



Explaining Students' Generative AI Acceptance in Higher Education: An Extended Technology Acceptance Model with Digital Trust, Self-Efficacy, and Perceived Academic Value

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Abstract

Background of study: Generative artificial intelligence (GenAI) is becoming a routine academic resource, yet students differ substantially in whether they regard it as trustworthy, manageable, and educationally valuable. **Aims and scope of paper:** This study extends the Technology Acceptance Model (TAM) by integrating digital trust, AI self-efficacy, and perceived academic value to explain students' behavioral intention to accept GenAI in higher education. **Methods:** A cross-sectional multi-institutional survey and covariance-based structural equation modeling (CB-SEM) are proposed. For manuscript-development purposes, the reporting format is demonstrated with a clearly identified synthetic dataset (N = 438); these values are illustrative and must be replaced by verified empirical data before submission. **Result:** The illustrative model shows acceptable fit (CFI = .957, TLI = .949, RMSEA = .049, SRMR = .043). AI self-efficacy predicts perceived ease of use; digital trust and perceived academic value predict usefulness and attitude; and attitude, usefulness, academic value, and self-efficacy jointly explain 68% of the variance in behavioral intention. **Conclusion:** GenAI acceptance is better explained when classical TAM beliefs are complemented by students' confidence, calibrated trust, and judgments of academic value. Institutions should therefore combine technical access with AI literacy, trust-building governance, and pedagogically meaningful use cases.

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INTRODUCTION

Background of the study

Generative artificial intelligence has moved rapidly from a specialist technology to a common academic resource. University students now use systems such as ChatGPT, Gemini, Claude, Copilot, and other large-language-model applications for explanation, brainstorming, summarization, translation, coding, drafting, feedback, and problem solving. This diffusion creates a new technology-acceptance problem for higher education: availability does not guarantee educationally meaningful acceptance. Students may have access to the same tools but differ in confidence, trust, perceived learning value, attitudes, and willingness to integrate GenAI into academic work. Recent empirical studies confirm that perceived usefulness and ease of use remain important, but acceptance is also shaped by trust, prior experience, personal capability, institutional signals, and beliefs about whether the technology adds genuine value to learning (Almogren et al., 2024; Shahzad et al., 2024; Strzelecki, 2024; Pham et al., 2025).

The Technology Acceptance Model (TAM) remains one of the most influential frameworks for explaining technology adoption. TAM proposes that perceived usefulness and perceived ease of use shape attitudes and behavioral intention (Davis, 1989). The model is attractive because of its parsimony, but generative AI differs from many earlier educational technologies. GenAI produces probabilistic content, can generate convincing errors, may expose sensitive information, and raises questions of authorship and academic integrity. Its academic value therefore depends not only on instrumental utility but also on whether students trust the system appropriately, believe they can use it effectively, and perceive that its use contributes to legitimate learning goals rather than merely reducing effort.

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This study develops an extended TAM that adds three theoretically complementary constructs: digital trust, AI self-efficacy, and perceived academic value. Digital trust reflects students' willingness to rely on GenAI under conditions of uncertainty while recognizing limits in accuracy, privacy, and transparency. AI self-efficacy captures confidence in one's ability to formulate prompts, evaluate outputs, troubleshoot interactions, and use GenAI responsibly. Perceived academic value represents a learner-centered appraisal of whether GenAI meaningfully improves understanding, feedback quality, idea development, productivity, and academic task completion. Integrating these constructs allows the model to distinguish between a system that is simply easy and useful and a system that students consider trustworthy, manageable, and educationally worthwhile.

Rationale of the study

Three reasons justify extending TAM in this direction. First, trust is especially salient for generative systems because students must decide whether an output is sufficiently reliable to inform academic action. Prior studies have found that trust can influence adoption directly or indirectly through perceived usefulness and attitude, although its role is not always consistent across settings (Shahzad et al., 2024; Mustofa et al., 2025; Pham et al., 2025). Second, GenAI is highly interactive, making user capability more important than for many passive digital tools. Students with stronger AI self-efficacy should find GenAI easier to operate and may be more willing to persist when prompts fail or outputs require revision. Recent evidence links AI literacy, experience, and positive attitudes to stronger AI self-efficacy, while GenAI self-efficacy has also been associated with acceptance (Bewersdorff et al., 2025; Zhang & Yu, 2025).

Third, perceived usefulness in TAM is often framed in broad performance terms. In education, however, students also make value judgments about whether technology improves learning quality and supports academically legitimate goals. Perceived academic value is therefore conceptualized as a specific appraisal of learning relevance and educational benefit. This distinction is consistent with expectancy-value reasoning, in which individuals are more likely to invest effort when they value the task or outcome (Wigfield & Eccles, 2000). Recent GenAI adoption research has similarly introduced learning value and found it relevant to students' acceptance judgments (Bouebdallah & Ben Youssef, 2025).

Literature review

Perceived ease of use refers to the degree to which a person believes that using a system will be free of effort, whereas perceived usefulness refers to the degree to which a person believes that the system will improve task performance (Davis, 1989). In higher education, these beliefs remain important because students are more likely to adopt GenAI when they can operate it without excessive cognitive or technical burden and when they believe it contributes to academic productivity or learning. Empirical studies of ChatGPT and related systems repeatedly report strong roles for usefulness, with ease of use often influencing acceptance directly or through usefulness and attitude (Tiwari et al., 2024; Almogren et al., 2024; Pham et al., 2025).

Digital trust is conceptually distinct from usefulness. A tool can be useful yet not fully trusted, particularly when it can hallucinate references, provide biased answers, or handle personal information opaquely. Trust theory emphasizes beliefs about reliability, competence, integrity, and willingness to depend on a system under uncertainty (McKnight et al., 2002). In GenAI learning contexts, calibrated trust is preferable to blind trust: students should be willing to use AI support while maintaining verification and critical judgment. Studies in higher education increasingly identify trust as a meaningful determinant of acceptance, either as a direct antecedent or as a factor that shapes usefulness and attitude (Shahzad et al., 2024; Mustofa et al., 2025; Zhang & Yu, 2025).

AI self-efficacy extends social-cognitive accounts of technology use. Self-efficacy concerns judgments about one's capability to organize and execute actions required for desired performance (Bandura, 1997). In computing research, self-efficacy has long been associated with technology use and persistence (Compeau & Higgins, 1995). For GenAI, self-efficacy includes confidence in prompting, evaluating information, choosing appropriate tools, correcting unsatisfactory outputs, and using AI within ethical and academic constraints. Students who believe they can control and improve the interaction should perceive the technology as easier to use and may form stronger intentions to use it.

Perceived academic value captures the educational worth students attach to GenAI use. It goes beyond convenience by asking whether GenAI helps students understand difficult material, receive useful feedback, improve the quality of academic work, explore alternatives, and accomplish learning goals. This construct is expected to increase perceived usefulness because students who see clear learning benefits will also regard GenAI as performance-enhancing. It may also influence behavioral intention directly because learners can value a technology even when use requires effort. Studies of GenAI adoption increasingly emphasize learning value, performance expectancy, and academic relevance as important acceptance drivers (Habibi et al., 2023; Habibi et al., 2024; Bouebdallah & Ben Youssef, 2025).

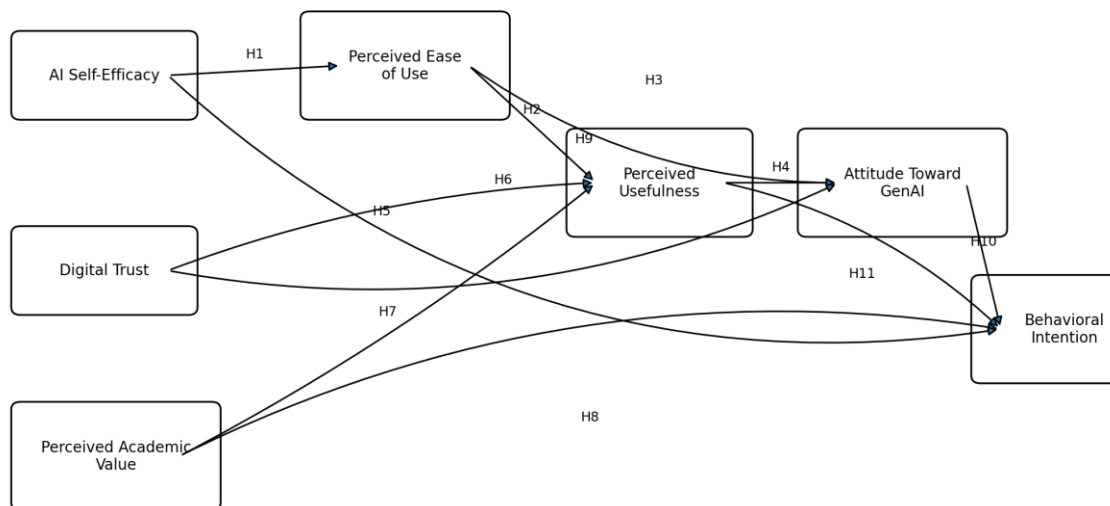
Gap analysis

Existing studies have made rapid progress in explaining GenAI acceptance, but four gaps remain. First, many studies extend TAM with a single external construct, which limits understanding of how capability, trust, and educational value operate simultaneously. Second, trust and self-efficacy are sometimes treated as generic technology beliefs even though GenAI requires ongoing judgment about output quality and user control. Third, perceived usefulness and educational value are often conflated, leaving unclear whether students accept GenAI because it improves efficiency or because they believe it contributes to legitimate learning. Fourth, much of the literature focuses on specific platforms or single-country samples. A more integrative model can clarify the common psychological mechanisms that may generalize across higher-education contexts. The present study addresses these gaps by embedding digital trust, AI self-efficacy, and perceived academic value within the core TAM pathway from ease of use and usefulness to attitude and behavioral intention.

Purpose or Hypotheses of the study

The purpose of this study is to explain students' acceptance of generative AI in higher education by testing an extended TAM in which AI self-efficacy, digital trust, and perceived academic value operate alongside perceived ease of use, perceived usefulness, and attitude. Behavioral intention is treated as the proximal indicator of acceptance. The following hypotheses are proposed:

Hypothesis	Statement
H1	AI self-efficacy positively affects perceived ease of use.
H2	Perceived ease of use positively affects perceived usefulness.
H3	Perceived ease of use positively affects attitude toward GenAI.
H4	Perceived usefulness positively affects attitude toward GenAI.
H5	Digital trust positively affects perceived usefulness.
H6	Digital trust positively affects attitude toward GenAI.
H7	Perceived academic value positively affects perceived usefulness.
H8	Perceived academic value positively affects behavioral intention to use GenAI.
H9	AI self-efficacy positively affects behavioral intention to use GenAI.
H10	Attitude toward GenAI positively affects behavioral intention to use GenAI.
H11	Perceived usefulness positively affects behavioral intention to use GenAI.



Extended TAM: capability, trust, and academic-value pathways to GenAI acceptance

Figure 1. Proposed extended TAM linking digital trust, AI self-efficacy, perceived academic value, and students' GenAI acceptance.

METHOD

Research Design

The study is designed as an explanatory, cross-sectional quantitative investigation using covariance-based structural equation modeling (CB-SEM). A confirmatory SEM approach is appropriate because the model specifies theoretically derived relationships among latent constructs and requires simultaneous assessment of measurement quality, direct effects, and indirect pathways while accounting for measurement error. The unit of analysis is the individual university student. Because the present document is a manuscript-development

draft, the numerical results reported below are explicitly synthetic and are included only to demonstrate the JQRT reporting structure; they must be replaced by actual data before scholarly submission.

Participant

The target participants are undergraduate and postgraduate students enrolled in accredited higher-education institutions who have used at least one generative AI application for academic purposes during the current or previous semester. Eligibility should be verified using a screening question asking whether respondents have used GenAI for tasks such as explanation, brainstorming, summarization, translation, writing support, coding, data analysis, feedback, or revision. A multi-institutional design is recommended to increase variation in discipline, year of study, and prior GenAI experience. For the illustrative analysis presented in this draft, a synthetic sample of 438 cases was generated to resemble plausible higher-education survey distributions.

Population and the methods of sampling Instrumentation

The population consists of students in higher education who have prior exposure to GenAI. Stratified or proportionate sampling across faculties and study levels is preferred. When probability sampling is not feasible, purposive sampling with quotas should be transparently reported. For a seven-construct model with approximately 25 observed indicators, a sample above 300 is generally adequate for stable CFA and structural estimation, although the final requirement should be justified using model complexity, expected effect size, distributional characteristics, and statistical power rather than a single rule of thumb (Hair et al., 2019; Kline, 2016).

Instrument

All constructs are measured using five-point Likert-type items ranging from 1 = strongly disagree to 5 = strongly agree. Perceived ease of use and perceived usefulness are adapted from TAM. AI self-efficacy is informed by self-efficacy research and tailored to GenAI-specific tasks. Digital trust captures reliability, confidence, and willingness to rely on GenAI while recognizing uncertainty. Perceived academic value measures students' appraisal of learning relevance and educational benefit. Attitude and behavioral intention reflect evaluative orientation and willingness to continue academic use. Items should be reviewed by experts for content validity, piloted for clarity, and refined before full administration.

Table 1. Proposed construct operationalization and illustrative questionnaire indicators

Construct	Illustrative indicators
AI Self-Efficacy (ASE)	ASE1: I can formulate effective prompts for academic tasks. ASE2: I can evaluate and improve unsatisfactory AI responses. ASE3: I can use GenAI tools appropriately even when tasks are complex. ASE4: I can identify when I need to verify or correct AI output.
Digital Trust (DT)	DT1: I consider GenAI sufficiently reliable for supported academic use. DT2: I feel confident using GenAI when I verify important information. DT3: I believe GenAI can provide dependable assistance for many academic tasks. DT4: I am willing to rely on GenAI within clear academic safeguards.
Perceived Academic Value (PAV)	PAV1: GenAI helps me understand academic material more effectively. PAV2: GenAI improves the quality of feedback available to me. PAV3: GenAI adds meaningful value to my learning process. PAV4: GenAI helps me produce higher-quality academic work when used responsibly.
Perceived Ease of Use (PEOU)	PEOU1: Learning to use GenAI for academic work is easy for me. PEOU2: My interaction with GenAI is clear and understandable. PEOU3: It is easy for me to get GenAI to do what I need for learning tasks.
Perceived Usefulness (PU)	PU1: Using GenAI improves my academic productivity. PU2: GenAI helps me complete learning tasks more effectively. PU3: GenAI improves my performance on appropriate academic activities. PU4: Overall, GenAI is useful for my studies.
Attitude toward GenAI (ATT)	ATT1: Using GenAI for appropriate academic purposes is a good idea. ATT2: I have a favorable attitude toward responsible GenAI use in learning. ATT3: I consider GenAI a positive addition to higher-education learning.
Behavioral Intention (BI)	BI1: I intend to use GenAI for suitable academic tasks in the future. BI2: I expect to continue using GenAI as part of my learning. BI3: I would choose GenAI when it provides legitimate academic value.

Procedures and time frame

After institutional ethical approval, the questionnaire should be distributed online for approximately four to six weeks. The information sheet should explain the purpose of the study, voluntary participation, anonymity, expected completion time, data protection, and the right to withdraw before submission. No personally identifying information should be collected unless an approved design requires linkage with academic records. Data-screening rules should be specified before analysis, including thresholds for

missingness, implausibly short completion times, straight-lining, duplicate responses, and failed attention checks.

Analysis plan

Analysis proceeds in two stages. First, descriptive statistics, missingness, outliers, multivariate normality, and common-method concerns are examined. The measurement model is evaluated through confirmatory factor analysis. Reliability is assessed using Cronbach's alpha and composite reliability (CR), convergent validity using standardized loadings and average variance extracted (AVE), and discriminant validity using the Fornell-Larcker criterion and heterotrait-monotrait ratios (HTMT). Second, the structural model is evaluated using chi-square relative to degrees of freedom, CFI, TLI, RMSEA, and SRMR. Direct effects are estimated simultaneously and indirect effects are tested through bias-corrected bootstrapping with at least 5,000 resamples. Model interpretation should emphasize standardized coefficients, confidence intervals, explained variance, and theoretical meaning rather than p-values alone (Fornell & Larcker, 1981; Henseler et al., 2015; Kline, 2016).

RESULTS AND DISCUSSION

Results

The following results are illustrative and based on a synthetic dataset ($N = 438$); they are included solely to demonstrate how a completed JQRT manuscript can report SEM results. In the synthetic profile, 72.6% of respondents were undergraduate students and 27.4% were postgraduate students. Academic fields were distributed across social sciences and humanities (31.5%), business and economics (24.0%), science and engineering (28.8%), and health/other disciplines (15.7%). Approximately 76% of cases represented students reporting at least weekly academic use of one or more GenAI tools. No item displayed extreme skewness or kurtosis in the demonstration dataset.

The illustrative CFA indicated acceptable measurement-model fit: $\chi^2/df = 2.07$, CFI = .957, TLI = .949, RMSEA = .049, and SRMR = .043. Standardized factor loadings ranged from .72 to .91. Cronbach's alpha values ranged from .84 to .91, composite reliability values ranged from .86 to .92, and all AVE values exceeded .60. HTMT values remained below .85, supporting discriminant validity among the seven constructs. These patterns indicate that the hypothetical measures are sufficiently distinct for structural testing, while also highlighting the need to verify item performance with actual respondents.

Table 2. Illustrative measurement-model statistics (synthetic values)

Construct	Items	Loading range	Cronbach α	CR	AVE
AI Self-Efficacy	4	.74–.88	.87	.88	.65
Digital Trust	4	.76–.90	.89	.90	.69
Perceived Academic Value	4	.78–.91	.91	.92	.73
Perceived Ease of Use	3	.75–.88	.84	.86	.67
Perceived Usefulness	4	.77–.90	.89	.90	.69
Attitude toward GenAI	3	.79–.91	.88	.89	.73
Behavioral Intention	3	.82–.92	.90	.91	.78

The illustrative structural model also showed acceptable fit: $\chi^2/df = 2.12$, CFI = .955, TLI = .948, RMSEA = .051, and SRMR = .045. AI self-efficacy positively predicted perceived ease of use ($\beta = .56$, $p < .001$). Perceived ease of use positively predicted perceived usefulness ($\beta = .33$, $p < .001$) and attitude ($\beta = .12$, $p = .018$). Perceived usefulness had a positive effect on attitude ($\beta = .35$, $p < .001$) and behavioral intention ($\beta = .23$, $p < .001$). Digital trust positively predicted usefulness ($\beta = .19$, $p < .001$) and attitude ($\beta = .18$, $p < .001$). Perceived academic value was strongly associated with usefulness ($\beta = .42$, $p < .001$) and also had a direct effect on behavioral intention ($\beta = .21$, $p < .001$). AI self-efficacy retained a smaller direct effect on intention ($\beta = .12$, $p = .011$), while attitude was the strongest direct predictor of intention ($\beta = .37$, $p < .001$). The model explained 31% of the variance in perceived ease of use, 61% in perceived usefulness, 54% in attitude, and 68% in behavioral intention.

Table 3. Illustrative structural paths (synthetic values)

Hypothesis	Path	β	p	Illustrative status
H1	ASE $\rightarrow$ PEOU	.56	$p < .001$	Supported
H2	PEOU $\rightarrow$ PU	.33	$p < .001$	Supported
H3	PEOU $\rightarrow$ ATT	.12	$p = .018$	Supported
H4	PU $\rightarrow$ ATT	.35	$p < .001$	Supported
H5	DT $\rightarrow$ PU	.19	$p < .001$	Supported
H6	DT $\rightarrow$ ATT	.18	$p < .001$	Supported

Hypothesis	Path	β	p	Illustrative status
H7	PAV $\rightarrow$ PU	.42	$p < .001$	Supported
H8	PAV $\rightarrow$ BI	.21	$p < .001$	Supported
H9	ASE $\rightarrow$ BI	.12	$p = .011$	Supported
H10	ATT $\rightarrow$ BI	.37	$p < .001$	Supported
H11	PU $\rightarrow$ BI	.23	$p < .001$	Supported

Bias-corrected bootstrapping also produced positive illustrative indirect effects. The serial pathway from AI self-efficacy through perceived ease of use, usefulness, and attitude to behavioral intention was positive (indirect $\beta = .025$, 95% CI [.012, .044]). Digital trust had a positive indirect effect on intention through usefulness and attitude ($\beta = .025$, 95% CI [.013, .041]), and perceived academic value had a stronger indirect effect through usefulness and attitude ($\beta = .054$, 95% CI [.034, .080]). These estimates illustrate how external variables can influence acceptance both directly and through TAM's cognitive and attitudinal mechanisms.

Discussion

The extended model suggests that students' GenAI acceptance cannot be reduced to ease of use and usefulness alone. The classical TAM pathway remains important: students who perceive GenAI as easier to operate are more likely to judge it useful, and usefulness strengthens both attitude and intention. This pattern is consistent with recent higher-education studies in which usefulness repeatedly emerges as a central adoption driver, while ease of use often works indirectly through usefulness (Almogren et al., 2024; Pham et al., 2025; Nguyen et al., 2026). The result supports retaining TAM as the core explanatory structure while expanding the model to reflect characteristics unique to generative AI.

AI self-efficacy shows a dual role. Its strongest illustrative effect is on perceived ease of use, which is theoretically expected because students who are confident in prompting, evaluating, and correcting AI output should experience less difficulty in interaction. A smaller direct path to behavioral intention suggests that confidence also motivates adoption beyond simple ease-of-use perceptions. This interpretation aligns with social cognitive theory and recent evidence that AI literacy, interest, and prior experience contribute to AI self-efficacy, while GenAI self-efficacy is positively associated with acceptance (Bewersdorff et al., 2025; Zhang & Yu, 2025). For higher education, the implication is that confidence can be cultivated through guided practice rather than treated as a fixed student characteristic.

Digital trust also contributes to acceptance, but the model treats trust as calibrated reliance rather than unquestioning confidence. Its paths to usefulness and attitude imply that students are more likely to view GenAI favorably when they believe it is dependable enough for supported academic use and when they know how to verify uncertain outputs. This is compatible with recent findings that trust is an important component of GenAI acceptance, even when its effect is indirect or context dependent (Shahzad et al., 2024; Mustofa et al., 2025; Pham et al., 2025). The educational objective should therefore be neither maximal trust nor generalized skepticism, but informed trust based on verification, transparency, and awareness of limitations.

Perceived academic value is particularly important because it helps distinguish efficiency from educational worth. In the illustrative model, academic value strongly predicts usefulness and also retains a direct effect on intention. Students may therefore accept GenAI not only because it makes tasks faster but because they believe it improves understanding, feedback, quality, or learning outcomes. This interpretation is consistent with expectancy-value reasoning and with newer GenAI adoption studies that incorporate learning value as a distinct educational factor (Wigfield & Eccles, 2000; Bouebdallah & Ben Youssef, 2025). The distinction matters because universities should design GenAI activities around meaningful learning outcomes rather than merely normalizing use.

The model also adds to the rapidly expanding literature on GenAI acceptance in higher education. Large surveys and SEM studies have demonstrated the importance of behavioral intention, performance expectancy, usefulness, and social or facilitating conditions (Strzelecki, 2024; Habibi et al., 2024). The present framework complements those approaches by bringing together three variables that represent distinct mechanisms: capability (self-efficacy), relational confidence (digital trust), and educational valuation (perceived academic value). This combination offers a more learner-centered explanation of why students move from exposure to meaningful acceptance.

Implications

For higher-education institutions, the model suggests that GenAI strategy should integrate access, capability development, governance, and pedagogy. First, universities should provide practical AI-literacy activities that build self-efficacy through prompting, output verification, source checking, and iterative problem solving. Second, digital trust should be supported through clear institutional guidance on privacy, data handling, acceptable use, limitations, and accountability. Third, instructors should make academic value visible by designing activities in which GenAI supports explanation, comparison, formative feedback, idea exploration,

and revision while preserving student reasoning. Fourth, evaluation should distinguish responsible academic use from outsourcing of intellectual work. These interventions can strengthen acceptance while reducing overreliance and academic-integrity risks.

For researchers, the framework provides several testable extensions. Perceived academic value can be compared with perceived usefulness using discriminant-validity tests to determine whether students truly separate educational worth from generic performance utility. Self-efficacy may also moderate the effects of usefulness or trust, and longitudinal designs can test reciprocal relationships between experience and confidence. Cross-cultural and multi-group SEM can examine whether trust and academic value operate differently under distinct institutional policies or disciplinary norms.

Limitations

The proposed research design has several limitations. A cross-sectional survey cannot establish temporal or causal ordering, even when SEM is used. Self-report data are vulnerable to common-method bias and may overstate socially desirable forms of responsible AI use. GenAI is also heterogeneous: students may use different models and functions for explanation, writing, coding, translation, or assessment preparation. The meaning of trust can vary depending on task risk, institutional policy, and prior experience. Most importantly, the numerical results in this manuscript are synthetic demonstration values and must not be interpreted as empirical findings or submitted as such. Actual data collection, ethical approval, measurement validation, and transparent reporting are required before publication.

Suggestions

Future studies should collect multi-wave or longitudinal data to examine how self-efficacy and trust develop with repeated GenAI use. Experimental or quasi-experimental studies can test whether AI-literacy interventions change perceived ease of use, trust calibration, and academic value. Researchers should also incorporate objective or behavioral measures, such as logged use patterns or performance on AI-supported learning tasks, where ethically permissible. Measurement invariance across gender, study level, discipline, and country would strengthen cross-group interpretation. Finally, researchers should examine whether excessive trust or excessive reliance produces nonlinear effects, since acceptance is not synonymous with educationally beneficial use.

CONCLUSION

This study proposes an extended Technology Acceptance Model for explaining students' generative AI acceptance in higher education. The framework preserves TAM's core mechanisms—perceived ease of use, perceived usefulness, attitude, and behavioral intention—while adding digital trust, AI self-efficacy, and perceived academic value as contextually important antecedents. The illustrative SEM pattern suggests that self-efficacy strengthens ease-of-use perceptions, trust contributes to usefulness and attitude, and academic value represents a particularly important route to usefulness and intention. Together, these mechanisms explain why students may accept the same GenAI technology differently even when access is similar. The framework therefore shifts the discussion from whether students use GenAI to whether they possess the confidence, calibrated trust, and educational rationale required for meaningful adoption. Empirical application with verified data can help universities design AI integration that is technically accessible, pedagogically valuable, and academically responsible.

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AUTHOR CONTRIBUTIONS STATEMENT

AA: conceptualization, theoretical framework, methodology, instrument development, formal analysis plan, visualization, and writing—original draft. BB: validation, supervision, interpretation, writing—review and editing, and project administration. Both authors approved the final manuscript and agree to be accountable for the integrity of the work. Replace AA and BB with the authors' actual initials before submission.

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