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Fear and Fun: Dual Impact of AI Anxiety and Perceived Enjoyment on Acceptance Intention of Generative AI Tools

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Abstract

With the pervasive integration of generative artificial intelligence across diverse social domains, user acceptance intention manifests a distinctive coexistence of "fun and fear." Grounded in the Technology Acceptance Model, this investigation develops an expanded model by integrating perceived enjoyment, AI anxiety, and privacy concerns, whilst assessing the moderating influence of professional background. Based on 486 valid questionnaires and structural equation modeling, the model shows acceptable fit ($\chi^2/df = 1.88$, RMSEA = 0.043, CFI/TLI > 0.90). Perceived enjoyment strengthens attitude ($\beta = 0.324$, $p < 0.001$) and perceived usefulness ($\beta = 0.284$, $p < 0.001$), while AI anxiety reduces perceived usefulness ($\beta = -0.296$, $p < 0.001$) and privacy concern weakens attitude ($\beta = -0.148$, $p = 0.021$); the core TAM path is supported (ATT $\longrightarrow$ BI: $\beta = 0.643$, $p < 0.001$; BI $\longrightarrow$ USE: $\beta = 0.535$, $p < 0.001$). By contrast, H7, H8, and H10 are not supported ($p > 0.05$), and professional background shows negligible moderation. These results suggest that promoting generative AI requires enhancing enjoyable interaction while reducing anxiety and privacy risks.

Keywords: AI Anxiety, Generative Artificial Intelligence, Perceived Enjoyment, Privacy Concerns, Professional Background, Technology Acceptance Model

Introduction

Generative Artificial Intelligence (GAI) tools are swiftly infiltrating education, healthcare, business, and creative sectors, propelling societal digital transformation (Dwivedi et al., 2023). Applications such as ChatGPT and Midjourney reveal considerable promise, yet users display intricate psychology throughout the acceptance process: firstly, the enjoyment and inventiveness of generative AI boost user involvement; conversely, anxiety and privacy considerations undermine adoption intention. This strain, defined by the simultaneous presence of "fear and fun," has emerged as a pivotal subject for comprehending user behavior.

The conventional Technology Acceptance Model (TAM) stresses that perceived usefulness (PU) and perceived ease of use (PEOU) shape usage attitude (ATT) and

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behavioral intention (BI) (Davis, 1989; Venkatesh & Davis, 2000). Nonetheless, as AI permeates daily existence, elements like enjoyment, anxiety, and privacy hazards have progressively evolved into unavoidable aspects (Zhang et al., 2025; Tao et al., 2025). Current investigations concentrate more on the functional merit of generative AI, frequently neglecting the part played by users' conflicting psychology. However, existing TAM-based research on generative AI adoption has not sufficiently articulated how hedonic motivation and AI-specific risk perceptions jointly shape acceptance, and evidence grounded in local or regional adoption contexts remains limited.

Perceived enjoyment (PENJ), serving as an internal drive, can heighten users' value perception and favorable disposition towards the tool (Kim et al., 2024). Concurrently, AI anxiety (AIA) and privacy concerns (PC) signify adverse psychological elements; research demonstrates they can lessen individuals' efficacy anticipations and adoption intention (Kim et al., 2025; Chen et al., 2025). Moreover, users' professional background exerts a moderating function between PU, PEOU, and attitude; individuals possessing more robust technical foundations are prone to cultivate positive attitudes, whilst those with weaker foundations are more affected by anxiety and risk perception (Schwesig et al., 2023).

Consequently, this study puts forward a "double-edged sword effect of AI anxiety and perceived enjoyment" structure, thoroughly scrutinizing the mechanisms via which PU, PEOU, perceived enjoyment, AI anxiety, and privacy concerns impact the acceptance intention of generative AI, and verifying the moderating effect of professional background. The significances of this research encompass: (1) broadening TAM by including affective and anxiety variables; (2) uncovering the adoption dilemma under coexisting positive and negative psychology; (3) supplying practical guidance for the design and promotion of generative AI tools that equilibrate amusement and a feeling of safety.

Objective

1. To establish a comprehensive theoretical framework that augments the traditional Technology Acceptance Model by incorporating the positive driver of perceived enjoyment and the negative barriers of AI anxiety and privacy concern, thereby specifying a “fun–fear” dual-route mechanism for generative AI adoption.

2. To reveal the double-edged sword effect by quantifying the opposing impacts of perceived enjoyment and AI anxiety on the psychological pathway leading to the acceptance of generative AI, including their effects on perceived usefulness (PU) and attitude (ATT), and their indirect effects on behavioral intention (BI) and actual use (USE).

3. To clarify the contingent role of users' professional background, examining its moderating influence on the key structural relationships in the extended TAM, thereby identifying user segments that are more sensitive to “fun” versus “fear” drivers.

Literature review

Since its introduction by Davis (1989), the Technology Acceptance Model has served as a fundamental theoretical structure in information system adoption research. This model underscores the crucial functions of perceived usefulness and perceived ease of use in molding user attitude and behavioral intention. Follow-up studies have additionally confirmed the notable impact of both: PU straightly decides whether users regard a technology as beneficial, whilst PEOU not solely influences attitude but also indirectly affects adoption intention by boosting PU (Venkatesh et al., 2003). Within the scenario of generative AI utilization, if users can tangibly sense that AI tools enhance efficiency and output caliber, their adoption intention will rise correspondingly; provided the tools are straightforward and instinctive to operate, they are more probable to be extensively embraced.

Yet, alongside the intensification of digital transformation, the purely function-oriented perception of TAM can no longer entirely elucidate user behavior. Researchers have steadily integrated affective components into investigation, with "perceived enjoyment" turning into a significant extension variable. Inquiry reveals that when the procedure of utilizing technology itself is pleasurable, users are more inclined to foster positive attitudes and strengthen adoption intention (Kang et al., 2024). Generative AI holds a elevated level of interactivity and originality; it is not just an instrument for increasing productivity but also furnishes delight and absorbing encounters (Kim & Kim, 2025). Hence, in the acceptance progression of generative AI, perceived enjoyment constitutes a vital impetus for stimulating user curiosity and continued use.

Corresponding to positive drives, unfavorable psychological elements likewise deeply affect the user acceptance process. AI anxiety, as an extension of technology anxiety, denotes the strain and apprehension users undergo when confronting AI owing to unpredictability, replacement, and ethical dangers (Li & Huang, 2020; Eren et al., 2025). Prevalent inquiry has discovered that anxiety can impair users' self-efficacy, decrease their faith in technology, and thus restrain adoption conduct (Tao et al., 2025). In the application setting of generative AI, users fret about the unmanageability of AI outputs, menaces to individual privacy, and even possible occupation substitution risks, all of which render AI anxiety a considerable obstacle influencing their acceptance intention.

Privacy concern represents another unavoidable negative variable. The IUIPC model suggested by Malhotra et al. (2004) highlights that users possess notable apprehensions concerning data gathering, control over usage, and transparency when employing the internet or emerging information systems. In the generative AI context, the input of substantial volumes of data that might be stored or repurposed by models induces stronger perceptions of privacy risk amongst users (Shahriar et al., 2023). Privacy concerns not only weaken users' perception of the tool's usefulness but also diminish

the possibility of forming a positive attitude, thereby hindering adoption intention (Lim & Shim, 2022).

Significantly, users' professional background performs a moderating role in the technology adoption process. In this study, “professional background” is operationalized as whether respondents have formal education or work experience in IT/AI-related fields. Respondents are grouped into an IT/AI-related group versus a non-IT/AI group for subsequent moderation tests. Gefen and Straub (1997) indicated that technical experience and specialized knowledge modify users' comprehension and acceptance of information systems. Regarding generative AI tools, users with solid professional backgrounds often can adapt more rapidly and completely exploit their potential, thus displaying a stronger positive correlation in the routes from PU and PEOU to attitude (Olatunde & Mohamed, 2025). In contrast, users deficient in pertinent backgrounds might be more vulnerable to the effect of anxiety and privacy concerns, accordingly exhibiting lower adoption intention (Shahriar, 2023).

Thus, this study endeavors to introduce variables like perceived enjoyment, AI anxiety, and privacy concerns building upon TAM, and examine the moderating effect of professional background, thereby yielding a more thorough clarification of users' acceptance intention regarding generative AI tools.

Critical synthesis and research gap. Although TAM has been widely applied to explain technology adoption through utilitarian beliefs (PU/PEOU) and their downstream effects (ATT/BI/USE), existing generative-AI adoption studies still show three limitations. First, many studies treat affect and AI-specific risks as parallel predictors, but seldom clarify whether they form a coherent “fun–fear” mechanism along the same psychological pathway. Second, prior work often reports significant effects without explicitly contrasting which paths belong to the original TAM versus which are newly added, making the incremental contribution of extended models less transparent. Third, user heterogeneity is frequently acknowledged but weakly operationalized; in particular, professional background is sometimes treated as a generic descriptor rather than a clearly defined grouping criterion that can test boundary conditions. To fill these gaps, this study (i) explicitly distinguishes the original TAM core paths from the newly introduced “fun–fear” extensions, (ii) quantifies how enjoyment, anxiety, and privacy concerns reshape the TAM psychological pathway, and (iii) tests whether these effects differ across clearly defined professional-background groups.

Original TAM vs. extended TAM in this study. The original TAM focuses on the utilitarian belief–attitude–intention chain, typically including PEOU $\longrightarrow$ PU, PEOU $\longrightarrow$ ATT, PU $\longrightarrow$ ATT, ATT $\longrightarrow$ BI, and BI $\longrightarrow$ USE. In contrast, the extended model in this paper adds (a) a hedonic driver, perceived enjoyment, to capture the “fun” component; (b) AI anxiety and privacy concerns to capture the “fear” component; and (c)

professional background as a boundary condition to test whether the above relationships vary across user groups.

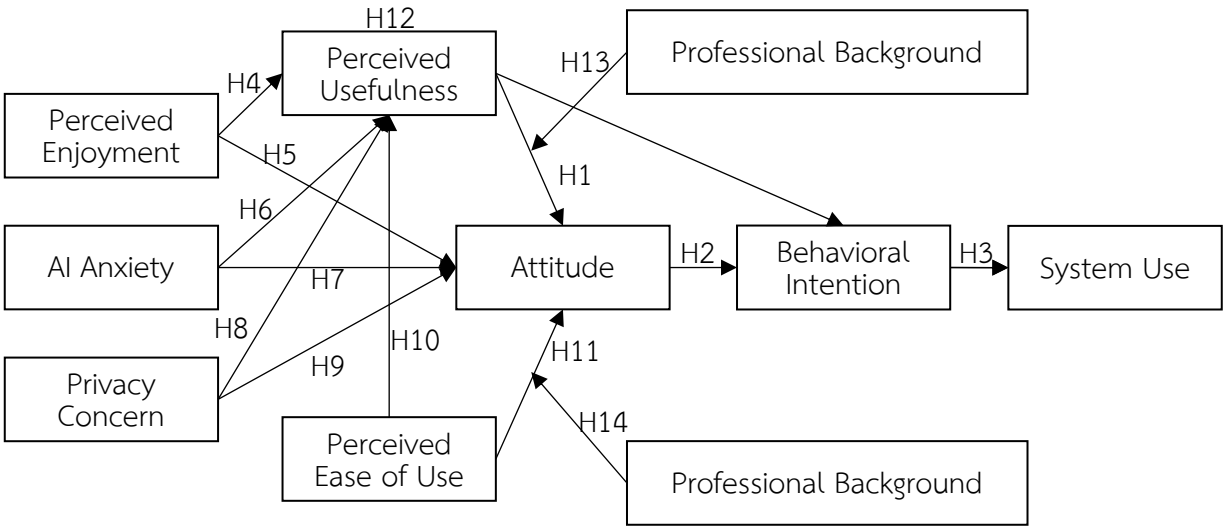


Figure 1 Extended TAM Framework for Generative AI Adoption

Research Hypotheses

Building upon the Technology Acceptance Model and associated expanded models, this study formulates a structural model for the acceptance intention of generative AI tools and advances hypotheses concerning the double-edged sword effect of "AI anxiety" and "perceived enjoyment." Specifically:

1. Perceived Value and Attitude Path

Prevalent research broadly concurs that an individual's perception of a system's usefulness straightly impacts their usage attitude (Davis, 1989; Venkatesh & Davis, 2000). Simultaneously, usage attitude further sways their behavioral intention, which subsequently determines the ultimate actual usage behavior. Based on this, this study proposes:

H1: Perceived usefulness exerts a significant positive influence on usage attitude.

H2: Usage attitude exerts a significant positive influence on behavioral intention.

H3: Behavioral intention exerts a significant positive influence on system use.

2. The Double-Edged Sword Effect of Perceived Enjoyment and AI Anxiety

Perceived enjoyment, serving as an internal drive, can amplify users' interest in and readiness to use the system (Kang et al., 2024). However, AI anxiety might weaken users' acceptance intention towards AI tools due to worries about risks, substitution consequences, and unmanageability (Tao et al., 2025). Hence, this study proposes:

H4: Perceived enjoyment exerts a significant positive influence on perceived usefulness.

H5: Perceived enjoyment exerts a significant positive influence on usage attitude.

H6: AI anxiety exerts a significant negative influence on perceived usefulness.

H7: AI anxiety exerts a significant negative influence on usage attitude.

3. The Role of Privacy Concern

With the extensive application of generative AI, users' sensitivity to privacy risks has intensified. Privacy concern can hamper individuals' positive recognition of the system's value and lessen usage attitude (Shahriar et al., 2023). Building on this, this study proposes:

H8: Privacy concern exerts a significant negative influence on perceived usefulness.

H9: Privacy concern exerts a significant negative influence on usage attitude.

4. Perceived Ease of Use Path

The Technology Acceptance Model highlights that perceived ease of use not solely straightly affects user attitude but also indirectly sways usage intention by enhancing perceived usefulness (Venkatesh et al., 2003). Therefore, this study proposes:

H10: Perceived ease of use exerts a significant positive influence on perceived usefulness.

H11: Perceived ease of use exerts a significant positive influence on usage attitude.

H12: Perceived usefulness mediates the association between perceived ease of use and usage attitude.

5. The Moderating Effect of Professional Background

Users' professional background could sway their cognitive process concerning AI tools. Users with stronger professional backgrounds might find it simpler to comprehend and employ AI tools, thus potentially demonstrating a stronger positive effect in the connections "perceived usefulness $\longrightarrow$ usage attitude" and "perceived ease of use $\longrightarrow$ usage attitude" (Olatunde & Mohamed, 2025). Consequently, this study proposes:

H13: Professional background positively moderates the association between perceived usefulness and usage attitude.

H14: Professional background positively moderates the association between perceived ease of use and usage attitude.

Methodology

4.1 Research Design

This investigation employs a quantitative research approach, constructing a structural model based on the expanded Technology Acceptance Model, encompassing variables such as perceived usefulness, perceived ease of use, perceived enjoyment, AI anxiety, privacy concern, and professional background. The research aims to probe the mechanism of generative AI acceptance intention under the coexistence of positive and negative psychological elements and to verify the moderating effect of professional

background. For this objective, this study devised a questionnaire survey tool and utilized empirical statistical techniques for confirmation.

4.2 Sample and Data Collection

The research participants were users with practice utilizing generative AI tools, incorporating university instructors and students, corporate staff, and freelancers. Data gathering was executed employing a mix of convenience sampling and snowball sampling, with the questionnaire circulated via online platforms. To guarantee sample variety, the study encompassed groups with differing ages, educational histories, and occupational backgrounds. An aggregate of 500 questionnaires were disseminated and recovered, out of which 486 were valid, yielding a valid response rate of 97.2%, satisfying the sample size prerequisites for Structural Equation Modeling (Hair et al., 2019). Throughout data collection, rigorous compliance with informed consent and anonymity principles was preserved to ensure ethical conformity.

Table 1 presents the demographic profile of the respondents (frequency and percentage), which helps assess sample representativeness and potential sampling bias.

Table 1 Respondent Demographics (N = 486)

Variable	Category	n	%
Gender	Male	252	51.85
	Female	234	48.15
Age	18–24	210	43.21
	25–34	175	36.01
	35–44	71	14.61
	45+	30	6.17
Education	High school or below	45	9.26
	College/Bachelor	315	64.81
	Master or above	126	25.93
Occupation/Industry	Student	185	38.07
	IT/Data/AI-related	148	30.45
	Education/Research	58	11.93
	Business/Services	80	16.46
	Other	15	3.09
Monthly income (RMB)	Low (≤ 5,000)	72	14.81
	Middle (5,001–10,000)	185	38.07
	High (≥ 10,001)	92	18.93
	No fixed income	137	28.19

4.3 Measurement Tools and Scales

Established scales were utilized for all variables in this study, suitably adjusted according to the generative AI context. All items employed a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Particulars are as follows:

Perceived Usefulness and Perceived Ease of Use: Modified from Davis (1989), 4 items each.

Perceived Enjoyment: Embraced from Van der Heijden (2004), 4 items.

AI Anxiety: Drew upon Compeau & Higgins (1995) and Parasuraman & Colby (2015), 4 items.

Privacy Concern: Modified from Malhotra et al. (2004) IUIPC scale, 4 items.

Usage Attitude and Behavioral Intention: Embraced items from Davis (1989) and Taylor & Todd (1995), 3 items each.

System Use: Utilized self-report items (frequency, duration, active days) merged with certain objective log data.

Professional Background: Gauged through education level, major classification, technical training background, and self-assessed technical skill, acting both as a control variable and a moderating variable.

All scales were examined for reliability and validity. Cronbach's α values exceeding 0.70 were deemed acceptable for reliability. KMO and Bartlett's sphericity tests were applied to inspect data suitability. Exploratory and Confirmatory Factor Analysis were utilized to evaluate construct validity.

In addition, the questionnaire contained two parts: Part A collected demographic information (gender, age, education, occupation/industry, and monthly income; see Table 1), and Part B measured the study constructs. The full item wording, item codes (PU1–PU4, PEOU1–PEOU4, PENJ1–PENJ4, AIA1–AIA3, IUIPC1–IUIPC4, ATT1–ATT3, BI1–BI3, USE1–USE3), and their sources/adaptations are provided in Appendix A to ensure transparency and replicability. Representative items include “Using this generative-AI tool improves my task efficiency” (PU), “Learning to use the tool is easy for me” (PEOU), “Using the tool is enjoyable” (PENJ), “I feel tense or uneasy when I think about using generative AI” (AIA), and “I am concerned about excessive collection of my personal/data when using the tool” (IUIPC).

To improve measurement clarity, professional background (PB) was operationalized as a binary indicator of whether respondents have an IT/Data/AI-related educational or work background (0 = No, 1 = Yes), rather than a broad “career background” label. This definition supports replicable grouping in multi-group SEM.

Statistical significance was evaluated using p-values ($p < 0.05$ as the primary criterion), and practical relevance was interpreted together with standardized effect sizes (β) and confidence intervals for indirect effects via bootstrapping.

4.4 Data Analysis Methods

Data analysis was carried out in three stages:

(1) Descriptive Statistics and Reliability/Validity Testing: Applying SPSS for mean, standard deviation, skewness, and kurtosis examinations, and inspecting Cronbach's α, convergent validity, and discriminant validity via CFA.

(2) Structural Equation Modeling Analysis: Applying AMOS for path analysis of the research model to test the significance of each hypothesized path.

(3) Moderating Effect Testing: Utilizing multi-group analysis, segmenting the sample into high and low PB groups to contrast path discrepancies.

Results

5.1 Reliability and Validity Analysis

Initially, reliability and validity assessments were performed on the scales. The Cronbach's α for all variables surpassed 0.7, denoting sound internal consistency of the scales. Confirmatory Factor Analysis outcomes indicated that the model fit indices satisfied suggested benchmarks ($\chi^2/df = 1.448 < 3$, RMSEA = 0.03 < 0.05, CFI, TLI, IFI > 0.90), denoting good construct validity. Regarding convergent validity, the standardized factor loadings for all latent variables were above 0.6, the Average Variance Extracted exceeded 0.5, and the Composite Reliability all surpassed 0.7. Discriminant validity test outcomes revealed that the square roots of the AVE for all latent variables were larger than their correlations with other variables.

Table 2 Scale Reliability and Validity Test Results

Variable	Cronbach's α	CR	AVE	Standardized Loading	KMO
PU	0.817	0.817	0.529	0.661–0.768	0.911
PEOU	0.826	0.827	0.544	0.695–0.767	
PENJ	0.811	0.812	0.520	0.646–0.776	
AIA	0.759	0.761	0.515	0.690–0.738	
PC	0.817	0.817	0.528	0.661–0.775	
ATT	0.772	0.774	0.533	0.718–0.748	
BI	0.764	0.767	0.523	0.689–0.751	
USE	0.772	0.773	0.532	0.704–0.752	

Table 3 Discriminant Validity Test Results

Variable	PU	EPOU	PENJ	AIA	ATT	PC	BI	USE
PU	0.727							
EPOU	0.485	0.738						
PENJ	0.586	0.594	0.721					
AIA	-0.572	-0.475	-0.569	0.718				
ATT	0.532	0.512	0.613	-0.490	0.727			
PC	-0.488	-0.506	-0.573	0.534	-0.517	0.730		
BI	0.449	0.469	0.531	-0.521	0.479	-0.428	0.723	

Variable	PU	EPOU	PENJ	AIA	ATT	PC	BI	USE
USE	0.549	0.523	0.568	-0.534	0.515	-0.475	0.455	0.730
Diagonal values are the square roots of AVE								

5.2 Descriptive Statistics and Correlation Analysis

Descriptive statistics were applied to examine the fundamental sample situation and variable traits. The outcomes demonstrated that the mean values of the variables varied between 2.5 and 3.5, with standard deviations between 0.9 and 1.1, signifying some scattering in the sample replies. Skewness and kurtosis resided within the ±2 span, fulfilling the presumption of normal distribution. Correlation analysis indicated significant positive correlations between PU, PEOU, PENJ, ATT, BI, and USE, whilst AI anxiety and privacy concern displayed significant negative correlations with PU, PEOU, PENJ, ATT, BI, and USE.

Table 4 Variable Means, Standard Deviations, and Correlations

Var	M	SD	Skewness	Kurtosis	PU	PEOU	PENJ	AIA	PC	ATT	BI	USE
PU	3.507	1.060	-0.613	-0.502	1							
PEOU	3.453	1.082	-0.650	-0.329	.330**	1						
PENJ	3.570	1.056	-0.695	-0.294	.400**	.417**	1					
AIA	2.522	0.990	0.626	-0.159	-.399**	-.298**	-.429**	1				
PC	2.537	1.054	0.581	-0.457	-.363**	-.355**	-.402**	.354**	1			
ATT	3.468	1.038	-0.698	-0.353	.388**	.360**	.423**	-.313**	-.370**	1		
BI	3.406	1.026	-0.559	-0.553	.304**	.364**	.373**	-.367**	-.274**	.348**	1	
USE	3.464	1.029	-0.638	-0.294	.407**	.341**	.441**	-.350**	-.339**	.375**	.350**	1

Note: *p < 0.05, **p < 0.01

5.3 Structural Model Testing

AMOS was utilized for structural equation modeling analysis of the research model. The model fit outcomes indicated sound overall fit (χ^2/df = 1.880 < 3, RMSEA = 0.043 < 0.05, CFI = 0.945, TLI = 0.938, IFI = 0.946 > 0.90).

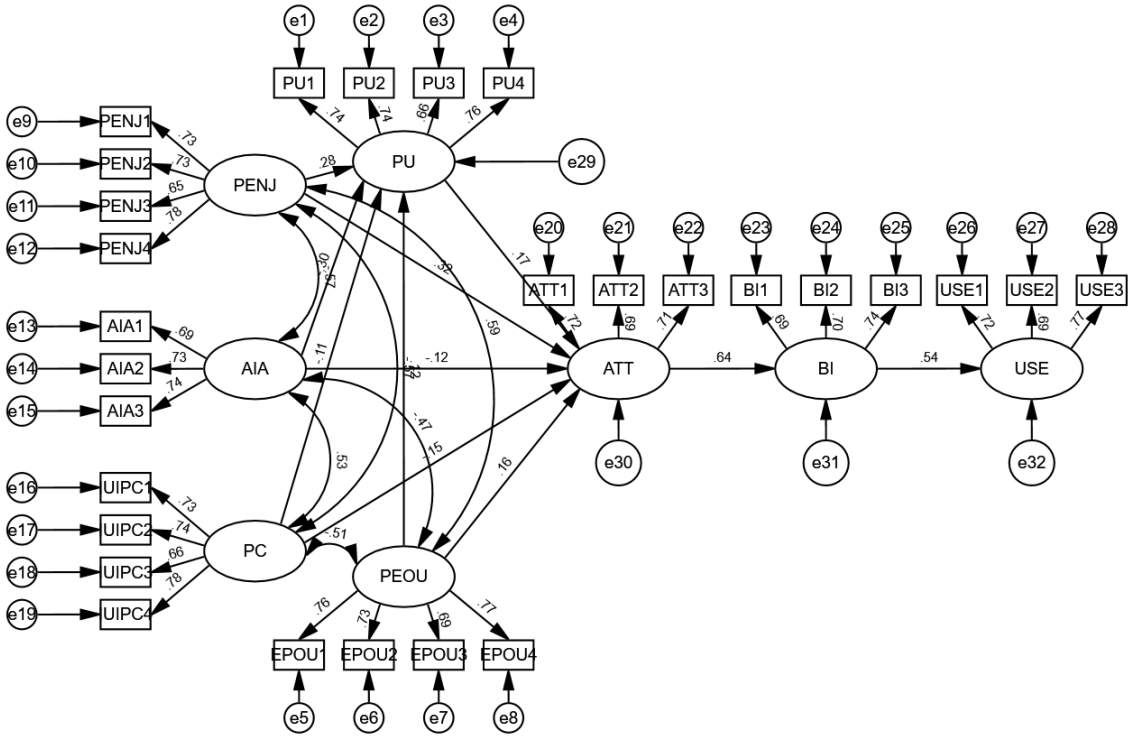


Figure 2 Structural Equation Model of Generative AI Adoption Intention

The path hypothesis test results showed:

PU has a significant positive impact on ATT (β = 0.175, p = 0.008). ATT has a significant positive impact on BI (β = 0.643, p < 0.001). BI has a significant positive impact on USE (β = 0.535, p < 0.001). Hypotheses H1, H2, H3 are all supported.

Perceived Enjoyment significantly positively affects PU (β = 0.284, p < 0.001) and ATT (β = 0.324, p < 0.001). Hypotheses H4, H5 are supported.

AI Anxiety has a significant negative impact on PU (β = -0.296, p < 0.001). H6 is supported. AI Anxiety's impact on ATT is not significant (β = -0.120, p = 0.084). H7 is not supported.

Privacy Concern's impact on PU is not significant (β = -0.105, p = 0.108). H8 is not supported. Privacy Concern has a significant negative impact on ATT (β = -0.148, p = 0.021). H9 is supported.

Perceived Ease of Use's impact on PU is not significant (β = 0.123, p = 0.055). H10 is not supported. Perceived Ease of Use has a significant positive impact on ATT (β = 0.159, p = 0.012). H11 is supported.

Most hypotheses in the model were validated, indicating that perceived enjoyment can enhance user acceptance intention, while AI anxiety and privacy concerns inhibit this intention to some extent; PU, ATT, BI, and USE form a stable acceptance path, and PEOU's influence is more directly reflected in attitude. Notably,

the three non-significant paths (H7: AIA ⟶ ATT, H8: PC ⟶ PU, and H10: PEOU ⟶ PU) suggest that (i) anxiety may primarily reduce acceptance through cognitive evaluation of usefulness rather than directly lowering attitude, (ii) privacy concerns may shape evaluative attitude more strongly than perceived utility, and (iii) in a sample with relatively frequent exposure to digital tools, ease-of-use may have a weaker incremental contribution to usefulness perceptions (p = 0.055). These interpretations are further discussed in the Discussion section as potential mechanism- and sample-structure explanations.

Table 5 Path Hypothesis Test Results

Hypothesis	Path	β	t	p	Result
H1	PU ⟶ ATT	0.175	2.637	0.008	Supported
H2	ATT ⟶ BI	0.643	9.57	***	Supported
H3	BI ⟶ USE	0.535	8.162	***	Supported
H4	PENJ ⟶ PU	0.284	3.787	***	Supported
H5	PENJ ⟶ ATT	0.324	4.226	***	Supported
H6	AIA ⟶ PU	-0.296	-4.219	***	Supported
H7	AIA ⟶ ATT	-0.12	-1.728	0.084	Not supported
H8	PC ⟶ PU	-0.105	-1.606	0.108	Not supported
H9	PC ⟶ ATT	-0.148	-2.31	0.021	Supported
H10	PEOU ⟶ PU	0.123	1.917	0.055	Not supported
H11	PEOU ⟶ ATT	0.159	2.52	0.012	Supported

Note: *p < 0.05, **p < 0.01, ***p < 0.001

5.4 Mediation Effect Test

This investigation examined the mediation effect of PEOU ⟶ PU ⟶ ATT. The outcomes demonstrated that the total effect of PEOU on ATT is substantial (β = 0.345, t = 8.487, p < .001, 95% CI [0.265, 0.425]). After accounting for the mediator variable PU, the direct effect of PEOU on ATT stays substantial (β = 0.250, t = 6.080, p < .001, 95% CI [0.169, 0.330]), implying partial mediation. Additional Bootstrap analysis discovered that the indirect effect of PEOU on ATT through PU is substantial (β = 0.096, Boot 95% CI [0.058, 0.138]). Thus, it can be concluded that PU performs a partial mediating function between PEOU and ATT.

Table 6 Mediation Effect Test Results (PEOU ⟶ PU ⟶ ATT)

Hypothesis	Path	Type	β	S.E.	t	p	Boot CI	Result
H12	PEOU ⟶ ATT	Total Effect	0.345	0.041	8.487	.000	[0.265, 0.425]	Partial Mediation
	PEOU ⟶ ATT	Direct Effect	0.250	0.041	6.080	.000	[0.169, 0.330]	
	PEOU ⟶ PU ⟶ ATT	Indirect Effect	0.096	0.021	—	—	[0.058, 0.138]	

5.5 Moderating Effect Test

To confirm the moderating effect of Professional Background, this investigation employed multi-group analysis. The sample was split into a group lacking professional background and a group possessing professional background for model comparison. In the PU ⟶ ATT route, both the PB=No group and the PB=Yes group displayed significant positive effects (β=.376 vs .392, both p<.001). In the PEOU ⟶ ATT route, the effects for both the PB=No group and the PB=Yes group were likewise significant (β=.364 vs .359, both p<.001). The disparity in effect strength between the two groups for both routes was minor, denoting that the moderating effect of professional background on these crucial routes is constrained.

Table 7 Moderating Effect Test Results (Multi-Group Analysis by PB)

Hypothesis	Path	Group (PB)	B	SE	β	t	p	Result
H13	**PU ⟶ ATT**	No PB	0.349	0.081	0.376	4.296	< .001	Supported
		Has PB	0.390	0.048	0.392	8.197	< .001	
H14	**PEOU ⟶ ATT**	No PB	0.348	0.084	0.364	4.131	< .001	Supported
		Has PB	0.344	0.047	0.359	7.395	< .001	

Discussion

Building upon the expanded TAM structure, this investigation probed the effects of perceived usefulness, perceived ease of use, perceived enjoyment, AI anxiety, and privacy concern on the acceptance intention of generative AI tools, and verified the moderating effect of professional background. The structural paths provide a coherent "fun–fear" account of generative AI acceptance. The model fit outcomes indicated sound overall fit, affirming the reasonableness of the research framework (χ^2/df = 1.880, RMSEA = 0.043, CFI = 0.945, TLI = 0.938).

Firstly, the central route comprised of PU, ATT, BI, and USE obtained substantial backing, PU positively predicts ATT (β = 0.175, p = 0.008), ATT strongly predicts BI (β = 0.643, p < 0.001), and BI predicts USE (β = 0.535, p < 0.001). If users trust that generative

AI can enhance efficiency and generate high-grade outcomes, they are more prone to foster positive attitudes, thus boosting behavioral intention and eventually resulting in actual use. This aligns with the inferences of Davis (1989) and Venkatesh and Davis (2000). It is noteworthy that the effect of PEOU on PU did not reach significance (H10: β = 0.123, p = 0.055), but its direct effect on ATT was significant (H11: β = 0.159, p = 0.012), signifying that in the setting of emerging AI, ease of use operates more by straightly elevating user attitude rather than being converted into perception of usefulness. A plausible behavioral interpretation is that, when users are already familiar with mainstream AI interfaces, ease of use becomes a "baseline expectation," reducing its incremental contribution to usefulness judgments while still shaping immediate evaluative attitude.

Secondly, this study discloses the double-edged sword effect of affective elements. Perceived enjoyment significantly positively forecasts PU and ATT, with PENJ $\longrightarrow$ PU (β = 0.284, p < 0.001) and PENJ $\longrightarrow$ ATT (β = 0.324, p < 0.001), confirming the function of enjoyment in advancing technology adoption (Van der Heijden, 2004), implying that generative AI is not solely an efficiency instrument but also a medium delivering interactive pleasure. At the same time, AI anxiety imposes a significant negative effect on PU (AIA $\longrightarrow$ PU: β = −0.296, p < 0.001), but its effect on ATT is not significant (H7: β = −0.120, p = 0.084); privacy concern imposes no significant effect on PU (H8: β = −0.105, p = 0.108), but imposes a significant negative effect on ATT (PC $\longrightarrow$ ATT: β = −0.148, p = 0.021). This partly aligns with the inquiry of Compeau and Higgins (1995) and Malhotra et al. (2004), demonstrating that users' sense of dread and privacy worries indeed form barriers to adoption, but the pathways of their effects vary. Importantly, "non-significant" does not imply "no meaning"; rather, it indicates insufficient evidence at the chosen criterion (typically p < 0.05). Here, the pattern suggests that anxiety primarily operates through cognitive evaluation (lowering PU), whereas privacy concern primarily operates through evaluative judgment (lowering ATT). Regarding the three unsupported hypotheses (H7, H8, H10), the findings suggest a mechanism-level explanation: (1) anxiety may be translated into reduced perceived usefulness before it shapes attitude; (2) privacy concerns may be activated as an attitudinal risk signal rather than as a utilitarian evaluation; and (3) ease of use may not materially change usefulness perceptions when users already expect baseline usability from widely deployed generative AI tools. In addition, privacy concerns may be domain-sensitive, and because the survey did not explicitly separate use cases, the PU-related effect of privacy concern may be averaged out across heterogeneous usage contexts.

Thirdly, the multi-group analysis outcomes demonstrate that although the effects of PU and PEOU on ATT are significant across both professional background groups, the between-group disparities are constrained, implying that the moderating

effect of professional background is not significant. The PU ⟶ ATT path is significant for both groups (β = 0.376 vs. 0.392, $p < 0.001$), and the PEOU ⟶ ATT path is also significant for both groups (β = 0.364 vs. 0.359, $p < 0.001$), with only minor differences in effect magnitude. This diverges somewhat from the perspective of "user group variations" stressed by Schwesig et al. (2023). The acceptance intention of generative AI relies more on the perceived value of the tool itself and the affective encounter, rather than the individual's professional background. Generative AI has become sufficiently "general-purpose" that core acceptance drivers are shared across occupational segments, while finer-grained heterogeneity may depend more on specific usage scenarios (use cases) than on broad professional-background labels. Overall, these results fill a key gap in prior TAM-based generative AI research by explicitly separating the original TAM core path from the newly introduced "fun–fear" extensions and by clarifying where negative perceptions enter the acceptance pathway (PU versus ATT)

Suggestion

Based on the dual psychological dynamics of "fear and fun" identified in this study, the following practical recommendations are proposed. For product design and promotion, a two-pronged strategy should be adopted. On one hand, it is crucial to enhance perceived enjoyment by improving interactivity and creativity, making the usage process more enjoyable. On the other hand, it is equally important to effectively alleviate AI anxiety and privacy concerns by increasing system transparency and granting users more control. Given that the moderating effect of professional background was not significant, universal communication strategies are recommended. Clearly communicating the product's usefulness, ease of use, and data security measures to all user groups would be more cost-effective than developing highly differentiated strategies for specific professional segments.

It is recommended to employ longitudinal tracking studies or experimental methods to more accurately capture the dynamics of user attitude changes and verify causal relationships. Simultaneously, researchers should explore other potential influencing factors, such as users' innovativeness or contextual factors like social influence. Furthermore, extending this research to specific application contexts such as education or healthcare to test the model's applicability and specificity in different domains would provide more precise guidance for the contextualized application of generative AI. Future studies can operationalize "use-case context" as a moderator and examine whether privacy concerns shift from attitudinal to utilitarian pathways under different governance and risk conditions.

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Appendix A

Questionnaire Instrument

Part A. Demographics

Variable	Options
Gender	(1) Male; (2) Female
Age	(1) 18–24; (2) 25–34; (3) 35–44; (4) 45+
Education	(1) High school or below; (2) College/Bachelor; (3) Master or above
Occupation/Industry	(1) Student; (2) IT/Data/AI-related; (3) Education/Research; (4) Business/Services; (5) Other
Monthly income (RMB)	(1) Low (≤ 5,000 RMB/month); (2) Middle (5,001–10,000 RMB/month); (3) High (≥ 10,001 RMB/month); (4) No fixed income

Part B. Measurement Items

Response scale: 5-point Likert scale (1 = Strongly disagree … 5 = Strongly agree).

PB coding: 0 = No, 1 = Yes.

Variables	Item	Wording	Source
Perceived Usefulness (PU)	PU1	Using this generative-AI tool improves my task efficiency.	Davis (1989)
	PU2	Using the tool enhances my job/study performance.	
	PU3	The tool helps me produce higher-quality results.	
	PU4	Overall, this tool is useful for my tasks.	
Perceived Ease of Use (PEOU)	PEOU1	Learning to use the tool is easy for me.	Davis (1989)
	PEOU2	It is easy to get the tool to do what I want.	
	PEOU3	Interacting with the tool is clear and understandable.	
	PEOU4	I find the tool easy to master.	
Perceived Enjoyment (PENJ)	PENJ1	Using the tool is enjoyable.	Van der Heijden (2004)
	PENJ2	The act of using the tool is fun in itself, regardless of outcomes.	
	PENJ3	I enjoy interacting with the tool.	
	PENJ4	The tool provides a sense of relaxation/entertainment.	
AI Anxiety (AIA)	AIA1	I feel tense or uneasy when I think about using generative AI.	Adapted from Compeau & Higgins (1995); Parasuraman & Colby (2015)
	AIA2	I worry that AI may produce unpredictable or hard-to-control outcomes.	
	AIA3	I fear AI may replace some of my abilities/work.	
Privacy Concern (UIPC)	UIPC1	I am concerned about excessive collection of my personal/data when using the tool.	Malhotra, Kim, & Agarwal (2004)
	UIPC2	I feel I lack control over how the tool uses my data.	
	UIPC3	I want clear knowledge of how the tool processes and shares data.	
	UIPC4	I would hesitate to use the tool without clear privacy statements.	

Variables	Item	Wording	Source
Attitude Toward Use (ATT)	ATT1	Using the tool is a wise idea.	Davis (1989); Taylor & Todd (1995)
	ATT2	I have a positive attitude toward using the tool.	
	ATT3	Using the tool is beneficial and satisfying.	
Behavioral Intention (BI)	BI1	I intend to continue using the tool in the future.	Davis (1989); Venkatesh & Davis (2000)
	BI2	Given the choice, I will prefer this tool for my tasks.	
	BI3	I am willing to recommend the tool to others.	
System Use (USE)	USE1	In the past month, I used the generative AI tool frequently.	Self-developed
	USE2	In the past month, my sessions with the generative AI tool were usually of long duration.	
	USE3	In the past month, I often used the generative AI tool to accomplish my core tasks.	
Professional Background (PB)	PB	My major/work field is related to computing, data, or AI. (0 = No, 1 = Yes)	Self-reported