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Keywords:
Conversational AI learning support tools; continuance intention; theory of planned behavior; AI trust; AI anxiety; construct overlap.

Chinese University Students' Continuance Intention to Use AI Chatbot Learning Support Tools: An Integrated Analysis of the Theory of Planned Behavior, AI Trust, and AI Anxiety

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ABSTRACT

This study examined Chinese university students' continuance intention to use conversational AI learning support tools by integrating the Theory of Planned Behavior, AI trust, and AI anxiety. Its objectives were to examine (1) associations of attitude, subjective norm, and perceived behavioral control with continuance intention; (2) AI trust's direct and statistical indirect relationships through attitude; and (3) AI anxiety's relationships with attitude, perceived behavioral control, and continuance intention, including their stability across model specifications. We yielded 428 complete responses from experienced student users and measured six constructs using 23 items. Analyses included descriptive statistics, reliability tests, Pearson correlations, HTMT diagnostics, hierarchical regression, and indirect-effect analysis using 5,000 bootstrap samples and bias-corrected 95% confidence intervals. Primary models controlled for educational level, discipline, usage frequency, and usage experience. The results uncover that attitude, subjective norm, and perceived behavioral control were positively associated with continuance intention. AI trust was positively associated with attitude and continuance intention, with a statistical indirect effect through attitude of 0.098 (95% CI [0.022, 0.181]). The proposed negative anxiety mechanism lacked robust support: positive zero-order correlations became weakly negative under some controls. Its indirect relationship through attitude was model-sensitive, while that through perceived behavioral control included zero. Cross-sectional data and limited discriminant validity restrict these findings to conditional associations, without establishing causality or temporal mediation. Substantial overlap among the positive constructs was evident. The study highlights construct

overlap and model sensitivity in AI continuance research. Universities may support responsible use by strengthening students' controllable use capabilities, clarifying norms, promoting calibrated trust, and encouraging output verification and disclosure. Future research should refine measurement and use independent samples, confirmatory factor analysis, and longitudinal designs.

1. INTRODUCTION

The application of artificial intelligence in education did not begin with generative AI. Early research focused primarily on intelligent tutoring systems, learning analytics, student profiling and prediction, automated assessment, and adaptive learning. These applications generally had clearly defined functional boundaries and predetermined task processes. In their systematic review of AI research in higher education, Zawacki-Richter et al. (2019) observed that existing studies concentrated largely on learner support, assessment, and prediction, while educators and teaching contexts themselves received comparatively little attention. Chiu et al. (2023) mapped 13 roles of AI across learning, teaching, assessment, and administration and identified associated learning outcomes and implementation challenges. This review describes the range of educational applications rather than demonstrating a single historical progression or a uniform improvement in learning.

Large language models marked a significant turning point in this technological trajectory. Conversational AI learning support tools allow students to ask successive questions in natural language and receive context-sensitive explanations, summaries, examples, feedback, translations, writing suggestions, and coding support. Their conversational interface supports iterative questioning and open-ended content generation, although accessibility, response quality, and usefulness depend on the tool and task. Lo's (2023) rapid review of early ChatGPT research found that ChatGPT could serve as a virtual tutor and teaching assistant, although its performance varied across disciplinary tasks. In a position paper, Kasneci et al. (2023) similarly discussed that large language models could enhance personalized support and feedback while also producing factual errors, fabricated information, bias, and overreliance. Accordingly, this study does not address all forms of 'AI learning software,' but rather general-purpose, large-language-model-based tools capable of sustained natural-language interaction.

From a learning-support perspective, generative AI can reduce the time students wait for explanations and feedback and can adjust the depth, presentation, and examples of an explanation in response to prompts. Students may use it for concept clarification, knowledge organization, language editing, brainstorming, debugging, and simulated question-and-answer practice. Chan and Hu (2023) found that higher education students generally recognized the potential benefits of generative AI for personalized learning, writing, and brainstorming, while also expressing concerns about accuracy, privacy, ethics, and personal development. Students therefore do not make choices solely on the basis of whether a tool is useful; they weigh learning benefits against potential costs.

This learning value is clearly conditional. First, output quality is jointly influenced by the model, prompting method, task domain, and currency of knowledge; linguistic fluency does not guarantee correctness. Second, immediate answers may scaffold knowledge, but they may also substitute for students' own work and allow them to bypass retrieval, reasoning, and reflection. Third, when unverified content is incorporated directly into assignments, tool use shifts from learning support to a potential problem of knowledge reliability and academic integrity. In an educational case study, Tlili et al. (2023) observed both positive expectations and concerns regarding cheating, authenticity, privacy, and manipulation. Explaining university students' adoption behavior therefore requires attention to perceived tool capability, emotional responses, the social environment, personal control, and institutional boundaries.

The central assessment challenge that generative AI poses to higher education is its capacity to produce coherent, natural-sounding text that is difficult to identify from surface features alone. Assessment centered on the final product therefore faces questions of authorship, attribution of contribution, and process authenticity. Cotton et al. (2024) argued that universities need new institutional arrangements that balance academic integrity with the use of technology to support learning, rather than relying only on prohibition or detection. The UNESCO guidance represented by Miao and Holmes (2023) likewise emphasizes human-centeredness, transparency, privacy protection, age appropriateness, and educational responsibility, and calls on educational institutions to define clear boundaries for generative AI use.

University rules on the academic integrity of generative AI use form an important context for students' continuance decisions. Course prohibitions, disclosure requirements, teacher attitudes, and consequences for misconduct all shape students' understanding of acceptable use. Rudolph et al. (2023) and Lo (2023) both argued that generative AI requires universities to reconsider

assessment design and policy arrangements. This study treats these institutional conditions as contextual and practical background rather than as core latent variables in the structural model.

Chinese university students are situated in an environment characterized by rapid iteration of generative AI tools, the coexistence of domestic and international products, and gradually emerging university rules. Tools differ in accessibility, Chinese-language capability, source citation, privacy terms, and campus-use policies. Because students use different tools for different tasks, a survey that asks only about 'AI tools' may elicit answers referring to chatbots, translation software, reference managers, or specialized learning platforms, thereby reducing measurement comparability. This study therefore required respondents to select the one conversational AI tool they had used most frequently for learning during the preceding three months and to anchor all measurement items to that tool.

Using grounded theory, Liu and Zhang (2024) identified external environment, technological revolution, user experience, and cognitive-emotional aspects as interconnected categories relevant to Chinese higher education students' intentions to use ChatGPT. In a survey of 320 Chinese university students, Shahzad et al. (2024) found that perceived trust moderated the relationships between ChatGPT awareness and perceived ease of use, usefulness, and intelligence. Their model concerned adoption intention rather than continuance. Because the present study includes students with prior use experience, its outcome is defined as continuance intention (Bhattacherjee, 2001). The present analysis considers TPB variables, AI trust, and AI anxiety together under this post-adoption behavioral anchor.

As generative AI becomes part of coursework, understanding existing users' continuance requires attention to their prior experience. Duong et al. (2024) related information and service quality to trust, satisfaction, and continuance intention. Tan et al. (2024) identified hedonic motivation, habit, facilitating conditions, and satisfaction as relevant to continuance, while Yu et al. (2024) examined perceived ease of use, usefulness, and satisfaction. These findings motivate a contextual investigation of continuance; they do not establish that social influence or every technology-evaluation variable is consistently significant across studies. Therefore, this study aims to answer:

RQ1: What conditional associations do the scale scores for attitude, subjective norm, and perceived behavioral control have with Chinese university students' continuance intention to use conversational AI learning support tools?

RQ2: How is AI trust related to attitude and continuance intention, and is there a statistical indirect relationship through attitude?

RQ3: What relationships does AI anxiety have with attitude, perceived behavioral control, and continuance intention, and are these relationships sensitive to model-control conditions?

2.1 Research Context

2.1.1 Evolution and Conceptual Boundaries of Conversational AI Learning Support Tools

Educational applications of AI have developed from specialized systems to general-purpose generative systems. Early intelligent tutoring, adaptive learning, and automated assessment systems generally relied on predefined knowledge structures and rules and were used mainly for content recommendation, learning-outcome prediction, and automated evaluation. The systematic review by Zawacki-Richter et al. (2019) showed that AI research in higher education focused principally on learner profiling and prediction, assessment, adaptive systems, and intelligent tutoring. Chiu et al. (2023) further summarized the roles of AI in education across learning, teaching, assessment, and educational administration.

Large language models have transformed the interaction mode of educational AI. These tools can interpret open-ended natural-language prompts and generate explanations, summaries, examples, feedback, code, and problem solutions through multi-turn dialogue. Compared with specialized systems with relatively fixed functions, conversational AI tools cover a wider range of tasks, respond faster, present lower interaction barriers, and generate content more flexibly, making them easier to incorporate into everyday learning.

This study defines a 'conversational AI learning support tool' as a general-purpose digital tool based on generative AI or a large language model that can sustain natural-language interaction and provide explanations, summaries, writing feedback, problem-solving, coding support, or other assistance for coursework. The definition emphasizes generativity, conversational interaction, and learning support. It is not limited to a single brand and does not directly include search engines, traditional question banks, or rule-based chatbots.

2.1.2 Learning Value and Risk Conditions in Higher Education

Research on generative AI in education clearly presents both opportunities and risks. Lo (2023) found that tools such as ChatGPT could support virtual tutoring, learning-material generation, language assistance, and collaborative learning, but could also produce misinformation, fabricated citations, and ways to circumvent academic assessment. Kasneci et al. (2023) noted

that large language models could improve personalized feedback and access to learning resources while posing risks related to bias, factual errors, privacy, and assessment validity.

Students' judgments of generative AI are therefore neither purely positive acceptance nor simple rejection. Chan and Hu (2023) found that university students recognized the value of generative AI for personalized learning, writing support, and brainstorming while also worrying about information accuracy, privacy, ethics, and personal development. Tlili et al. (2023) similarly showed that educational value is intertwined with content quality, emotional experience, and ethical concerns.

This dual context directly shapes students' willingness to continue using AI tools. Rapid feedback and low-barrier interaction may foster positive attitudes, whereas uncertainty in outputs may reduce trust or cause tension and unease. Course rules, teacher attitudes, and peer evaluations may create social norms, while access, verification skills, and autonomy may affect perceived behavioral control. Continuance is therefore not simply a question of usefulness, but a behavioral decision involving personal evaluation, social support, self-control, trust in the tool, and emotional response.

2.1.3 Chinese Universities and the Continuance Context of Existing Users

Chinese university students encounter different learning tasks, tool-access conditions, and academic-integrity expectations. Liu and Zhang (2024) identified external environment, technological revolution, user experience, and cognitive-emotional aspects in students' accounts of ChatGPT use. Their qualitative findings provide contextual categories for the present research rather than numerical estimates of the effects of individual TPB variables.

Generative-AI research must also distinguish initial adoption from continuance. Initial adoption reflects whether a person is willing to try a technology without much direct experience; continuance follows actual experience and concerns whether the person plans to keep using it. Bhattacherjee (2001) identified information-systems continuance as a stage distinct from initial acceptance. Existing users can draw on output quality, convenience, emotional experience, and practical constraints encountered in previous use.

All respondents in this study had experience using conversational AI for learning. The study therefore does not examine whether students will try AI for the first time, but whether they plan to continue using the selected tool during the next three months. The outcome is accordingly defined as continuance intention. Taken together, this context calls for a behavioral theory capable of explaining personal evaluation, social norms, and behavioral control, supplemented by

trust and anxiety to address the uncertainty and emotional characteristics of AI tools. The Theory of Planned Behavior provides the parent theoretical foundation, while AI trust, AI anxiety, and information-systems continuance research constitute the fields directly related to the study variables.

2.2 Theory of Planned Behavior

2.2.1 Basic Logic of the Theory of Planned Behavior

The Theory of Planned Behavior proposes that behavioral intention is an important proximal predictor of actual behavior and is jointly shaped by attitude, subjective norm, and perceived behavioral control (Ajzen, 1991). Attitude reflects a person's positive or negative evaluation of performing the target behavior; subjective norm reflects important others' support for or opposition to the behavior; and perceived behavioral control reflects the person's judgment of the capabilities, resources, opportunities, and autonomy required to perform it.

The theory emphasizes compatibility in behavioral measurement: attitude, subjective norm, perceived behavioral control, and behavioral intention should refer to the same behavioral target, context, and time frame (Ajzen, n.d.). When variables refer to inconsistent behavioral scopes, their statistical relationships may be affected by differences in measurement framing. In this study, all four TPB variables refer to the same target behavior: 'continuing to use the selected conversational AI learning support tool for coursework during the next three months.' This common anchor reduces inconsistency in behavioral object and time frame across constructs.

This study examines continuance intention only and does not include actual behavior in the theoretical model. Usage frequency during the preceding month is used to describe the sample and control for prior-use differences; it is not treated as an outcome predicted by future continuance intention. The study therefore examines conditional relationships between proximal TPB variables and continuance intention, rather than the complete intention-behavior process.

2.2.2 Attitude

Attitude is a person's overall positive or negative evaluation of performing a specific behavior (Ajzen, 1991). In the AI-learning context, attitude is not merely an assessment of whether the tool is advanced, convenient, or effective; it is an evaluation of whether continuing to use the tool for coursework is valuable, wise, and generally good or bad. To preserve construct boundaries, this study limits attitude to the overall evaluation of continuance behavior and does not directly use statements such as 'improves efficiency,' 'raises grades,' or 'provides accurate answers.' Such

considerations may influence attitude but are not equivalent to attitude itself. The more positive a student's evaluation of continued AI use, the stronger the expected continuance intention.

2.2.3 Subjective Norm

Subjective norm is a person's perception of whether important others think the person should perform a behavior; it represents social support or pressure (Ajzen, 1991, n.d.). In higher education, important others may include instructors, classmates, supervisors, and other people who influence learning decisions. This study limits subjective norm to whether people who matter to the student's learning support and approve of continued AI use. It does not combine peers' actual use, institutional rules, and course policies within the same scale. Greater perceived support from important others is expected to be associated with stronger continuance intention.

2.2.4 Perceived Behavioral Control

Perceived behavioral control is a person's subjective judgment of the capabilities, resources, opportunities, and autonomy required to perform a target behavior (Ajzen, 1991, n.d.). Effective use of conversational AI requires not only basic operating skills but also stable internet access, suitable devices, tool access, and the capacity to verify and integrate outputs. Research on computer self-efficacy indicates that people's judgments of their technical capabilities influence technology-use decisions (Compeau & Higgins, 1995). In this study, perceived behavioral control includes whether students believe they have the capabilities and resources to continue using the tool and can decide autonomously whether to do so. Stronger perceived capability, access, and autonomy are expected to be associated with stronger continuance intention.

2.3 Construct Definitions

2.3.1 Continuance Intention

Continuance intention concerns a person’s intention to keep using a technology after prior experience. Bhattacherjee (2001) distinguished continuance from initial acceptance. In generative-AI research, Tan et al. (2024) linked habit, facilitating conditions, hedonic motivation, and satisfaction with continuance, and Yu et al. (2024) examined usefulness, ease of use, and satisfaction. Duong et al. (2024) investigated information and service quality in relation to trust, satisfaction, and continuance. The constructs and pathways differ across these studies and are not interchangeable with the TPB variables measured here.

This study operationally defines continuance intention as a student's intention, plan, and expectation to continue using the selected conversational AI tool for coursework during the next

three months. Usage frequency and length of experience are treated only as sample characteristics and control variables; they do not replace continuance intention.

2.3.2 Core TPB Variables and Continuance Intention

Attitude represents a student's overall evaluation of continuance behavior. A positive attitude means that the student regards continued AI use as a valuable, wise, and generally favorable choice. Under the Theory of Planned Behavior, a positive evaluation increases willingness to perform the behavior. The more positive the attitude toward continued AI use, the stronger the expected continuance intention.

Subjective norm reflects the support for continuance that students perceive from important others. In higher education, evaluations by instructors, classmates, and supervisors may provide behavioral reference points. When students believe that important others support their appropriate use of AI tools, continued use may be seen as a more acceptable learning behavior, thereby strengthening continuance intention.

Perceived behavioral control reflects whether students possess the capabilities, resources, and autonomy needed for continued use. Even when students value an AI tool and receive social support, lack of access, operating capability or decision-making autonomy may constrain continuance intention. Conversely, stronger capability beliefs and resource availability can increase the perceived feasibility of continued use.

2.3.3 AI Trust and Its Pathways

Trust can guide reliance on automation when users cannot fully evaluate a complex system (Lee & See, 2004). Jian et al. (2000) developed an empirical questionnaire for trust in automated systems. In a different setting, Gefen et al. (2003) integrated trust in an online vendor with technology-acceptance beliefs to explain intended online shopping behavior. These studies provide conceptual background; they do not by themselves validate a four-item conversational-AI learning scale or establish a direct effect on students' continuance intention.

Students using conversational AI must judge the dependability of outputs that may contain errors. Shahzad et al. (2024) examined trust as a moderator of awareness-related technology perceptions in ChatGPT adoption. Duong et al. (2024) found relationships of information and service quality with trust, satisfaction, and continuance intention. These findings make trust relevant to the present research, but neither study directly tests the specific trust–attitude–continuance pathway proposed here.

AI trust is defined here as a student's judgment of whether the selected conversational AI tool is reliable, dependable, predictable, and generally trustworthy for coursework. AI trust does not imply unconditional acceptance of outputs or the abandonment of verification.

AI trust may be related to continuance intention through two pathways. First, the more students believe that a tool provides relatively reliable and stable learning support, the stronger their willingness to continue using it may be. Second, reliable experience may foster a more positive evaluation of continuance, creating a statistical indirect relationship through attitude. AI trust principally evaluates the tool's capability and reliability, whereas perceived behavioral control evaluates the student's own capabilities, resources, and autonomy. To preserve construct distinctiveness, the model does not specify a path from AI trust to continuance intention through perceived behavioral control.

2.3.4 AI Anxiety and Its Pathways

AI anxiety is operationalized here as tension, unease, anxiety, or discomfort associated with actual or anticipated coursework use of the selected tool. Wang and Wang (2022) developed a 21-item, four-dimensional AI Anxiety Scale covering learning, job replacement, sociotechnical blindness, and AI configuration. That instrument provides conceptual background, but its validation does not transfer automatically to the present four-item, task-specific adaptation.

Anxiety in generative-AI learning may arise from unfamiliarity with operations, uncertainty about one's capabilities, or concern about the consequences of outputs. To avoid conceptual overlap with trust, academic integrity, and perceived behavioral control, however, this study measures only tension, unease, anxiety, and discomfort while using the selected tool for coursework. Judgments about accuracy, dependence, misconduct consequences, and resource conditions are not included in the AI-anxiety scale.

Negative associations between AI anxiety, positive attitudes toward AI, and generative-AI acceptance were reported by Cengiz and Peker (2025). Their cross-sectional model concerns broad AI anxiety and acceptance and does not establish that anxiety temporally causes a decline in attitude or continuance. In the present study, negative relationships with continuance, attitude, and perceived control are theoretical expectations to be examined, rather than findings already demonstrated for the present four-item scale. The proposed link with perceived behavioral control is an extension requiring its own empirical assessment.

Relationships involving anxiety should also be interpreted in context. Budhathoki et al. (2024) reported different anxiety-related results in UK and Nepalese university samples. Avcı (2026)

examined demographics, creative mindsets, anxiety, and attitudes in generative-AI acceptance and reported positive attitudes and creative mindsets among the significant predictors. These findings do not establish a universal anxiety effect or an anxiety-related moderation mechanism. Wang et al. (2025) identified an English-learning profile combining high engagement and high anxiety. These studies motivate contextual caution rather than a universal negative-effect assumption.

2.3.5 Coexistence and Construct Boundaries of AI Trust and AI Anxiety

AI trust and AI anxiety may be negatively correlated, but they are not simple opposites. AI trust asks whether a tool is reliable, dependable, and predictable; AI anxiety asks whether using the tool causes tension or unease. A student may trust an AI tool for general concept explanation while feeling anxious about using it for thesis writing, examinations, or tasks involving sensitive data.

Chan and Hu (2023) reported that students recognized potential learning benefits while expressing concerns about accuracy, privacy, and ethics. Such concerns are not identical to a validated anxiety score or a measure of trust. Zhu et al. (2025) investigated ethical awareness, perceived ethical risks, and ethical anxiety within an extended adoption model; ethical anxiety differs from the task-specific emotional response measured here. Treating trust and anxiety as parallel antecedents is therefore a modeling choice in the present study, not a result established by those papers. No directional relationship between the two is assumed.

2.3.6 Synthesis of Prior Research and Research Gaps

Reviews discuss potential educational uses of generative AI alongside risks involving accuracy, privacy, overreliance, and academic integrity (Kasneci et al., 2023; Lo, 2023). These reviews do not demonstrate uniform learning benefits. For the present research, it is also important to distinguish initial acceptance from continuance among existing users, as emphasized in information-systems continuance theory (Bhattacherjee, 2001).

A further concern in the present design is the semantic proximity of positively worded measures. Judgments that a tool is trustworthy, that continued use is positive, that continued use is feasible, and that one intends to continue may share an overall evaluative tendency. This is a measurement risk to investigate in the current data, rather than evidence that prior studies necessarily used identical or invalid items.

The present model considers trust and anxiety together without assigning a causal direction between them. Contextual variation in anxiety-related findings (Budhathoki et al., 2024) and the

EFL profile reported by Wang et al. (2025) justify examining zero-order relationships and sensitivity to controls. Their results do not establish that the same processes hold across all tools, courses, or student populations.

Table 1 Representative Literature and the Positioning of This Study

Representative Literature	Study Type/Participants	Main Conclusion	Implication for This Study
Zawacki-Richter et al. (2019)	Review of AI systems in higher education	Applications centered on prediction, assessment, adaptation, and tutoring; educators' perspectives were underrepresented	Establishes the background of AIEd evolution
Chiu et al. (2023)	Systematic review of AIEd systems, 2012-2021	Synthesized opportunities and challenges in learning, teaching, assessment, and administration	Shows the coexistence of educational value and risk
Lo (2023)	Rapid review of ChatGPT in education	Virtual tutoring and material support coexist with misinformation and assessment risks	Supports the tool boundaries and risk rationale
Kasneci et al. (2023)	Position paper on large language models in education	Personalized support and feedback alongside bias, hallucination, and privacy risks	Provides contextual rationale for considering benefits and risks; does not test the present paths
Chan & Hu (2023)	Study of higher education students	Students recognized benefits while worrying about accuracy, privacy, ethics, and development	Provides evidence of perceived benefits and concerns, not direct validation of trust–anxiety mechanisms
Bhattacherjee (2001)	Information-systems continuance research	Distinguished initial adoption from continuance intention among existing users	Supports the population and reframing of the outcome
Liu & Zhang (2024)	Grounded-theory study of Chinese university students	Identified external environment, technological revolution, user experience, and cognitive-emotional aspects	Reinforces the need for the Chinese context

Wang & Wang (2022)	Development and validation of an AI-anxiety scale	Developed a 21-item, four-dimensional AI-anxiety scale	Conceptual basis for an adaptation; does not validate the present four-item scale
Tan et al. (2024)	Continuance study of Malaysian university students	Satisfaction, habit, and facilitating conditions helped explain ChatGPT continuance intention	Adds recent evidence from the continuance stage
Duong et al. (2024)	Continuance study of Vietnamese university students	Information and service quality were related to trust, satisfaction, and continuance	Contextual evidence on quality and trust; not a test of the present attitude-mediated pathway
Budhathoki et al. (2024)	Cross-national study of UK and Nepalese students	The role of AI anxiety varied across higher education contexts	Supports testing ANX sensitivity to model and context
Yu et al. (2024)	Study of university ChatGPT users	User satisfaction was an important correlate of continuance intention	Reinforces the distinction between initial adoption and continuance
Wang et al. (2025)	Latent-profile study of Chinese university students using LLMs for EFL learning	Identified a user profile combining high engagement with high anxiety	Illustrates profile heterogeneity; does not validate an ambivalence construct in the present sample

In response to these gaps, the study does not simply add more predictors. Instead, it seeks to define the boundaries of six constructs under a common behavioral anchor, examine the relationships of proximal TPB variables, AI trust, and AI anxiety with continuance intention, and cautiously analyze specified statistical indirect pathways.

2.4 Theoretical Model and Research Hypotheses

2.4.1 Theoretical Model

Continuance intention is the outcome of the research model. Attitude, subjective norm, and perceived behavioral control are the proximal TPB variables and each is directly related to continuance intention. AI trust and AI anxiety enter the model as distal variables reflecting characteristics of the generative-AI context.

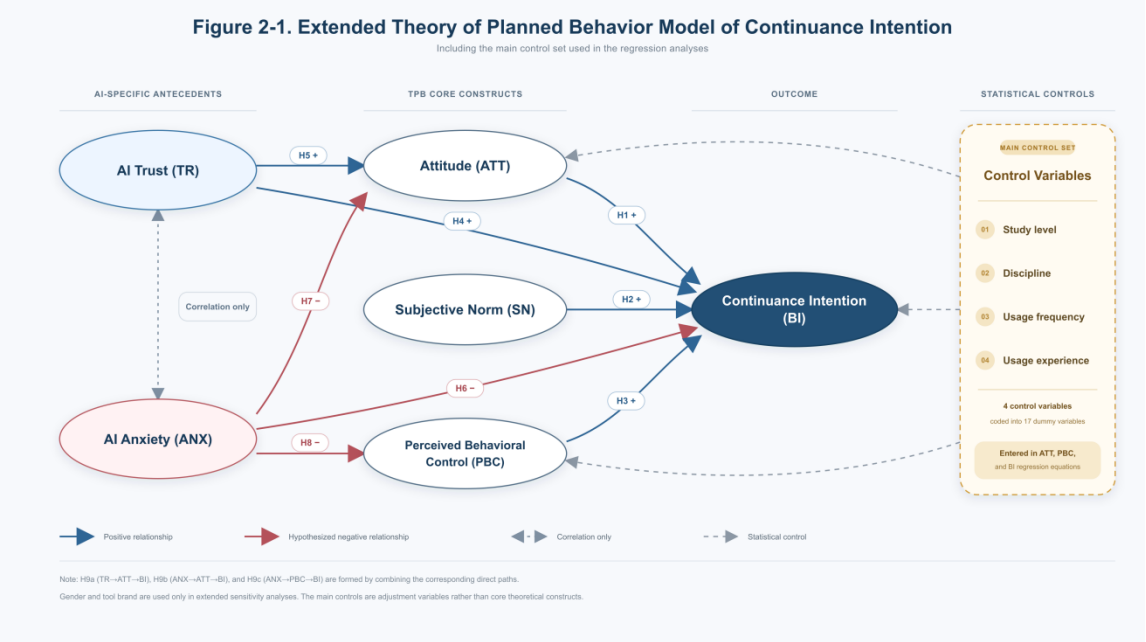
Two direct paths are specified for AI trust: its relationship with continuance intention and its relationship with attitude. A statistical indirect path from AI trust to continuance intention

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through attitude is also specified. AI anxiety is related directly to continuance intention, attitude, and perceived behavioral control, with two statistical indirect paths to continuance intention through attitude and perceived behavioral control. AI trust and AI anxiety are allowed to correlate, but no directional causal path or interaction hypothesis is specified between them.

Educational level, academic discipline, usage frequency, and usage experience are included as control variables in the empirical analyses and are not core constructs in the theoretical model.

Figure 1 Extended Theory of Planned Behavior Research Model



Solid lines represent the theorized direct relationships. Combined paths from AI trust or AI anxiety through attitude or perceived behavioral control to continuance intention constitute specified statistical indirect relationships. AI trust and AI anxiety are connected by a correlational line with no directional path.

2.4.2 Research Hypotheses

According to the Theory of Planned Behavior, the more positively a person evaluates a target behavior, the stronger the intention to perform it. Therefore:

H1: Attitude is positively related to Chinese university students' continuance intention to use conversational AI learning support tools.

Support from important others can increase the social acceptability of a target behavior. Therefore:

H2: Subjective norm is positively related to Chinese university students' continuance intention to use conversational AI learning support tools.

The more students believe they possess the capabilities, resources, and autonomy required for continued use, the more likely they are to form continuance plans. Therefore:

H3: Perceived behavioral control is positively related to Chinese university students' continuance intention to use conversational AI learning support tools.

Greater AI trust can reduce uncertainty about tool outputs and increase willingness to continue use. Therefore:

H4: AI trust is positively related to Chinese university students' continuance intention to use conversational AI learning support tools.

Reliable and predictable tool experiences may promote a more positive evaluation of continued use. Therefore:

H5: AI trust is positively related to Chinese university students' attitude toward continuing to use conversational AI learning support tools.

Tension and unease while using AI may lead students to avoid or reduce future use. Therefore:

H6: AI anxiety is negatively related to Chinese university students' continuance intention to use conversational AI learning support tools.

Negative emotional experiences may lower students' overall evaluation of continuance. Therefore:

H7: AI anxiety is negatively related to Chinese university students' attitude toward continuing to use conversational AI learning support tools.

AI anxiety may weaken students' judgments of their operating capability and control over the use process. Therefore:

H8: AI anxiety is negatively related to Chinese university students' perceived behavioral control over continuing to use conversational AI learning support tools.

AI trust may also be indirectly related to continuance intention by improving students' overall evaluation of continued use. Therefore:

H9a: AI trust has a positive statistical indirect relationship with continuance intention through attitude.

AI anxiety may be indirectly related to continuance intention by lowering the overall evaluation of continued use. Therefore:

H9b: AI anxiety has a negative statistical indirect relationship with continuance intention through attitude.

AI anxiety may also be indirectly related to continuance intention by weakening judgments of capability, resources, and autonomy. Therefore:

H9c: AI anxiety has a negative statistical indirect relationship with continuance intention through perceived behavioral control.

Table 2 Summary of Research Hypotheses

Hypothesis	Relationship	Expected Direction
H1	Attitude -> continuance intention	Positive
H2	Subjective norm -> continuance intention	Positive
H3	Perceived behavioral control -> continuance intention	Positive
H4	AI trust -> continuance intention	Positive
H5	AI trust -> attitude	Positive
H6	AI anxiety -> continuance intention	Negative
H7	AI anxiety -> attitude	Negative
H8	AI anxiety -> perceived behavioral control	Negative
H9a	AI trust -> attitude -> continuance intention	Positive indirect effect
H9b	AI anxiety -> attitude -> continuance intention	Negative indirect effect
H9c	AI anxiety -> perceived behavioral control -> continuance intention	Negative indirect effect

3 Research Methodology

3.1 Research Design

This study employed a quantitative, cross-sectional design and collected individual-level self-report data through an online questionnaire. The analytic population comprised currently enrolled Chinese university students who reported experience using conversational AI learning support tools. Mean scale scores for TR, ANX, ATT, SN, PBC, and BI were subjected to uniform quality screening, descriptive statistics, Cronbach's alpha, Pearson zero-order correlations, HTMT diagnostics, hierarchical multiple regression in SPSS, and 5,000 bootstrap replications. The conclusions are jointly constrained by nonprobability sampling, cross-sectional design, common-source measurement, and limited discriminant validity.

3.2 Research Instrument and Measurement

3.2.1 Questionnaire Structure and Response Anchor

The questionnaire comprised four parts: informed consent and screening, demographic information, tool anchoring, and formal measurement items. Respondents first confirmed that they were full-time students enrolled at a Chinese university and had used at least one

conversational AI tool for a learning task during the preceding three months. Those who did not meet the criteria exited the survey. Eligible respondents selected the one tool used most often for learning during that period, and all subsequent items referred to the selected tool.This study used a five-point scale to measure six core variables. AI trust, AI anxiety, subjective norms, perceived behavioral control, and intention to continue use were measured using a five-point Likert agreement scale, with scores ranging from 1 to 5, representing "strongly disagree," "disagree," "neutral," "agree," and "strongly agree," respectively. Attitude variables were measured using a five-point bipolar rating scale based on the measurement principles of the Theory of Planned Behavior (Ajzen, n.d.). All items were uniformly coded from 1 to 5, and the average score for each item was calculated as the scale score for the corresponding variable; higher scores indicated a higher level of agreement with the corresponding construct. For example, a higher AI anxiety score indicated a higher level of anxiety about use, while a higher attitude score indicated a more positive overall evaluation of continued use behavior.

The formal measurement section contained 23 items: four for AI trust, four for AI anxiety, four for attitude, four for subjective norm, four for perceived behavioral control, and three for continuance intention. Attitude used five-point bipolar semantic differentials; all other items used five-point Likert scales (1 = strongly disagree, 5 = strongly agree). A demographic item measured actual usage frequency during the preceding month for screening, description, and prespecified control, not as the outcome. Sources, original item meanings, and contextual adaptations are documented in Appendix B of the Supplementary Materials.

3.2.2 Operationalization of Variables

Table 3 Variable Definitions and Measurement Structure

Variable	Operational Definition	Items	Conceptual and Adaptation Sources
AI trust (TR)	Judgments of the anchored tool's reliability, dependability, predictability, and overall trustworthiness	4	Jian et al. (2000); study-specific contextual adaptation
AI anxiety (ANX)	Tension, unease, anxiety, and discomfort when using the anchored tool for coursework	4	Wang & Wang (2022); study-specific contextual adaptation
Attitude (ATT)	Overall evaluation of continuing to use the anchored tool during the next three months	4	Ajzen (1991, n.d.)

Subjective norm (SN)	Support and approval from important others for continuing to use the anchored tool during the next three months	4	Ajzen (1991, n.d.)
Perceived behavioral control (PBC)	Judgment of the capabilities, resources, and autonomy required for continued use	4	Ajzen (1991, n.d.); Compeau & Higgins (1995)
Continuance intention (BI)	Intention, plan, and expectation to continue using the anchored tool during the next three months	3	Ajzen (n.d.); Bhattacherjee (2001)

3.2.3 Questionnaire Adaptation and Measurement Diagnostics

The questionnaire uses context-specific wording and a shared target behavior. The TPB questionnaire guide provides measurement principles and examples rather than a validated questionnaire for conversational-AI continuance (Ajzen, n.d.). Trust and anxiety items were treated as study-specific adaptations informed by earlier conceptual work, rather than verbatim reproductions of complete validated instruments (Jian et al., 2000; Wang & Wang, 2022). Appendix B distinguishes conceptual sources from wording developed for this study. Independent content validation and pilot confirmation were not documented; measurement evidence is therefore limited to the diagnostics reported for the current sample.

3.3 Sample and Data Collection

3.3.1 Target Population and Inclusion Criteria

The target population consisted of full-time undergraduate and graduate students enrolled at regular higher education institutions in China. Inclusion criteria were: at least 18 years of age; current full-time enrollment; at least three uses of conversational AI for coursework during the preceding three months; and voluntary informed consent. The questionnaire collected no directly identifying personal information.

3.3.2 Sample Size and Group Coverage

The achieved analytic sample comprised 428 complete responses. Sample-size planning for regression can use explicit assumptions about effect size, significance level, statistical power, and the predictor set (Faul et al., 2009). A reproducible a priori calculation with these inputs is not reported here, so the sample is not presented as meeting a verified power target. Sample size also cannot compensate for nonprobability sampling or limited measurement distinctiveness.

The sample included students across educational levels and disciplines: 322 undergraduates (75.2%) and 106 graduate students (24.8%), with representation from science and engineering, business and management, humanities and social sciences, arts, and other fields. These variables were used for sample description and regression control; no post hoc multigroup comparisons were conducted. Because the questionnaire did not collect university names or locations, no unsupported claim is made about the number of institutions or regional quotas.

3.3.3 Sampling and Administration

A nonprobability sample was collected through the Wenjuanxing online platform. The questionnaire link was disseminated mainly through WeChat, including personal social networks and student-group forwarding. It contained three eligibility screens, and all formal scale items were required. Because participation was voluntary and recruitment relied on WeChat networks, the sample may be affected by convenience sampling, network homogeneity, and self-selection and cannot automatically represent all Chinese university students.

3.4 Data Analysis Procedures

3.4.1 Data Cleaning and Descriptive Statistics

All 428 responses were checked consistently for eligibility, missing core items, values outside the 1-5 range, completion duration, uniform responses across all items, runs of 15 or more identical responses, duplicate 23-item vectors, and duplicate IP addresses. All three eligibility indicators equaled 1; the 23 core items had no missing or out-of-range values. Completion time ranged from 160 to 516 seconds, with a median of 391.5 seconds, and none of the remaining rules was triggered. Because no verifiable ex ante time threshold existed, duration was described but not used for retrospective exclusion. The final analytic sample was 428.

3.4.2 Exploratory Diagnosis of Common Method Bias

The questionnaire used a single self-report source at one time point. The first principal component of the 23-item correlation matrix explained 40.02% of the variance. This single-component diagnostic is insufficient to rule out common method bias. Possible method effects must instead be considered alongside the questionnaire design, item wording, and construct-overlap diagnostics (Podsakoff et al., 2003).

3.4.3 Internal Consistency and Item Diagnostics

Cronbach's alpha, corrected item-total correlations, and alpha-if-item-deleted were calculated for all six scales. Alpha reflects internal consistency but is not evidence of unidimensionality or structural validity. Because no independent pilot sample was available, these results are not described as a pilot EFA, and items were not mechanically deleted on the basis of the same sample.

3.4.4 Zero-Order Correlations and HTMT Diagnostics

HTMT was used as a diagnostic of scale distinctiveness (Henseler et al., 2015). When most pairs of positively worded constructs exceeded .90, subsequent regressions were interpreted as conditional relationships among highly overlapping scale scores; the latent-variable structure was not treated as validated.

3.4.5 Hierarchical Regression, Robustness Regression, and Statistical Indirect Effects

Data were analyzed in SPSS. TR, ANX, ATT, SN, and PBC were calculated as arithmetic means of four items, and BI as the mean of three items. ANX1-ANX4 were scored directly from 1 to 5 and were not reverse-coded. Before testing the principal results, educational level, discipline, usage frequency, and usage experience were prespecified as controls: educational level and discipline may correspond to different course tasks and rule environments, while usage frequency and experience may be related to familiarity, trust, anxiety, and continuance judgments. With category 1 as the reference, 17 dummy variables were created and retained as a common control set in the primary models rather than selected post hoc by significance. Hierarchical and multiple regressions used ordinary least squares and reported B, standard error, standardized beta, t, p, 95% confidence intervals, R-squared, adjusted R-squared, and VIF. The three statistical indirect effects used 5,000 nonparametric bootstrap replications with bias-corrected 95% intervals. Bootstrap estimation of statistical indirect relationships follows the methodological approach discussed by Preacher and Hayes (2008). Resampling does not establish temporal ordering; cross-sectional indirect estimates should not be equated with longitudinal mediation (Maxwell & Cole, 2007).

4 Results

The data came from a raw Wenjuanxing export containing 428 complete responses. All three eligibility-screening indicators equaled 1. The 428 responses were analyzed once under a common set of rules and were not divided by collection stage.

4.1 Descriptive Analysis

4.1.1 Data-Quality Screening

As shown in Table 4, the 23 core scale items had no missing values and all fell within the 1-5 range. Completion time ranged from 160 to 516 seconds, with a median of 391.5 seconds. No response was uniform across all 23 items; no run of 15 or more identical answers, completely duplicate item vector, or duplicate IP address was found. Because no verifiable ex ante duration threshold existed, time was descriptive only. The uniform review excluded no responses, leaving N = 428; this does not prove that the sample source was unbiased.

Table 4 Uniform Sample Quality-Screening Results

Screening Item	Decision Rule/Statistic	Result	Action
Eligibility screening	All three conditions passed	428/428	Retained
Core-item completeness	No missing values in 23 items	428/428	Retained
Scale range	All within 1-5	428/428	Retained
Completion duration	160-516 seconds; median 391.5 seconds	Descriptive only	No ex ante threshold; no exclusion
Uniform responses	All 23 items identical	0	No exclusion
Long identical run	15 or more consecutive identical responses	0	No exclusion
Completely duplicate pattern	Identical 23-item answer vectors	0 groups	No exclusion
Duplicate IP	Multiple responses from the same IP	0 groups	No exclusion

Note: The same rules were applied to all 428 responses; the main analysis did not divide the sample by stage.

4.1.2 Sample Characteristics

The sample included 197 men (46.0%), 195 women (45.6%), and 36 respondents (8.4%) who selected another gender or preferred not to disclose. Undergraduates predominated (n = 322, 75.2%), while graduate students numbered 106 (24.8%). Disciplines included science and engineering, business and management, humanities and social sciences, arts, and other fields. The most frequently used tools were Doubao (24.8%), DeepSeek (21.0%), ERNIE Bot (19.6%), ChatGPT (16.8%), Kimi (13.6%), and other tools (4.2%). Respondents who had used the selected tool at least eight times during the previous month accounted for 57.9%, and those with at least seven months of experience accounted for 57.0%, indicating substantial prior use in the sample.

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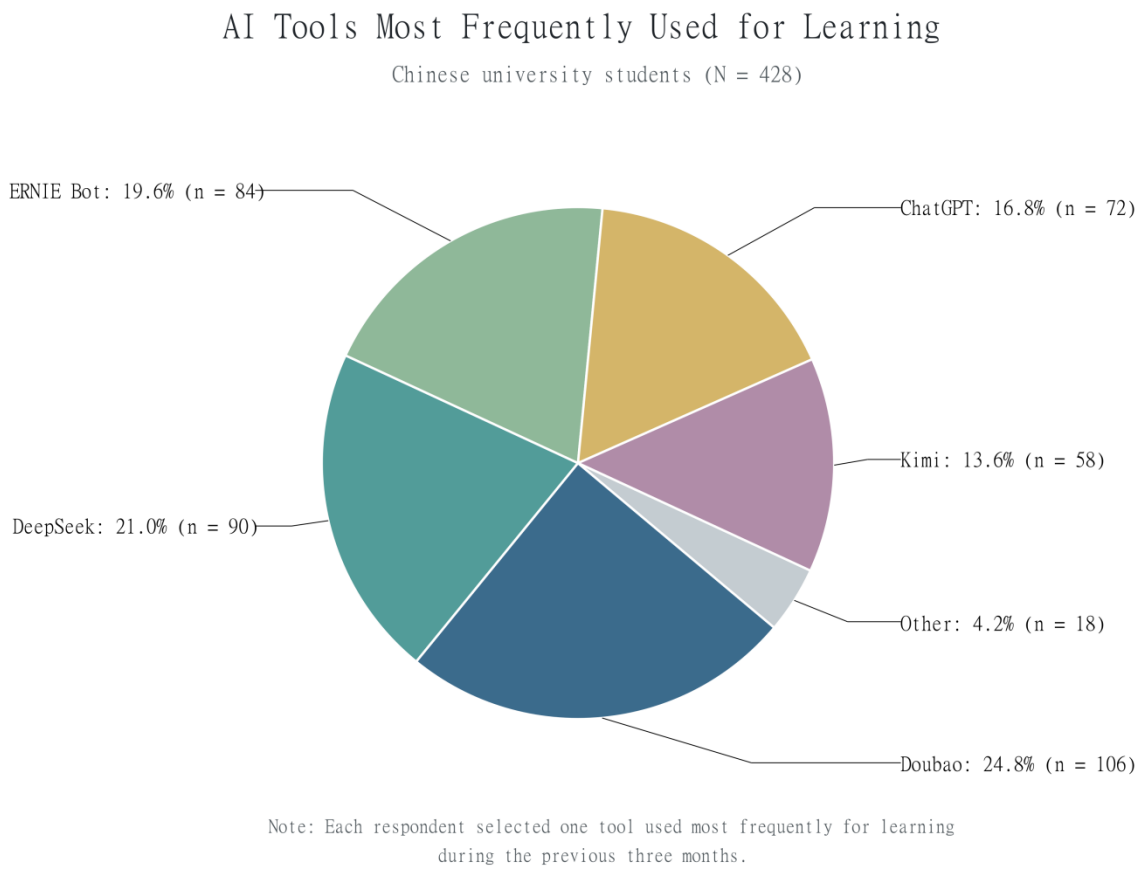


Figure 2 AI Tools Most Frequently Used for Learning (N = 428)

Table 5 Sample Characteristics (N = 428)

Variable	Category	n	Percentage (%)
Gender	Male	197	46.0
	Female	195	45.6
	Other/Prefer not to disclose	36	8.4
Educational level	Undergraduate	322	75.2
	Graduate student	106	24.8
Discipline	Science and engineering	133	31.1
	Business and management	103	24.1
	Humanities and social sciences	110	25.7
	Arts	49	11.4
	Other	33	7.7
Most frequently used tool	ChatGPT	72	16.8
	DeepSeek	90	21.0
	ERNIE Bot	84	19.6
	Doubao	106	24.8
	Kimi	58	13.6
	Other	18	4.2

Frequency during past month	Less than once	31	7.2
	1-3 times	47	11.0
	4-7 times	102	23.8
	8-15 times	126	29.4
	16 times or more	122	28.5
Usage experience	Less than 1 month	27	6.3
	1-3 months	59	13.8
	4-6 months	98	22.9
	7-12 months	123	28.7
	More than 1 year	121	28.3

Note: The two nonbinary codes in the export were combined as 'other/prefer not to disclose.' Percentages may not sum to 100% because of rounding.

4.1.3 Descriptive Statistics and Internal Consistency

Table 6 presents the six scale means. PBC had the highest mean (M = 3.576) and ANX the lowest (M = 2.425). Absolute skewness did not exceed 0.647 and absolute excess kurtosis did not exceed 0.872. Cronbach's alpha ranged from 0.742 to 0.775 for TR, ANX, ATT, SN, and PBC; alpha for BI was 0.695, slightly below .70. Corrected item-total correlations for the three BI items ranged from 0.463 to 0.537, and alpha if an item was deleted ranged from 0.568 to 0.661; no item was mechanically removed post hoc.

Table 6 Construct Descriptive Statistics and Internal Consistency

Construct	Items	M	SD	Skewness	Excess kurtosis	α
TR	4	3.459	0.944	-0.480	-0.491	0.759
ANX	4	2.425	0.956	0.325	-0.872	0.745
ATT	4	3.480	0.927	-0.558	-0.350	0.742
SN	4	3.275	0.935	-0.280	-0.641	0.746
PBC	4	3.576	0.924	-0.647	-0.374	0.775
BI	3	3.502	0.963	-0.479	-0.606	0.695

Note: M = mean; SD = sample standard deviation; alpha = Cronbach's alpha. All scales are arithmetic means of their items. Alpha does not establish unidimensionality or discriminant validity.

4.2 Scale Diagnostics and Zero-Order Relationships

4.2.1 Diagnosis of Common Method Risk

The first principal component of the 23-item correlation matrix explained 40.02% of total variance. This descriptive result does not establish the absence of common method bias. The common source, uniformly positive wording of several measures, and high inter-scale correlations remain limitations to interpretation (Podsakoff et al., 2003).

4.2.2 Zero-Order Correlations among the Six Scales and Hierarchical ANX Diagnostics

Zero-order correlations among the six scales appear below the diagonal in Table 8. Correlations among TR, ATT, SN, PBC, and BI ranged from .704 to .772 (all $p < .001$), indicating substantial overlap among the positive scales. All zero-order correlations of ANX with TR, ATT, SN, PBC, and BI were positive ($r = .301$-$.427$, all $p < .001$), contrary to the prespecified negative relationships. Hierarchical regression showed further that ANX predicting ATT changed from beta = .332 to beta = .016 after controlling for TR and then to beta = -.088 after the 17 dummy controls were added. For PBC, ANX similarly changed from beta = .301 to beta = -.080. The negative sign depended on model specification.

Table 7 Hierarchical Regression and Sign Changes in ANX

Outcome	Model	Entered Variables	ANX β	p	R^2	ΔR^2
ATT	M 1	ANX	0.332	<0.001	0.110	0.110
ATT	M 2	+TR	0.016	0.643	0.583	0.473
ATT	M 3	+17 dummy control variables	-0.088	0.028	0.614	0.031
PBC	M 1	ANX	0.301	<0.001	0.091	0.091
PBC	M 2	+17 dummy control variables	-0.080	0.126	0.345	0.254
BI	M 1	ATT+SN+PBC	—	—	0.617	0.617
BI	M 2	+TR+ANX	-0.004	0.911	0.631	0.014
BI	M 3	+17 dummy control variables	-0.070	0.064	0.664	0.033

Note: Continuous variables were standardized. M3/M2 controlled for 17 dummy variables representing educational level, discipline, usage frequency, and usage experience. The negative ANX sign appeared only after controls were added and constitutes a conditional sign reversal.

4.2.3 HTMT and Scale-Distinctiveness Diagnostics

The upper triangle of Table 8 presents HTMT values calculated from item correlations. Ten of the 15 construct pairs exceeded .90, chiefly among TR, ATT, SN, PBC, and BI; TR-ATT, TR-SN, and ATT-SN all exceeded 1. HTMT between ANX and the other constructs ranged from .398 to .573 and indicated comparatively greater distinctiveness. These results do not validate the latent-variable structure; rather, they raise substantial concerns about discriminant validity among the five positive scales (Henseler et al., 2015).

Table 8 Zero-Order Correlations and HTMT Diagnostics

Construct	TR	ANX	ATT	SN	PBC	BI
TR	—	0.557	1.017	1.025	0.918	0.981
ANX	0.418	—	0.447	0.573	0.398	0.447
ATT	0.764	0.332	—	1.019	0.958	0.991
SN	0.772	0.427	0.759	—	0.946	0.994
PBC	0.704	0.301	0.727	0.719	—	0.968
BI	0.712	0.321	0.712	0.716	0.710	—

Note: The lower triangle contains Pearson correlations among scale means (all p < .001); the upper triangle contains HTMT. HTMT > .90 indicates inadequate discriminant validity.

4.2.4 Analytical Positioning and Subsequent Strategy

CFA or structural-equation-model results were not used to decide support for the hypotheses. Given the reproducible high correlations and HTMT values, the statistical conclusions are limited to cross-sectional relationships among scale scores in the sample of 428.

To answer the research questions, standardized regressions of scale means with control variables are reported below. Standard errors, two-tailed p values, and 95% confidence intervals follow conventional SPSS ordinary least squares output. The analyses show how coefficients change when the specified controls and other scale scores are held constant; they do not establish independent causal effects.

4.3 Exploratory Associations and Statistical Indirect Effects

4.3.1 Primary Robustness Regressions

The ATT equation simultaneously included TR, ANX, and 17 dummy controls and explained R-squared = .614 (adjusted R-squared = .596). TR had a significant positive relationship (beta = .614, p < .001). ANX had a weak negative relationship (beta = -.088, p = .028), but because this negative sign was absent both at the zero-order level and when only TR was controlled, it is interpreted as a model-dependent sign reversal. The PBC equation explained R-squared = .345 (adjusted R-squared = .316); ANX was beta = -.080 (p = .126) and did not reach the .05 significance level.

The BI equation simultaneously included ATT, SN, PBC, TR, ANX, and the 17 dummy controls and explained R-squared = .664 (adjusted R-squared = .646). ATT (beta = .159, p = .003), SN (beta = .172, p = .002), PBC (beta = .269, p < .001), and TR (beta = .161, p = .004) had significant positive relationships. ANX did not reach the .05 level (beta = -.070, p = .064). The maximum VIF among the five core predictors was 3.651. Because the scales were highly correlated, these coefficients represent conditional relationships after controlling for other variables, not independent causal effects.

Table 9 Composite-Score Regression Results for Direct Paths

Relationship	β	SE	t	p	95% CI	Conclusion
ATT→BI	0.159	0.053	3.037	0.003	[0.057, 0.262]	Significant positive
SN→BI	0.172	0.054	3.168	0.002	[0.066, 0.279]	Significant positive
PBC→BI	0.269	0.047	5.705	<0.001	[0.176, 0.361]	Significant positive
TR→BI	0.161	0.055	2.932	0.004	[0.053, 0.269]	Significant positive

ANX→BI	-0.07	0.038	-1.855	0.064	[-0.144, 0.004]	Weakly negative but not significant
TR→ATT	0.614	0.045	13.714	<0.001	[0.526, 0.702]	Significant positive
ANX→ATT	-0.088	0.04	-2.202	0.028	[-0.167, -0.010]	Significantly negative, but conditional sign reversal exists.
ANX→PBC	-0.08	0.052	-1.532	0.126	[-0.182, 0.022]	Negative but not significant

Note: Core continuous variables were standardized. With code 1 as the reference, 17 dummy variables represented educational level, discipline, frequency, and experience. Beta is the standardized conditional coefficient; standard errors and p values use the conventional SPSS OLS approach. Table 9 reports core terms; Tables 4-8 to 4-10 report all control coefficients.

4.3.2 Specified Indirect Effects

Across 5,000 bootstrap replications, the statistical indirect effect TR -> ATT -> BI was .098, with a bias-corrected 95% interval [.022, .181], consistent with the expected direction. ANX -> ATT -> BI was -.014, with interval [-.028, -.002]. However, the negative ANX -> ATT component appeared only after controls were added and became nonsignificant with expanded controls; therefore, a nonzero interval is not treated as evidence of a stable anxiety-mediation process. ANX -> PBC -> BI was -.021, with interval [-.051, .001], which included zero. The cross-sectional product terms do not establish temporal mediation.

Table 10 Bootstrapped Specified Indirect Effects

Indirect Path	Effect	Bootstrap SE	BC 95% CI	Conclusion
TR→ATT→BI	0.098	0.04	[0.022, 0.181]	Directionally consistent
ANX→ATT→BI	-0.014	0.009	[-0.028, -0.002]	Sign-dependent; not supported
ANX→PBC→BI	-0.021	0.013	[-0.051, 0.001]	Interval includes 0

Note: Bootstrap = 5,000; BC 95% CI = bias-corrected 95% confidence interval. A nonzero interval indicates only a detectable indirect product in the specified statistical model. Substantive support must also consider the component-path direction, theoretical interpretability, and robustness across control models.

4.3.3 Full Regressions and Sensitivity Analysis

Tables 4-8 to 4-10 report all coefficients. Control coefficients are adjustments and are not interpreted theoretically post hoc. When dummy variables for gender and tool brand were added in an expanded model, ANX -> ATT changed to beta = -.082 (p = .079), further demonstrating sensitivity of the negative relationship to the control set.

Table 11 Full Regression for ATT

Variable	B	SE	β	t	p	95% CI
Constant	-0.449	0.194	—	-2.322	0.021	[-0.829, -0.070]
TR	0.614	0.045	0.614	13.714	<0.001	[0.526, 0.702]
ANX	-0.088	0.04	-0.088	-2.202	0.028	[-0.167, -0.010]
Educational level: Undergraduate Year 2 (reference = Undergraduate Year 1)	0.109	0.099	0.045	1.105	0.270	[-0.085, 0.304]
Educational level: Undergraduate Year 3 (reference = Undergraduate Year 1)	0.140	0.106	0.056	1.330	0.184	[-0.067, 0.347]
Educational level: Undergraduate Year 4 or above (reference = Undergraduate Year 1)	0.304	0.124	0.106	2.447	0.015	[0.061, 0.548]
Educational level: Master's student (reference = Undergraduate Year 1)	0.228	0.114	0.088	2.002	0.046	[0.005, 0.452]
Educational level: Doctoral student (reference = Undergraduate Year 1)	0.221	0.154	0.055	1.434	0.152	[-0.081, 0.523]
Discipline: Business and management (reference = science and engineering)	0.117	0.09	0.05	1.308	0.191	[-0.058, 0.293]
Discipline: Humanities and social sciences (reference = science and engineering)	0.272	0.095	0.119	2.878	0.004	[0.087, 0.457]
Discipline: Arts (reference = science and engineering)	0.265	0.119	0.085	2.221	0.027	[0.031, 0.499]
Discipline: Other (reference = science and engineering)	0.282	0.137	0.075	2.060	0.040	[0.014, 0.550]
Usage frequency: 1—3 times (reference = less than once)	-0.097	0.151	-0.030	-0.640	0.522	[-0.393, 0.200]
Usage frequency: 4—7 times (reference = less than once)	0.096	0.140	0.041	0.686	0.493	[-0.179, 0.371]
Usage frequency: 8—15 times (reference = less than once)	0.089	0.144	0.041	0.618	0.537	[-0.193, 0.371]
Usage frequency: 16 times or more (reference = less than once)	0.137	0.154	0.062	0.889	0.374	[-0.165, 0.439]
Usage experience: 1—3 months (reference = less than 1 month)	-0.121	0.151	-0.042	-0.799	0.425	[-0.418, 0.176]

Usage experience: 4—6 months (reference = less than 1 month)	0.005	0.145	0.002	0.028	0.970	[-0.278, 0.289]
Usage experience: 7—12 months (reference = less than 1 month)	0.139	0.149	0.063	0.929	0.354	[-0.154, 0.431]
Usage experience: More than 1 year (reference = less than 1 month)	0.171	0.156	0.077	1.093	0.275	[-0.135, 0.477]

Note: Coefficients for continuous core variables are standardized conditional coefficients; dummy-variable coefficients represent standardized outcome differences relative to the reference group.

Table 12 Full Regression for PBC

Variable	B	SE	β	t	p	95% CI
Constant	-1.465	0.224	—	-6.54	<0.001	[-1.905, -1.026]
ANX	-0.080	0.052	-0.080	-1.532	0.126	[-0.182, 0.022]
Educational level: Undergraduate Year 2 (reference = Undergraduate Year 1)	0.090	0.128	0.028	0.706	0.480	[-0.161, 0.341]
Educational level: Undergraduate Year 3 (reference = Undergraduate Year 1)	0.230	0.135	0.091	1.701	0.090	[-0.035, 0.495]
Educational level: Undergraduate Year 4 or above (reference = Undergraduate Year 1)	0.419	0.156	0.146	2.689	0.007	[0.114, 0.725]
Educational level: Master's student (reference = Undergraduate Year 1)	0.405	0.144	0.157	2.809	0.005	[0.123, 0.688]
Educational level: Doctoral student (reference = Undergraduate Year 1)	0.249	0.197	0.062	1.266	0.206	[-0.136, 0.634]
Discipline: Business and management (reference = science and engineering)	0.380	0.114	0.163	3.336	<0.001	[0.157, 0.603]
Discipline: Humanities and social sciences (reference = science and engineering)	0.497	0.120	0.218	4.131	<0.001	[0.261, 0.733]
Discipline: Arts (reference = science and engineering)	0.670	0.152	0.213	4.415	<0.001	[0.372, 0.967]
Discipline: Other (reference = science and engineering)	0.717	0.174	0.191	4.130	<0.001	[0.377, 1.057]

Usage frequency: 1—3 times (reference = less than once)	0.237	0.195	0.064	1.214	0.225	[-0.146, 0.620]
Usage frequency: 4—7 times (reference = less than once)	0.360	0.177	0.154	2.038	0.042	[0.014, 0.707]
Usage frequency: 8—15 times (reference = less than once)	0.453	0.180	0.207	2.518	0.012	[0.100, 0.806]
Usage frequency: 16 times or more (reference = less than once)	0.651	0.189	0.294	3.455	<0.001	[0.282, 1.021]
Usage experience: 1—3 months (reference = less than 1 month)	0.008	0.197	0.003	0.038	0.969	[-0.378, 0.393]
Usage experience: 4—6 months (reference = less than 1 month)	0.346	0.188	0.146	1.845	0.066	[-0.022, 0.714]
Usage experience: 7—12 months (reference = less than 1 month)	0.631	0.192	0.286	3.287	0.001	[0.255, 1.008]
Usage experience: More than 1 year (reference = less than 1 month)	0.739	0.199	0.333	3.712	<0.001	[0.349, 1.130]

Note: Coefficients for continuous core variables are standardized conditional coefficients; dummy-variable coefficients represent standardized outcome differences relative to the reference group.

Table 13 Full Regression for BI

Variable	B	SE	β	t	p	95% CI
Constant	-0.216	0.185	—	-1.171	0.242	[-0.578, 0.146]
ATT	0.159	0.053	0.159	3.037	0.003	[0.057, 0.262]
SN	0.172	0.054	0.172	3.168	0.002	[0.066, 0.279]
PBC	0.269	0.047	0.269	5.705	<0.001	[0.176, 0.361]
TR	0.161	0.055	0.161	2.932	0.004	[0.053, 0.269]
ANX	-0.070	0.038	-0.070	-1.855	0.064	[-0.144, 0.004]
Educational level: Undergraduate Year 2 (reference = Undergraduate Year 1)	-0.113	0.093	-0.046	-1.214	0.225	[-0.295, 0.069]
Educational level: Undergraduate Year 3 (reference = Undergraduate Year 1)	-0.002	0.099	-0.001	-0.023	0.982	[-0.197, 0.192]
Educational level: Undergraduate Year 4 or above (reference = Undergraduate Year 1)	0.128	0.117	0.044	1.087	0.278	[-0.103, 0.358]

Educational level: Master's student (reference = Undergraduate Year 1)	0.177	0.107	0.068	1.646	0.101	[-0.034, 0.387]
Educational level: Doctoral student (reference = Undergraduate Year 1)	0.337	0.145	0.083	2.323	0.021	[0.053, 0.622]
Discipline: Business and management (reference = science and engineering)	0.123	0.126	0.053	1.459	0.145	[-0.042, 0.289]
Discipline: Humanities and social sciences (reference = science and engineering)	0.248	0.090	0.108	2.760	0.006	[0.072, 0.424]
Discipline: Arts (reference = science and engineering)	0.206	0.113	0.066	1.823	0.069	[-0.016, 0.428]
Discipline: Other (reference = science and engineering)	0.185	0.129	0.049	1.428	0.154	[-0.069, 0.438]
Usage frequency: 1—3 times (reference = less than once)	-0.194	0.142	-0.061	-1.373	0.170	[-0.472, 0.083]
Usage frequency: 4—7 times (reference = less than once)	-0.083	0.131	-0.036	-0.635	0.526	[-0.341, 0.174]
Usage frequency: 8—15 times (reference = less than once)	0.129	0.136	0.059	0.955	0.340	[-0.136, 0.395]
Usage frequency: 16 times or more (reference = less than once)	-0.006	0.145	-0.003	-0.042	0.966	[-0.291, 0.279]
Usage experience: 1—3 months (reference = less than 1 month)	-0.004	0.142	-0.002	-0.032	0.975	[-0.283, 0.274]
Usage experience: 4—6 months (reference = less than 1 month)	-0.023	0.137	-0.009	-0.165	0.869	[-0.290, 0.245]
Usage experience: 7—12 months (reference = less than 1 month)	0.087	0.141	0.039	0.617	0.537	[-0.189, 0.363]
Usage experience: More than 1 year (reference = less than 1 month)	0.080	0.148	0.036	0.538	0.591	[-0.210, 0.369]

Note: Coefficients for continuous core variables are standardized conditional coefficients; dummy-variable coefficients represent standardized outcome differences relative to the reference group.

4.3.4 Summary of Theoretical Expectations and Answers to the Research Questions

Table 14 Summary of Theoretical Expectations and Exploratory Results

Expectation	Relationship	Statistical Result	Interpretive Level
H1	ATT positively related to BI	Directionally consistent	Exploratory
H2	SN positively related to BI	Directionally consistent	Exploratory
H3	PBC positively related to BI	Directionally consistent	Exploratory
H4	TR positively related to BI	Directionally consistent	Exploratory
H5	TR positively related to ATT	Directionally consistent	Exploratory
H6	ANX negatively related to BI	p = .064	Not robustly supported
H7	ANX negatively related to ATT	Positive at zero order; negative in the full model	Sign reversal; not supported
H8	ANX negatively related to PBC	Positive at zero order; p = .126 in the full model	Not robustly supported
H9a	Statistical indirect relationship of TR through ATT	BC CI excludes 0	Directionally consistent; exploratory
H9b	Statistical indirect relationship of ANX through ATT	BC CI excludes 0, but path a is unstable	No substantive support
H9c	Statistical indirect relationship of ANX through PBC	BC CI includes 0	Not supported

Note: 'Directionally consistent' means only that the direction and interval of the conditional coefficient in the specified composite-score model matched the expectation; it does not validate a latent mechanism or causal hypothesis.

For RQ1, ATT, SN, and PBC scale scores were all positive in the specified BI equation, and PBC had the largest conditional coefficient. Their high correlations with BI, however, preclude ranking the importance of the underlying mechanisms. For RQ2, the relationships of TR with ATT and BI and the statistical indirect relationship through ATT were directionally consistent, but the cross-sectional data do not establish temporal mediation. For RQ3, all zero-order

relationships of ANX were positive, and negative coefficients appeared only under some controls. Thus, the proposed negative anxiety mechanism was not robustly supported and showed pronounced model sensitivity. These answers represent conditional patterns among scale scores in this sample only.

5 Discussion

This section interprets the exploratory results in relation to the research questions, the Theory of Planned Behavior, and the literature on AI in education. Because there was no independent measurement validation and the positive scales lacked adequate distinctiveness, statistical significance is not equivalent to validation of the theoretical model. The discussion is limited to directionally consistent conditional relationships, sensitivity involving ANX, and causal mechanisms that the study cannot determine.

5.1 Theoretical Implications

5.1.1 Proximal TPB Factors and Continuance Intention

For RQ1, ATT, SN, and PBC each had a positive conditional relationship in the specified BI equation, consistent in direction with the basic propositions of TPB (Ajzen, 1991). Because the participants were experienced users, the outcome concerns continuance rather than initial adoption (Bhattacherjee, 2001). The scales were highly correlated, however, and the results do not demonstrate three independent mechanisms.

PBC had the largest conditional coefficient among the three proximal TPB variables. Venkatesh (2000) modeled computer self-efficacy, facilitating conditions, and computer anxiety as antecedents of perceived ease of use. That finding offers a conceptual comparison concerning capability and resources; it does not directly test PBC or establish its causal priority in AI continuance. The high correlations of ATT, SN, and PBC with BI in the present data further prevent a definitive ranking of independent latent mechanisms.

5.1.2 Differentiated Roles of AI Trust and AI Anxiety

For RQ2, the present conditional relationships involving trust were positive. The relevance of trust to intended behavior has been examined in online shopping (Gefen et al., 2003) and in a review of reliance on automation (Lee & See, 2004). Shahzad et al. (2024), however, modeled trust as a moderator of awareness-related perceptions in ChatGPT adoption, rather than testing the direct and attitude-mediated continuance relationships examined here. Those distinctions limit comparisons across the studies. The present results do not confirm an independent causal trust mechanism.

For RQ3, the negative anxiety–BI and anxiety–PBC coefficients were nonsignificant, whereas the anxiety–attitude coefficient became weakly negative under controls. Cengiz and Peker (2025) reported negative associations of broader AI anxiety with positive attitudes and generative-AI acceptance, but those associations concern different measures and do not establish the present causal paths. Here, the positive zero-order anxiety–attitude relationship changed sign in the multiple regression. Changes after conditioning on other variables can involve suppression or confounding, which cannot be distinguished as causal mechanisms solely from regression patterns (MacKinnon et al., 2000). Budhathoki et al. (2024) and the EFL profiles of Wang et al. (2025) provide contextual comparisons. The present sign reversal remains a model-sensitive result requiring independent replication.

The lack of support for H8 and H9c should be treated as a theoretical caution, not presented as a definitive contribution based on nonsignificance. In this sample, tension or discomfort did not necessarily imply a lack of capability, resources, or autonomy. Anxiety is an emotional response, whereas PBC is a judgment of capability and conditions; they are theoretically related but should not be treated as opposite ends of one psychological continuum.

The comparison with earlier work is qualified. Tan et al. (2024) associated continuance with hedonic motivation, habit, facilitating conditions, and satisfaction; their social-influence path was not significant. Yu et al. (2024) emphasized ease of use, usefulness, and satisfaction. These results do not uniformly validate the TPB paths tested here. Duong et al. (2024) examined quality, trust, satisfaction, and continuance, while Shahzad et al. (2024) examined trust as a moderator in adoption. Neither is a direct replication of the present trust–attitude–continuance relationship. Wang et al. (2025) identified a high-engagement, high-anxiety EFL profile, but this does not independently confirm the present sign reversal or an ambivalence construct. The present findings therefore warrant comparison at the level of context and conditional associations, with measurement distinctiveness and model sensitivity remaining central limitations.

5.1.3 Measurement Implications of Construct Overlap

High correlations and HTMT values among the positive scales are not merely analytical limitations; they also provide measurement implications for future examination. ATT, SN, PBC, and BI share the behavioral anchor of 'continuing to use during the next three months,' and most items are positively worded. Respondents may have compressed these items into a more general evaluation of 'support for continued AI use' or 'positive views of continuance.' Composite-score

regression can therefore describe scale relationships under specified controls but cannot demonstrate that TR, ATT, SN, PBC, and BI are fully independent latent mechanisms.

The contribution to an extended TPB must consequently be delimited as follows: within a cross-sectional sample of experienced Chinese university students, composite scale scores showed conditional relationships partially consistent with TPB, AI trust, and AI anxiety while revealing discriminant-validity risks created by placing multiple positive constructs in one self-report questionnaire. The study does not claim final validation of a complete six-factor latent-variable model. This boundary helps prevent strong fit indices from obscuring measurement problems and offers specific directions for measure improvement.

5.1.4 New Insights Generated by the Study

First, the novelty lies not in again reporting significant TPB-related variables, but in showing that TR, ATT, SN, PBC, and BI may overlap substantially under uniformly positive wording and a common behavioral anchor. Generative-AI continuance research should therefore address construct semantics and measurement distinctiveness before merely enlarging samples or testing additional paths.

Second, the high correlation and HTMT between TR and ATT suggest that experienced students may partially combine 'the tool is trustworthy' and 'continuing to use the tool is positive' into a broader overall evaluation. The present study cannot resolve this boundary issue, but it provides a concrete basis for cognitive interviews, item revision, and independent CFA.

Third, the positive zero-order relationships of ANX together with weak negative coefficients in some controlled models suggest that experienced users may simultaneously exhibit strong usage intention and some anxiety. This may tentatively be described as 'ambivalence among experienced users,' but it is an interpretive proposition based on the present findings and related literature, not a newly validated construct or causal mechanism.

5.2 Practical Implications

5.2.1 Implications for Universities and Instructors

First, universities should not manage student use of generative AI solely through an allow-or-prohibit approach. The relationship between PBC and BI suggests attention to controllable-use capabilities through AI-literacy courses, prompt-design training, fact checking, citation disclosure, and examples of task boundaries. UNESCO's human-centered, transparent, and responsible principles can be translated into course-level checklists requiring students to identify

the tool used, the stages at which it was used, how outputs were verified, and which judgments remained their own (Miao & Holmes, 2023).

Second, the positive conditional relationship between SN and BI suggests that clarity of norms merits attention. Universities may provide institution-wide minimum principles, while instructors specify permitted, restricted, and prohibited uses in relation to course objectives and use process-based assessment, oral explanation, or version histories to support academic integrity (Cotton et al., 2024; Rudolph et al., 2023). The present study does not itself establish the effectiveness of these measures.

Third, the TR findings are consistent with the practical idea of calibrated trust. Learning activities may require students to compare AI outputs with textbooks, original literature, or authoritative data sources and to identify fabricated citations and outdated information. This recommendation follows the principle of appropriate reliance on automation (Lee & See, 2004); it was not tested as an intervention here.

5.2.2 Implications for Tool Developers and Students

For developers, explanations of reliability, source information, time stamps, citation tracing, expressions of confidence and error-reporting channels may support more calibrated and responsible continuance. Interfaces for education can warn clearly that outputs may be inaccurate and provide verifiable sources for important conclusions. Privacy settings, data-use explanations, and learning-task modes should also be more transparent. These recommendations draw on appropriate-reliance and educational-governance principles (Lee & See, 2004; Miao & Holmes, 2023); the study did not compare the relative effects of interface features.

For students, continued use should not mean delegating more tasks to AI. A more appropriate process is to define the learning goal, use AI for explanation, feedback, or brainstorming, verify facts and citations, record the rationale for revisions, and retain the ability to construct the core argument independently. For students who feel tense or uncertain, stepwise practice and explicit verification checklists may reduce uncertainty during use, although their effects require intervention studies.

5.3 Limitations and Future Research

5.3.1 Limitations

First, this cross-sectional self-report survey can examine contemporaneous associations and conditional indirect relationships, but cannot establish temporal order or causality. Cross-sectional mediation estimates may differ substantially from longitudinal processes (Maxwell &

Cole, 2007). Actual follow-up use was not measured, so the study cannot determine whether continuance intention translates into subsequent use.

Second, the sample was collected through Wenjuanxing and disseminated via WeChat as a nonprobability convenience sample. The questionnaire did not record specific universities, regions, or sample counts by dissemination channel. Thus, 428 responses cannot automatically represent all Chinese university students; homogeneity within WeChat social networks, self-selection, and source concentration may limit generalizability.

Third, measurement posed substantive limitations. Alpha for BI was .695, and TR, ATT, SN, PBC, and BI were highly correlated; 10 of 15 HTMT values exceeded .90. Without an independent pilot and reproducible CFA output, formal SEM validation was not completed. Direct and indirect results are exploratory evidence at the composite-score level and may be influenced by common method, uniformly positive wording, and social desirability.

Fourth, anchoring responses to the 'most frequently used tool' reduced ambiguity across conversational AI tools, but unobserved heterogeneity remained across tools, disciplinary tasks, and university rules. The study also did not measure output-verification skills, clarity of academic-integrity norms, perceived usefulness, or actual learning outcomes and therefore cannot explain all variation in continuance.

5.3.2 Directions for Future Research

Future research should first prioritize measurement revision rather than simply increasing the sample size for the same questionnaire. Target-action-context-time compatibility should guide expert content validation, cognitive interviews, and independent piloting for each construct. Repetitive 'overall support/willingness to continue' wording should be reduced across the positive scales, and more specific semantics should distinguish attitude, norm, control, and intention. After revision, CFA should be completed in an independent sample, with latent correlations, Fornell-Larcker criteria, and HTMT jointly used to assess discriminant validity before structural modeling.

Second, a T1-T2 design could test the intention-behavior relationship. TR, ANX, ATT, SN, PBC, and BI could be measured at T1; four to eight weeks later, the same respondents could report actual usage frequency or provide consented logs at T2. Anonymous self-generated codes could match waves without collecting names or student IDs. If reliable follow-up is infeasible, focusing on continuance intention is preferable to forcing a retrospective UB measure into the model.

Third, recruitment should span multiple universities and regions using stratified or quota approaches and record institution type, region, course, disciplinary task, and sample counts by channel. After measurement invariance is established, tool differences could be compared among ChatGPT, DeepSeek, Doubao, and other major tools, or replications could focus on one tool and one course task. Behavioral logs, assignment versions, or interviews could be combined with survey data to reduce reliance on a single self-report source.

Finally, if the revised measurement model passes CFA, covariance-based SEM could formally test H1-H9c and report direct, total indirect, and specified indirect effects. Multigroup comparisons should be considered only when sample size, group proportions, and measurement invariance are adequate. Paths or samples should not be added or removed post hoc merely to obtain significant results.

6 Conclusion

Using an extended TPB as its organizing framework, this study conducted an exploratory reanalysis of scale scores from 428 raw responses. ATT, SN, PBC, and TR had positive conditional relationships in the specified BI regression, and the statistical indirect relationship from TR through ATT was directionally consistent. ANX correlated positively with the positive scales at the zero-order level, while negative coefficients appeared only under some controls; AI anxiety should therefore not be described as a stable negative mechanism. More importantly, high correlations and HTMT among TR, ATT, SN, PBC, and BI indicate substantial empirical overlap among several positive constructs in the context of generative-AI continuance.

Practically, universities may attend simultaneously to controllable-use capabilities, clarity of norms, and calibrated trust without assigning a definitive causal ranking to variables on the basis of this study. The academic boundaries are equally clear: independent measurement validation and latent-variable SEM were not completed, scale distinctiveness was limited, and ANX involved a sign reversal. The value of the study lies in providing reproducible results for a sample of 428 and in identifying measurement distinctiveness, sampling representativeness, and longitudinal validation as priorities for the next research cycle.

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