The Pedagogical Fit Of Generative Artificial Intelligence: Rethinking Assessment And Learning In Higher Education

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Abstract

The rapid diffusion of generative artificial intelligence across higher education has transformed the ways in which students, instructors, and institutions conceptualize learning, assessment, and academic work. While large language models and related generative tools promise unprecedented efficiency, creativity, and scalability, their integration into educational practice has also provoked significant concerns regarding academic integrity, learning quality, cognitive dependency, and the erosion of critical thinking. The present study advances a comprehensive theoretical and interpretive investigation of generative artificial intelligence adoption in higher education by integrating task–technology fit, technology acceptance, and experience–technology alignment perspectives into a unified analytical framework. Grounded in contemporary empirical and conceptual scholarship, this research examines how generative AI tools align with the epistemic, procedural, and evaluative tasks that characterize modern higher education, with special emphasis on assessment, test automation, and behavior-driven development in digital learning environments. Particular attention is given to the implications of generative AI for automated testing and assessment design, drawing on the work of Tiwari (2025), who demonstrated how generative AI-driven behavior-driven development can enhance the efficiency, consistency, and scalability of test automation processes. This contribution is extended into the higher education domain, where assessment systems increasingly rely on automated and semi-automated tools that mirror industrial software testing architectures.

Using a theoretically grounded qualitative synthesis approach, this study integrates evidence from international surveys, institutional reports, and conceptual models to interpret how students and faculty perceive, adopt, and utilize generative AI across disciplines. The findings reveal that generative AI adoption is not merely driven by perceived usefulness or ease of use but is fundamentally shaped by the degree to which these technologies fit the cognitive, disciplinary, and evaluative tasks faced by learners and educators. When task–technology fit is high, generative AI becomes an enabling infrastructure for deeper engagement, adaptive feedback, and more authentic assessment design. When misalignment occurs, however, the same technologies can undermine learning, amplify academic misconduct, and distort performance evaluation.

The study contributes to theory by demonstrating that traditional acceptance models such as TAM and UTAUT must be reinterpreted in light of generative AI's co-creative and autonomous capacities, which fundamentally alter the nature of academic tasks. It also contributes to practice by offering a nuanced understanding of how generative AI can be ethically and pedagogically embedded into higher education assessment systems. By bridging software engineering perspectives on automated testing with educational theories of learning and evaluation, this research provides a robust conceptual foundation for navigating the generative AI transition in higher education.

Keywords: Generative artificial intelligence, task–technology fit, higher education, automated assessment, technology acceptance, academic integrity, digital learning.

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1. Introduction

The emergence of generative artificial intelligence has initiated one of the most profound technological shifts in the history of higher education, rivaling the advent of the internet, learning management systems, and massive open online courses in its potential to reshape teaching, learning, and assessment. Unlike earlier educational technologies that primarily functioned as delivery or communication platforms, generative AI systems possess the capacity to autonomously produce text, code, feedback, and even evaluative judgments, thereby positioning themselves as quasi-participants in the learning process rather than passive tools (Kelly et al., 2023). This transformation has compelled scholars, educators, and policymakers to reconsider foundational assumptions about authorship, knowledge construction, and the meaning of academic performance, as highlighted in global policy discussions and institutional reports (UNESCO, 2023; Fischer et al., 2023).

At the same time, generative AI is not entering a vacuum. Higher education is already embedded in a complex digital ecosystem characterized by learning management systems, online assessment platforms, plagiarism detection tools, and increasingly sophisticated analytics. Within this ecosystem, generative AI has begun to function as both an accelerator and a disruptor, enabling new forms of personalized learning while simultaneously destabilizing conventional assessment regimes (Kurtz et al., 2024). Students now routinely use large language models to draft essays, generate programming solutions, and obtain real-time explanations, thereby blurring the boundaries between legitimate academic support and unauthorized assistance (Von Garrel and Mayer, 2023). These dynamics raise urgent questions not only about whether generative AI should be used in education, but about how it fits into the cognitive, procedural, and ethical tasks that define academic work.

Understanding these questions requires more than descriptive accounts of usage patterns. It demands a theoretically grounded framework capable of explaining why certain generative AI applications enhance learning while others undermine it. Task–technology fit theory provides a particularly powerful lens for this purpose. Originally developed to explain how information systems improve individual performance when their functionalities align with task requirements, task–technology fit has been widely applied across domains such as mobile banking, online learning, and knowledge management (Furneaux, 2012; Zhou et al., 2010; Lafi, 2023). Within educational contexts, task–technology fit has been shown to shape not only adoption intentions but also learning outcomes, motivation, and engagement (Wu and Chen, 2017; Elci and Abubakar, 2021). When a technology supports the specific cognitive and procedural demands of a task, users are more likely to experience it as useful, trustworthy, and performance-enhancing.

Generative AI introduces a qualitatively different kind of task–technology relationship. Unlike traditional educational technologies, which primarily support information access or communication, generative AI actively participates in task execution by producing substantive outputs that can be directly submitted, evaluated, or acted upon (Abbas et al., 2024). This capacity raises profound questions about the nature of academic tasks themselves. If a student uses a generative model to write a literature review or solve a coding problem, is the task still being performed by the student, or has it been partially outsourced to the technology? From a task–technology fit perspective, this blurring of agency complicates the very notion of fit, because the technology is no longer merely supporting the task but reshaping it.

The relevance of this issue becomes particularly salient in the domain of assessment, where the alignment between tasks and technologies is critical to the validity and reliability of academic evaluation. Assessment tasks are designed to measure learning, skill acquisition, and critical thinking, yet generative AI can complete many of these tasks with minimal human input, thereby threatening the integrity of traditional evaluation systems (Ngo, 2023; Johnston et al., 2024). At the same time, generative AI also offers new opportunities for designing more adaptive, authentic, and feedback-rich assessments that may better capture complex learning outcomes (Krause et al., 2024). Whether these opportunities are realized depends largely on how well generative AI is integrated into the assessment process in a way that preserves, rather than erodes, the pedagogical purpose of evaluation.

A particularly instructive parallel can be found in the field of software engineering, where generative AI has already been deployed to automate testing and quality assurance through behavior-driven development frameworks. Tiwari (2025) demonstrated that generative AI can significantly enhance the efficiency and consistency of automated testing by translating natural language specifications into executable test cases, thereby aligning technological capabilities with the formalized behavioral tasks of software validation. This work illustrates a high level of task–technology fit, in which generative AI supports, rather than replaces, human-defined objectives. The relevance of this insight for higher education lies in the structural similarity between software testing and educational assessment: both involve the systematic evaluation of performance against predefined criteria, and both increasingly rely on automation to achieve scalability and consistency.

By drawing on Tiwari's (2025) framework, this study conceptualizes generative AI in education not merely as a tool for content generation but as an emerging infrastructure for assessment design, feedback generation, and learning analytics. Just as behavior-driven development uses generative AI to formalize and automate testing tasks, educational institutions are beginning to explore how similar technologies can be used to generate formative feedback, evaluate student submissions, and even construct adaptive assessments (Hosseini et al., 2023). However, unlike software systems, students are not deterministic entities, and learning is not a purely mechanical process. This makes the question of task–technology fit in education both more complex and more consequential.

The literature on technology acceptance and educational technology adoption provides further insight into these dynamics. Models such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology have consistently shown that perceived usefulness and ease of use are key predictors of adoption across contexts (Zhou et al., 2010; Sun and Guo, 2022). In the context of generative AI, however, these constructs are intertwined with ethical, epistemic, and identity-related concerns. Students may perceive generative AI as highly useful for completing assignments, yet simultaneously worry that its use undermines their learning or violates institutional norms (Grájeda et al., 2024). Similarly, instructors may recognize the efficiency gains offered by automated grading or feedback, while fearing that such systems erode the human dimension of teaching (Malmstrom et al., 2023).

Recent empirical studies underscore the heterogeneity of student experiences with generative AI. Surveys conducted across Europe, Asia, and North America reveal wide variation in awareness, confidence, and perceived legitimacy of AI tools, with factors such as discipline, study level, and cultural context shaping attitudes toward use (Strzelecki and ElArabawy, 2024; Zhou et al., 2024). These findings suggest that generative AI adoption cannot be understood solely in terms of individual preferences but must be situated within the broader institutional and task environments in which students operate.

Despite the rapid growth of this literature, a significant gap remains in the integration of task–technology fit theory with generative AI research in higher education. While numerous studies have examined acceptance, ethical concerns, and learning outcomes, few have explicitly analyzed how the alignment between academic tasks and generative AI capabilities shapes these phenomena. Moreover, the insights from software engineering and automated testing, as exemplified by Tiwari (2025), have rarely been brought into dialogue with educational theory, even though both domains grapple with similar issues of automation, validation, and human oversight.

This study seeks to address this gap by developing a comprehensive, theoretically grounded analysis of generative AI in higher education through the lens of task–technology fit, technology acceptance, and experience–technology alignment. By synthesizing findings from diverse empirical and conceptual sources, it aims to illuminate how generative AI can be integrated into educational systems in ways that enhance, rather than undermine, learning and assessment. In doing so, it contributes not only to the scholarly understanding of AI in education but also to the practical challenge of designing policies and pedagogies for an AI-augmented academic future.

2. Methodology

The present research adopts a theoretically integrative qualitative synthesis methodology designed to examine the role of generative artificial intelligence within higher education through the combined lenses of task–technology fit, technology acceptance, and experience–technology alignment. This approach is particularly appropriate for a domain characterized by rapid technological change, diverse empirical findings, and complex ethical and pedagogical considerations, as it allows for the systematic interpretation and integration of heterogeneous sources into a coherent analytical narrative (Pallant, 2013). Rather than generating new primary data, this study constructs a robust conceptual and interpretive framework grounded in the existing body of peer-reviewed research, institutional reports, and theoretical models related to generative AI, educational technology, and information systems.

At the core of this methodology is a structured qualitative synthesis of the reference corpus provided, which encompasses studies on task–technology fit, technology acceptance, generative AI in higher education, and the organizational and cognitive impacts of AI-driven systems. Each source was treated as a theoretical or empirical lens through which the phenomenon of generative AI adoption could be examined, allowing the analysis to move beyond surface-level trends to explore underlying mechanisms and causal relationships (Carver and Nash, 2011). This process involved iterative reading, thematic coding, and cross-comparison of findings, with particular attention paid to how different studies conceptualized tasks, technologies, and performance outcomes.

A central methodological principle guiding this synthesis is the notion of theoretical triangulation. By drawing simultaneously on task–technology fit theory, acceptance models, and experience-based perspectives, the study avoids the limitations of any single framework and instead constructs a multidimensional understanding of generative AI in education (Furneaux, 2012). For example, while technology acceptance models emphasize perceptions of usefulness and ease of use, task–technology fit theory foregrounds the structural alignment between technological capabilities and task requirements, and experience–technology fit highlights the subjective quality of user engagement (Jung et al., 2023). Integrating these perspectives enables a more nuanced interpretation of why generative AI is embraced in some educational contexts and resisted or misused in others.

The analytical process began with the identification of core constructs across the reference corpus, including academic tasks, generative AI functionalities, assessment practices, learning outcomes, and ethical considerations. These constructs were then mapped onto the dimensions of task–technology fit, such as task complexity, interdependence, and information requirements, as well as onto acceptance-related variables such as perceived usefulness, perceived risk, and social influence (Zhou et al., 2010; Wu and Chen, 2017). This mapping allowed for the systematic comparison of how generative AI aligns or misaligns with different educational tasks, ranging from essay writing and coding to formative feedback and summative assessment.

A distinctive feature of this methodology is the incorporation of insights from software engineering and automated testing, as articulated by Tiwari (2025), into the educational analysis. Tiwari’s work on automating behavior-driven development with generative AI provides a detailed account of how natural language specifications can be translated into executable test cases, thereby enhancing efficiency and consistency in software validation. Methodologically, this study treats this framework as an analogical model for understanding how generative AI might be used to automate and standardize educational assessment processes. By systematically comparing the structural characteristics of software testing and academic assessment, the analysis explores how similar principles of task specification, automation, and validation can be applied across domains.

To ensure rigor and transparency, the synthesis followed a multi-stage interpretive procedure. First, each reference was analyzed individually to extract its key theoretical propositions, empirical findings, and methodological assumptions. Second, these elements were compared across studies to identify convergences, divergences, and gaps in the literature. Third, the emerging themes were integrated into a coherent conceptual model that links generative AI capabilities to educational tasks and outcomes through the mediating mechanisms of fit, acceptance, and experience. Throughout this process, particular care was taken to preserve the contextual specificity of each study, recognizing that generative AI adoption is shaped by cultural, institutional, and disciplinary factors (Strzelecki and ElArabawy, 2024; Zhou et al., 2024).

The limitations of this methodology must also be acknowledged. As a secondary analysis based on existing literature, the study is constrained by the quality, scope, and methodological diversity of the available sources. Many studies on generative AI in education rely on self-reported survey data, which may be subject to social desirability bias or limited by respondents' evolving understanding of the technology (Hosseini et al., 2023). Moreover, the rapid pace of technological development means that empirical findings can quickly become outdated, posing challenges for longitudinal generalization (Kelly et al., 2023). Nevertheless, by grounding its analysis in well-established theoretical frameworks and by integrating insights from multiple domains, the study seeks to produce findings that are both robust and adaptable to future developments.

In summary, this methodological approach provides a systematic and theoretically informed basis for examining the complex interplay between generative AI and higher education. By combining qualitative synthesis, theoretical triangulation, and cross-domain analogical reasoning, it enables a deep exploration of how generative AI fits within the cognitive, procedural, and ethical tasks that define contemporary academic practice, in line with the analytical rigor advocated in educational and information systems research (Al-Maatouk et al., 2020; Przegalinska et al., 2024).

3. Results

The interpretive synthesis of the reference corpus reveals a set of interrelated patterns that illuminate how generative artificial intelligence is being adopted, perceived, and utilized within higher education, particularly when viewed through the lens of task–technology fit and related theoretical frameworks. One of the most salient findings is that generative AI adoption is not uniform across academic tasks but is highly contingent on the degree to which its capabilities align with the cognitive, procedural, and evaluative demands of those tasks, a conclusion that echoes core propositions of task–technology fit theory (Furneaux, 2012). Students and instructors are more likely to perceive generative AI as beneficial when it supports tasks that involve information synthesis, drafting, or exploratory learning, whereas tasks that are designed to assess individual understanding or originality tend to generate greater ambivalence and resistance (Ngo, 2023).

Across multiple studies, students consistently report high perceived usefulness of generative AI for tasks such as brainstorming, summarizing readings, and generating initial drafts of assignments, reflecting a strong fit between the technology's text-generation capabilities and the exploratory and preparatory phases of academic work (Kelly et al., 2023; Zhou et al., 2024). This pattern aligns with the extended Technology Acceptance Model, which predicts that perceived usefulness is a primary driver of continued use (Wu and Chen, 2017). However, the same studies also reveal a persistent tension between utility and legitimacy, as many students express uncertainty about whether such uses are ethically or institutionally sanctioned, a dynamic that underscores the importance of contextual and normative factors in shaping technology adoption (Johnston et al., 2024).

From a task–technology fit perspective, this tension can be interpreted as a misalignment between the informal tasks that students are performing, such as managing workload and coping with academic pressure, and the formal tasks that institutions intend assignments to represent, such as demonstrating independent learning and critical thinking. Generative AI fits the former tasks exceptionally well by reducing effort and increasing efficiency, but it fits the latter more ambiguously, as its outputs may obscure the extent of student learning (Abbas et al., 2024). This duality helps explain why generative AI can simultaneously enhance student satisfaction and undermine academic integrity, a paradox that has been widely reported in the literature (Von Garrel and Mayer, 2023).

The synthesis also reveals significant variation across disciplines and study levels, consistent with research on the moderating effects of contextual factors on technology acceptance (Strzelecki and ElArabawy, 2024). In fields such as computer science and engineering, where tasks often involve code generation, debugging, and problem solving, generative AI tools are frequently perceived as legitimate aids that align closely with professional practices, thereby exhibiting high task–technology fit (Pan et al., 2024). In contrast, in disciplines that emphasize interpretive analysis or creative expression, such as the humanities, students and instructors are more likely to view generative AI with skepticism, perceiving a poorer fit between the technology's outputs and the epistemic goals of the discipline (Zhou et al., 2024).

A particularly important set of findings emerges in relation to assessment and feedback. Multiple studies indicate that students value generative AI for its ability to provide immediate, personalized feedback on drafts and problem solutions, a function that aligns well with the formative assessment tasks of guiding learning and identifying areas for improvement (Malmstrom et al., 2023; Krause et al., 2024). This high level of task–technology fit enhances engagement and self-regulated learning, as students can iteratively refine their work based on AI-generated suggestions. However, when generative AI is used in summative assessment contexts, such as producing final submissions or answering exam questions, the fit becomes problematic, as the technology effectively performs the task that the assessment is meant to measure (Hosseini et al., 2023).

The analogy to automated software testing, as articulated by Tiwari (2025), provides a useful interpretive lens for these findings. In behavior-driven development, generative AI is used to automate the execution of predefined test cases, thereby increasing efficiency without undermining the validity of the testing process, because the criteria for success remain human-defined. In higher education, by contrast, when generative AI is allowed to generate the substantive content of an assignment, it alters the locus of performance in a way that compromises the assessment's purpose. The results of the synthesis suggest that generative AI exhibits high task–technology fit in roles analogous to test automation, such as generating feedback or checking consistency, but low fit when it replaces the learner's cognitive labor in producing assessable outputs.

Another key finding concerns the role of experience–technology fit in shaping students' emotional and motivational responses to generative AI. Studies of extended reality and other immersive technologies have shown that positive experiential alignment can significantly influence consumption and engagement behaviors (Jung et al., 2023), and similar patterns are evident in the generative AI literature. Students who report enjoyable, intuitive, and confidence-enhancing interactions with AI tools are more likely to integrate them into their study routines, even when they harbor ethical reservations (Grájeda et al., 2024). This suggests that experiential factors can sometimes override rational evaluations of fit or appropriateness, leading to widespread but potentially problematic adoption.

At the institutional level, the synthesis highlights a growing interest in leveraging generative AI for organizational efficiency and knowledge management, consistent with resource-based and task–technology fit perspectives on collaborative AI (Przegalinska et al., 2024; Lafi, 2023). Universities are exploring the use of generative AI for tasks such as curriculum design, student support, and assessment analytics, motivated by the promise of scalability and cost reduction (IDC, 2023). These initiatives reflect a high-level perception of fit between generative AI and administrative tasks, even as the fit with pedagogical tasks remains contested.

Taken together, these results indicate that generative AI's impact on higher education is fundamentally shaped by the alignment between its capabilities and the tasks to which it is applied. Where this alignment is strong, as in formative feedback, exploratory learning, and administrative support, generative AI tends to enhance performance, satisfaction, and efficiency. Where it is weak, particularly in summative assessment and demonstrations of independent learning, generative AI introduces risks to validity, integrity, and educational value, a conclusion that resonates with both educational and information systems research (Elci and Abubakar, 2021; Sun and Guo, 2022).

4. Discussion

The findings of this study underscore the necessity of moving beyond simplistic narratives of generative artificial intelligence as either a revolutionary boon or an existential threat to higher education. Instead, they point to a more nuanced reality in which the educational value of generative AI is contingent upon the degree of alignment between technological capabilities and the cognitive, pedagogical, and evaluative tasks that define academic work. This central insight is deeply rooted in task–technology fit theory, which has long emphasized that performance outcomes depend not on technology per se but on how well it supports the specific tasks users must perform (Furneaux, 2012). In the context of generative AI, however, this principle takes on new complexity because the technology does not merely support tasks but can also perform them, thereby reshaping the boundaries of human and machine agency.

One of the most theoretically significant implications of this study is the need to reconceptualize academic tasks in an era of generative AI. Traditional task–technology fit models were developed in contexts where technologies primarily facilitated information processing, communication, or data retrieval, leaving the core cognitive work to human users (Zhou et al., 2010). Generative AI, by contrast, is capable of producing substantive intellectual outputs, such as essays, code, and analytical summaries, which were previously the exclusive domain of students. This shift challenges the assumption that tasks are stable and independent of the technologies used to perform them, an assumption that underlies much of the existing literature on technology acceptance and performance (Wu and Chen, 2017).

The analogy to behavior-driven development and automated testing, as articulated by Tiwari (2025), provides a powerful framework for navigating this conceptual challenge. In software engineering, the introduction of generative AI into testing workflows did not eliminate the need for human-defined requirements or validation criteria; rather, it transformed how those requirements were operationalized. Generative AI translated natural language specifications into executable tests, thereby increasing efficiency while preserving the integrity of the evaluation process. This represents a high level of task–technology fit, in which the technology amplifies human intent without supplanting it. Applying this logic to higher education suggests that generative AI should be designed and governed in ways that support, rather than replace, the pedagogical objectives embedded in academic tasks.

From this perspective, the most promising applications of generative AI in education are those that align with formative and supportive tasks, such as providing feedback, scaffolding learning, and facilitating exploration. These tasks are inherently iterative and dialogic, making them well suited to the interactive and adaptive capabilities of large language models (Malmstrom et al., 2023; Krause et al., 2024). When students use generative AI to receive explanations, test their understanding, or refine their drafts, the technology functions as a cognitive partner rather than a surrogate, thereby preserving the learner's agency and responsibility. This alignment helps explain why students often report positive experiences and enhanced confidence when using AI for these purposes, even as they remain wary of its use in high-stakes assessment (Grájeda et al., 2024).

In contrast, the use of generative AI for summative assessment tasks represents a fundamental misalignment of task and technology. Summative assessments are designed to measure what a student knows or can do, yet when a generative model produces the assessed output, the technology effectively becomes the performer, rendering the assessment invalid (Hosseini et al., 2023). From a task–technology fit standpoint, this is a classic case of misfit, in which the technology's capabilities exceed and override the intended scope of the task. This misalignment not only undermines academic integrity but also distorts students' perceptions of what constitutes legitimate learning and achievement, as evidenced by widespread uncertainty and ethical ambivalence in student surveys (Johnston et al., 2024; Ngo, 2023).

The implications of these dynamics extend beyond individual classrooms to the institutional and systemic level. Universities are increasingly under pressure to adopt generative AI for reasons of efficiency, competitiveness, and innovation, as highlighted in industry and policy reports (IDC, 2023; Gartner, 2023). From a resource-based and task–technology fit perspective, such adoption can enhance organizational performance by automating routine tasks, improving data analytics, and supporting decision making (Przegalinska et al., 2024; Lafi, 2023). However, if these technologies are deployed without careful attention to their pedagogical fit, they risk exacerbating inequalities, eroding trust, and commodifying learning in ways that conflict with the core mission of higher education (UNESCO, 2023).

A further theoretical contribution of this study lies in its integration of experience–technology fit into the analysis of generative AI adoption. While task–technology fit emphasizes functional alignment, experience–technology fit highlights the subjective quality of user interactions, including enjoyment, immersion, and emotional resonance (Jung et al., 2023). The findings suggest that generative AI often scores highly on experiential dimensions, offering intuitive, conversational, and responsive interfaces that can make learning feel more engaging and less intimidating. This experiential appeal can drive widespread adoption even in contexts where the functional fit is questionable, such as using AI to complete assignments. In this sense, experience–technology fit can act as both an enabler and a risk factor, amplifying the influence of generative AI on student behavior in ways that may not always align with educational goals.

Critically, these insights call into question the sufficiency of traditional technology acceptance models for understanding generative AI in education. While constructs such as perceived usefulness and ease of use remain relevant, they do not capture the deeper epistemic and ethical dimensions of AI-mediated learning (Sun and Guo, 2022; Al-kfairy, 2024). Students may find generative AI extremely useful and easy to use, yet still worry that it compromises their learning or violates institutional norms. This suggests the need for an expanded acceptance framework that incorporates perceptions of task legitimacy, academic integrity, and identity, building on recent calls for more holistic models of AI adoption in education (Abbas et al., 2024).

The study also highlights important limitations and directions for future research. One limitation lies in the rapidly evolving nature of generative AI technologies, which makes it difficult to draw stable conclusions about their long-term impact. As models become more sophisticated and integrated into educational platforms, the nature of task–technology fit may change, necessitating ongoing empirical investigation (Kelly et al., 2023). Additionally, most existing studies rely on self-reported data from students and faculty, which may not fully capture actual usage patterns or learning outcomes. Future research should incorporate observational and experimental designs to more directly assess how generative AI affects performance and engagement across different tasks and contexts (Pan et al., 2024).

Moreover, there is a need for comparative and cross-cultural studies that examine how institutional policies, disciplinary norms, and cultural attitudes shape the fit between generative AI and academic tasks. The variation observed across countries and study levels suggests that there is no one-size-fits-all solution to AI integration, reinforcing the importance of context-sensitive governance and pedagogy (Strzelecki and ElArabawy, 2024; Zhou et al., 2024). Finally, interdisciplinary research that bridges education, information systems, and software engineering, as exemplified by the integration of Tiwari's (2025) work into this study, holds particular promise for developing innovative and ethically grounded approaches to AI-enabled assessment and learning.

5. Conclusion

This study has demonstrated that the impact of generative artificial intelligence on higher education cannot be adequately understood without careful attention to the alignment between technological capabilities and academic tasks. Through a comprehensive synthesis of contemporary scholarship and the integration of task–technology fit, technology acceptance, and experience–technology alignment theories, it has shown that generative AI can both enhance and undermine learning depending on how it is embedded within educational practice. The insights drawn from software engineering, particularly the work of Tiwari (2025) on automating behavior-driven development, provide a valuable analogical framework for understanding how generative AI can support assessment and feedback without displacing human-defined learning objectives.

When generative AI is used to scaffold, guide, and evaluate learning in ways that preserve student agency and pedagogical intent, it exhibits high task–technology fit and contributes positively to educational outcomes. When it replaces the cognitive labor that assessments are designed to measure, however, it introduces a fundamental misalignment that threatens academic integrity and the meaning of achievement. Navigating this tension requires not only technological innovation but also thoughtful policy, pedagogy, and ongoing research grounded in robust theoretical frameworks. By situating generative AI within the broader tradition of task–technology fit research, this study offers a pathway for harnessing its potential while safeguarding the core values of higher education.

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