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From Prediction to Pedagogy: A Systematic Review and Integrated Framework for LLM Adoption in Higher Education

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Abstract

As large language models (LLMs), such as ChatGPT, gain traction in higher education, pressing questions emerge regarding their pedagogical utility, ethical implications, and adoption drivers. This systematic review synthesises 29 empirical studies examining student adoption of LLMs through established models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Adopting a theory-informed, mixed deductive–inductive methodology, the review integrates thematic analysis with synthesis of reported beta coefficients to assess conceptual patterns and theoretical limitations. Findings reaffirm Perceived Usefulness and Performance Expectancy as dominant predictors; however, traditional models exhibit a utilitarian bias, underrepresenting constructs vital to educational contexts, such as ethical ambiguity, pedagogical misalignment, and institutional trust. Facilitating Conditions were notably context-dependent, often shaped by these broader socio-ethical dimensions. Importantly, there was no consistent alignment between a construct's theoretical prominence and empirical predictive power. To address these gaps, the review proposes the Generative Adoption Model in Education (GAME), which centres trust calibration, ethical ambiguity, and pedagogical fit as key mediators of adoption. GAME encourages a shift from performance-based models toward frameworks that better capture the socio-institutional dynamics underpinning student engagement with generative AI.

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Introduction

The accelerating uptake of Large Language Models (LLMs) by students in higher education marks a pivotal transformation in digital learning and academic engagement (Bond et al., 2024; Chan, 2023). These systems, exemplified by tools such as ChatGPT, extend beyond routine automation; their generative, probabilistic, and epistemically opaque outputs introduce new challenges for trust, control, and interpretation in the student context (Chen et al., 2024; Ortmann, 2025; Shahzad et al., 2025). The rapid diffusion of LLMs among higher education students raises urgent questions about the adequacy of established theoretical frameworks for understanding adoption, a gap that hinders effective pedagogical integration, evidence-based ethical guideline development, and responsive institutional policy formulation.

Historically, technology adoption research has centred on deterministic, task-oriented systems, with foundational models such as the Technology Acceptance Model (TAM; Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) emphasising user intention and perceived utility. However, the interactive, adaptive, and non-deterministic character of LLMs introduces theoretical challenges that may exceed the explanatory reach of these established models, particularly when applied to student engagement and learning in higher education. TAM-based research rarely integrates ethics, subjective norms, and trust dimensions, which are increasingly relevant in educational settings shaped by generative AI (Mustofa et al., 2025). These limitations suggest the need for a more integrative approach to AI adoption research in education, one that better reflects the sociotechnical complexity and normative considerations of LLM use in pedagogical practice.

Rethinking Adoption Models: Theoretical and Empirical Limitations

To address this critical gap, this review reassesses the conceptualisation of LLM adoption in higher education through a theory-informed synthesis of empirical research. Guided by the proposition that established models such as TAM and UTAUT may inadequately account for the dynamic, adaptive, and socially embedded nature of generative AI chatbots, this analysis critically evaluates their explanatory capacity within the context of students' academic engagement. Through systematic synthesis, the review identifies three core limitations, positioning this present study as a conceptual and methodological advancement.

Predictor Significance

While TAM and UTAUT propose broad predictors of adoption, their empirical salience in student-LLM contexts within higher education remains underexamined. This review systematically maps and compares predictor variables across studies, using reported standardised β coefficients as a standard metric of effect size to identify which constructs exert the most decisive influence. This approach provides an empirical foundation for assessing the relevance of predictors, which is often lacking in existing critiques (Peterson & Brown, 2005).

Architectural Misalignment

These established adoption models (TAM, UTAUT) are typically optimised for deterministic, task-specific technologies such as smart home technology or e-commerce tools (Daruwala, 2025; Rauschnabel & Ro, 2016). Research using co-citation analyses (Hsiao & Yang, 2011) affirms the historical fit of TAM with systems characterised by stable utility structures. In contrast, LLMs in higher education involve fluid epistemic interaction, evolving user norms (Sharma et al., 2025), and ethical ambiguity (Qadhi et al., 2024). These dynamics necessitate fundamentally revised or integrative frameworks, rather than merely extending existing models.

Conceptual and Cultural Misfit

The adoption drivers and patterns of LLMs vary substantially across institutional and cultural contexts. While TAM and UTAUT prioritise individual behavioural intention, alternative frameworks, such as Diffusion of Innovation (Rogers, 2003) and Task–Technology Fit (Goodhue & Thompson, 1995), highlight contextual and organisational dimensions. Cross-cultural research further suggests that adoption drivers differ between individualist and collectivist cultures (Hofstede, 2011). This review synthesises cross-disciplinary evidence showing how current models are insufficiently addressing these culturally and institutionally embedded variables.

Emerging Constructs for a Generative Era

While legacy predictors, such as perceived ease of use and perceived usefulness, remain highly relevant, the generative nature of LLMs calls for a critical recalibration of traditional adoption methodologies. These systems introduce novel cognitive and ethical challenges for students, including the need to navigate prompt engineering self-efficacy (Liu et al., 2023), tolerate occasional inaccuracies through hallucination tolerance (Leiser et al., 2023), and develop a foundational level of AI literacy (Chang et al., 2024). These constructs underscore a shift in the cognitive and ethical demands placed on students that legacy frameworks often overlook (Mustofa et al., 2025; Qadhi et al., 2024). As such, emerging research highlights the importance of rethinking adoption not simply as a matter of ease or utility, but as a complex, situated process shaped by new forms of uncertainty, skill, and judgment. Determining which of these constructs most strongly influences adoption remains an open empirical question. Findings indicate that trust, ethical judgement, and perceptions of reliability are especially salient (Choudhury & Shamszare, 2023; Mustofa et al., 2025; Shahzad et al., 2025). These trends highlight the limits of legacy models in accounting for the probabilistic, relational, and ethically charged dimensions of LLM use. In response, this review advances an integrated conceptual and empirical agenda attuned to the evolving landscape of generative AI in higher education.

Synthesising Prior Systematic Reviews on LLMs in Education

Recent systematic reviews converge on a dual characterisation of LLMs as both a pedagogical enhancer and a disruptive force within higher education. Albadarin et al. (2024) and Zhang and Tur (2024) highlight the transformative benefits, such as personalised instruction, virtual tutoring, and dynamic scaffolding affordances.

However, these same reviews caution against emergent risks, including the erosion of critical thinking, the undermining of collaborative learning, and intensified concerns around academic integrity. Dempere et al. (2023) extend this view by foregrounding institutional tensions: while AI adoption may improve service efficiency and retention, it also raises significant challenges related to data privacy, automation-induced depersonalisation, and the weakening of interpersonal learning relationships.

From a theoretical standpoint, Al-Kfairy (2024) affirms the ongoing utility of established models such as TAM and UTAUT, with constructs like perceived usefulness and performance expectancy remaining predictive of adoption. However, findings across the reviewed papers underscore persistent variability in the influence of facilitating conditions and social influence, particularly across diverse institutional contexts. Several studies reviewed by the authors recommend expanding existing frameworks to incorporate neglected factors, including hedonic motivation, ethical apprehension, and usability perceptions, which more accurately reflect real-world adoption dynamics in generative AI environments.

Entrenched ethical and regulatory concerns also shape adoption. Bonsu and Baffour-Koduah (2023) and Jafari and Keykha (2023) note widespread unease around data exposure and inadvertent plagiarism, while Chukwuere (2024) draws attention to legal grey zones and institutional opacity that undermine user confidence. These issues are especially pronounced in higher education, where the stakes surrounding authorship, compliance, and academic integrity are magnified. Accordingly, systematic reviews advocate for robust institutional safeguards, transparent communication strategies, and a more precise articulation of pedagogical utility defined here as the degree to which LLMs support, enrich, or transform core educational processes. Finally, methodological insights from Baig and Yadegaridehkordi (2024) emphasise the value of multi-layered models that situate adoption within broader technological, organisational, and environmental contexts. Nevertheless, such complexity is rarely addressed in dominant frameworks. Baytak further notes a significant oversight in the literature on rejection behaviours despite increasing institutional mandates for LLM disclosure; few models consider reluctance, ethical abstention, or policy-driven avoidance as legitimate adoption outcomes. These reviews delineate both the promise and the limitations of current research on LLM adoption in higher education. They reveal substantial pedagogical potential while drawing attention to gaps in ethical reasoning, cross-contextual generalisability, and the evolving nature of user trust.

Advancing the Field: The Present Study's Contribution

Responding to these gaps, this review introduces the Generative Adoption Model in Education (GAME), a context-sensitive framework designed not only to map adoption pathways but also to account for resistance, ambiguity, and institutional ethics as intrinsic components of AI-mediated learning. Synthesising thematic patterns across recent empirical studies, GAME foregrounds under-theorised yet increasingly salient constructs that reflect the unique dynamics of generative AI use in academic settings. Ethical calibration captures students' ongoing judgments about the alignment of LLM outputs with academic norms, institutional rules, and personal values (Qadhi et al., 2024). This construct is especially salient given that generative AI often produces plausible yet unverified content, thereby demanding critical ethical judgment (Mustofa et al., 2025). Traditional adoption models often marginalise ethical considerations, but recent studies underscore their predictive significance (Agyare et al., 2025; Choudhury & Shamszare, 2023).

Relational trust refers to students' evolving confidence in both the generative and institutional structures governing their use. Rather than assuming trust to be static, recent findings suggest it develops through iterative interaction, institutional transparency, and perceived endorsement (Polyportis, 2024; Shahzad et al., 2025). Adaptive outcomes denote the behavioural and cognitive adjustments students make in response to system feedback and increasing familiarity. These adaptations include modified study practices, iterative prompt design, and evolving epistemic strategies, signalling a shift from binary adoption decisions to context-sensitive, dynamic engagement (Ortmann, 2025; Zhang & Tur, 2024). Such shifts often reflect students' appraisal of *pedagogical alignment,* the extent to which LLMs facilitate, enrich, or transform essential learning processes within higher education. Therefore, this systematic review aims to: (1) Synthesize empirical findings on student LLM adoption in HE; (2) Critically evaluate the applicability and limitations of dominant technology acceptance models (TAM, UTAUT) in this context; (3) Identify key emergent constructs and empirical gaps; and (4Assess the cultural influence within the adoption literature; and (5) Propose and justify the Generative Adoption Model in Education (GAME) as an integrative framework addressing these limitations.

Method

Research Design and Conceptual Rationale

This review followed PRISMA 2020 guidelines (Page et al., 2021). It adopted a critical realist perspective (Bhaskar, 2013), recognising that patterns in LLM adoption reflect real-world phenomena, but that their interpretation is shaped by prevailing theoretical and cultural frameworks. This dual perspective enabled a layered synthesis, one that aggregated empirical findings while simultaneously interrogating the theoretical architectures underlying them. Given the theoretical diversity and global dispersion of the included studies, a mixed-methods synthesis was a methodologically appropriate approach. This approach enabled both statistical aggregation of path coefficients and reflexive critique of theoretical structures, ensuring analytical depth without compromising empirical rigour.

Search Strategy and Information Sources

A three-tiered search strategy was implemented from March to May 2025:

- Exploratory Mapping. Preliminary scans of Scopus, Web of Science, and Google Scholar using broad descriptors (e.g., "ChatGPT acceptance," "generative AI in education") informed keyword refinement.
- Targeted Retrieval. Boolean searches emphasising known theoretical constructs (e.g., ("TAM" OR "UTAUT") AND ("LLM" OR "ChatGPT") AND ("university" OR "student") helped isolate studies with explicit model-based foundations.
- Citation Network Analysis. Forward and backwards citation chaining of relevant studies ensured comprehensive coverage, minimised publication bias, and identified emerging research networks.

Eligibility Criteria

Inclusion and exclusion criteria were developed to ensure conceptual coherence and statistical comparability:

Table 1. Inclusion and Exclusion Criteria for Systematic Review

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles	Non-peer-reviewed formats
English-language publications	Non-English texts
Higher education population focus	General user or undefined populations
Students	Educators
Published between 2022–2025	Pre-2022 publications
Model-based frameworks (TAM)	Opinion or descriptive works
Structural/path models with β values	Qualitative or non-standard designs

Study Selection and Quality Appraisal

The study selection process followed a multi-stage filtering approach. First, two reviewers independently conducted title and abstract screening, yielding high inter-rater reliability (Cohen's κ = 0.91). Full-text assessments were conducted by the primary reviewer, with a 30% random sample cross-validated by a secondary reviewer. Each study was evaluated using an adapted Critical Appraisal Skills Programme (CASP) rubric. Methodological quality was scored on a 10-point scale, assessing sample representativeness, measurement validity, and statistical robustness. Theoretical adequacy was evaluated on a 5-point scale, measuring construct distinctiveness, model justification, and acknowledgement of boundary conditions. Studies scoring below 6 (methodological) or 3 (theoretical) were excluded, resulting in a final corpus of 29 high-quality studies.

Data Extraction and Synthesis Approach

Data extraction captured study metadata (country, year, sample size), theoretical models, predictor constructs, standardised regression coefficients (β), contextual modifiers (e.g., infrastructural limitations, pedagogical environment), and model validation indices. A mixed-methods synthesis was used:

Quantitative Meta-Analysis

A targeted quantitative synthesis was conducted to examine the empirical strength of predictor constructs commonly used in LLM adoption studies. Constructs were eligible for inclusion if they appeared in *three or more studies* and reported standardised β coefficients derived from inferential models, including structural equation modelling (SEM), partial least squares SEM (PLS-SEM), or multiple regression. For each construct, both *mean β* and *peak β* values were recorded to capture central and maximal effect sizes. To assess the relationship between a construct's *frequency of use* in the literature and its *predictive strength*, **a** *Pearson correlation* was planned using construct frequency as the independent variable and mean β magnitude as the dependent variable. All statistical computations were conducted using IBM SPSS Statistics (Version 29; IBM Corp.).

Thematic Analysis. A narrative synthesis was conducted using *thematic analysis* following the reflexive approach outlined by Braun and Clarke (2023). This involved a multi-phase process: initial familiarisation with the dataset, generation of initial codes from the findings and discussion sections of each included study, and inductive theme development through constant comparison and iterative refinement. Coding was conducted manually, with attention to both *semantic-level content* (explicitly reported factors) and *latent-level constructs* (implicit theoretical or contextual assumptions).

Themes were organised to capture variation across three primary domains: (1) *theoretical developments* in adoption modelling, (2) *regional and contextual constructs*, and (3) *emerging dynamics* unique to LLM use in educational practice. Coding was conducted by the lead reviewer and discussed with peers for reflexive triangulation. Thematic maps and matrix logs were used to ensure traceability across studies and coherence within and across themes. Complete methodological transparency, including the study selection flow, is represented in the PRISMA diagram (see Figure 1).

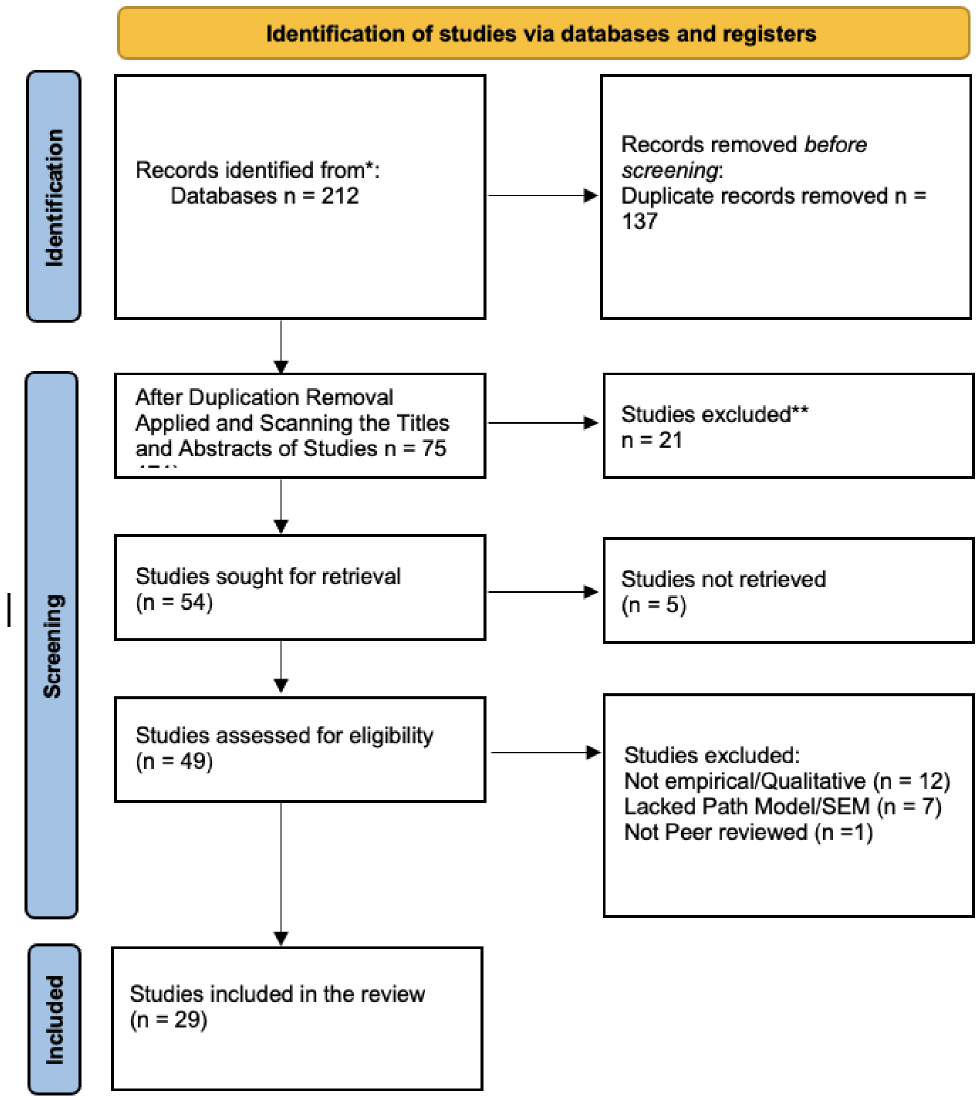

Figure 1. PRISMA Flow Diagram of Study Selection

This multi-pronged methodological strategy ensured that the review not only synthesised global evidence but also exposed the theoretical blind spots and cultural asymmetries shaping current LLM adoption research. The coding matrix, PRISMA flowchart, and CASP evaluation tables generated and analysed during this review are publicly available in the Zenodo repository: https://doi.org/10.5281/zenodo.15663506.

Results

Theoretical Foundations of LLM Adoption Research

This review identified 32 theoretical frameworks used across 29 empirical studies on LLM adoption in higher education from 2023 to May 2025. All studies employed path-based quantitative designs, reporting standardised regression coefficients (β) to predict behavioural intention or actual use.

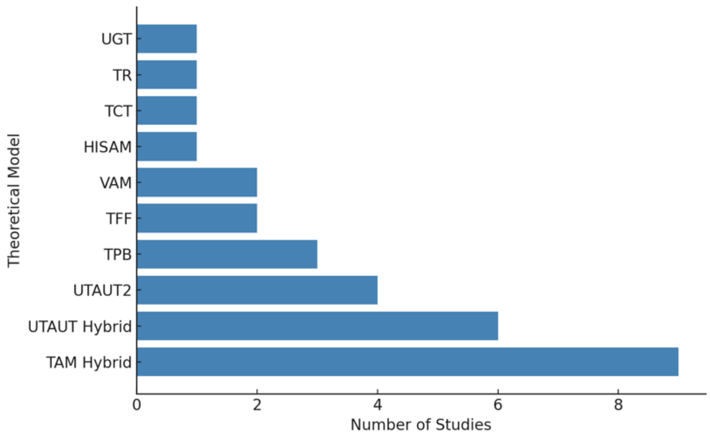

Figure 2. Adoption Models Used in Higher Education: Frequency Distribution

As illustrated in Figure 2, TAM Hybrid models appeared in 9 studies (28.1%), while UTAUT-based models (UTAUT Hybrid and UTAUT2) were featured in 10 studies (31.3%). Other frameworks, such as the Theory of Planned Behaviour by Ajzen (1991) (TPB) (3 studies), Task–Technology Fit (TTF) and Value-Based Adoption Model (VAM) (2 studies each), and the Hedonic Motivation System Adoption Model (HMSAM) (1 study), appeared far less frequently. This distribution suggests a continued reliance on legacy models, despite the conceptual challenges posed by generative AI.

Theoretical Insularity: Homogenised Constructs and Temporal Blindness

Table 2 provides an overview of the papers chosen for the review. Cultural homogenisation pervaded 83% of studies, applying Western models (e.g., TAM, UTAUT) without contextual adaptation. Constructs like Perceived Ease of Use were identically operationalised in differing locations (Foroughi et al., 2024; Agyare et al., 2025), while culturally salient factors (e.g., "Knowledge Sharing" Duong et al., 2023) were marginalised. Temporal dimensions fared worse: only Polyportis (2024) and Strzelecki (2024) quantified dynamic processes (Trust Change: β = .386; Habit decay), despite evidence of skill atrophy (Rahman et al., 2024). This theoretical stance, prioritising convenience over ecological validity, ignores LLMs' fluid interaction patterns.

Table 2. Top Predictors of LLM Adoption in Global Higher Education

#	Author & Year	Country	Sample Size	Model Used	Top Predictor 1	β	Top Predictor 2	β
1	Saif et al. (2024)	Pakistan	156	TAM	Perceived Stress	.797	Perceived Usefulness	-.677
2	Jasrai (2025)	India	311	Extended UTAUT	Performance Expectancy	.314	Habit	.229
3	Polyportis (2024)	Netherlands	222	Concept	Trust Change	.386	Emotional Creepiness (–)	–.139
4	Mahmud et al. (2024)	Bangladesh	369	Extended VAM, ANN	Self-Efficacy	.242	Personal Innovativeness	.241
5	Masa'deh et al. (2024)	Jordan	880	TAM	Perceived Ease of Use	.772	Perceived Usefulness	.122
6	Duong et al. (2023)	Vietnam	392	SOR/UTAUT	Performance Expectancy	.528	Effort Expectancy	.457
7	Qu & Wu (2024)	UK & China	189	HMSAM	Perceived Usefulness	.492	Flow Immersion	.231
8	Habibi et al. (2024)	Indonesia	2078	UTAUT, TPB	Perceived Behavioural Control	.361	Attitude toward ChatGPT	.195
9	Habibi et al. (2024)	Indonesia	1117	UTAUT 2	Facilitating Conditions	.302	Performance Expectancy	.301
10	Foroughi et al. (2024)	Malaysia	406	TPB + TTF	Performance Expectancy	.207	Learning Value	.175
11	Sobaih et al. (2024)	Saudi Arabia	520	UTAUT2	Performance Expectancy	.141	Social Influence	.070
12	Hasan et al. (2024)	USA	142	TAM + TR	Interaction & Engagement	.377	Accuracy & Responsiveness	.269
13	Almogren et al. (2024)	Saudi Arabia	458	Smart Ed. TAM	Perceived Ease of Use	.360	Attitude toward GPT	.240
14	Alshammari (2024)	Saudi Arabia	136	UTAUT	Performance Expectancy	.542	Facilitating Conditions	.353
15	Le et al. (2024)	Vietnam	283	TAM + UGT	Perceived Usefulness	.338	Novelty	.247
16	Sun & Wang (2024)	China	120	TAM	Growth Mindset	.424	Perceived Usefulness	.007

#	Author & Year	Country	Sample Size	Model Used	Top Predictor 1	β	Top Predictor 2	β
17	Albayati (2024)	South Korea	285	TAM + Privacy, Trust, SI	Attitude toward GPT	.755	Trust	.138
18a	Strzelecki & ElArabawy (2024)	Egypt	385	UTAUT	Social Influence	.398	Facilitating Conditions	.206
18b	Strzelecki & ElArabawy (2024)	Poland	543	UTAUT	Performance Expectancy	.504	Effort Expectancy	.230
19a	Chang et al. (2024)	China (low skills)	303	TAM + TPB + LC	PBC	.472	Subjective Norms	.110
19b	Chang et al. (2024)	China (high skills)	303	TAM + TPB + LC	PBC	.435	Subjective Norms	.176
20	Agyare et al. (2025)	Ghana, Jordan, USA	804	TAM + Ethics	Subjective Norms	.148	Perceived Ease of Use	.090
21	Parikesit et al. (2025)	Indonesia	100	TAM + PLS-SEM	Perceived Ease of Use	.480	Perceived Usefulness	.466
22	Fu et al. (2024)	Indonesia	445	UTAUT + PMT	Performance Expectancy	.300	Task Efficiency	.252
23	Gupta et al. (2025)	India	780	TCT + TTF	Social Influence	.580	Task–Technology Fit	.560
24	Strzelecki (2024)	Poland	503	UTAUT2 + PI	Habit	.339	Performance Expectancy	.260
25	Rahman et al. (2023)	Bangladesh	344	TAM +	Personal Innovativeness	.391	Perceived Ease of Use	.213
26	Chopra et al. (2025)	Poland	528	UTAUT	Performance Expectancy	.548	Effort Expectancy	.280
27	Chopra et al. (2025)	India	546	UTAUT	Performance Expectancy	.384	Social Influence	.304
28	Sun et al. (2025)	China	339	TAM +	Perceived Ease of Use	.512	Perceived Usefulness	.428
29	Polyportis & Pahos (2025)	Netherlands	355	UTAUT+	Facilitating Conditions	.671	Performance Expectancy	.580

Dominant Predictors of Adoption Behaviour

Across 29 empirical studies in 15 countries, consistent predictors of LLM adoption in higher education were identified. Performance Expectancy was most frequent (41.4%), showing cross-cultural robustness (e.g., India, Poland) with a mean $\bar{\beta}$ = .40. Perceived Ease of Use yielded the highest individual score (β = .772; Jordan) but ranked third in frequency. Perceived Behavioural Control had the highest mean ($\bar{\beta}$ = .42), especially among skill-diverse groups. Facilitating Conditions (β = .671; Netherlands) and Effort Expectancy ($\bar{\beta}$ = .32) were key in resource-constrained settings. Attitude showed strong, context-dependent effects (β max = .755; South Korea). Emotional Creepiness (β = –.139) was the only significant negative predictor. UTAUT constructs dominate, especially in productivity-driven contexts. Cultural trends also emerged in collectivist regions, which emphasised Social Influence; individualist ones favoured Personal Innovativeness. Education-specific variables appeared but lacked consistent inclusion (see Table 3).

Table 3. Top LLM Adoption Predictors in Higher Education

Rank	Predictor	Freq.	Highest β	Mean β
1	Performance Expectancy	12	.580	.40
2	Perceived Usefulness	7	.492	.18
3	Perceived Ease of Use	6	.772	.41
4	Facilitating Conditions	4	.671	.38
5	Social Influence	4	.580	.34
6	Perceived Behavioural Control	3	.472	.42
7	Effort Expectancy	3	.457	.32
8	Subjective Norms	3	.176	.15
9	Attitude	3	.755	.40
10	Personal Innovativeness	2	.391	.32

Note. Frequency indicates the number of studies where the construct appeared as a significant predictor; Mean β represents the average standardised coefficient.

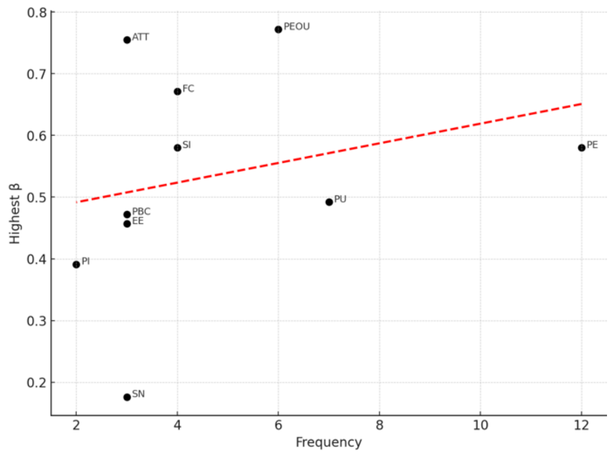

Figure 3a. Frequency and Highest β Values of Adoption Predictors

Although Perceived Usefulness (PU) was frequently positioned as a top predictor, its mean effect size ($\bar{\beta}$ = .18) was substantially reduced due to one outlier study (Saif et al., 2024), which reported a significant negative association (β = –.677). This anomaly likely reflects contextual or methodological divergence rather than diminished theoretical relevance, as PU otherwise demonstrated positive and moderate-to-high effects across most studies. *Subjective Norms* (SN) and *Personal Innovativeness* (PI) also underperformed across both metrics. Pearson correlations revealed no significant relationship between frequency and predictive strength (highest β: r=.27, p=.46; mean β: r=.12, p=.74).

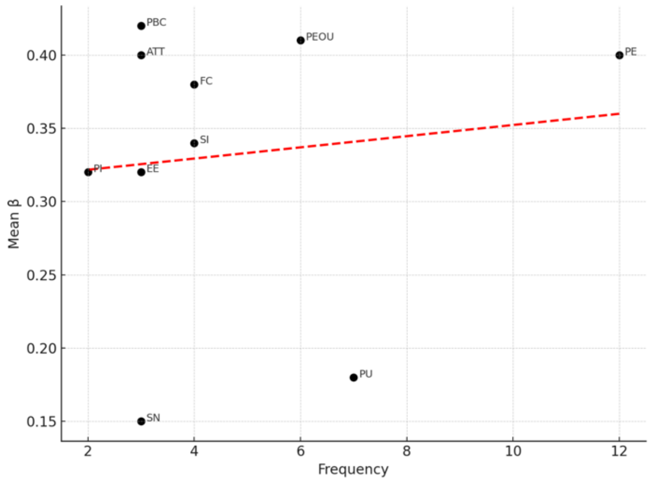

Figure 3b. Frequency and Mean β values of Adoption Predictors

These findings indicate that commonly used predictors are not always the most effective, underscoring the need for more context-sensitive, empirically driven variable selection in LLM adoption research. Figure 4 shows the interpretation of predictor performance through the display of both the maximum standardised beta coefficient (β max) and the mean beta ($\bar{\beta}$) for each key variable across studies.

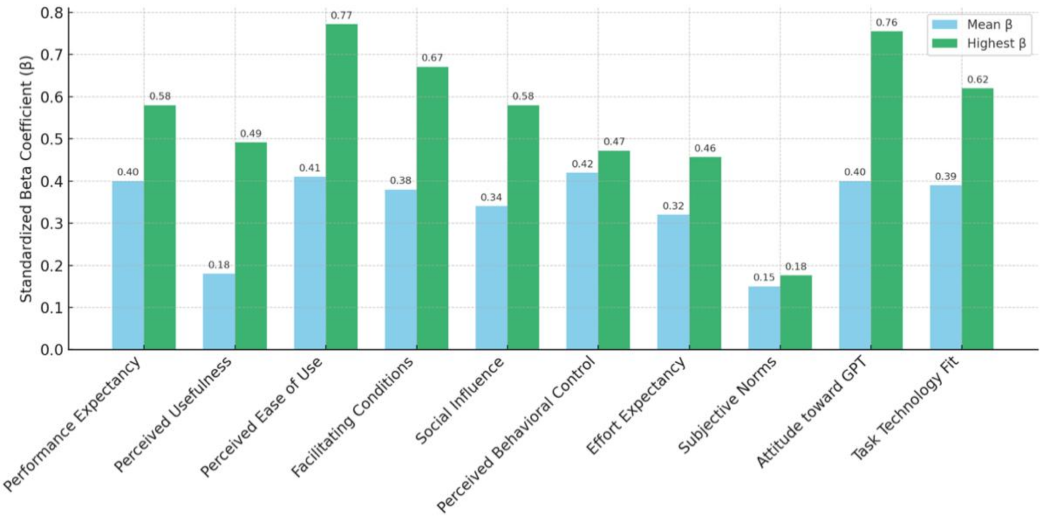

Figure 4. Mean vs. Max βs for LLM Adoption Predictors

This comparative visual serves three primary analytic purposes in comprehending LLM adoption in higher education:

Differences between maximum (β max) and average ($\bar{\beta}$) standardised coefficients illustrate how predictor effectiveness varies by context. Perceived Ease of Use (β max = .772; $\bar{\beta}$ = .41) showed high variability, while Task–Technology Fit (β max = .62; $\bar{\beta}$ = .39) was more consistent across studies. Facilitating Conditions reached a peak of β = .671 in well-equipped settings, underscoring the importance of infrastructure. In contrast, Perceived Usefulness, though often included, never exceeded β = .492. Attitude toward GPT (β max = .755; $\bar{\beta}$ = .40) had strong effects but was underreported due to its mediating role. Social Influence (β max = .580; $\bar{\beta}$ = .34) revealed strong but culturally variable influence.

Regional Variations in Predictors of LLM Adoption in Higher Education

Country Representation in LLM Adoption Research

Among 33 country-samples derived from 29 studies on LLM adoption in higher education, 16 countries were represented. Asia dominated with 10 countries (62.5%), led by China and Indonesia (n = 4 each), followed by India and Saudi Arabia (n = 3 each), and Vietnam, Jordan, Bangladesh, Pakistan, Malaysia, and South Korea (n = 1–2). Western nations included the United States (2) and the United Kingdom (1), while Poland (3) and the Netherlands (2) represented Europe. Africa contributed two country-samples, one each from Egypt and Ghana. The top five countries (China, Indonesia, India, Saudi Arabia, and Poland) accounted for 51.5% of country-samples (17/33), highlighting a concentration in select regions.

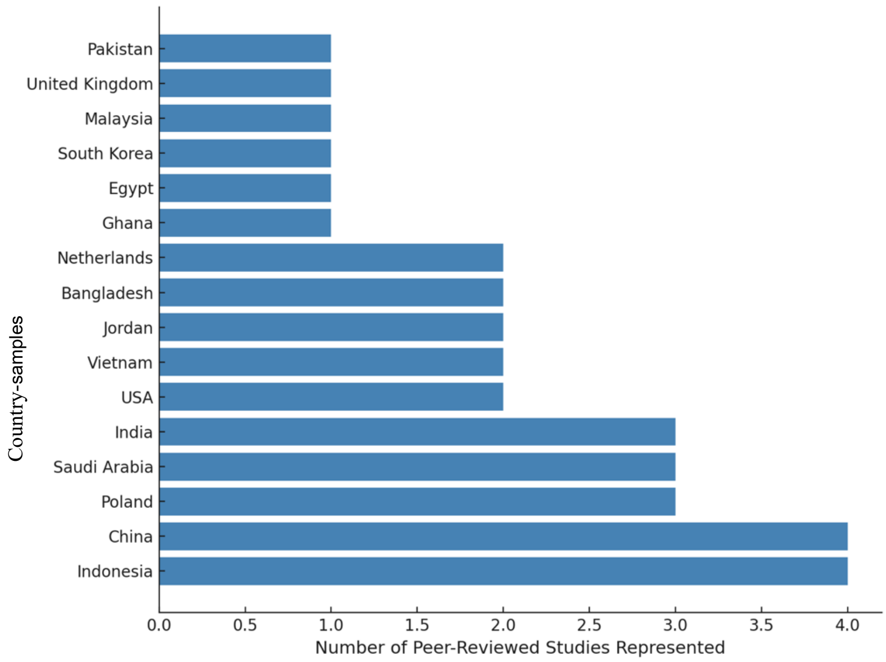

Figure 5. LLM Adoption Country-samples in Higher Education by Country (n = 33)

Regional Distribution of LLM Adoption Studies

The country-sample distribution by region is presented in Figure 6. The West exhibited the highest overall representation, contributing 8 of 33 country-samples (24.2%), followed by Southeast Asia (21.2%), South Asia (18.2%), and both the Middle East and East Asia (15.2% each). Africa accounted for two studies (6.1%), with no representation from Latin America or Oceania. Although Asia leads in participation, disaggregated data show no subregion exceeds the West, revealing a more balanced global research distribution.

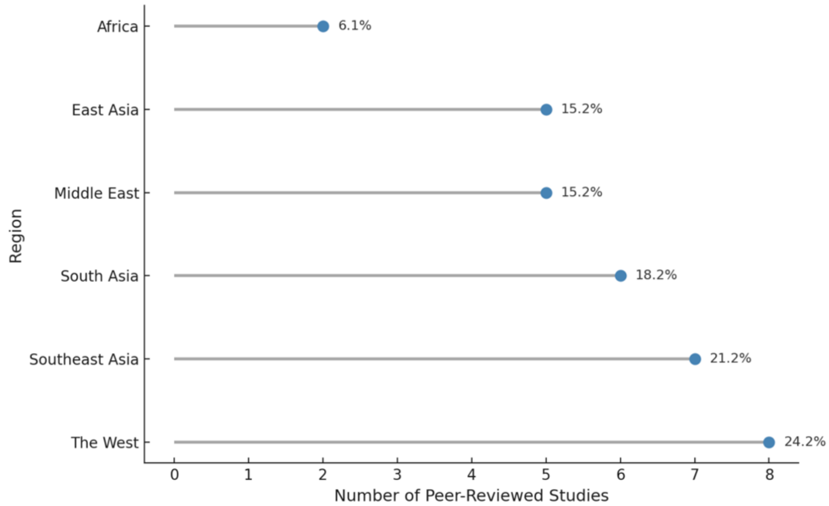

Figure 6. LLM Adoption in Higher Education: Regional Research Distribution

Trend in Adoption

To assess regional trends in LLM adoption, predictors were disaggregated by global region and ranked according to average standardised beta coefficients (β) and frequency. Table 4 presents the two most prominent predictors per region, along with mean β values and the number of studies (freq) in which each predictor was identified as a top-ranked factor.

Table 4. Most Significant Adoption Predictors of LLM in Higher Education by Region

Region	Top Predictor 1	β (Avg)	Freq.	Top Predictor 2	β (Avg)	Freq.
Southeast Asia	Performance Expectancy	.434	4	Perceived Usefulness	.429	3
South Asia	Performance Expectancy	.407	4	Social Influence	.391	3
East Asia	Perceived Usefulness	.316	4	Perceived Behavioural Ctrl	.454	2
The West	Performance Expectancy	.437	4	Trust	.300	3
Middle East	Perceived Ease of Use	.537	3	Performance Expectancy	.228	3
Africa	Social Influence	.398	1	Facilitating Conditions	.206	1

Regional Variations in Predictors

Performance Expectancy was the most frequently cited top predictor, appearing in four of the six global regions. In the Middle East, Perceived Ease of Use had the highest average β (.537), surpassing its global mean (.41) by a notable margin. African findings were based on only two studies, where Social Influence (β = .398) and

Facilitating Conditions (β = .206) were the top predictors. Interpretations should remain cautious due to the limited data. Southeast and South Asia prioritised performance-based predictors; however, South Asia uniquely highlighted Social Influence (β = .391), reflecting collectivist educational norms. In the West, Trust (β = .300) emerged as a distinctive secondary predictor, possibly indicating regional emphasis on ethical concerns. East Asia focused on Perceived Behavioural Control (β = .454), underscoring the importance of self-efficacy within Confucian learning traditions.

Regional Network Graph of LLM Predictors

Figure 7 visualises these patterns across regions, categorising predictors by theoretical dimension (cognitive, social, or affective) and illustrating co-occurrences through node-link structures. Figure 7 shows regional predictors of LLM adoption using node size, colour, and co-occurrence links to illustrate theoretical patterns.

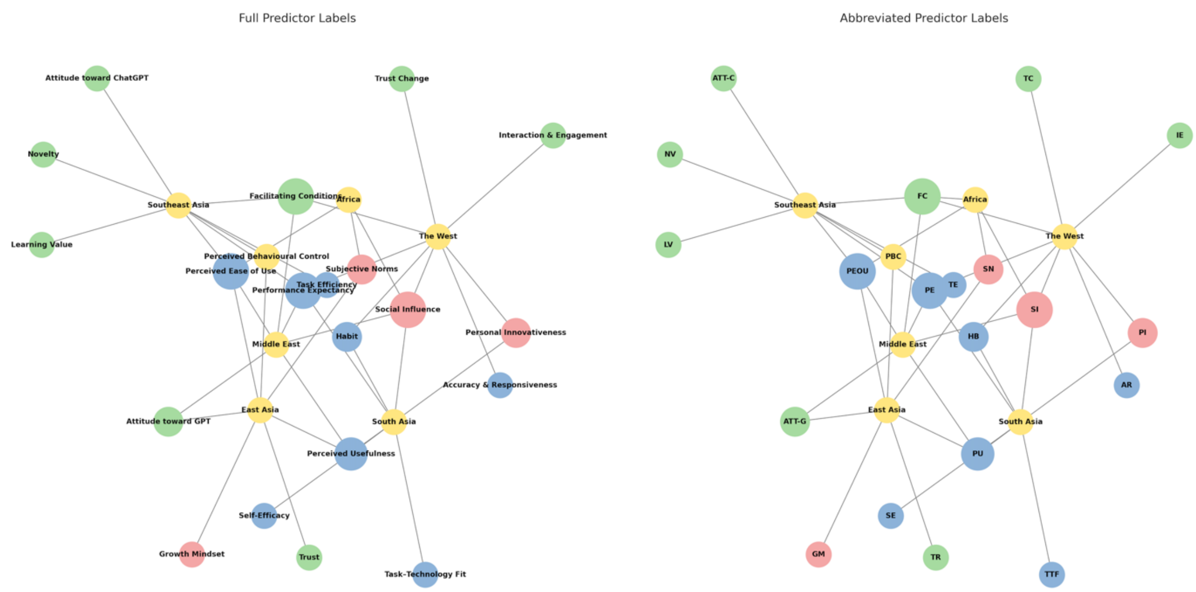

Figure 7. Networked Drivers of LLM Adoption in Global Higher Education

Note. Node sizes proportional to frequency and colours aligned by predictor type

- Cognitive
- Social
- Contextual/Affective
- Region nodes

Performance Expectancy and Perceived Ease of Use emerged as central predictors, linked to multiple regions including Southeast Asia, South Asia, the Middle East, and East Asia. Social Influence and Trust showed a lower frequency but regional spread. Unique predictors, such as Facilitating Conditions (Africa) and Interaction and Engagement (West), were exclusive to their respective regions. Network density varied: Southeast and South Asia showed broader connections, while Africa and the Middle East had fewer. The network highlights both shared and context-specific adoption factors across regions.

Discussion

Legacy Framework Overuse: Familiarity Over Fit

This review synthesises fragmented literature to highlight key limitations in current adoption models and proposes GAME as a principled response (Siddaway et al., 2019). The dominance of TAM and UTAUT, which appear in over 75% of studies, reflects a theoretical conservatism. However, over half (55%) apply hybrid forms, signalling an awareness that new constructs are needed. These adaptations tend to incorporate functionally narrow variables (e.g., hedonic motivation, habit), with minimal engagement in pedagogical, ethical, or relational dimensions central to LLM adoption (Agyare et al., 2025; Sonkar et al., 2024; Stahl & Eke, 2024).

Emergent constructs such as relational trust, hallucination tolerance, and AI literacy are frequently discussed but rarely operationalised (Chang et al., 2024). Even the original developers of UTAUT acknowledge its limited scope for technologies characterised by user co-agency and emergent functionality features that define LLMs (Venkatesh et al., 2012). Theoretical stagnation is not total, but the selective application of legacy models risks framing novel constructs as anomalies rather than as evidence of a conceptual misfit. The limited use of alternative frameworks, such as TTF, VAM, HMSAM, or evidence-based conceptual models, reinforces the need for greater epistemic pluralism (Griffiths, 1997). This study addresses the necessity for frameworks specifically designed to consider the educational and ethical dynamics of LLMs. These gaps motivate the Generative Adoption Model in Education (GAME), introduced in the ‘Constructing the GAME Framework’ section, which embeds pedagogical alignment, ethical calibration, and relational trust as core constructs.

Dominant Predictors of Adoption Behaviour: Productivity Over Pedagogy

Instrumental Dominance and the Ethical Blind Spot

The empirical dominance of performance-related constructs warrants critical reflection on their limits and the broader adoption context. Performance Expectancy continues to be the primary explanatory factor in the adoption of LLMs within higher education. Across diverse studies and cultural contexts (Chopra et al., 2025; Gupta et al., 2025), the allure of increased productivity and enhanced academic performance remains a central focus. This instrumental emphasis reflects a long-standing tradition in educational technology research, which is grounded in efficiency, task support, and measurable gains (Duong et al., 2023). However, such dominance also restricts the field’s conceptual perspective.

What these models frequently overlook is not the capability of LLMs, but the conditions under which they are trusted, accepted, or ethically challenged. Recent research suggests that ethical concerns related to misinformation, privacy, and academic integrity meaningfully shape behavioural intentions (Agyare et al., 2025; Farazouli et al., 2024). These are not abstract moral issues but real adoption barriers that current frameworks often fail to capture. The persistence of ethical exclusion within TAM and UTAUT derived models leaves little room for constructs that account for user hesitation, critical judgment, or institutional accountability.

The analysis shows that Ease of Use continues to influence how students adopt LLMs, especially when the tools are familiar and straightforward to use. However, this factor mainly affects individual experiences. In contrast, Facilitating Conditions played a more varied role across studies. These findings suggest that successful adoption depends not only on how easy a tool is to use but also on broader conditions that support its meaningful integration. Meanwhile, constructs such as Subjective Norms and Social Influence typically play a supporting rather than a central role, implying that social approval, while relevant, may require reinforcement from ethical and functional considerations to influence adoption meaningfully (Chang et al., 2024; Sobaih et al., 2024). Together, these patterns highlight the importance of moving beyond performance-centric logic. They also set the stage for examining more nuanced dimensions of LLM adoption, specifically, the affective signals and attitudinal undercurrents that shape users' willingness to embrace or resist these technologies.

Affective Signals and the Attitudinal Undercurrent

Affective and cognitive dimensions remain underrepresented in much of the current modelling of LLM adoption, despite accumulating evidence for their impact. Attitude, in particular, warrants renewed scrutiny. In the reviewed literature, Attitude was most frequently modelled as a mediating variable, in keeping with the conventions of technology acceptance frameworks such as TAM and UTAUT (Venkatesh et al., 2012; Strzelecki, 2024). Direct modelling of Attitude as an independent predictor of LLM adoption was rare, which reflects established practice rather than oversight. Notably, when modelled as a direct predictor (e.g., Albayati, 2024; Almogren et al., 2024), Attitude demonstrated significant explanatory power, suggesting its role may be structurally underestimated in mediation-heavy frameworks.

Prevailing analytical traditions often position Attitude as a mediator between independent variables and behavioural intention to use. This means that its primary impact is usually shaped by structural modelling choices rather than empirical evidence. These reviews' findings only included Attitude towards LLMs when used as an independent variable, omitting its mediation roles. Had Attitude been systematically examined in both roles, it might have emerged as the strongest predictor of adoption. This highlights the need for greater flexibility and contextual awareness in future models. Polyportis (2024) highlighted the effect of emotional creepiness, suggesting that feelings of discomfort or distrust can meaningfully deter the uptake of LLMs. These subtle psychological barriers are particularly consequential in educational settings, where trust and legitimacy are essential prerequisites for the acceptance of technology.

Contextual Sensitivity and Predictive Inconsistency in LLM Adoption

A central lesson from this review is that the most frequently cited predictors are not always the most stable or explanatory across diverse higher education contexts. Constructs such as Perceived Ease of Use, Attitude, and Facilitating Conditions frequently appear in LLM adoption models, but their predictive influence fluctuates significantly depending on the context. The treatment of Perceived Usefulness is especially instructive, as it is routinely included in frameworks, but its observed effects have varied widely. The anomalous negative association reported by Saif et al. (2024) was not a general indictment of PU, but rather an illustration of how mediation and students' stress can invert expected relationships. Such findings demonstrate the risks of assuming that legacy constructs will behave consistently in novel AI settings.

The weak correlation between predictor frequency and effect size (β) undermines reliance on convention over evidence, urging context-driven variable selection. This suggests that researchers often default to conventional variables, rather than allowing model content to be guided by direct empirical observation. Similarly, the influence of Social Influence emerges as highly variable, shaped by the cultural or institutional environment, a nuance echoed by cross-cultural studies (Agyare et al., 2025; Strzelecki & ElArabawy, 2024). These insights emphasise the need for context-sensitive, empirically justified predictor selection in LLM adoption research. Future frameworks should prioritise variables that reflect the realities of specific educational settings, moving beyond the automatic replication of established models to deliver a more robust and actionable understanding of LLM adoption dynamics.

Regional Patterns in LLM Adoption: Shared Predictors, Divergent Pathways

Regional Representation and Research Imbalance

The landscape of LLM adoption research reveals notable regional disparities. While Asian countries, especially China, Indonesia, and India, contributed the highest number of studies, a closer regional analysis shows Western nations remain the most comprehensively represented. This complexity challenges any straightforward narrative of Asian dominance, instead highlighting an uneven and patchwork research ecosystem. Strikingly, Latin America and Oceania are absent from current datasets, underscoring persistent global blind spots. The lack of empirical work from key educational regions undermines the generalisability of current conclusions. It underscores the pressing need to incorporate underrepresented contexts, particularly those with unique infrastructural or ethical challenges that influence AI integration.

Converging Constructs, Diverging Emphases

Performance Expectancy emerged as the most consistently reported construct, serving as a primary predictor across most regions and underscoring the centrality of perceived academic enhancement in driving the adoption of LLMs. However, important regional differences persist in secondary constructs. In the Middle East, Perceived Ease of Use is particularly salient, suggesting that technological usability remains a key concern in settings where digital infrastructure or pedagogical openness may lag. Western studies, by contrast, emphasise Trust as a significant secondary construct, reflecting ongoing debates around ethics, transparency, and academic integrity (Agyare et al., 2025; Idris et al., 2024; Polyportis, 2024). South Asia demonstrates the strong influence of Social Influence, which resonates with collectivist academic cultures. At the same time, East Asia's focus on Perceived Behavioural Control is congruent with values of mastery and self-discipline. These divergent emphases underscore the risks of imposing global models without regard for regional and cultural nuances.

Conceptual Networks and Implications for Theory

This analysis reveals consistent and divergent patterns in how factors drive LLM adoption across global higher education contexts. At the broadest level, functional drivers related to efficiency gains and operational simplicity, including Task Efficiency, Performance Expectancy, and Perceived Ease of Use, demonstrate universal relevance. These form a stable core observed in all regions, reflecting students' shared pragmatic focus on academic productivity and tool usability. Beyond this common foundation, however, adoption dynamics diverge sharply. Trust exemplifies this variability: while universally present, it manifests in distinct regional configurations. In Middle Eastern contexts, trust correlates closely with technical concerns such as accuracy and responsiveness, whereas Western studies link it to Ethical Calibration and institutional transparency. Similarly, Social Influence operates as a primary adoption lever in South Asia, amplified by cultural collectivism and visibility of use, but functions more peripherally elsewhere. Southeast Asian contexts uniquely intertwine Learning Value and Novelty with a Growth Mindset, revealing pedagogy-focused adoption pathways that are absent in other regions. Personal Innovativeness further illustrates contextual nuance, moderating between functional and social drivers in culturally specific ways. Critically, these variable factors, though less ubiquitous than efficiency-focused constructs, frequently exert decisive influence where locally salient. Their omission or homogenisation in standardised models risks overlooking key adoption barriers or accelerators.

The GAME framework addresses this limitation by design. Its core components (Ethical Calibration, Relational Trust, Pedagogical Alignment) operate as modular priorities rather than fixed variables. Their influence dynamically scales to reflect regional imperatives: pedagogical alignment dominates where learning innovation drives adoption (e.g., Southeast Asia), while relational trust intensifies in settings that prioritise technical reliability (e.g., the Middle East). This built-in adaptability positions GAME as a context-responsive alternative to one-size-fits-all models, better equipped to navigate the global diversity of higher education.

Constructing the GAME Framework

Synthesising the empirical patterns and conceptual gaps identified in this review, the Generative Adoption Model in Education (GAME) advances theoretically and empirically grounded constructs that encapsulate the complex dynamics of LLM adoption within higher education (Figure 8). Central to GAME is Perceived Academic Benefit (PAB), an endogenous mediator construct that synthesises Performance Expectancy and Perceived Usefulness, thereby representing students' holistic evaluations of academic enrichment, productivity enhancement, and pedagogical relevance (Chopra et al., 2025; Masa'deh et al., 2024). By explicitly linking perceived benefits to educational outcomes, PAB effectively addresses the limitations of traditional, generic adoption constructs.

GAME extends beyond existing models by conceptualising adoption as *ethically and contextually mediated*, theorising identity conflicts surrounding academic integrity, productivity, and policy navigation, factors that TAM and UTAUT typically reduce to "barriers" (Al-Kfairy, 2024; Bonsu & Baffour-Koduah, 2023). It also addresses *power asymmetries*, including covert use driven by restrictive institutional policies (Chukwuere, 2024), and reconceptualises LLMs as *generative co-agents* rather than static tools. Constructs such as *prompt literacy, epistemic trust, and output ownership* reflect the dynamic, dialogic nature of LLM interaction, which is often overlooked in classical "ease of use" paradigms. By situating students as pedagogical agents within complex ethical and institutional ecosystems, GAME provides a context-sensitive model that is more attuned to the realities of integrating generative AI in contemporary higher education.

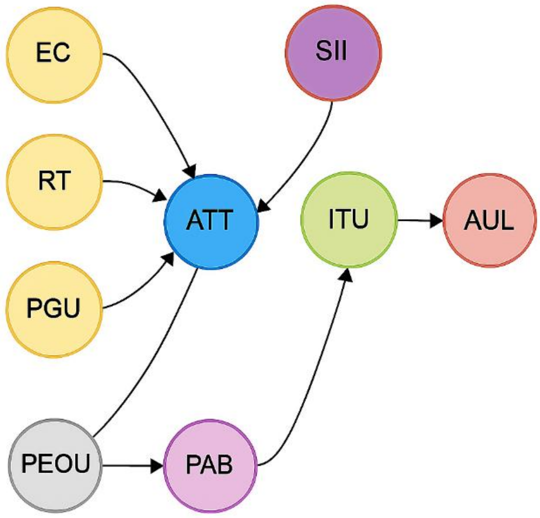

Figure 8. Structural Model of the GAME Framework

Note: Visual representation of core constructs and relationships in the Generative Adoption Model in Education (GAME). EC = Ethical Calibration, RT = Relational Trust, ATT = Attitude, ITU = Intention to Use, SII = Social and Institutional Influence, AUL = Academic Use of LLMs, PGU = Pedagogical Utility, PEOU = Perceived Ease of Use, PAB = Perceived Academic Benefit.

Attitude (ATT) serves as a crucial mediating mechanism, functioning both as an evaluative driver and as a gateway that captures students' cognitive-affective appraisals of LLM acceptability (Albayati, 2024; Strzelecki, 2024). Despite frequent empirical validation, ATT's mediating role has not been sufficiently theorised; explicitly modelling its mediating relationships improves both predictive precision and practical utility for targeted educational interventions. Ethical Calibration (EC), Relational Trust (RT), and Pedagogical Utility (PGU) are exogenous constructs that each directly influence Attitude. Ethical Calibration encompasses students' ongoing interpretation of institutional policies and personal ethical norms related to AI utilisation, emphasising the necessity of reducing bias and ensuring accuracy to foster adoption intentions (Agyare et al., 2025; Idris et al., 2024; Razafinirina et al., 2024). Relational Trust outlines evolving confidence in LLM technologies and institutional transparency, which is particularly critical in contexts characterised by reliability and accountability concerns (Polyportis, 2024; Shahzad et al., 2025). Pedagogical Utility explicitly addresses perceptions of LLMs' potential to enrich or transform educational practices, recognising the broader educational alignment and instructional enhancement beyond mere efficiency gains (Idris et al., 2024; Razafinirina et al., 2024).

Perceived Ease of Use (PEOU) serves as a uniquely dual-mediated construct within GAME, influencing Attitude directly and additionally mediated through PAB. This dual-mediated role highlights PEOU's context-sensitive yet influential position, especially in environments with technological constraints or resistance (Masa'deh et al., 2024; Parikesit et al., 2025). The Intention to Use (ITU), considered an endogenous dependent construct, mediates the relationships between Attitude and PAB towards the outcome construct, Academic Use of LLMs (AUL).

Together, categorised as exogenous (EC, RT, PGU), dual-mediated (PEOU), single-mediated (ATT), secondary-mediated (PAB), and endogenous dependent (ITU, AUL), these constructs collectively establish GAME as an advanced, theoretically robust, and empirically sound framework that is ideally suited for guiding research, shaping policy, and informing practice regarding generative AI adoption in higher education. Supporting these constructs, Social and Institutional Influence is an option if researchers intend to explore the nuanced effects of peer norms, faculty guidance, and institutional policy, which are particularly significant in compliance-oriented and collectivist educational cultures (Habibi et al., 2024; Gupta et al., 2025).

Limitations

Although the synthesis of β coefficients provides a quantitative lens on the predictive strength of key constructs, this approach has inherent limitations. Specifically, the mean and peak β values reported for constructs are derived from studies with diverse modelling strategies, sample characteristics, and contextual assumptions. As such, these effect sizes do not reflect repeated tests of identical constructs under uniform conditions; instead, they represent aggregate estimates across studies with varying scientific aims and structural configurations. This heterogeneity limits the comparability of β scores and advises against over-interpreting numerical averages as universally generalisable effects. While this heterogeneity limits direct comparability, it further validates GAME’s context-adaptive design, a priority for future validation studies.

Conclusion

The main contribution of this review is to demonstrate that the accelerating adoption of Large Language Models in higher education exposes the conceptual limitations of established technology acceptance frameworks. While legacy models remain influential, the empirical evidence of hybridisation suggests they are insufficient to capture the complex, multi-layered realities of generative AI use. The persistent prominence of productivity-related constructs indicates that the sector remains anchored in instrumental logic. However, the analytic findings also highlight crucial undercurrents, ethical dilemmas, evolving trust relationships, affective responses, and context-dependent social and institutional pressures that shape adoption in more nuanced ways than previous models have acknowledged.

This study argues that adoption is not merely a product of perceived utility or technological convenience, but rather a negotiated process embedded in institutional, ethical, and relational contexts. The introduction and empirical validation of the GAME framework mark a substantive advance, moving beyond incremental adaptation of established models. By integrating constructs such as Perceived Academic Benefit, Ethical Calibration, Relational Trust, and Pedagogical Utility, the model reconceptualises adoption as dynamic and multidimensional. The study’s broader significance lies in its challenge to theoretical conservatism and its advocacy for adoption models attuned to the generative and institutionally situated nature of AI systems. This reconceptualization provides a foundation for future research, policy, and educational design that addresses the full range of cognitive, ethical, and social factors now shaping LLM integration. By capturing these emergent dynamics, this review establishes a more rigorous and responsive agenda for the responsible and effective adoption of LLMs in higher education, equipping stakeholders with a robust conceptual and empirical foundation.

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