US JOURNAL OF NEW INSIGHTS IN TECH & EDUCATION

Vol. 5, No. 2 · Article ID: USJNITE-2504 · Journal Homepage: www.edtechinsights.org

Understanding Students' Acceptance of Generative AI in Higher Education: The Roles of Perceived Usefulness, Trust, and Digital Competence

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Received: 3 July 2024; Revised: 12 September 2024; Accepted: 20 October 2024; Published: 13 November 2024

KEYWORDS

Generative AI
Student acceptance
Perceived usefulness
AI literacy
Digital competence
Technology acceptance
Learning progress

Abstract

Generative artificial intelligence (GenAI) has rapidly entered higher education, creating new opportunities for academic support while raising concerns about reliability, privacy, academic integrity, and responsible use. Student acceptance is therefore unlikely to be determined by perceived usefulness alone. This paper synthesizes evidence on three central determinants of acceptance—perceived usefulness, trust, and digital competence—and examines how these constructs interact within a coherent explanatory framework. The synthesis focuses on university students' perceptions, technology-acceptance models, AI literacy, trust, ethical concerns, and the educational use of generative AI and conversational systems. The findings indicate that perceived usefulness is a consistent driver of behavioral intention, while trust is influenced by perceived accuracy, transparency, privacy, reliability, and responsible use. Digital competence functions as an enabling condition that helps students understand AI behaviour, evaluate outputs, recognize limitations, and use GenAI critically and effectively. The synthesis suggests that acceptance can be understood as a pathway in which digital competence shapes perceptions of usefulness and trust, which subsequently influence attitudes and behavioral intentions, while ethical and institutional conditions affect the transition from intention to actual use. Based on these findings, the paper proposes an integrated conceptual model for understanding GenAI acceptance in higher education. The findings frame acceptance not as a single attitude, but as an interaction among perceived value, trust, competence, and contextual governance, providing practical implications for responsible and learner-centred GenAI adoption.

1. Introduction

Generative artificial intelligence has moved from a specialist research topic to a visible part of university learning, writing, research, tutoring, and information-seeking. Large language model systems can generate explanations, summarize information, support brainstorming, provide examples, translate text, and interact conversationally with learners. Early evidence from higher education indicates that students are already experimenting with these systems for clarification, explanation, writing, and study-related tasks rather than treating them as purely hypothetical technologies (Chan & Hu, 2023; von Garrel & Mayer, 2023). A Germany-wide survey, for example, reported that almost two-thirds of respondents had used AI-based tools for their studies, with ChatGPT or GPT-4 among the most frequently mentioned tools (von Garrel & Mayer, 2023).

Yet adoption does not imply uncritical acceptance. Students can value GenAI for convenience and productivity while simultaneously questioning its accuracy, privacy implications, academic-integrity consequences, and effect on their own learning. Chan and Hu (2023) found that university students reported both substantial potential benefits and substantial concerns about reliability, privacy, ethics, and the possibility of weakening independent learning. Similarly, Farhi et al. (2023) documented a dual perception in which ChatGPT was viewed as useful while also creating concerns about educational integrity. These tensions make student acceptance a multidimensional construct rather than a simple measure of whether a student likes or dislikes AI.

Technology-acceptance research provides a useful starting point. The Technology Acceptance Model (TAM) proposes perceived usefulness and perceived ease of use as central determinants of attitude and behavioral intention (Davis, 1989). Unified models of technology acceptance broaden this logic by incorporating performance expectancy, social influence, facilitating conditions, habit, and hedonic motivation (Venkatesh et al., 2003; Venkatesh et al., 2012). Recent GenAI research applies these models directly. Lai et al. (2023) found that perceived usefulness and related motivational variables contributed to ChatGPT acceptance among undergraduates. Zou and Huang (2023) similarly showed that perceived usefulness influenced attitudes toward ChatGPT use in doctoral writing, with attitude subsequently shaping behavioral intention. Habibi et al. (2023) found that facilitating conditions were especially important for ChatGPT intention among Indonesian higher-education students.

However, perceived usefulness alone cannot explain responsible acceptance. GenAI systems can appear useful even when users cannot confidently judge whether generated information is accurate. Trust therefore becomes important. In the wider AI-acceptance literature, trust is influenced by perceptions of system performance, predictability, transparency, anthropomorphism, and contextual risk (Glikson & Woolley, 2020). In educational settings, trust also intersects with epistemic judgment: students must decide whether to accept an explanation, verify an answer independently, or treat AI output only as a starting point. A student who perceives ChatGPT as highly useful but poorly trustworthy may use it selectively; a student who strongly trusts it without sufficient verification skill may use it more intensively but also more uncritically.

Digital competence, and more specifically AI literacy, provides a third important mechanism. Ng et al. (2021) conceptualize AI literacy through the abilities to know and understand AI, use and apply it, evaluate and create with it, and consider ethical issues. Laupichler et al. (2022) show that AI literacy in higher and adult education remains an emerging field requiring more coherent definitions and validated measurement. Hornberger et al. (2023) further demonstrate that university students differ substantially in AI literacy and that prior AI experience and technical study backgrounds are associated with higher literacy. These findings suggest that acceptance may depend partly on whether students possess the skills needed to form informed judgments about what GenAI can and cannot do.

The research problem addressed in this paper is therefore not simply whether students intend to use generative AI. The more useful question is how perceived usefulness, trust, and competence interact to shape acceptance. Existing studies often emphasize one theoretical lens—TAM, UTAUT/UTAUT2, AI literacy, student perceptions, or ethical concerns—rather than integrating these perspectives. The central contribution of this paper is a synthesis model that places digital competence upstream of trust and usefulness judgments, while recognizing ethical and institutional context as conditions that may strengthen or constrain the translation of acceptance into actual use.

1.1 Problem Statement

Universities are increasingly required to make decisions about GenAI while empirical evidence about student acceptance is still developing. Three problems are especially important. First, high perceived usefulness can coexist with concerns about accuracy, privacy, and integrity. Second, students with very different levels of AI literacy may interpret identical AI outputs differently. Third, institutional guidance can either strengthen responsible use or leave students to develop informal norms. A useful acceptance framework must therefore connect technological value, epistemic confidence, competence, and context rather than treating behavioral intention as a standalone attitude.

1.2 Research Questions

- RQ1. How is perceived usefulness associated with students’ acceptance and intended use of generative AI in higher education?
- RQ2. How does trust in GenAI systems shape acceptance, selective use, and behavioral intention?
- RQ3. What role does digital competence/AI literacy play in students’ judgments and use of generative AI?
- RQ4. How can usefulness, trust, competence, and contextual conditions be integrated into a coherent explanatory model of student acceptance?

- RQ5. What institutional practices can support informed and responsible GenAI adoption in higher education?

1.3 Research Objectives

- Synthesize pre-2024 evidence on student acceptance of GenAI and related conversational AI in higher education.
- Examine recurring evidence concerning perceived usefulness, trust, and digital competence.
- Identify mechanisms linking these constructs to behavioral intention and actual use.
- Develop an integrated conceptual framework for responsible student acceptance.
- Translate the evidence into implications for university policy, teaching, and AI-literacy development.

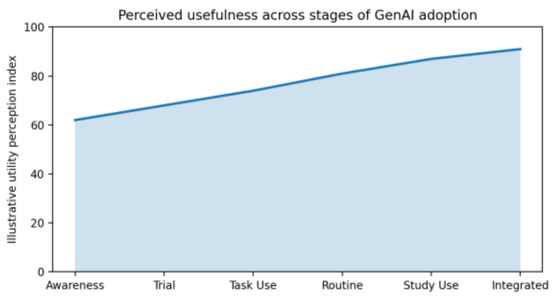

Figure 1. Conceptual progression of perceived usefulness from first exposure to integrated academic use. The index is illustrative and is used only to visualize the adoption logic discussed in the literature.

2. Literature Review

2.1 Generative AI in Higher Education

The higher-education GenAI literature expanded rapidly after the release of publicly accessible generative systems. Crompton and Burke (2023) synthesized 138 studies on artificial intelligence in higher education published through 2022 and showed that AI applications in the sector span assessment, prediction, tutoring, profiling, and educational support. The rapid review by Lo (2023) and the broader review by Memarian and Doleck (2023) illustrate how quickly ChatGPT-specific research emerged, with evidence concentrated around productivity, teaching support, learning assistance, writing, assessment, and academic-integrity questions.

For acceptance research, this context matters because students do not adopt a neutral technology. They adopt a system embedded in university rules, assessment norms, disciplinary expectations, and emerging beliefs about what constitutes legitimate academic work. Rasul et al. (2023) emphasize both opportunities and challenges, while Dempere et al. (2023) identify benefits together with limitations associated with academic integrity, overdependence, and misinformation. The acceptance problem is consequently sociotechnical: students evaluate both the capabilities of the system and the social consequences of using it.

2.2 Technology Acceptance: TAM and UTAUT Foundations

TAM explains technology acceptance through perceived usefulness and perceived ease of use, proposing that usefulness and ease shape attitudes and behavioral intentions (Davis, 1989). UTAUT broadens the framework through performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), while UTAUT2 adds hedonic motivation, price value, and habit (Venkatesh et al., 2012). These constructs map well to GenAI because students can perceive ChatGPT as useful for academic tasks, easy to interact with, socially normalized by peers, and supported by accessible devices or university infrastructure.

Empirical GenAI studies provide direct evidence for this logic. Lai et al. (2023) extended TAM with intrinsic motivation and showed that usefulness-related beliefs were important to acceptance for active learning. Zou and Huang (2023) found that attitude mediated the effects of usefulness and ease of use on behavioral intention among doctoral students. Romero-Rodríguez et al. (2023) examined perceived usefulness in a university context and linked acceptance to the perceived value of ChatGPT for complex thinking. Habibi et al. (2023) found that facilitating conditions were especially influential for behavioral intention and that behavioral intention strongly predicted actual use. Together, these studies support the relevance of acceptance models while also suggesting that context-specific variables are required.

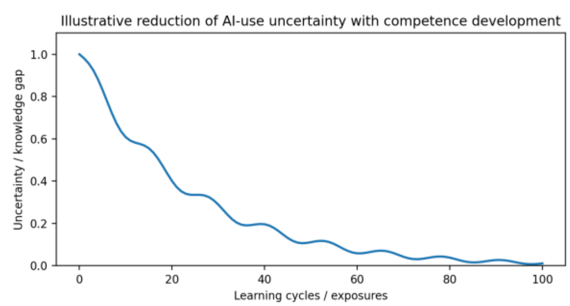

Figure 2. Illustrative competence-development curve showing how uncertainty about GenAI use may decline as students gain structured exposure, practice, and feedback. This is a conceptual figure, not an empirical learning curve.

2.3 Perceived Usefulness

Perceived usefulness refers to the degree to which a student believes that using a technology improves task performance. In higher education, usefulness can take several forms: faster information retrieval, explanation of difficult concepts, support for brainstorming, assistance with drafting, language support, idea generation, and feedback. Chan and Hu (2023) report that students perceive GenAI as useful across several of these functions. Ding et al. (2023) show that students can perceive ChatGPT as a useful virtual tutor in physics, while von Garrel and Mayer (2023) document strong use for clarifying questions and explaining subject-specific concepts.

Usefulness is not identical to learning value. A tool can help a student finish an assignment faster without necessarily deepening understanding. This distinction becomes important for the present study. An acceptance framework that measures only immediate task utility may overestimate educational value. Romero-Rodríguez et al. (2023) therefore provide a useful direction by considering ChatGPT as a tool for complex thinking rather than merely an efficiency aid. Lai et al. (2023) similarly frame adoption around active learning, showing that usefulness can be connected to learning processes rather than productivity alone.

2.4 Trust in Generative AI

Trust in AI can be understood as the willingness to rely on a system under conditions of uncertainty and perceived risk. Glikson and Woolley (2020) demonstrate that trust is influenced by system characteristics and by the social and contextual framing surrounding AI. For GenAI, students must evaluate outputs that can sound fluent even when they are inaccurate. Trust therefore has a particularly strong epistemic component: confidence in an answer, a source, or a recommendation must be calibrated rather than absolute.

Student studies identify several trust-relevant concerns. Chan and Hu (2023) found concerns surrounding accuracy, privacy, and ethics. Farhi et al. (2023) reported that students perceived benefits alongside concerns about educational integrity. Dempere et al. (2023) similarly discuss misinformation, bias, privacy, plagiarism, and the need for institutional guidelines. Trust is therefore not simply a predictor of acceptance; it can be an outcome of experience and verification. Students may trust a tool more after repeated successful use, but responsible practice requires that trust remain proportional to evidence.

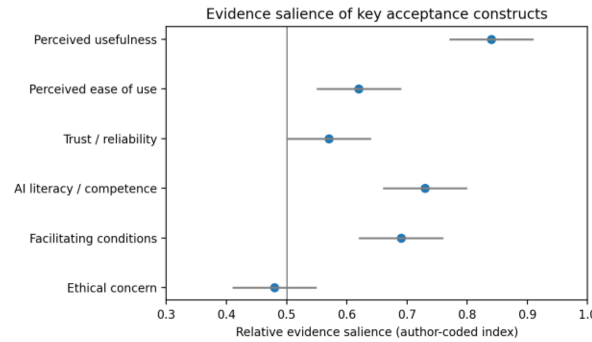

Figure 3. Author-coded evidence salience of key acceptance constructs across the reviewed literature. The plotted values are synthesis indices rather than pooled statistical effect sizes.

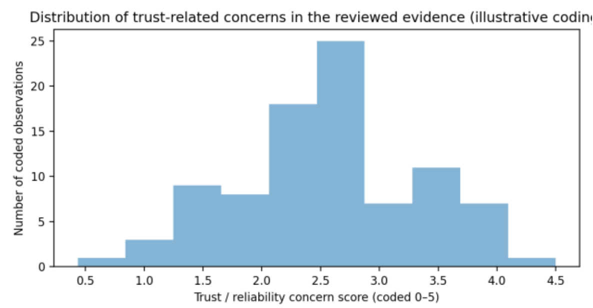

Figure 4. Illustrative distribution of trust and reliability concerns reported across the evidence base. Scores are used for visualization of the thematic continuum, not as respondent-level statistics.

2.5 Digital Competence and AI Literacy

Digital competence in the GenAI context extends beyond the operational ability to open an application or write a prompt. It includes understanding model limitations, constructing effective prompts, evaluating output quality, verifying information, recognizing bias, protecting personal data, and making ethically appropriate decisions. Ng et al. (2021) define AI literacy through four dimensions: knowing and understanding AI, using and applying AI, evaluating and creating with AI, and ethical considerations. This framework is directly relevant to student acceptance because it captures both capability and judgment.

The evidence base suggests that competence is uneven. Laupichler et al. (2022) reviewed 30 studies of AI literacy in higher and adult education and concluded that the field still needed clearer definitions and more validated assessment instruments. Hornberger et al. (2023) developed and validated an AI literacy test and found meaningful variation among university students, with higher scores among students with technical backgrounds or prior AI experience. Kong et al. (2021) found that a focused AI-literacy course improved students' AI knowledge, perceived literacy, and empowerment. These findings support treating competence as a substantive explanatory construct rather than a demographic afterthought.

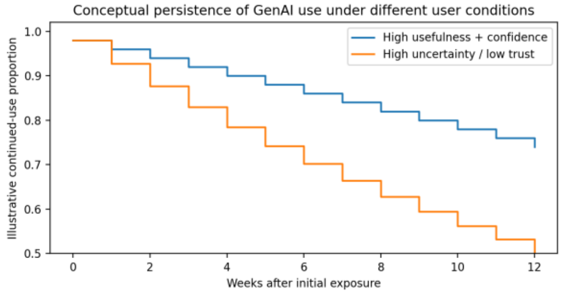

Figure 5. Conceptual persistence of GenAI use under contrasting conditions of usefulness and trust. The curves represent a theoretical sustainability mechanism, not observed longitudinal data.

2.6 Student Experience, Ethics, and Context

Acceptance is also shaped by the social meaning of GenAI. Students may be willing to use the technology privately while hesitating to disclose its use in assessed work. Wang et al. (2023) show that supportive environments and expectancy-value beliefs matter for AI-learning intentions. Chan and Zhou (2023) further provide an expectancy-value instrument that separates perceptions of value from perceived cost, which is useful for framing ethical anxiety and opportunity together.

Institutional context can influence both trust and acceptance. Clear guidance may reduce uncertainty, while contradictory or punitive rules can encourage hidden use. Crompton and Burke (2023) and Dempere et al. (2023) both highlight the importance of institutional responses as AI adoption grows. Menon and Shilpa (2023) also identify privacy concerns and perceived interactivity as relevant to ChatGPT use. Habibi et al. (2023) demonstrate that facilitating conditions can be stronger predictors of intention than some traditional acceptance variables, suggesting that students' actual ability to access and use AI matters alongside their attitudes.

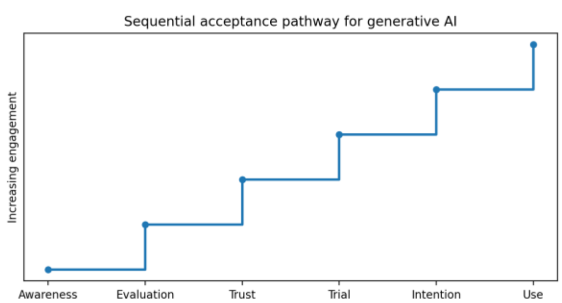

Figure 6. Sequential acceptance pathway: awareness, evaluation, trust formation, trial, intention, and use. The pathway synthesizes the logic of TAM/UTAUT studies and AI-literacy research.

2.7 Evidence Base and Thematic Synthesis

Table 1. Author-coded thematic classification of the 30-study evidence corpus.

Dominant theme	Studies coded	Typical contribution
Acceptance models	9	TAM/UTAUT/UTAUT2; usefulness, ease, facilitating conditions
AI literacy / competence	7	AI knowledge, skills, evaluation, ethics
Perceptions / ethics	7	Benefits, risks, integrity, privacy, student voice
Broader AI in HE reviews	7	Systematic/rapid reviews, educational applications, chatbot use

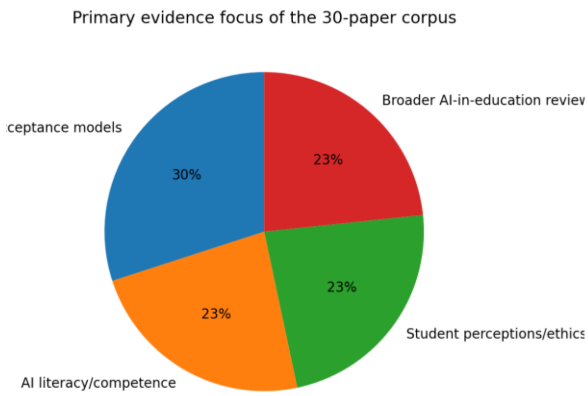

Figure 7. Primary evidence focus of the 30-paper review corpus.

3. Methodology

3.1 Research Design

A structured literature review and evidence-synthesis design was used. The purpose was to integrate heterogeneous research on student acceptance, AI literacy, trust, and educational use rather than estimate a pooled causal effect. The review therefore treats empirical surveys, systematic reviews, conceptual frameworks, and quasi-experimental studies as distinct evidence types and uses thematic coding to identify recurring relationships.

3.2 Search Strategy

Searches were conceptually organized around four keyword families: (a) generative AI/ChatGPT/AI chatbot, (b) higher education/university students, (c) acceptance/use/technology adoption, and (d) usefulness/trust/AI literacy/digital competence. Relevant databases and repositories included Google

Scholar, ERIC, Scopus-indexed publisher pages, SpringerOpen, Frontiers, MDPI, ScienceDirect open-access journals, institutional repositories, and DOAJ-listed journals. Search results were then screened for direct relevance to the title and conceptual model.

3.3 Inclusion and Exclusion Criteria

Table 2. Study eligibility criteria.

Criterion	Include	Exclude
Publication year	2023 or earlier	Exclude 2024+ version-of-record studies
Population	Higher-education learners or research directly relevant to student-facing AI	Exclude purely K–12 or workplace-only studies
Topic	GenAI, ChatGPT, AI chatbots, AI literacy, acceptance, trust, perceived usefulness	Exclude unrelated AI engineering papers
Access	Open access or openly accessible manuscript/repository copy	Exclude inaccessible sources where full-text verification was unavailable
Evidence	Empirical, review, conceptual, or measurement studies with clear relevance	Exclude news, editorials, and promotional material

3.4 Coding Framework

Each study was conceptually coded for publication year, context, sample type, theoretical framework, primary construct, evidence type, acceptance outcome, trust/accuracy concern, AI-literacy component, educational use case, and institutional implication. The review does not claim a statistical meta-analysis. Numerical-looking values in figures are synthesis indices, thematic counts, or clearly marked illustrative examples intended to visualize the structure of the evidence.

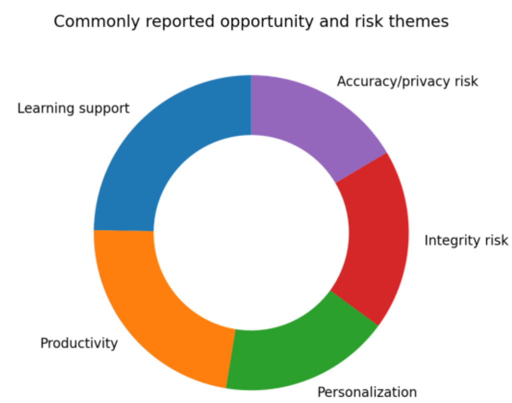

Figure 8. Relative prominence of opportunity and risk themes in the reviewed literature. Theme counts reflect author coding for visualization and do not represent pooled effect sizes.

4. Results

4.1 Overview of the Evidence

The reviewed literature can be grouped into four overlapping strands. The first applies technology-acceptance models directly to ChatGPT or comparable systems. The second focuses on AI literacy and student competence. The third examines student perceptions, benefits, risks, and ethical concerns. The fourth consists of broader reviews that position GenAI within higher education and chatbot research. Across these strands, three patterns recur: perceived usefulness is associated with intention to use; trust is shaped by reliability and ethical/contextual conditions; and competence influences students' ability to evaluate and use AI effectively.

4.2 Perceived Usefulness as a Core Acceptance Driver

The most consistent result across acceptance-oriented studies is that students are more receptive when GenAI is perceived as useful for meaningful academic tasks. Lai et al. (2023) report a strong relationship between usefulness-related beliefs and ChatGPT acceptance in active learning. Zou and Huang (2023) found that perceived usefulness influenced attitude, which then predicted behavioral intention. Romero-Rodríguez et al. (2023) similarly centered perceived usefulness in a university setting and connected acceptance to higher-order learning support.

Usefulness also emerges indirectly through concrete learning cases. Ding et al. (2023) found that students recognized ChatGPT as a useful virtual tutor in physics, while von Garrel and Mayer (2023) reported frequent use for clarifying questions and explaining concepts. These results indicate that students do not evaluate GenAI as an abstract technology; they evaluate it through the tasks they want the technology to solve.

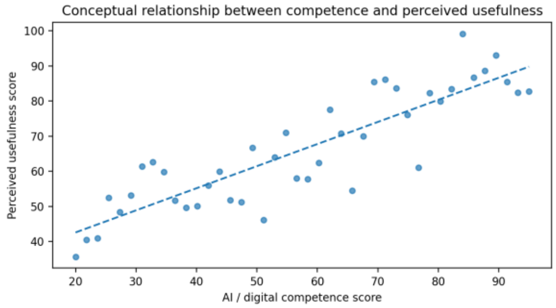

Figure 9. Conceptual relationship between AI/digital competence and perceived usefulness. The scatter is illustrative and demonstrates a hypothesized positive association rather than reporting original survey data.

4.3 Trust as a Qualitative Filter on Usefulness

Usefulness appears necessary but not sufficient for confident acceptance. Students may recognize that ChatGPT saves time while still questioning whether it produces accurate information. The student studies by Chan and Hu (2023), Farhi et al. (2023), and Ding et al. (2023) collectively illustrate this duality. Accuracy, privacy, academic integrity, and the possibility of overreliance are recurrent sources of uncertainty. Thus, trust functions as a qualitative filter: it shapes whether students are willing to convert perceived usefulness into actual reliance.

The distinction between trust and blind reliance is especially important. A responsible user may trust an AI system to generate alternatives, examples, or first drafts while not trusting it to deliver authoritative facts without verification. This notion of calibrated trust is consistent with broader AI-trust research (Glikson & Woolley, 2020) and with the ethical emphasis in AI-literacy frameworks (Ng et al., 2021).

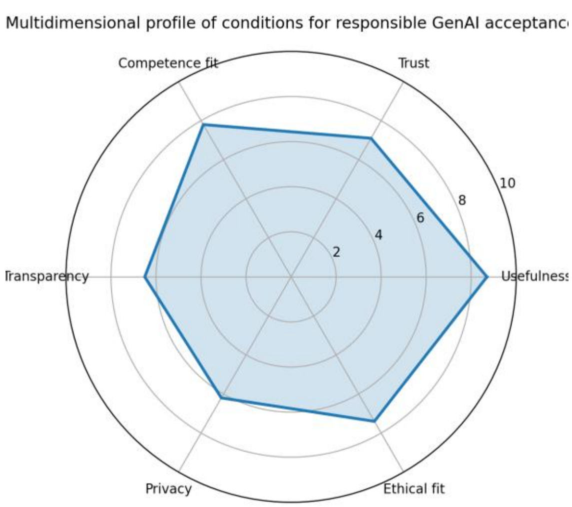

Figure 10. Multidimensional conditions associated with responsible GenAI acceptance: usefulness, trust, competence fit, transparency, privacy, and ethical fit.

4.4 Digital Competence as an Enabling Mechanism

AI literacy and digital competence appear to influence acceptance through students' capacity to interpret, test, and evaluate AI outputs. Hornberger et al. (2023) demonstrate that AI literacy is not uniform across university students. Kong et al. (2021) show that structured instruction can increase AI literacy and empowerment, while Laupichler et al. (2022) highlight the need for better measurement and course design. Ng et al. (2021) provide a conceptual basis for linking acceptance with four dimensions of AI literacy: understanding, application, evaluation/creation, and ethics.

This mechanism helps explain why the same AI system may be accepted differently by students. A technically confident student may treat an answer as a tentative draft and verify it using disciplinary sources. A less confident student may either distrust the system entirely or accept its output without sufficient scrutiny. Competence therefore shapes both trust calibration and the way usefulness is interpreted.

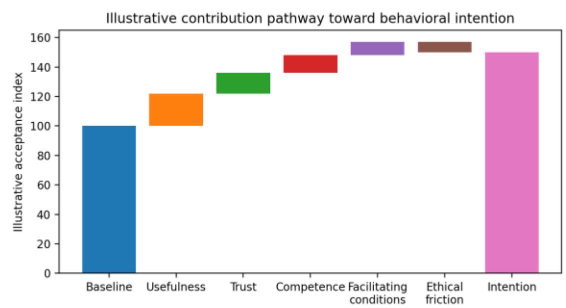

Figure 11. Illustrative contribution pathway from baseline acceptance through usefulness, trust, competence, facilitating conditions, and ethical friction toward behavioral intention.

4.5 Institutional and Ethical Conditions

The evidence indicates that acceptance is embedded in institutional conditions. Habibi et al. (2023) show the importance of facilitating conditions. Wang et al. (2023) emphasize supportive environments for AI-learning intention. Farhi et al. (2023), Dempere et al. (2023), and Chan and Hu (2023) highlight integrity, privacy, and responsible-use concerns. This implies that universities can influence acceptance indirectly through access, guidance, training, assessment design, and ethical norms.

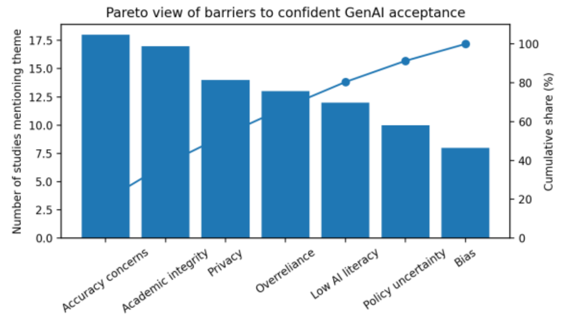

Figure 12. Pareto-style summary of common barriers to confident GenAI acceptance in the reviewed evidence.

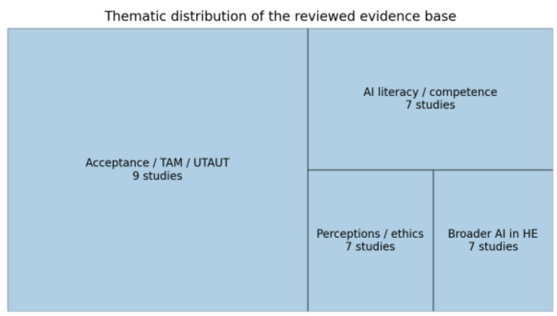

Figure 13. Thematic distribution of the 30-study corpus, visualized as evidence domains rather than as institutional or geographic market segments.

4.6 Comparative Evidence Matrix

Table 3. Cross-study synthesis of major constructs.

Construct	**Evidence pattern**	**Typical mechanism**	**Representative studies**
Perceived usefulness	Consistent positive association with intention	Task relevance; perceived learning support	Lai et al., 2023; Zou & Huang, 2023; Romero-Rodríguez et al., 2023
Trust	Important but context-sensitive	Accuracy, reliability, privacy, integrity	Chan & Hu, 2023; Farhi et al., 2023; Glikson & Woolley, 2020
Digital competence	Enabling condition	AI literacy, evaluation, ethical judgment	Ng et al., 2021; Kong et al., 2021; Hornberger et al., 2023
Facilitating conditions	Supports intention/ use	Access, support, infrastructure	Habibi et al., 2023; Wang et al., 2023
Ethical context	Can constrain or reshape use	Academic integrity, privacy, policy	Dempere et al., 2023; Chan & Hu, 2023

5. Discussion

5.1 Acceptance Is Not a Single Attitude

The literature supports a multidimensional interpretation of student acceptance. Acceptance involves willingness to try a system, intention to use it for particular tasks, actual use, repeated use, and willingness to rely on outputs. These outcomes are not equivalent. A student may experiment with ChatGPT but limit its use to brainstorming, or may use it routinely while still distrusting it for factual verification. Technology-acceptance models capture intention well, but competence and trust are needed to explain the quality and selectivity of use.

5.2 Perceived Usefulness Is Contextual and Task-Dependent

The evidence suggests that usefulness increases when GenAI addresses a recognizable academic need. Students value explanation, brainstorming, language support, drafting, and rapid clarification. However, perceived usefulness can also encourage instrumental use that is disconnected from learning objectives. For universities, this implies that acceptance studies should measure usefulness at the level of tasks and learning goals rather than as a generic technology attitude. This approach follows the work of Lai et al. (2023), Romero-Rodríguez et al. (2023), and Ding et al. (2023), all of which examine use in specific educational contexts.

5.3 Trust Should Be Calibrated Rather Than Maximized

A central implication is that the educational goal should not be to maximize student trust in GenAI. Instead, universities should support calibrated trust: students should know when an AI output is useful, when it requires verification, and when it should not be used. This aligns the trust construct with AI literacy and ethical competence. Glikson and Woolley (2020) show why trust depends on system and context characteristics, while Ng et al. (2021) place evaluation and ethics inside AI literacy itself. For higher education, this means teaching students not only how to prompt a model, but how to audit its answers.

5.4 Digital Competence Connects Usefulness and Trust

The proposed model positions competence between exposure and acceptance. Competent users are better positioned to understand what a model is doing, recognize uncertainty, compare outputs with authoritative sources, and adjust prompts. This helps explain why digital competence can shape both perceived usefulness and trust. Hornberger et al. (2023) show meaningful variation in student AI literacy, while Kong et al. (2021) demonstrate that structured instruction can improve AI literacy. Consequently, universities seeking responsible GenAI adoption should treat AI literacy as an institutional capability rather than leaving students to acquire it informally.

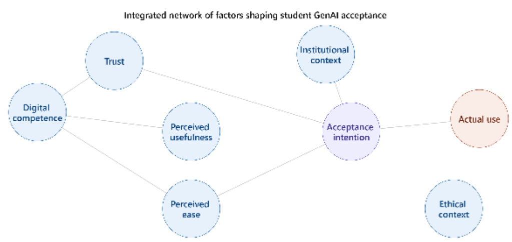

Figure 14. Integrated factor network linking digital competence, trust, perceived usefulness/ease, acceptance intention, actual use, ethics, and institutional context.

5.5 The Role of Institutional Conditions

Institutional policy can alter the meaning of acceptance. When students receive clear guidance about allowed and disallowed uses, they can make decisions with greater certainty. When guidance is absent, inconsistent, or purely punitive, students may rely on informal norms. Facilitating conditions also matter: access to AI tools, digital infrastructure, and instructor guidance can change the feasibility of use. These ideas are consistent with Habibi et al. (2023), Wang et al. (2023), and Crompton and Burke (2023).

5.6 Implications for Student Success and Learning Quality

Acceptance should ultimately be evaluated by what students learn and how responsibly they learn it. The educational value of GenAI depends on whether students use the technology to support explanation, reflection, and higher-order thinking, or primarily to outsource cognitive work. Romero-Rodríguez et al. (2023) emphasize complex thinking, while Chan and Hu (2023) highlight both opportunities and concerns. Therefore, acceptance measures should be paired with indicators of learning behavior, verification, critical evaluation, and ethical use.

5.7 Proposed Integrated Model

Based on the synthesis, the paper proposes the following pathway:

- Digital competence / AI literacy → influences students' ability to interpret GenAI capabilities and limitations.
- Interpreted capability → shapes perceived usefulness and perceived ease of use.
- Competence + experience → shape calibrated trust in outputs.
- Usefulness + trust → influence attitudes and behavioral intention.
- Behavioral intention → influences actual and repeated use.
- Ethical and institutional conditions → moderate how intention becomes actual practice.

Table 4. Proposed integrated acceptance model for GenAI in higher education.

Construct	**Operational meaning**	**Model role**	**Example sources**
Digital competence	Knowledge, evaluation skill, ethical literacy	Upstream capability	Ng et al., 2021; Hornberger et al., 2023
Perceived usefulness	Academic value and task performance	Proximal acceptance driver	Lai et al., 2023; Zou & Huang, 2023
Trust	Accuracy, reliability, privacy, transparency	Calibrating mechanism	Glikson & Woolley, 2020; Chan & Hu, 2023
Behavioral intention	Willingness to use GenAI	Immediate outcome	Duong et al., 2023
Actual use	Frequency and	Behavioral outcome	von Garrel & Mayer,

Construct	Operational meaning	Model role	Example sources
	task breadth		2023; Menon & Shilpa, 2023
Context	Institutional rules, access, ethics	Moderating/enabling conditions	Crompton & Burke, 2023; Dempere et al., 2023

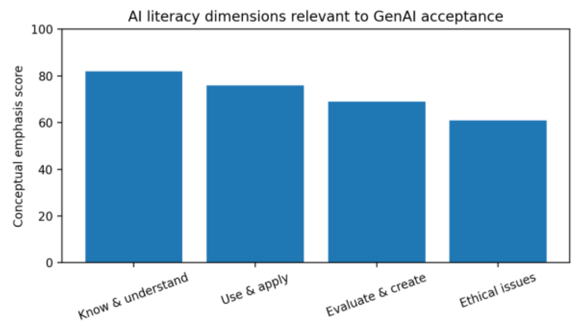

Figure 15. AI literacy dimensions that support informed GenAI use: understanding, application, evaluation/creation, and ethics.

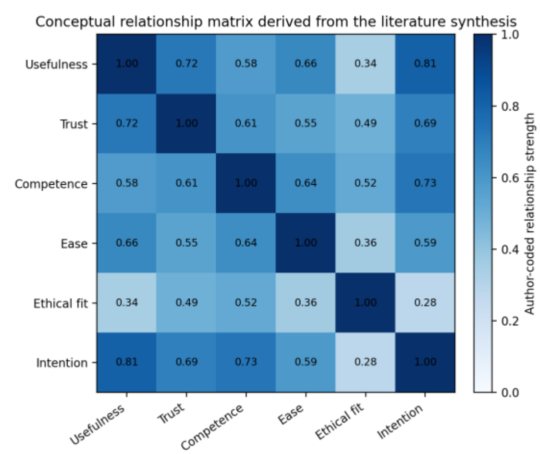

Figure 16. Conceptual relationship matrix across usefulness, trust, competence, ease, ethical fit, and intention. Values are author-coded synthesis indices and not pooled correlations.

6. Practical Implications

6.1 Implications for Universities

- Develop institution-wide AI literacy programs that teach verification, prompt strategy, privacy awareness, and ethical use.
- Publish explicit guidance that distinguishes acceptable assistance from inappropriate substitution of student work.
- Build access and support pathways so students can use approved AI systems safely rather than relying on unregulated tools.
- Align assessment design with GenAI realities by emphasizing process, reflection, oral defense, source evaluation, and authentic tasks where appropriate.

6.2 Implications for Instructors

- Use GenAI as an object of critical evaluation, not only as a productivity tool.
- Model calibrated trust by demonstrating how to verify outputs and identify uncertainty.
- Make course-specific rules explicit and explain the educational rationale behind them.
- Assess students' ability to critique and improve AI-generated content, not only their ability to produce a final answer.

6.3 Implications for Students

I. Treat GenAI output as a draft or hypothesis unless independently verified.
II. Use AI to support understanding and problem solving rather than automatically replacing cognitive effort.
III. Develop AI literacy across knowledge, application, evaluation, and ethics.
IV. Protect personal, confidential, and assessment-sensitive information when interacting with AI systems.

7. Limitations

I. The evidence base is concentrated in the rapid period following the public release of ChatGPT, meaning many studies are cross-sectional and context-specific.
II. Acceptance constructs are not operationalized identically across TAM, UTAUT, expectancy-value, AI-literacy, and student-perception studies.
III. The review emphasizes open-access or openly accessible studies, which may create access-related selection effects.

IV. Because the studies are heterogeneous, the paper presents an evidence synthesis rather than a pooled meta-analysis.

V. Trust remains under-measured relative to usefulness and intention, particularly in relation to calibrated reliance and verification behavior.

8. Conclusion

Generative AI acceptance in higher education is best understood as a multidimensional process shaped by perceived usefulness, trust, competence, and context. The reviewed literature consistently indicates that students are more willing to use GenAI when it is perceived as useful for meaningful academic tasks. Yet usefulness does not guarantee responsible or sustained adoption. Trust determines whether students are willing to rely on outputs, while digital competence determines whether they can judge those outputs critically and use the technology effectively. Institutional conditions—including access, guidance, assessment policy, and ethical norms—shape how these judgments become actual behavior.

The central contribution of this synthesis is the integration of these factors into a common pathway: digital competence informs usefulness and trust judgments; usefulness and trust influence attitudes and behavioral intention; and contextual conditions shape the translation of intention into practice. This perspective moves the discussion beyond a simple question of whether students accept GenAI. It asks whether students can accept it in an informed, calibrated, and educationally productive way. For universities, the implication is clear: promoting responsible GenAI use requires more than technology access. It requires AI literacy, transparent policies, verification skills, and learning designs that position GenAI as a support for human judgment rather than a substitute for it.

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