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A Study on Technology Acceptance and Learning-Behavior Mechanisms of Generative AI–Assisted Learning from an Integrated TAM–SOR Perspective

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ABSTRACT

Generative artificial intelligence (Generative AI), together with AI-enabled tutoring and learning analytics tools, is rapidly reshaping learning practices in higher education; nevertheless, the mere availability of tools does not automatically translate into effective learning. Grounded in the Technology Acceptance Model (TAM) and the Stimulus – Organism – Response (SOR) framework, this paper constructs an explanatory chain linking perceived usefulness (PU) and perceived ease of use (PEOU) to attitudes, behavioral intentions, actual use, and subsequent learning behaviors. To enhance contextual sensitivity, the model further considers situational factors salient to women's universities, including gendered expectations, institutional culture, and technology accessibility. The study contributes (a) a structural integration of TAM and SOR, (b) a reusable conceptual scaffold—together with operationalizable constructs and an analysis pathway—appropriate for AI-in-education research, and (c) theoretical support for developing student-centered, ethically responsible strategies for integrating Generative AI into higher education.

KEYWORDS

Generative artificial intelligence; Technology acceptance model; Learning behavior

1 Introduction

Artificial intelligence is spreading across higher education at an unprecedented pace. Intelligent tutoring systems, adaptive learning platforms, learning-analytics dashboards, and generative language models such as DeepSeek, Kimi, and Doubao have created new infrastructures for personalized guidance, timely feedback, and data-informed instructional decisions. Yet increased tool supply does not automatically improve learning quality: whether students are willing to use AI, whether they can use it competently, and whether they use it appropriately is largely shaped by their perceptions, attitudes, and intentions. At the same time, ethical concerns, overreliance, and threats to academic integrity may offset potential benefits. Existing studies often focus on elite universities and system-level deployments, offering limited explanatory depth regarding behavioral change mechanisms among students in mainstream undergraduate institutions, particularly women's universities in China.

At the theoretical level, many studies rely on TAM or SOR in isolation, which constrains a coherent account of how cognitive appraisal (usefulness/ease of use), affective attitudes, and behavioral responses connect in a single explanatory chain.

2 Theoretical Perspective and Conceptual Model Development

2.1 From "Technology Acceptance" to "Learning-behavior Mechanisms"

With Generative AI entering university learning contexts, the central challenge is no longer whether students will use AI, but how they use it, why different usage patterns emerge, and how such patterns translate into changes in learning behavior. A pure adoption lens tends to stop at attitudes and intentions, whereas an exclusive focus on learning environment or affect may underplay the cognitive chain of technology acceptance. Accordingly, this study adopts a dual perspective—technology acceptance explanation plus context – psychology – behavior explanation—to incorporate cognitive appraisal, affective experience, and institutional context within a unified framework and to provide a coherent account of acceptance, use, and downstream behavioral consequences.

2.2 Integration Logic: TAM as the Adoption Chain; SOR as Contextual and Psychological Mechanisms

TAM is well-suited to describing the adoption judgment process shaped by tool characteristics, capturing the basic pathway from cognitive appraisal to attitude/intention and ultimately to use. SOR explains how external stimuli influence behavioral responses through internal states, allowing the incorporation of contextual factors—such as course assessment signals, instructor guidance, peer norms, and accessibility—as well as psychological states including trust, anxiety, dependence, and self-efficacy. In short, TAM answers why students use AI (or whether they intend to), while SOR explains how they use it and what consequences follow; integrating the two better reflects the real complexity of Generative AI-assisted learning.

2.3 Focal Issues

This paper concentrates on three interrelated issues:

(1) How key tool features and learning-environment factors of Generative AI affect students' internal psychological states;

(2) How different psychological states lead to differentiated patterns of actual use (e.g., assistive use, substitutive use, verification-oriented use, iterative use);

(3) How different usage patterns are associated with changes in learning behavior (e.g., enhancing self-regulation versus triggering dependence; promoting deep learning versus fostering superficial compliance).

Rather than merely replicating existing adoption models, the goal is to provide a transferable "mechanism-explanatory scaffold" that can support subsequent empirical testing and serve as an actionable lever for course and assessment reform—by optimizing stimulus-layer elements, shaping organism-layer states, and improving response-layer outcomes.

3 Research Background and State of the Art

3.1 Opportunities and Tensions as Generative AI Enters Higher Education Learning Contexts

In recent years, AI technologies have been increasingly integrated into higher education. Intelligent tutoring systems, adaptive platforms, learning analytics, and large-scale generative models (e.g., DeepSeek, Kimi, Doubao) are reshaping the structure of "teaching–learning–assessment" and patterns of student engagement. At the learning level, Generative AI offers timely feedback, linguistic and structural scaffolding, information integration, and exemplar generation; consequently, it is widely used for pre-class preparation, assignment writing, information search, code generation, and concept explanation, with potential to improve efficiency and personalized support. However, mere availability does not guarantee effective learning. Whether students adopt AI, how they embed it into their learning workflow, and whether sustained behavioral change occurs depend on cognitive appraisal, value judgments, and institutional and assessment signals.

Moreover, Generative AI raises salient issues—including academic integrity, overreliance, algorithmic bias, data privacy, and ethical boundaries—which may undermine deep engagement and scholarly norms. Therefore, progress is needed simultaneously in two dimensions: mechanism-based explanation of learning effects and the design of ethically responsible governance and instructional arrangements.

From a contextual perspective, existing studies often focus on resource-rich elite universities or macro-level deployments, while paying limited attention to women's universities characterized by distinct gender composition and campus culture. In contexts such as Shandong Women's University, gendered expectations, institutional culture, and technology accessibility may moderate students' perceptions and behavioral outcomes, thereby affecting the fairness and effectiveness of AI integration. Hence, there is a need for student-centered studies that are grounded in concrete learning scenarios and that provide methodologically disciplined, mechanism-oriented explanations.

3.2 From Technology-enhanced Learning to Generative AI-driven Reconstruction of Learning Ecology: International Research Trends

International research has broadly shifted from evaluating the effects of AI-enabled instructional tools to balancing adoption mechanisms with governance frameworks:

(1) Outcome-oriented studies examine how intelligent tutoring, recommender systems, and adaptive platforms influence achievement, learning efficiency, and engagement, emphasizing AI as a learning support system.

(2) Adoption-mechanism studies apply TAM, UTAUT, and related models to explain learners' acceptance of educational technology, focusing on pathways among usefulness, ease of use, attitudes, and intentions to predict use.

(3) With large models entering classrooms, Generative AI research has expanded to prompt literacy, output reliability (hallucinations), learner trust and dependence, and impacts on writing and critical thinking. Methods increasingly combine surveys, experiments, learning analytics, and interviews; nevertheless, explanatory continuity from intention to actual usage patterns to learning-behavior change remains insufficient.

(4) Ethics and governance studies increasingly address academic integrity, bias and fairness, and privacy protection, often converging on governance orientations such as policy boundaries, curriculum-based literacy, assessment reform, and support services—yet these are sometimes disconnected from mechanism models of learning behavior.

Overall, international scholarship provides relatively mature theoretical tools and issue framings; however, more fine-grained and transferable mechanism models and research designs are still needed for cross-cultural and cross-institutional adaptation, particularly regarding how tool use translates into learning behavior.

3.3 Domestic Research in China: Rapid Expansion of Practice, but Limited Mechanism Testing and Contextual Explanation

AI-in-education practices in Chinese universities are expanding rapidly and diversifying. Generative AI is widely used for writing support, information retrieval, course tutoring, and programming assistance, accelerating shifts in teaching and learning modalities. Concurrently, scholarship has accumulated experiential summaries and recommendations on AI-enabled teaching reform, AI literacy cultivation, and smart-course development.

However, from the standpoint of rigorous empirical inquiry, several limitations persist: (1) discussions are often conceptual or tool-centric, with relatively few systematic tests of the complete mechanism chain from PU/PEOU to attitudes, intentions, actual use, and learning behavior; (2) many studies measure only intention or usage frequency, offering limited depiction of how students use AI across tasks, whether they verify outputs, and whether they develop strategy use and self-regulation; (3) attention to contextual and group differences—such as mainstream undergraduate institutions, regional universities, and women's universities—remains insufficient, including the moderating roles of gender composition, cultural climate, and accessibility.

4 Theoretical Foundations of TAM and SOR

4.1 TAM: Core Propositions and Interpretive Boundaries in Generative AI-assisted Learning

The Technology Acceptance Model posits that learners form subjective judgments about whether a technology improves performance and whether it is easy to learn and use, which in turn shape attitudes and intentions and ultimately actual use. In Generative AI-assisted learning, TAM explains why adoption is not random: it is associated with learners' judgments about efficiency, understanding quality, and task completion quality. When tool barriers, interaction costs, prompt-learning costs, and verification costs are reduced, sustained intention becomes more likely. Importantly, attitude and intention also reflect an initial value positioning of AI's role in learning—whether as scaffolding or as a substitute.

Nevertheless, TAM has inherent limitations in the Generative AI context. It pays comparatively little attention to institutional and cultural signals, peer norms, ethical boundaries, and affective experiences—factors that often determine whether intention translates into high-quality usage patterns and whether use supports deep learning versus superficial substitution. Accordingly, TAM is best treated as a foundational adoption chain that requires complementary theories capable of incorporating contextual and psychological mechanisms.

4.2 SOR: a Mechanism Framework Linking Contextual Stimuli, Psychological States, and Behavioral Responses

The SOR model explicitly links the external environment to internal psychology: external stimuli do not directly yield behavioral outcomes; instead, they influence cognition and affect, which then manifest as differentiated behavioral responses. In Generative AI-learning research, SOR offers at least three advantages: (1) it accommodates institutional and course signals such as assessment orientation (product-focused vs. process-focused), teachers' usage boundaries and demonstrations, and academic integrity policies; (2) it incorporates key psychological mechanisms including trust and uncertainty, anxiety and risk perception, dependence, and academic self-efficacy; and (3) it explains "different use of the same tool," whereby exposure to the same Generative AI leads some learners to develop iterative verification practices while others drift toward substitutive dependence.

4.3 Variable Mapping: Structuring the Generative AI Learning Ecology as S–O–R

Stimulus (S) includes tool-layer factors (output reliability, interaction convenience, explainability, feedback speed), course-layer factors (task authenticity, process-evidence requirements, citation and disclosure rules), support-layer factors (teacher guidance, training resources, technological accessibility), and social-layer factors (peer norms and usage climate).

Organism (O) encompasses technology-acceptance states (attitudes, intentions) and affect–cognition states (trust/anxiety, dependence tendency, moral judgment, academic self-efficacy).

Response (R) refers to usage patterns and learning-behavior outcomes, including depth of use (one-shot generation vs. multi-round iteration), verification behaviors (checking and triangulating), compliance (disclosure and boundary adherence), and learning-behavior changes (self-regulation, time management, strategic engagement, and depth of cognitive investment).

The key value of this mapping is operational: it reveals leverage points for governance and instructional design—optimizing stimulus-layer elements (tasks, assessment, support, and boundaries) to shape organism-layer states and guide response-layer behavior from substitutive use toward learning-enhancing, collaborative use.

4.4 Complementary Integration: a Theoretical Basis for Explaining the "Double-edged" Effects of Generative AI Learning

Generative AI learning exhibits a pronounced double-edged effect. On the one hand, Generative AI may increase efficiency, provide scaffolding, and strengthen self-regulated learning; on the other hand, it may trigger overreliance, superficial completion, and integrity risks. Using TAM alone can yield a linear conclusion (high PU/PEOU → high intention → high use) yet fail to explain why high use does not necessarily produce high-quality learning. Using SOR alone without an acceptance chain may under-specify adoption decisions. Therefore, TAM is used to characterize learners' cognitive appraisal and adoption inclination, while SOR explains how institutional contexts and psychological states shape usage patterns and, ultimately, learning-behavior outcomes.

5 Conclusions and Implications

Against the backdrop of Generative AI's entry into higher education learning contexts, this paper responds to limitations in existing research—insufficient mechanism explanation, limited incorporation of contextual factors, and the fragmentation of cognitive and affective variables—by clarifying the internal logic and complementarity of TAM and SOR. The analysis supports the suitability of an integrated TAM – SOR framework for explaining the chain linking AI technologies, learner psychology, and learning-behavior outcomes. Specifically, TAM provides a stable structure for technology adoption decisions, delineating the cognitive – behavior pathway from PU/PEOU to attitude, intention, and use. SOR adds crucial explanatory power for contextual and affective dynamics, incorporating environmental variables (institutional support, instructor guidance, peer norms, accessibility) and internal psychological states (trust, anxiety, dependence) within a unified framework, thereby better reflecting authentic learning ecology.

5.1 Theoretical Significance: Toward Integrated Mechanism Explanations in AI-in-education Research

First, the integrated TAM – SOR framework offers a coherent explanation spanning cognition, emotion, and behavior. Generative AI-assisted learning is neither purely rational choice nor single-emotion response; rather, it is jointly shaped by rational benefit appraisal (usefulness/ease), affective experience (trust/anxiety), and institutional signals (allow/ban, assessment orientation). Structuring these factors within one framework strengthens explanatory completeness and testability.

Second, the integration expands TAM's explanatory boundary in Generative AI contexts. Although usefulness and ease of use matter, they do not explain why learners with similarly high PU may display markedly different usage patterns (e. g., scaffolding-oriented assistance vs. substitutive outsourcing). By introducing environment stimuli and internal psychological states as key mechanisms, the model explains differentiated paths from intention to usage pattern to learning outcomes, thereby advancing TAM from an adoption-prediction model toward a learning-behavior mechanism model.

Third, the integrated framework clarifies principles for organizing variables in subsequent research. External variables can be systematically allocated to the stimulus layer (institution, course, support, peers, accessibility), internal variables to the organism layer (attitude, intention, trust/anxiety/self-efficacy), and behaviors and outcomes to the response layer (usage patterns, learning-behavior change). This organization improves the reusability, comparability, and cumulative value of research designs.

5.2 Practical Significance: Supporting Ethical and Deep-learning-oriented Generative AI Integration in Universities

Practically, the paper highlights how universities can steer Generative AI from "tool enthusiasm" to "learning value creation." First, institutions should move from mere availability to competent use by reducing access barriers and trial-and-error costs: provide stable, equitable tool access and foundational training (prompting strategies, verification methods, citation and disclosure practices), thereby converting ease of use into sustainable conditions for learning. Simultaneously, pedagogical demonstrations can make AI's value visible in understanding, feedback, and structured expression, strengthening perceived usefulness.

Second, governance should shift from usage frequency to usage quality through an SOR lens. The key issue is not whether students use AI, but how they use it. Universities should treat institutional support, teacher guidance, and course assessment as core stimuli to shape internal psychological states and usage patterns—clarify boundaries, strengthen process-based and authentic assessment, and encourage iterative and reflective evidence—so as to reduce substitutive use and overreliance while promoting strategic engagement and deep processing.

Third, discussions of risk must evolve into an operational governance loop by embedding ethics and equity into practice. Integrity, bias, privacy, and fairness concerns cannot remain at the level of appeals; they must be implemented through an integrated loop of rules – curriculum – assessment – support: rules provide boundaries, curriculum builds competencies, assessment sets incentives, and support ensures equity. Because SOR emphasizes behavioral shaping by environmental stimuli, governance should be viewed as educational design that cultivates appropriate habits rather than as external constraint alone.

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