The Dominant Position of Perceived Usefulness and the Limited Role of Artificial Intelligence Anxiety: Determinants of Generative Artificial Intelligence Adoption Intention among University Students in Learning

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Abstract. The integration of generative artificial intelligence (GenAI) into the educational landscape of China is advancing at a pace marked by unprecedented speed, which requires researchers to re-examine the psychological mechanisms underlying students' technology adoption. Despite the established role of Perceived Usefulness (PU) as a core cognitive driver, the interplay between this factor and the emerging emotional barrier of Artificial Intelligence Anxiety (AIA) has not been sufficiently examined. This study theoretically bridges the Technology Acceptance Model (TAM) and the emotional cognitive perspective. Through a questionnaire survey of 192 Chinese university students, the impact of PU, AIA and their interaction on the intention of learning behavior using GenAI was systematically tested. Hierarchical regression analysis shows that PU emerged as a robust predictor of Behavioral Intention (BI) ($\beta = 0.697$, $p < .01$); however, AIA exerted no significant direct or interactive (with PU) effect on intention. Further exploratory analysis shows that even if AIA is deconstructed into three sub-dimensions of learning anxiety, sociotechnical blindness anxiety and AI configuration anxiety, its predictive effect on BI is still not significant, and the dominant role of PU remains robust ($\beta = 0.720$, $p < .001$). The research results show that under the present learning context, the adoption decision-making of university students shows the phenomenon of "intention-emotion decoupling", that is, it is mainly driven by the rational evaluation of the value of the tool, and different types of AIA do not substantially intervene in the process of intention formation.

Keywords: Technology Acceptance Model, Perceived Usefulness, Behavioral Intention, Artificial Intelligence Anxiety, Generative Artificial Intelligence

1. Introduction

Generative artificial intelligence (GenAI) tools, including Wenxinyiyan, Gemini and ChatGPT, is reshaping the landscape of higher education at an unprecedented speed. It shows great potential in academic writing, information retrieval and complex problem-solving [1,2]. Furthermore, it gradually evolves from an auxiliary tool to a key component of the learning ecosystem. This change in the technical paradigm requires researchers to move beyond the traditional Technology Acceptance Model (TAM) and explore complex intertwining of rational calculation and emotional response in students' adoption decision-making in more detail.

Within the TAM framework, Perceived Usefulness (PU) serves as a key variable in forecasting the acceptance of a wide range of educational technologies [3,4]. In the context of GenAI, recent studies have continuously verified the key role of PU [5,6]. However, technology adoption is often influenced by both emotional and cognitive factors, which leads to the process not being carried out in a purely rational situation [7,8]. Additionally, with the deep coupling of artificial intelligence technology and social life, a specific emotional response - AI anxiety (AIA) - has increasingly emerged in recent studies [9]. This kind of tension, anxiety and concern about AI technology is considered to hinder the willingness to adopt new technologies. Although existing studies have focused on the potential inhibitory effect of AIA, there are still differences in conclusions, and most of them regard it as a single-dimensional negative cause [10].

In the actual decision-making process, users often carry out "benefit evaluation" and "threat assessment" at the same time [11]. This phenomenon is also reflected in students' willingness to use technology. Specifically, when students perceive that a technology can effectively assist knowledge understanding or academic performance, they tend to actively adopt the technology; conversely, if students believe that the technology may pose a potential threat to their learning and cause anxiety, their willingness to use it may be suppressed. However, there is a scarcity of robust empirical evidence to clarify whether the above-mentioned cognitive-emotional dual-path mechanism is established in the real education scenario, especially in China's unique educational culture and social background.

To fill the above research gaps, this study has built an integrated analysis framework, which includes PU and AIA at the same time. This framework aims to go beyond the traditional interpretation path that only focusses on a single cognitive belief. By integrating PU, which represents the evaluation of rational tools, and AIA, which reflects the evaluation of emotional threats, it systematically tests the independent impact and interaction effects of the two on the BI of Chinese university students using GenAI to learn. This research helps to deeply reveal the complex psychological mechanism behind the acceptance of GenAI technology. Furthermore, it provides empirical-based theoretical basis and practical inspiration for universities to promote value advocacy and emotional support when promoting relevant technologies.

2. Literature review

2.1. The core role of TAM and PU

TAM is a classical theory that explains the adoption behavior of individual information technology [3]. The model posits that individuals' intention to adopt technology is predominantly driven by users' cognitive evaluations - especially PU, and BI is the strongest predictor that drives the actual use behavior [3,4]. Among them, PU refers to the degree to which users believe that using a specific system can improve their work or learning performance, and it has been widely demonstrated to be a significant predictor of BI [3].

In the research vein of digital learning in higher education, the key role of PU has been repeatedly verified in different technical applications, such as online learning platforms, learning management systems and mobile learning tools [12]. With the rise of GenAI, this core proposition continues to be tested and consolidated in the new context. Recent empirical studies consistently show that students' perception of the usefulness of GenAI tools (such as Wenxinyiyan) is a fundamental catalyst for their adoption intention [3,6,13]. The specific expression of its willingness to use is mainly reflected in the improvement of use frequency, the enhancement of learning initiative, and the more active use of AI tools in academic tasks. For example, existing studies have directly verified that PU acts as a robust predictor of students' behavioral intention to use GenAI in educational settings [3]. The empirical analysis based on TAM further reveals that students' awareness of the usefulness of ChatGPT directly enhances their willingness to use it. In addition, it indirectly promotes it by improving the intrinsic learning motivation [6]. Similarly, in higher education scenarios, students' positive evaluation of the learning value of AI tools is the main cognitive basis for their willingness to use them [13]. This situation is not limited to the student group. Research on university teachers also found that PU is also the core impact factor of their adoption of GenAI for teaching and scientific research activities, which is manifested in teachers' AI to improve teaching efficiency, support course preparation, generate scientific research texts and analysis data [14]. The high cognitive usefulness of the aspect, thus enhancing its actual intention and frequency of use. This shows that unlike previous educational technologies, GenAI is directly involved in high-risk academic tasks such as writing, problem solving and assessment preparation, thus significantly strengthening the prominent and decisive role of PU in technology adoption decision-making.

Based on a solid theoretical and empirical foundation, this research posits the following:

H1: Perceived Usefulness has a significant positive impact on the Behavioral Intention of university students to use generative AI tools to learn.

2.2. AIA

AIA is a specific situational anxiety that occurs in the process of interacting with artificial intelligence systems. Especially when using GenAI tools (such as ChatGPT), users may experience concerns regarding the uncertainty, potential errors or uncontrollability of their generated results, usually manifested as nervousness, anxiety, psychological burden, worry and even fear [15,16]. This anxiety may stem from concerns about technological complexity, unpredictability, ethical risks, and substitution of individual capacity [16].

Existing research shows that technical anxiety has a significant inhibitory effect in the process of technology adoption, mainly because high anxiety is easy to stimulate the tendency to avoid risk. For example, early studies found that computer anxiety can reduce students' intention to use new technologies and online learning platforms [10]. In the context of artificial intelligence, similar mechanisms also exist. An empirical study of Middle Eastern university students based on TAM found that AIA weakens users' intention to adopt GenAI to a certain extent, especially when individuals lack a clear understanding of technical norms and ethical boundaries [17]. In addition, research on university students points out that AIA may directly affect BI and indirectly affect technology adoption decision-making through attitude, trust and psychological security [15]. This phenomenon can be explained by the emotion-motivation theory. High-level anxiety may activate avoidance motivation, thus reducing the possibility of students actively using GenAI tools for learning [7].

However, AIA is not a homogeneous whole. Instead, it may be composed of multiple dimensions that are interrelated but have different functions. Existing studies have pointed out that AIA can be divided into at least several types, such as "learning anxiety (LA)" about one's own learning ability that may be damaged or weakened, "sociotechnical blindness anxiety (STA)" about the social, ethical and fair issues brought about by artificial intelligence, and the complexity and opacity of the technical system [9]. And the "AI configuration anxiety (ACA)" of uncontrollability. AIA in different dimensions does not necessarily produce consistent behavioral consequences: for example, LA may encourage individuals to reduce their dependence on GenAI tools to avoid erosion of their own capabilities; while ACA may inhibit the continuous use of tools, arising from concerns about wrong output or system out of control; by contrast, STA is more reflected in normative or ethical concerns, and its impact on specific usage behavior may be more indirect [9]. Although overall, AIA is often regarded as an important psychological factor in inhibiting the adoption of technology, existing studies still lack a systematic discussion on the differentiation of its internal structure and the impact of differentiated behavior caused by different anxiety dimensions. This shows that the behavioral consequences of AIA are theoretically ambiguous, rather than unified inhibition.

Based on the mainstream view, this study puts forward a hypothesis:

H2: AI anxiety has an important negative impact on the Behavioral Intention of university students to use generative AI tools for learning.

2.3. The regulating effect of PU: the trade-off perspective of cognition and emotion

According to the cognitive assessment theory, individual behavioral decision-making comes from a comprehensive trade-off between potential benefits and threats in the situation [11]. In the context of technology adoption, PU represents "benefit evaluation", while AIA represents "threat assessment". The theory of protective motivation further points out that when the effectiveness perception of coping behavior (which can be analogous to PU here) is high, the negative impact of threat perception (anxiety) on behavior may be weakened [18,19]. In other words, if students firmly believe that GenAI can greatly improve the learning effect (high PU), they may be more willing to tolerate or overcome the accompanying anxiety and worry (AIA), thus weakening the inhibitory effect of anxiety on the intention to use it. The recent TAM extension research provides empirical clues for this interaction mechanism. For example, perceived risk has been found to be able to weaken the positive impact of PU on the intention of technology use, indicating that negative cognitive factors may interfere with the path of cognitive benefits on BI [20].

At the same time, some studies have pointed out that different types of artificial intelligence functions perceive different values in work and learning scenarios. When individuals have a strong sense of the usefulness of technology (PU), their tolerance for technology-related risks or anxiety may increase, thus cushioning the inhibitory effect of negative emotions on the intention to adopt [21]. However, whether PU necessarily reduces the impact of AIA is still an open question of experience.

Based on this theoretical logic, this study proposes:

H3: Perceived usefulness plays a regulating role between Artificial Intelligence Anxiety and Behavioral Intention. Compared with students with low Perceived Usefulness, the Artificial Intelligence Anxiety of students with high Perceived Usefulness exhibit a weaker negative effect on Behavioral Intentions.

3. Method and data

3.1. Research sample

A cross-sectional research design was utilized through the administration of a questionnaire. The data are collected through online questionnaire platforms (such as "Questionnaire Star"), and the questionnaire links are distributed in WeChat groups and course platforms of students in many universities in China. The study adopts a convenience sampling method. Although convenience sampling may limit the generalization, it is still suitable for theoretical test research focusing on relationship mechanisms rather than population estimation. In addition, to motivate participation, the researchers set up small random red envelope rewards. There is an informed consent statement prior to the questionnaire.

In the end, a total of 215 questionnaires were recovered, and 23 invalid questionnaires with too short answer time, failed attention test questions or obvious regular answers were eliminated, and 192 valid questionnaires were obtained, yielding an effective response rate of 89.3%. The sample characteristics are shown in Table 1. The sample covers multiple professional backgrounds and different grade levels, and the gender structure is relatively balanced, which can reflect the characteristics of different student groups to a certain extent. And most students (96.87%) have experience in the use of GenAI, which is in line with the context in which this study focusses on "intention of adoption" rather than "initial contact".

Table 1. Participants

Variables	Category	n	%
Gender	Female	122	63.54
	Male	70	36.46
Grade	Freshman	9	4.69
	Sophomore	55	28.65
	Junior	60	31.25
	Senior	68	35.42
Major	Humanities / Social Sciences	84	43.75
	STEM / Medical / Agriculture	93	48.44
	Arts / Sports	15	7.81
Frequency of use	Never (0 times)	6	3.13
	Rarely (1-2 times per month)	61	31.77
	Regularly (1-2 times per week)	81	42.19
	Frequently (3-5 times per week)	44	22.92
Total		192	100.0

3.2. Measuring tools

All core variables are measured on the Likert five-point scale (1 = "very much disagree", 5 = "very much agree"). The scales are derived from mature English scales and follow the standard "translation-back translation" procedure to ensure semantic reciprocity, and then a small group of university students were pre-tested to adjust the expression.

3.2.1. PU scale

Adapted from the classic scale of Davis, there are 5 questions in total (e.g.: "I think using AI tools helps me improve my learning efficiency") [3]. In this study, the Cronbach's α coefficient of the scale is 0.739, and its value higher than 0.7 indicates that the scale has favorable internal consistency.

3.2.2. AIA scale

Study adopts a previously validated AIA scale and is moderately revised in combination with the learning and use situation of GenAI [9]. The scale depicts the nervousness, uneasiness and worry of individuals in the face of artificial intelligence technology from a multi-dimensional perspective.

Based on the theoretical framework of the original scale and combined with the learning situation of higher education, this study mainly focusses on the three content dimensions of AIA: (1) learning anxiety (LA), reflecting the concern of individuals about the impairment of their own learning ability or deepening dependence in the process of using AI tools for learning; (2) sociotechnical blindness anxiety (STA) refers to individuals' concerns about the social adaptation risks and ethical uncertainty brought about by the accelerated advancement of technology of AI; (3) AI configuration anxiety (ACA) reflects individuals' unease about the complexity, uncontrollability and operation mechanism of AI technology. The overall scale demonstrated excellent internal consistency (Cronbach's $\alpha > .924$), and all subscales also showed good reliability ($\alpha > .84$).

It should be noted that in the subsequent empirical analysis, AIA is mainly modelled as an overall psychological concept to test its overall impact on the intended use of GenAI learning. At the same time, to understand the potential path of different sources of anxiety in more detail, this study conducts an exploratory test of the above three sub-dimensions in the supplementary analysis.

3.2.3. BI scale

Adapted from Davis's intention scale, there are 5 questions in total (e.g.: "I plan to continue to use AI tools to assist my study in the future") [3]. In this study, the Cronbach's α coefficient of the scale is 0.752, which means it is good.

3.2.4. Control variables

Among them, the following control variables were included gender (0 = male, 1 = female), grade (1-4), professional categories (in three broad categories see table 1) and frequency of AI use (treated as a sequential variable). Existing studies have consistently shown that these variables have systematically shaped the technology adoption model by affecting the individual's accessibility, degree of contact with technology and discipline norms [22]. Therefore, this study incorporates gender, professional type and artificial intelligence use frequency as control variables in the regression model to exclude their potential confounding effects, to more accurately estimate the influence on students' technology adoption decisions within GenAI-supported learning contexts.

3.3. Data analysis

Use SPSS 26.0 for data analysis. First, carry out the common method bias test. The results of Harman's single factor test show that the first factor extracted when not rotated only explains 29.47% of the total variance (below the critical threshold of < 40%), indicating that the common method variance (CMV) problem is not serious. Subsequently, the reliability of the scale was tested by calculating the Cronbach's α coefficient and conducting exploratory factor analysis (EFA). Subsequently, calculate the descriptive statistics of the main variables and the Pearson correlation coefficients. Finally, Hypotheses were tested using hierarchical multiple regression analysis: the first layer adds control variables; the second layer adds the centered independent variable AIA; the third layer adds the centered moderator variable PU; the fourth layer adds the interaction term of the two. All regression models have been diagnosed for variance inflation factor (VIF), and the VIF values are far below 5, indicating that there is no multicollinearity problem. If the interaction is significant, a simple slope analysis is carried out.

4. Research results

4.1. Results of preliminary analyses

Table 2 shows the means, Pearson correlation coefficients and reliability coefficients, of the main variables in the study. Overall, the sample exhibited strong intentions to integrate GenAI into their learning activities ($M = 4.03$, $SD = 0.57$), and the level of PU is also high ($M = 4.09$, $SD = 0.55$), while the level of AIA is moderate ($M = 3.19$, $SD = 0.83$). Due to Cronbach's α coefficients higher than the recommended threshold of .70, this means that all core constructs show good internal consistency. Among them, the reliability of the overall AIA scale demonstrates a high level of reliability ($\alpha = .924$). The results of the correlation analysis show a strong positive correlation between PU and BI ($r = .737$, $p < .01$). In contrast, the correlation between AIA and BI is not significant ($r = -.079$, $p > .05$), and its correlation with PU does not reach statistical significance ($r = -.064$, $p > .05$).

Table 2. Descriptive statistics, Pearson correlation coefficients and reliability

Variables	Mean	SD	Cronbach's α	1	2	3
BI_mean	4.034	0.573	.752	1		
AIA_mean	3.192	0.832	.924	-.079	1	
PU_mean	4.085	0.553	.739	.737	-.064	1

Table 3. Results of exploratory factor analysis for reliability and validity tests

Scale	Items	Cronbach's α	KMO	Bartlett's χ^2 (p)	Cumulative Variance Explained (%)
PU	5	0.739	0.77	197.40, p < .001	49.37
BI	5	0.752	0.77	209.25, p < .001	50.50
AIA	13	0.924	0.92	1439.96, p < .001	63.29
LA	5	0.873	0.85	461.90, p < .001	66.41
STA	4	0.845	0.82	300.85, p < .001	68.33
ACA	4	0.870	0.81	70.61, p < .001	72.05

Before the hypothesis test, the construct validity of all scales was examined. The results of EFA, presented in Table 3, show that the data are appropriate for exploratory factor analysis (all KMO values are greater than .70, and Bartlett's test of sphericity is significant, $p < .001$). The cumulative variance explained by each scale or sub-dimension is close to or exceeds 50%, supporting their good construct validity.

The factor analysis results for the AIA scale show a relatively concentrated factor structure at a high level, with the extracted primary factor explaining 63.29% of the total variance. This result indicates that although AIA is theoretically multi-dimensional, in the context of GenAI-supported learning, learners' subjective experiences of anxiety from different sources are generally consistent.

Given that the central aim of this research is to examine the influence of AIA as an overall emotional experience on learning usage intention, it is treated as a higher-order construct in the main regression analysis. This approach is consistent with treatments in existing technology anxiety research and helps to maintain model parsimony [9]. At the same time, each sub-dimension demonstrates a good level of reliability (Cronbach's α is greater than .84), providing a reliable measurement basis for subsequent exploratory analysis.

4.2. Hypothesis test: hierarchical multiple regression analysis

To test the research hypotheses, hierarchical multiple regression analysis was employed. All predictor variables were mean-centered before entering the model.

As shown in Table 4, the direct effect of AIA on BI did not reach statistical significance ($\beta = -.010$, $p > 0.05$), which suggests the potential presence of moderator variables or effects offsetting across dimensions. Hypothesis H2 is therefore not supported. When PU was entered into the model, it demonstrated a significant and strong positive predictive effect on BI ($\beta = .720$, $p < .01$) and significantly enhanced the model's explanatory power ($\Delta R^2 = .416$), thus providing strong support for hypothesis H1.

In the final model, the interaction term between AIA and PU did not reach statistical significance ($\beta = -.103$, $p > 0.05$), and the increment in the model's explanatory power was relatively limited and non-significant ($\Delta R^2 = .005$). Further simple slope analysis revealed that when PU was at low, average, and high levels of the moderator (defined as −1 SD, the mean, and +1 SD, respectively), the effect of AIA on BI remained non-significant (all $p > .05$). Therefore, hypothesis H3 is not supported.

Table 4. Hierarchical regression analysis

Variable	Model 1 (β)	Model 2 (β)	Model 3 (β)
Gender	-0.035	-0.084	-0.088
Grade	0.046	-0.002	-0.003
Major	-0.104	-0.082	-0.079
Frequency of use	0. 234**	0.075*	0.077*
AIA	-0.010	-0.006	0.017
PU		0.720**	0.697**
AIA × PU			-0.103
R^2	0.152	0.569	0.574
Adjusted R^2	0.129	0.555	0.557
ΔR^2		0.416	0.005
F-value	6.681	40.664	35.367

Note: * p<0.05 ** p<0.01.

4.3. Exploratory regression analysis: sub-dimensions of AIA

To further explore the potential reasons why the overall effect of AIA is not significant, this study conducts exploratory regression analysis of three sub-dimensions (LA, ACA and STA) of this dimension.

As shown in Table 5, PU is still the most significant and s positive factor in predicting BI ($\beta = .720$, $p < .001$). In contrast, the three sub-dimensions of AIA have not reached the statistical significance level ($p > .05$), but its impact trend is differentiated: Learning adaptation anxiety (LA, β

= −.108) and academic integrity anxiety (ACA, β = −.051) have a negative impact on BI, while social and technical anxiety (STA, β = .125) show a positive trend.

Table 5. Exploratory regression coefficients

	Unstandardized Coefficient		Standardized Coefficient	t	p	95% CI	VIF
	B	SE	Beta				
Constant	0.999	0.241	-	4.146	0.000***	0.524 ~ 1.475	-
LA	-0.064	0.039	-0.108	-1.645	0.102	-0.141 ~ 0.013	1.805
ACA	-0.029	0.044	-0.051	-0.671	0.503	-0.115 ~ 0.057	2.416
STA	0.080	0.047	0.125	1.708	0.089	-0.012 ~ 0.173	2.234
PU	0.747	0.051	0.720	14.584	0.000***	0.646 ~ 0.848	1.025

Note: Dependent variables = BI_mean; ***p<0.001

5. Discussion

Data analysis establishes the structural dominance of PU in predicting students' BI to adopt (β = 0.697, $p < 0.01$). This result strongly confirms the continued relevance of the TAM in explaining technology adoption within complex intelligent learning environments, further revealing that within the highly performance-oriented context of higher education, students' rational evaluation of technical instruments is the primary logic to drive their adoption and decision-making.

However, contrary to some theoretical expectations, the overall construct of AIA has not shown a significant direct inhibitory effect. This "non-significant" finding is valuable. Exploratory analysis provides a key structural explanation for this: the influence of different dimensions of AIA on BI is directionally heterogeneous. Specifically, LA (β = -0.108) and ACA (β = -0.051) show a weak negative trend, while STA (β = 0.125) shows a slight positive impact. This differentiation of internal structure shows that it may be too simplified to regard AIA as a homogeneous inhibitory concept. Among them, the path of "defensive adoption" revealed by STA is particularly worthy of attention - that is, concerns about the social impact of AI may be transformed into the motivation to actively learn and master technology to cope with future uncertainty.

The different directions of sub-dimensional effects lead to the "neutralization" of the overall AIA effect, which provides a microscopic basis for understanding the complex role of emotional variables in technical acceptance. More critically, the analysis reveals that PU fails to moderate the relationship between AIA and BI. This implies that in the specific educational decision-making situation of this study, the cognitive belief (PU) representing instrumental benefit evaluation and the AIA representing emotional threat assessment may not directly compete within the same psychological trade-off framework in individual decision-making.

Based on this, this study puts forward the interpretation framework of "intention-emotional decoupling". The framework believes that in the "initial adoption decision-making stage" of GenAI education application, students' behavioral intentions are mainly dominated by the rational calculation of the value of tools; while the anxious emotional experience that exists at the same time may be "suspended" outside the core decision-making path. The complex impact of AIA may be more fully reflected in the "specific use stage" after adoption, such as affecting the prudence of the use strategy, the degree of dependence on technology, and the sensitivity to ethical issues.

The above mechanisms need to be understood in the unique context of higher education in China. The performance-oriented culture and fierce academic competition prevalent in Chinese universities have systematically shaped and strengthened students' rational orientation through performance rankings and scholarships. In this situation, the value of any tool that can significantly improve learning performance is sharply amplified, thus consolidating the central position of PU in decision-making, while making emotional reactions such as AIA relatively marginalized in the weight of decision-making. Therefore, the conclusion of this study can also be regarded as a concrete embodiment of highly institutionalized instrumental rationality in technology adoption behavior.

6. General discussion: synthesis, implications, and future research

6.1. Contributions of the integrated research framework

This research expands the theory of technology acceptance from three progressive levels, the core of which is to reveal a new mechanism of "intention-emotional decoupling" in the learning situation of GenAI.

First, under the background of the complex technology of GenAI, the research once again confirms the core position of PU in the TAM model and consolidates the foundation of rational interpretation of tools. Secondly, by incorporating the AIA system into the analysis framework and finding that its internal dimensions (such as STA and ACA) have a heterogeneous impact on behavioral intentions, the study has broken through the limitation of treating emotions as a single inhibitory factor and clarified the complexity and boundary conditions of emotional variables.

The most important thing is that the study found that PU does not regulate the relationship between AIA and behavioral intention, which directly reveals the structural phenomenon of "intention-emotional decoupling": in the formation stage of adoption of decision-making, students' instrumental evaluation (PU) dominates absolutely, and AIA, as an accompanying emotional experience, does not Enter the core decision-making trade-off path. This finding fundamentally challenges the implicit assumption that traditional research regards anxiety as an obstacle, or that implicit cognition and emotion must be weighed against each other in decision-making and provides a more refined and more staged theoretical perspective for understanding the psychological mechanism accepted by intelligent technology.

6.2. Practical implications

To ensure the responsible implementation and effective application of GenAI in education, universities should adopt integrated strategies: at the cognitive level, focus on helping students rationally evaluate their learning value and usage boundaries through curriculum integration and case teaching; at the emotional level, accept and guide students' complex emotions about AI, and cultivate prudent and reflective attitudes through ethical discussion and literacy education; at the institutional level, build a supportive environment including technical platforms, usage norms and ethical guidelines to improve efficiency and prevent and control long-term dependence and ethical risks.

6.3. Limitations and implications for future research

This study has several shortcomings. First, this research uses cross-sectional data for analysis, which means that it cannot confirm causal relationships. Secondly, students' self-reported BI may deviate from actual usage behavior. Finally, the external validity of this study is limited by its reliance on a convenience sampling method. Therefore, future studies could adopt experimental designs to clarify casual relationships. Researchers can also combine the actual use of data to supplement the behavioral intention of self-reporting. In addition, the adoption of stricter sampling methods, such as random sampling or stratified sampling, will improve the representativeness of the survey results.

7. Conclusion

This study reveals that in the early stage of generative artificial intelligence education, there is a significant phenomenon of "intention-emotional decoupling": students' decision-making is dominated by the rational evaluation of tool value, while emotional experiences such as anxiety are suspended, and its complex impact is more reflected in the use stage. This revises the traditional view that anxiety is simply regarded as an obstacle to adopt and provides universities with a differentiated promotion path of "emphasizing value demonstration in the early stage and emotional and ethical guidance in the later stage". Future research needs to pay attention to the dynamic evolution of this "decoupling" phenomenon and its long-term impact.

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