

Technology Anxiety and Pre-service Teachers' Intention to Use Generative Artificial Intelligence: An Integrated TAM–TPB Approach

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ABSTRACT:

The rapid diffusion of generative artificial intelligence (GenAI) has raised important questions about how future educators perceive and adopt AI-based tools for learning and teaching. This study investigates Chinese pre-service teachers' intention to use GenAI by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), with technology anxiety positioned as a focal affective antecedent. A quantitative survey was conducted among 489 pre-service teachers from five normal universities in Jilin Province, China, and the data were analyzed using partial least squares structural equation modelling (PLS-SEM). The results show that perceived usefulness and perceived ease of use positively influence attitudes toward AI, while attitude, subjective norm, and perceived behavioral control positively predict intention to use AI. Technology anxiety has significant negative effects on both attitude and intention, but its effects on perceived usefulness, perceived ease of use, subjective norm, and perceived behavioral control are not significant. The indirect effects of technology anxiety on intention through belief-based pathways are also unsupported. These findings suggest that anxiety primarily operates as a direct affective inhibitor rather than through cognitive belief erosion. The study highlights the need for anxiety-sensitive AI training, clear institutional guidance, and responsible-use support in teacher education programs.

Keywords: Generative artificial intelligence, technology anxiety, pre-service teachers, TAM–TPB integration, AI adoption intention

1. Introduction

Generative artificial intelligence (GenAI) is rapidly reshaping higher education by enabling the production of text, images, and other content through natural-language interaction. The diffusion of large language model tools such as ChatGPT has accelerated students' use of AI for brainstorming, explanation, drafting, language support, and problem solving, making GenAI both accessible and highly visible in everyday academic work (Feuerriegel et al., 2024; Kasneci et al., 2023; Murugesan & Cherukuri, 2023).

At the same time, GenAI adoption in education has raised governance and pedagogical concerns, including academic integrity, over-reliance, biased or low-quality outputs, privacy and data protection, and the need to preserve human agency in learning. These

issues are now central to institutional decision-making, assessment redesign, and classroom practice rather than being peripheral considerations (Chan, 2023; Chan & Hu, 2023; Moorhouse et al., 2023).

Technology acceptance frameworks remain useful for explaining why learners adopt GenAI and which mechanisms translate initial curiosity into sustained educational use. Across higher-education contexts, belief-based predictors such as perceived usefulness and perceived ease of use are robust antecedents of attitudes and intention, consistent with classic acceptance theory (Davis et al., 1989; Venkatesh et al., 2003). Recent GenAI studies similarly report that utility expectations, effort perceptions, trust, perceived risk, and social influence shape students' intention to use ChatGPT or related tools for learning and

assessment support (Lai et al., 2024; Saif et al., 2024; Strzelecki, 2024; Tiwari et al., 2024).

However, GenAI adoption is not only a cognitive cost-benefit calculation. Affective barriers, including technology anxiety, can suppress favorable attitudes and reduce intention even when users acknowledge the potential benefits of a technology. This issue is particularly salient for pre-service teachers, who must negotiate both their immediate learning needs as students and their anticipated professional accountability as future educators (Meuter et al., 2003; Li & Thien, 2025; Wang et al., 2024).

The present study investigates how technology anxiety (TA) shapes Chinese pre-service teachers' intention to use GenAI by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). TAM explains intention through perceived usefulness (PU) and perceived ease of use (PEOU) shaping attitude (ATT), whereas TPB emphasizes subjective norm (SN) and perceived behavioral control (PBC) as additional determinants of intention (Ajzen, 1991; Davis et al., 1989). Integrating these perspectives is appropriate in teacher education because AI-related decisions are embedded in institutional guidance, peer practices, assessment expectations, and perceived capability (Ivanov et al., 2024; Wang et al., 2021).

The Chinese context offers an informative setting because national efforts toward educational

digitalization and AI-enabled innovation are accelerating, potentially amplifying both adoption drivers and uncertainty-related anxiety. The study therefore contributes to the literature by locating technology anxiety within an integrated TAM-TPB structure and by testing whether anxiety works mainly through cognitive belief erosion or as a direct affective inhibitor of attitude and intention.

Based on the integrated framework, the following hypotheses were proposed:

H1: Perceived usefulness (PU) positively influences attitude toward using AI (ATT).

H2: Perceived ease of use (PEOU) positively influences attitude toward using AI (ATT).

H3: Attitude toward using AI (ATT) positively influences intention to use AI (INT).

H4: Subjective norm (SN) positively influences intention to use AI (INT).

H5: Perceived behavioral control (PBC) positively influences intention to use AI (INT).

H6a-H6d: Technology anxiety (TA) negatively influences PU, PEOU, SN, and PBC.

H6e-H6f: Technology anxiety (TA) negatively influences ATT and INT.

H7a-H7b: Technology anxiety (TA) indirectly and negatively influences INT through PU/PEOU and ATT.

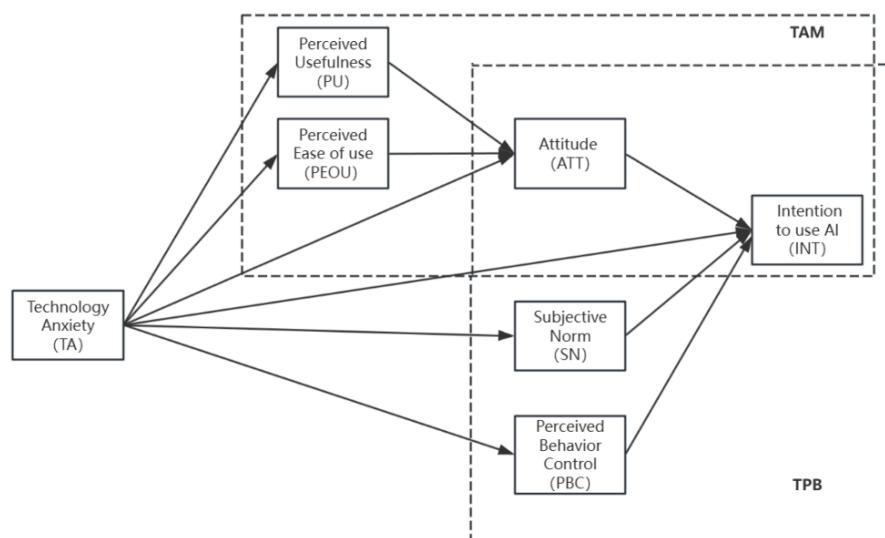


Figure 1. Conceptual framework and hypothesized relationships.

Note. TA = technology anxiety; PU = perceived usefulness; PEOU = perceived ease of use; ATT = attitude toward using AI; SN = subjective norm; PBC = perceived behavioral control; INT = intention to use AI.

2. Methodology

Design: A quantitative cross-sectional survey design was adopted. This design was suitable because the

study measured multiple latent psychological constructs and tested hypothesized relationships within an integrated TAM–TPB model.

Participants/Sample: The target population was pre-service teachers, defined as undergraduate normal university students in Jilin Province, China. Questionnaires were distributed across five institutions: Northeast Normal University, Jilin Normal University, Changchun Normal University, Jilin Engineering Normal University, and Tonghua Normal University. A total of 550 questionnaires were distributed evenly across the five institutions. Of these, 502 responses were returned, and 489 valid responses were retained after screening incomplete or invalid submissions.

Instruments: The questionnaire contained two sections. Section A collected demographic information, including gender, household registration type, grade, academic major, and institution. Section B measured TA, PU, PEOU, ATT, SN, PBC, and INT using multi-item 5-point Likert-type scales ranging from strongly disagree to strongly agree. The items were adapted to the GenAI learning context while retaining the conceptual meaning of the original constructs.

Procedure: Before formal data collection, the questionnaire was reviewed for clarity, content relevance, and contextual appropriateness for teacher education. Participants were informed of the study purpose, voluntary participation, anonymity, and confidentiality. The survey was administered online with institutional assistance, and the collected responses were screened before analysis.

Data Analysis: Descriptive statistics and preliminary checks were conducted in SPSS. Structural equation modelling was performed in SmartPLS using a variance-based PLS-SEM approach. Following the two-stage logic of SEM, the measurement model was evaluated before interpreting structural paths. Bootstrapping with 5,000 resamples was used to evaluate path coefficients and specific indirect effects (Anderson & Gerbing, 1988; Hair et al., 2021).

3. Results

Descriptive analysis was first performed to summarize the demographic profile of the respondents. Structural equation modelling was then used to examine the hypothesized relationships among the constructs.

Table 1. Respondents' demographic data (n = 489)

Demographic characteristic	Category	Frequency	Percentage (%)
Gender	Male	237	48.47
Gender	Female	252	51.53
Household registration type	Rural household registration	194	39.67
Household registration type	Township household registration	295	60.33
Grade	Year 1	138	28.22
Grade	Year 2	123	25.15
Grade	Year 3	113	23.11
Grade	Year 4	115	23.52
Major	Humanities and Social Sciences	229	46.83
Major	Science and Engineering	260	53.17
School	Northeast Normal University	202	41.31
School	Jilin Engineering Normal University	67	13.70
School	Jilin Normal University	103	21.06
School	Tonghua Normal University	64	13.09

Demographic characteristic	Category	Frequency	Percentage (%)
School	Changchun Normal University	53	10.84

Table 1 indicates that the sample was relatively balanced by gender, with females accounting for 51.53% and males accounting for 48.47%. The respondents were also distributed across grade levels,

majors, and five teacher-education institutions, supporting the institutional coverage required by the study design.

Table 2. Multicollinearity results (dependent variable: INT)

Construct	Tolerance	VIF
ATT	0.953	1.049
PBC	0.951	1.052
SN	0.951	1.051

The tolerance values for ATT, PBC, and SN were above 0.95, and the corresponding VIF values were close to 1. These results indicate that collinearity was

not likely to bias the estimation of path coefficients in the intention equation.

Table 3. Early-late respondent comparison (nonresponse bias test)

Construct	Early (n = 241), Mean $\pm$ SD	Late (n = 248), Mean $\pm$ SD	t	p
PU	3.53 $\pm$ 0.73	3.55 $\pm$ 0.73	-0.373	0.709
PEOU	3.61 $\pm$ 0.71	3.58 $\pm$ 0.74	0.455	0.649
ATT	2.83 $\pm$ 0.86	2.80 $\pm$ 0.77	0.302	0.763
SN	2.84 $\pm$ 0.75	2.89 $\pm$ 0.82	-0.731	0.465
PBC	2.85 $\pm$ 0.70	2.81 $\pm$ 0.73	0.618	0.537
INT	2.69 $\pm$ 0.79	2.62 $\pm$ 0.77	1.021	0.308
TA	2.10 $\pm$ 0.63	2.15 $\pm$ 0.66	-0.779	0.437

The differences between early respondents and late respondents were not statistically significant across all constructs (all p-values > 0.05), suggesting that response timing did not systematically influence the observed construct scores.

After the preliminary checks, the structural model was assessed using bootstrapping in SmartPLS. Table 4 reports the path coefficients, t-values, p-values, and significance decisions.

Table 4. Path coefficients, t-statistics, and significance levels

Hypothesized path	β (O)	t-value	p-value	Significance
ATT $\rightarrow$ INT	0.074	2.819	0.005	Yes
PBC $\rightarrow$ INT	0.070	2.891	0.004	Yes
PEOU $\rightarrow$ ATT	0.128	3.875	< 0.001	Yes
PU $\rightarrow$ ATT	0.123	3.720	< 0.001	Yes
SN $\rightarrow$ INT	0.081	3.055	0.002	Yes
TA $\rightarrow$ PBC	-0.039	1.057	0.291	No
TA $\rightarrow$ PEOU	-0.053	1.301	0.194	No

Hypothesized path	β (O)	t-value	p-value	Significance
TA $\rightarrow$ PU	-0.054	1.236	0.217	No
TA $\rightarrow$ SN	-0.031	0.853	0.394	No
TA $\rightarrow$ ATT	-0.200	> 3.310	< 0.001	Yes
TA $\rightarrow$ INT	-0.139	2.521	0.012	Yes

Note. p-values reported as 0.000 in software outputs are interpreted as $p < 0.001$.

The core TAM-TPB paths were statistically significant. PU and PEOU positively predicted ATT, while ATT, SN, and PBC positively predicted INT. TA did not significantly predict PU, PEOU, SN, or

PBC. However, TA showed significant negative effects on ATT and INT, indicating that anxiety operated primarily as a direct emotional barrier to favorable evaluation and adoption intention.

Table 5. Specific indirect effects of technology anxiety on intention

Specific indirect path	O	M	STDEV	t	p
PU $\rightarrow$ ATT $\rightarrow$ INT	0.101	0.103	0.019	5.380	< 0.001
PEOU $\rightarrow$ ATT $\rightarrow$ INT	0.103	0.105	0.018	5.713	< 0.001
TA $\rightarrow$ PU $\rightarrow$ ATT	-0.007	-0.007	0.006	1.167	0.243
TA $\rightarrow$ PEOU $\rightarrow$ ATT	-0.007	-0.007	0.006	1.167	0.243
TA $\rightarrow$ PU $\rightarrow$ ATT $\rightarrow$ INT	-0.001	-0.001	0.001	1.000	0.317
TA $\rightarrow$ PEOU $\rightarrow$ ATT $\rightarrow$ INT	-0.001	-0.001	0.001	1.000	0.317

The belief-attitude-intention chains from PU and PEOU to INT through ATT were significant. In contrast, indirect effects from TA through PU/PEOU and ATT were not significant, which is consistent with the non-significant direct paths from TA to PU and PEOU.

Table 6. Standardized root mean square residual (SRMR) values for model fit

Model type	SRMR (O)	Sample mean (M)	95% CI	99% CI
Saturated Model	0.049	0.044	0.046	0.047
Estimated Model	0.057	0.047	0.050	0.052

The SRMR values for both the saturated model and the estimated model were below commonly used cut-offs, indicating acceptable overall fit for the proposed structural specification.

4. Discussion

This study examined Chinese pre-service teachers' intention to adopt GenAI by foregrounding technology anxiety as an affective inhibitor within an integrated TAM-TPB framework. The findings support the belief-evaluation-intention logic of TAM:

PU and PEOU were significant antecedents of ATT, and ATT significantly predicted INT. The results also support TPB by showing that SN and PBC exerted significant positive effects on intention. These findings suggest that pre-service teachers' AI adoption is shaped not only by perceived learning value and ease of use but also by perceived expectations and perceived capability (Ajzen, 1991; Davis et al., 1989; Venkatesh et al., 2003).

The central contribution concerns the role of TA. TA had significant negative relationships with ATT and INT, indicating that affective readiness can suppress adoption even when users recognize the potential benefits of GenAI. This result is consistent with earlier evidence that anxiety can reduce willingness to engage with digital technologies and with emerging work showing that AI anxiety can dampen adoption in educational contexts (Meuter et al., 2003; Li & Thien, 2025; Wang et al., 2024).

At the same time, TA did not significantly predict PU, PEOU, SN, or PBC, and the corresponding indirect effects through belief-based mediators were unsupported. This differentiated pattern suggests that TA functions primarily as a direct affective inhibitor rather than a belief-formation mechanism in this context. A plausible explanation is that pre-service teachers may already accept the general narrative that GenAI is useful and relatively easy to access, while still feeling uneasy about consequences such as academic integrity, privacy, over-reliance, professional judgment, and the acceptable boundaries of AI-supported learning (Chan, 2023; Chan & Hu, 2023; Kasneci et al., 2023; Moorhouse et al., 2023).

Theoretically, the findings extend AI adoption research in teacher education by clarifying how affective barriers operate alongside cognitive and socio-behavioral factors. Many adoption models prioritize usefulness and ease of use, but the present results indicate that emotional barriers can remain decisive even when cognitive beliefs are stable. The inclusion of TPB-related drivers also reinforces that adoption among future educators is embedded in social and capability contexts rather than being merely an individual preference.

Practically, the findings imply that teacher education programs should treat anxiety reduction as an explicit instructional goal. Institutions can combine technical skill development with scenario-based learning, prompt literacy, output verification, bias checking, and explicit guidance on acceptable and ethical use. Clarifying institutional policies and

providing approved tools and support may also strengthen subjective norms and perceived behavioral control, thereby promoting responsible and sustainable GenAI adoption.

Several limitations should be acknowledged. First, the cross-sectional survey design limits causal inference and does not capture how anxiety and attitudes may change as GenAI becomes more embedded in learning routines. Second, the sample was drawn from five institutions in one Chinese province, so generalization to all pre-service teachers should be made cautiously. Third, TA may be multidimensional, including competence anxiety, ethical-boundary anxiety, privacy anxiety, and professional-identity anxiety. Future research could use longitudinal and mixed-method designs to examine how these dimensions develop and how targeted training may reduce anxiety over time.

5. Conclusion

The rapid diffusion of GenAI has intensified the need to understand how future teachers evaluate and adopt AI tools for learning and teaching. This study demonstrates that pre-service teachers' intention to use GenAI is supported by cognitive, social, and control mechanisms: PU and PEOU strengthen ATT, while ATT, SN, and PBC positively predict INT. More importantly, TA directly reduces both ATT and INT, while its indirect effects through PU/PEOU and ATT are not supported.

These findings indicate that promoting GenAI adoption in teacher education requires more than technical training or tool access. Effective programs should address emotional readiness, provide clear ethical and institutional guidance, and embed AI use in authentic teacher tasks such as lesson planning, formative feedback, and micro-teaching preparation. Future research should examine how anxiety-sensitive interventions, policy clarity, and repeated guided exposure influence pre-service teachers' responsible and confident use of GenAI over time.

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8. Author Declaration

Originality: The authors declare that this manuscript is original, has not been published previously, and is not under consideration for publication elsewhere.

Conflicts of interest: The authors declare that they have no conflicts of interest.

Data availability: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author contributions: All authors contributed to the conception and design of the study. Data collection, data analysis, and manuscript preparation were carried out collaboratively. All authors reviewed and approved the final version of the manuscript.