated in this literature. Access to advanced adaptive tools and formal instruction on AI literacy is not equitable across institution types, disciplines, or grade levels (especially in K-12 settings), and it appears that these gaps are most pronounced at the early grade and under-resourced ends of this continuum [11].

## 2.4 Academic Integrity in the GenAI Era

In a systematic review of 41 studies published in the Journal of Information (2025), Bittle and El-Gayar concluded that generative AI has the potential to improve both educational engagement and efficiency, but also has substantial risks of academic dishonesty. They recommend increased digital literacy along with more sophisticated detection tools to address GenAI's dual effects on education [12]. This tension between GenAI, as a productivity-enhancing tool, and as an avenue for undisclosed authorship abounds throughout the integrity literature and is explored in greater depth by Slimi (2026) in a systematic critical review of the literature, which identifies two competing modes of governance in the literature: a "policing model" that is more common in technical and detection-oriented research, and a "pedagogical-trust model" supported by education researchers, who believe over-reliance on detection is pedagogically alienating and undermines student-instructor trust without addressing root integrity issues. Slimi (2026) also identified a shift in discourse over time: 61% of the studies published in 2023 focused on detection and integrity policing, whereas a minority of studies published in 2025 increasingly addressed pedagogical transformation and ethical integration, an evolution that is well captured by the institutional-governance-maturity index this study (Section 4.2) developed [13].

LLMs that generate human-level text blur traditional notions of authorship and make it difficult to determine the validity of assessments, whereas institutional policy responses have been largely reactive. According to the OECD (2026), the majority of teachers in lower secondary schools have a negative perception of the potential impact of AI on academic integrity, noting that issues of integrity are not exclusive to higher education [14].

## 2.5 AI Literacy and Ethical Frameworks

AI literacy has become a multidimensional construct that encompasses awareness of how AI systems work, the critical evaluation of AI-generated output, ethical use, and the creative or productive application of AI tools. Compared with surveys regarding early grade instruction, a much lower rate of formal AI literacy instruction is reported by educators of secondary education, as reported in surveys, indicating that the gap in AI literacy increases with lower education levels [15]. While literature-driven ethical frameworks often emphasise dimensions such as privacy, equity, transparency, and intellectual ownership as the most central aspects that institutions are expected to manage, there is a common theoretical "hole" in the current literature, namely the lack of a generally accepted instrument to measure AI literacy specifically in the higher-education segment of the population, a gap addressed by this study's proposed 45-item survey instrument.

## 2.6 Theoretical Framework

### 2.6.1 Underpinning Theories

- Constructivist Learning Theory (Vygotsky) treats AI as a learning scaffolding agent in a learner's zone of proximal development.

- The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use are factors driving the continued and future use of AI by students and faculty.
- SDT places autonomy, competence, and relatedness as psychological needs that are either fostered or inhibited in AI-mediated learning environments [16].

**Table 1a.** Comparative Summary of the Three Underpinning Theories

| Theory | Core Unit of Analysis | Key Constructs | Contribution to AAPIM |
|---|---|---|---|
| Constructivist Learning Theory (Vygotsky, 1978) | Learner cognition within a social/scaffolded context | Zone of proximal development; scaffolding; mediated cognition | A scaffolded AI learning outcomes pathway is proposed as "Frames AI."It is proposed that the pathway to AI Literacy and the learning outcomes should be scaffolded through an agent called "Frames AI" |
| Technology Acceptance Model (Davis, 1989) | Individual adoption decision | Perceived usefulness; perceived ease of use; behavioral intention | Frames AI Tool Access<br>Pedagogical Redesign as a pathway of adoption |
| Self-Determination Theory (Deci & Ryan, 1985) | Psychology needs satisfaction | Autonomy; competence; relatedness | Frames Learning Outcomes and Integrity Governance as motivational, not purely mechanical, outcomes |

Artificial intelligence (AI), specifically generative AI, mutates the entire education system by changing the structure of mentoring and guidance, knowledge, and evaluation patterns. An examination based on this suggests that AI boosts individual and comprehensive knowledge outcomes by delivering elasticity of choices and appropriate recommendations. Nevertheless, its widespread and primitive uses elevate apprehension regarding intellectual ethics, creativity, and validation in learners' assignments [17]. The survey shows that the Decoding and Disrupting the Disciplines (DDD) scheme emphasises that AI has the most impact on crucial factors in the educational field, which encompasses academic hindrances, fostering academic growth, and the ability to execute learners' grasp of knowledge. AI beyond this limit may have negative effects on prolific logical endeavours, nurture deep thinking, and obscure interruptions in academic acquisition, because scholars and learners detach from the tendency to thoroughly analyse and review assignments. Thereupon, investigators endorse their view of remodelling conventional judging techniques, highlighting constructive, structural evaluation procedures, imitating pivotal roles, and mutuality in figuring out crucial issues instead of concentrating primarily on ultimate yield. Collectively, this literature indicates that while AI proposes substantial opportunities for academic growth, its road to prosperity necessitates curicullar tactics which defend probity in the academic framework, cultivate abysmal erudition, and justify the central principles of the advanced educational pillar [18].

Recent surveys have verified that artificial intelligence (AI) can significantly modify academia by enriching desired educational objectives, assisting individualised learning, and promoting progressive education. An organised research synthesis engaging the PRISMA paradigm and quantitative examination of 181 Scopus archived papers (2019–2025) unveiled a swift surge in AI-interrelated academic study, alongside a radical transition from prevailing AI applications paving the way for niche fields, including generative AI, ChatGPT, and student-centred learning. Various opinions infer that while AI has the ability to rehabilitate academic drive, documentation proficiency, and professional development, pedagogic (instructional) investigation of educational constructivism remains reasonably little-studied. In addition, considerable barriers abide, which creates a sense of uncertainty regarding ethical conduct, technological dependency, cultural inclusivity, and the probable deterioration of analytical evaluation and self-awareness because of undue reliance on AI. This literature overview underscores the significance of enacting a user-centric tactic for AI convergence by disseminating moral policies, professional development, multilateral cooperation, and accountable execution. In summary, the literature insinuates that AI has ample possibilities to embellish emancipatory pedagogy in academics. However, its smooth integration relies on creating an equilibrium of technological ingenuity with principled, instructional, and educational reflections to guarantee feasible and purposeful academic attainment [19].

Emerging analysis demonstrates that the orchestration of Artificial Intelligence (AI) in the educational pitch has a favourable influence on mentoring, knowledge intake, and academic impact. Utilising a statistical analysis strategy, an investigation examined 250 academic staff members and learners from Indian universities to determine the function of AI in educational bodies. The results revealed a hopeful link between AI espousal and elevated teaching excellence, maximised learning success, heightened gratification in academia, and extensive instructional reformation. In addition, AI can establish and optimise administrative processes and advocate for a mixed-mode learning atmosphere by aiding institutional convention capacity. Despite these perks, the survey cites the vitality of mentioning complications regarding academic misconduct and focuses on the necessity of an explicit instructional framework, professional enrichment initiative, and pragmatic approaches to assure a liable and productive consolidation of the academic system. Altogether, this study deduces that AI has the notable capability to reconstruct the educational structure, given that its accomplishment is navigated by well-tailored academic protocols and moral quandaries [20].

Existing literature points out that artificial intelligence (AI) has grown into a consequential propeller of academic breakthroughs by boosting the adaptive intake of knowledge, refining educational delivery, and upholding operational facilitation. This was achieved through a structured evaluation of ongoing research comprising scenario investigations. Analysts have shown that intelligent automation, such as customised learning environments and smart technology-based platforms, elevates academic proficiency by directing individualised instruction and rapid recommendations, particularly in mathematics, linguistic education, and medical knowledge. However, the broad acceptance of AI also poses substantial hurdles, including barriers connected to abstract righteousness, data confidentiality, computational discrimination, and heavy dependence on AI, which might impair learners' analytical ability and freedom in thinking. Additionally, divergence in AI literacy among instructors leads to access inequity and deployment of AI mechanisms. The composition thus underlines the requirement for prescribed educational mandates, integrated educator preparation, professional norms, and a stabilised synergistic partnership to secure an amenable, all-encompassing, and seamless aggregation of AI in the educational system, as well as leveraging its academic advantages and diminishing prospective threats to achieve optimal outcomes [21].

Current compositions highlight the increasing capacity of artificial intelligence (AI) to catalyse the entire academic body, including discipline, mastering, probing, and authoritative measures. AI has culminated in macro programs and sophisticated platforms competent in conducting focused coaching sessions, deepening learner immersion, rationalising administrative efficiency, and optimising operational performance. These upheavals bolster academic development by facilitating flexible learning spaces that satisfy specific educational demands, as well as widening students' reach and academic attainment. At the same time, this review also emphasises the harmonious unification of AI requisites; meticulous attention to moral dimensions; and ensuring equity, absolute clarity, liability, reclusion, and avoiding any sort of prejudice and mismanagement. Instead of completely trusting evidence-based approaches, this research presents a conceptual framework on the rising role of AI in the education system, debating that accountable execution backed by a proper code of conduct is imperative for escalating the advantages of AI while shielding scholarly ethics and inclusive education and guaranteeing impartiality [22].

### 2.6.2 Proposed Framework: AI-Augmented Pedagogy Integration Model (AAPIM)

Based on the three theoretical streams and the empirical patterns discussed, this research suggests five dimensions of the AI-Augmented Pedagogy Integration Model (AAPIM) that illustrate the structural pathway from access to the AI tool to the development of AI literacy, pedagogical redesign, learning outcomes, and integrity governance, with digital equity, institutional policy maturity, and student self-regulation modelled as mediating variables, and discipline type, geographic context, and institution size as moderating variables. Figure 4 illustrates this conceptual model.

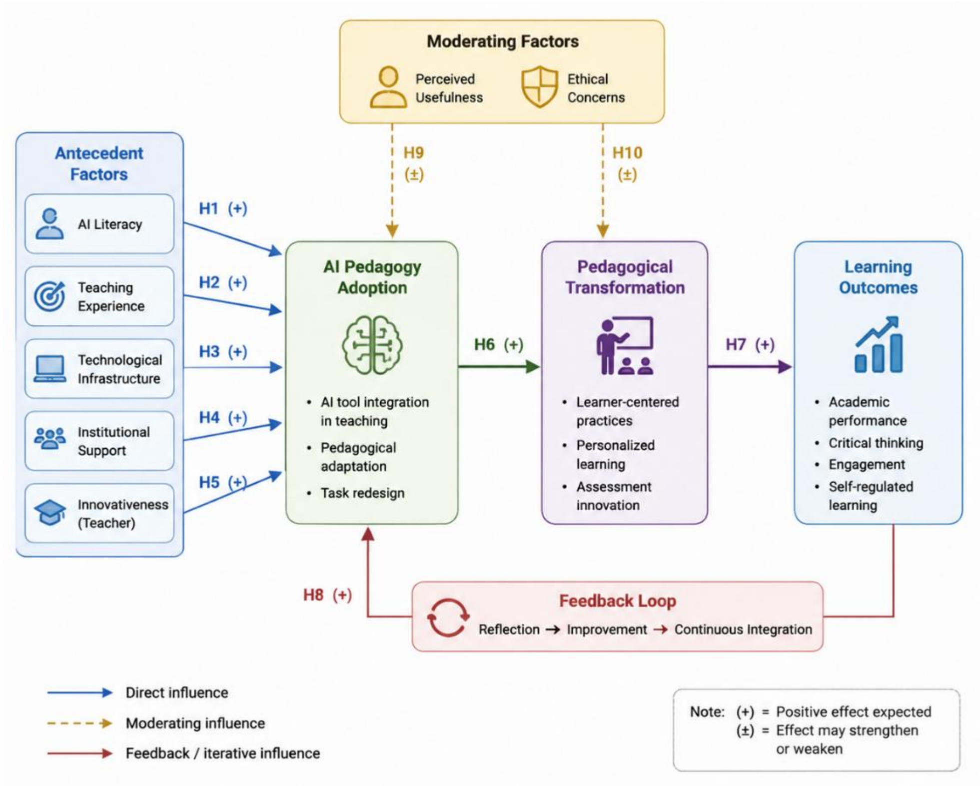


***Figure 4**. Conceptual AI-Augmented Pedagogy Integration Model (AAPIM). Pathway is theoretically derived; structural coefficients will be estimated via SEM once survey data are collected*

**Table 1b.** Synthesis of Key Empirical Sources Informing This Study (2023–2026)

| Source | Design / Sample | Core Finding Relevant to This Study |
|---|---|---|
| Kestin et al. (2025), Scientific Reports | RCT; undergraduate physics students | There was a significant difference in the amount of learning achieved by AI-tutored students compared to active learning students, with higher reported engagement and motivation. |
| Bittle & El-Gayar (2025), Information | Systematic review, k = 41 studies (2021–2024) | GenAI can bring increased engagement/efficiency to the table but also more academic dishonesty risk; it requires digital literacy and detection mechanisms. |
| Liu, Guo, He, & Hu (2025), J. Educ. Comput. Res. | Meta-analysis, k = 49 studies (K-12 & higher ed) | There were larger gains for higher education and text-based interaction (mean effect sizes g = 0.857 (achievement) and g = 0.803 (motivation), respectively). |
| Ma et al. (2025) J. Computer Assisted Learning | Meta-analysis, k = 34 studies | The overall effect was g = 0.68, very strong in the cognitive dimension (g = 0.795); effectiveness was not differently distributed by discipline, but by tool type. |
| Gu and Yan (2025), J. Educ. Comput. Res. | Meta-analysis, k = 19 studies, 24 effect sizes | The overall effect g = 0.683; teacher-supported interaction (g = 1.426) was much greater than the unsupported interaction (g = 0.077). |
| Slimi (2026), Frontiers in Education | Systematic critical review, 54 studies + 6 policy docs<br><br>(2023–2025) | Recognises policing vs. pedagogical-trust governance models and records a shift in 2023-2025 from detection to redesign. |

| | | |
|---|---|---|
| Freeman / HEPI (2025), Student Generative AI Survey | Survey, n = 1,041 UK undergraduates | AI tool use rose from 66% (2024) to 92% (2025), and AI use in the assessed work rose from 53% to 88%. |
| OECD (2026), Digital Education Outlook | Policy synthesis of international evidence | The benefits of GenAI are not always signs of learning; there is a need for purposefully designed pedagogically sound educational AI. |
| Digital Education Council (2025), Global AI Faculty Survey | Global faculty survey | The majority (61 percent) of faculty reported using AI in teaching, with most faculty describing the extent of the faculty's adoption as minimal compared to students. |

## 3. Methodology

### 3.1 Research Design

A convergent mixed-methods design was proposed, using parallel data collection of quantitative data from survey questionnaires and a quasi-experimental pre-post design, as well as qualitative data from semi-structured interviews and focus group discussions, and analysing the qualitative data using joint display matrices to interpret the quantitative data. This design is illustrated in the analytical flow in Figure 5.

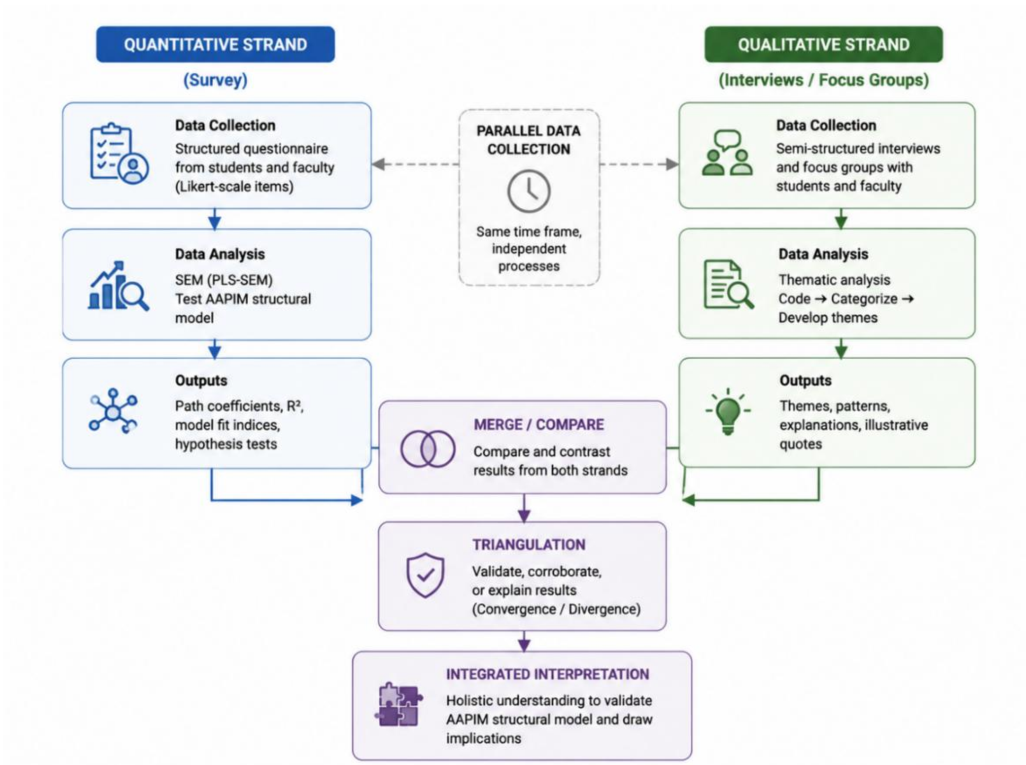


***Figure 5.*** *Convergent mixed-methods design: Quantitative and qualitative strands were collected in parallel, analysed independently, and triangulated to validate the AAPIM structural model.*

### 3.2 Participants and Sampling

- *Target sample:* 420 participants (350 undergraduate students and 70 faculty members) from three HEIs.
- *Sampling:* Stratified purposive sampling, which provided disciplinary diversity in STEM, social sciences, and the humanities.

- *Eligibility conditions:* One semester must have used AI tools, and the student must have been enrolled in the institution for the entire academic year.
- *Ethics:* IRB approval will be obtained prior to recruitment, informed consent will be required, data storage will be anonymised, and the GDPR will be compliant.

### 3.3 Instruments

- *Survey instrument:* A questionnaire with 45 questions assessing the level of AI literacy and perceptions of pedagogical redesign, including the use of AI tools, which were validated by a Cronbach's alpha of at least 0.80.
- *Academic performance measures:* pre-post grade point average and rubric-based standardized assignment assessment.
- *Qualitative protocol: A* 12-item semi-structured interview guide with the support of three focus group sessions of six to eight participants.

### 3.4 Planned Data Analysis

This was done using quantitative methods, namely, structural equation modelling (SEM) using SmartPLS 4, descriptive statistics, and ANOVA for between-group comparisons.

- *Qualitative:* Thematic analysis, according to Braun and Clarke (2006), was supported by coding using NVivo and member checking for interpretive validity.
- *Integration of mixed methods:* joint display matrices, convergence coding, and disconfirmation analysis.

### 3.5 Validity and Reliability Measures

- *Content validity:* Prior to instrument deployment, five educational technology scholars reviewed the content.
- *Construct validity*: Confirmatory factor analysis (CFA) of the final survey instrument.
- *Triangulation*: Convergence across quantitative, qualitative, and institutional document (AI policy) data sources.

**Table 2.** Planned Data Sources and Their Function in the Design

| Data Source | Target N / Scope | Primary Analytic Use |
|---|---|---|
| 45-item Likert survey | 350 students + 70 faculty (n = 420) | SEM estimation of AAPIM pathways; descriptive AI-literacy profiling |
| Pre-post assessment scores | Quasi-experimental subsample, 3 institutions | Effect estimation for AI-augmented vs. traditional pedagogy (RQ1) |
| Semi-structured interviews (12 items) | Purposive subsample across disciplines | Thematic analysis of pedagogical redesign perceptions (RQ2) |
| Focus groups (3 sessions) | 6–8 participants per session | Deeper exploration of integrity governance perceptions (RQ3) |
| Institutional AI-policy documents | 3 participating institutions | Document review for governance-framework triangulation (RQ3, RQ4) |

## 4. Hypothesized Relationships and Analysis Plan

This section takes the place of the Results section, but data collection has not yet been carried out. It states the pre-registered hypotheses of the study and outlines in advance how each hypothesis is tested when data are available, which is the conventional structure of a registered report [26].

### 4.1 Pre-Registered Hypotheses

H1: There will be significant differences between the assessment scores of students assigned to AI-augmented learning conditions and those assigned to the comparison condition (traditional pedagogy).

H2: AI literacy positively mediates the relationship between generative AI tool use and learning outcomes.

H3: The maturity of institutional AI-governance frameworks (HI) negatively moderates the relationship between the use of generative AI tools and academic integrity concerns; in other words, the more mature the AI-governance framework, the less academic integrity concerns at a given level of generative AI tool use.

H4: Digital equity (device, connectivity and access to AI tools) will mediate the relationship between AI literacy and learning outcomes.

**Table 3.** Hypothesis-to-Analysis Mapping (Planned, Pre-Registered)

| Hypothesis | Predicted Direction | Planned Statistical Test | Prior Evidence Motivating the Hypothesis |
|---|---|---|---|
| H1 | AI-augmented > traditional | ANOVA/ANCOVA, controlling for baseline GPA | Kestin et al. (2025) RCT; meta-analytic g = 0.68–0.86 (Liu et al. 2025; Ma et al. 2025; Gu & Yan 2025) |
| H2 | AI literacy mediates positively | SEM mediation path (SmartPLS 4) | Purpose built use argument, OECD (2026): teacher support moderation, Gu & Yan (2025) |
| H3 | Governance maturity moderates negatively | Interaction term, AI-use × governance-maturity index | Slimi (2026) argued that the relationship between policing and pedagogical trust typology can be fragmented. However, Slimi (2026) contends that the connection between policing and pedagogical-trust typology is weak |
| H4 | Digital equity moderates positively | SEM moderation path (SmartPLS 4) | The literature reviewed in Section 2.3, in the context of digital-equity issues, OECD (2026) equity concerns |

### 4.2 Planned Quantitative Analysis

Pre- and post-assessment scores were compared between conditions using between-group comparisons (ANOVA/ANCOVA with baseline GPA as a covariate) to assess H1. The full AAPIM structural model will be tested for H2 and H4 with SEM, with AI literacy as a mediating path and digital equity as a moderating path, and the model fit will be assessed using CFI, RMSEA, SRMR, and conventional thresholds. H3 is measured using a moderation term that links the use intensity of AI with an institutional governance-maturity index based on the document-review element of the design [23].

### 4.3 Planned Qualitative Analysis

Themes will be identified in the transcripts of interviews and focus groups using Braun and Clarke's (2006) thematic coding approach. The literature reviewed in Section 2 suggests four candidate themes that will be examined as sensitising concepts or findings: faculty ambivalence regarding the use of AI-supported assessment, student instrumentalism (the use of AI to facilitate learning efficiently instead of deeply and meaningfully), equity and access gaps in the availability of AI tools, and an absence of governance with inconsistent enforcement of institutional policy. These themes are similar to those identified by Slimi (2026) in his systematic critical review of the wider literature, but were drawn out independently. As coding continues, the final themes are permitted to stray from these expectations [24].

### 4.4 AAPIM Framework Validation Plan

The AAPIM model in Figure 1 will be assessed as a formal structural model after the survey data are gathered, with CFA to validate the measurement of each latent construct and then using full SEM path estimation to quantify the direct and mediated effects between the five dimensions of AAPIM. If the initial fit indices are not within the acceptable ranges, the model specification is performed in a normal iterative manner [25].

## 5. Discussion

### 5.1 Anticipated Interpretation

The results of the study will be analyzed based on the theoretical frameworks of constructivism, TAM, and SDT. Drawing from the literature reviewed, this study expects that the learning benefits of AI will depend on the level of AI literacy among teachers and students, as well as the maturity of institutional governance and the nature of the pedagogical guidance provided for its use in learning processes. The overall pattern is in line with the OECD's (2026) findings that AI supports learning when embedded in a clear pedagogical framework, but that unguided use could boost task performance without lasting learning benefits. Gu and Yan (2025) conducted a meta-analysis of all AI and GenAI studies involving teachers and found that teacher-supported GenAI interaction yielded significant learning gains compared to teacher-unsupported interaction ($g = 1.426$ vs. $g = 0.077$). Ma et al. (2025) found that the effect size of GenAI varies meaningfully by discipline, and AAPIM's moderator structure is explicitly designed to detect this variation in empirical studies.

### 5.2 Contribution to Theory

The aim of AAPIM is to provide a generic and empirically testable framework for studies on educational technology adoption.

- The model combines integrity governance and digital equity as structural (as opposed to peripheral) constructs with the TAM.
- The AAPIM is designed as a model that can continually evolve to fit the continued development of the LLM and can be re-estimated longitudinally, rather than a single static validation.
- APIM contributes to the transition to a "principled adaptation" of institutional governance, as called for by Slimi (2026), by codifying institutional governance maturity as a first-class moderating variable.
- as an empirically testable construct and not as a normative goal.

### 5.3 Practical Implications

- For institutions: A methodology based on evidence for AI governance and academic integrity policies.
- For teachers: A guide to using AI literacy teaching in disciplines
- For EdTech developers: Principles for creating purposeful educational AI consistent with OECD (2026) recommendations for sustainable learning outcomes.
- For policymakers, an equity-focused framework for implementing an AI deployment plan in low-resource schools

### 5.4 Limitations

- The quasi-experimental portion of the study weakens causal inference from a fully randomised study, and longitudinal replication is suggested.
- The results of a sample of three institutions may not be broadly applicable to other cultural and national higher education settings.
- As capabilities change with generative AI systems, the results can be re-validated as needed.
- This study's own effect estimates should be read in light of the fact that the published meta-analyses cited in Section 2.2 have different magnitudes of effect ($g = 0.68$ to $g = 0.86$) based on inclusion criteria and operationalization of outcomes; the actual magnitude of the effect in this study should not be compared with any single figure.

## 6. Conclusion

By filling this gap in the empirical literature that connects generative AI research and learning science with academic governance, this protocol offers valuable insights into both AI and education. This protocol is important for both AI and educational communities because it helps bridge the gap in the literature. The study design aimed to provide higher education stakeholders with a theoretically informed and methodologically clear framework for evaluating the responsible integration of AI after data collection. The design explicitly aligns with the OECD's imperative for a purpose-built educational AI evaluation system and was developed to support the increasing evidence base about AI-related EdTech policy, which has increased significantly since the original protocol draft, as evidenced by the four additional meta-analyses and one large systematic critical review published in 2025-2026. Further study directions involve cross-national comparative studies, replication over time, additional AI literacy scale development, and studies of AI-human co-teaching models in K-12 environments.

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