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AI anxiety and knowledge payment: the roles of perceived value and self-efficacy

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Abstract

Background The integration of Artificial Intelligence (AI) into daily life raises significant challenges and uncertainties, notably concerning job security and skill relevance. This has led to the emergence of ‘AI anxiety’—a stress response to potential impacts of AI on individuals’ futures. This study examines AI anxiety’s effects on individuals’ willingness to pay for knowledge, focusing on the roles of perceived value and self-efficacy.

Methods This study consisted of two experiments. Study 1 utilized a one-factor between-subjects design (AI anxiety vs. neutral emotion) with 297 participants to examine the mediating role of perceived value in the relationship between AI anxiety and willingness to pay for knowledge. Study 2 employed a 2 × 2 between-subjects design (AI anxiety vs. neutral emotion) × self-efficacy (high vs. low) with 506 participants to investigate the moderating effect of self-efficacy on this relationship.

Results Study 1 showed that AI anxiety significantly increases the willingness to pay for knowledge, with perceived value partially mediating this effect. Study 2 demonstrated that self-efficacy moderates the influence of AI anxiety: higher self-efficacy levels weaken, whereas lower levels strengthen, the willingness to pay for knowledge. Furthermore, self-efficacy also negatively moderates the effect of AI anxiety on perceived value.

Conclusions AI anxiety positively influences payment for knowledge, with critical roles for perceived value and self-efficacy. These findings offer a new framework for understanding AI anxiety’s impact on consumer behavior and provide actionable insights for platforms and policymakers.

Keywords Artificial intelligence, AI anxiety, Knowledge payment, Perceived value, Self-efficacy

Introduction

In the context of the rapid development of artificial intelligence (AI) technologies, AI has not only transformed the operational mechanisms of traditional industries but has also profoundly impacted individuals’ career trajectories, daily lives, and learning processes [1, 2]. As AI technologies become more widespread and advanced,

individuals are increasingly aware of the challenges and uncertainties they bring. This uncertainty, particularly regarding job displacement risks and the need for skill updates associated with technological applications, has sparked feelings of anxiety among individuals [3, 4]. A growing body of research is focusing on the phenomenon of “AI anxiety,” which refers to the anxiety and stress individuals experience due to their inability to fully comprehend or master AI technologies and the potential impacts on their future careers and lives [5, 6]. Despite the widespread attention the concept of AI anxiety has garnered in the fields of psychology and management, its specific effects on behavior—particularly concerning

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consumption behaviors related to knowledge acquisition and learning—remain underexplored.

In the digital economy era, knowledge payment has gradually become an important means for individuals to acquire knowledge and enhance skills [7]. In this study, willingness to pay for knowledge is defined as an individual's subjective intention to purchase knowledge products or services. Specifically, it refers to the individual's willingness to invest in AI-related knowledge products or services in the future. Knowledge payment products are characterized as structured and systematized knowledge services accessed through paid means. These products encompass online courses, e-books, expert consultations, and topic-specific webinars, all designed to provide users with curated content that facilitates skill acquisition and knowledge enhancement. Within the context of AI anxiety, such products often include AI-focused learning resources, such as AI courses, AI-related reading materials, coding tutorials, applications of AI technologies, which aim to help individuals navigate uncertainties and enhance their adaptability to technological advancements.

The producers of knowledge payment products play a critical role in this ecosystem by synthesizing insights from books, theoretical frameworks, and diverse sources of information. By systematically organizing and structuring complex information, they create a variety of offerings tailored to meet users' needs, ranging from online courses to expert consultations. These products are specifically designed to enable rapid knowledge acquisition and enhance users' competitiveness in an evolving technological landscape [8]. In the face of challenges posed by AI technologies, an increasing number of individuals are opting to cope with this uncertainty and anxiety through knowledge payment. Existing research suggests that anxiety can increase individuals' reliance on external resources, thereby prompting them to take action to alleviate their anxiety [9]. However, how AI anxiety specifically influences individuals' willingness to engage in knowledge payment, as well as the psychological mechanisms involved, remains a critical area for further investigation.

The theoretical framework of this study integrates behavioral decision theory and consumer decision theory to explain how AI anxiety influences consumer behavior, particularly its impact on the willingness to pay for knowledge. Additionally, perceived value theory provides insight into the psychological mechanism underlying this relationship, while self-efficacy theory explains the moderating role of individual differences in coping strategies [10]. AI anxiety is particularly relevant in this context, as it reflects individuals' emotional responses to the uncertainties surrounding AI technologies, influencing their perceived risks and motivations for seeking knowledge.

In decision-making processes, anxiety can shape individuals' evaluation of available resources, leading them to perceive paid knowledge products either as a necessity or as an ineffective response to technological challenges. To understand this mechanism, perceived value serves as a key explanatory factor. Rooted in consumer decision theories, perceived value captures how individuals assess the benefits and costs of a product, making it a critical mediator that connects AI anxiety with willingness to pay [11]. However, this relationship is not uniform across individuals, as self-efficacy plays a moderating role. In the context of AI anxiety and knowledge payment, individuals with high self-efficacy may feel more capable of acquiring knowledge through self-directed learning, thereby perceiving lower value in paid knowledge products. Conversely, those with lower self-efficacy may view structured, paid knowledge as a necessary means of coping with AI-related uncertainties.

Through two experimental studies, this paper aims to validate these hypotheses and provide new theoretical insights into the complex effects of AI anxiety on consumer behavior. The significance of this research is substantial. In an era marked by rapid changes in artificial intelligence technology, the demand for knowledge among individuals is intensifying [12], and the knowledge payment market is experiencing robust growth. Understanding how AI anxiety drives individuals to choose paid knowledge acquisition will not only enrich the research on the relationship between AI anxiety and consumer behavior but also offer empirical support for knowledge payment platforms in designing more targeted user management and market strategies. By exploring the mechanisms through which AI anxiety influences willingness to pay for knowledge, this study aims to contribute new ideas and theoretical frameworks for future research on consumer behavior in the context of artificial intelligence technology.

In summary, this paper will experimentally verify the impact of AI anxiety on willingness to pay for knowledge, examining the mediating role of perceived value and the moderating effect of self-efficacy. It is hoped that the findings of this research will provide theoretical support for further understanding the behavioral consequences of AI anxiety while offering practical insights for managing user behavior in the face of technological change.

Theoretical foundations and research hypotheses

AI anxiety and willingness to pay for knowledge

Anxiety is a complex emotional state characterized by feelings of tension, unease, and worry when individuals face potential threats or uncertainties [13]. In the context of rapid advancements in artificial intelligence (AI) technologies, AI anxiety has emerged as a novel emotional response that has garnered increasing academic

attention. This anxiety stems from individuals' concerns about their roles in the AI era, particularly regarding job security, mastery of technical skills, and the perceived uncontrollable risks associated with AI advancements [5, 14]. AI anxiety not only reflects deep-seated concerns about technological change but also intensifies individuals' motivation for future learning and personal growth. As AI technologies continue to evolve, individuals who perceive themselves as unable to keep pace with technological advancements or fear that their jobs may be replaced by AI experience heightened anxiety. As a reaction to technological uncertainty and potential threats, AI anxiety drives individuals to adopt proactive coping strategies to mitigate negative emotions and enhance their sense of control over the future [15].

Behavioral decision theory posits that individuals facing heightened uncertainty actively seek information to mitigate risks and regain a sense of control over their future choices [16, 17]. In uncertain environments, individuals tend to engage in extensive information acquisition as a means of reducing ambiguity and enhancing decision-making confidence [18]. AI anxiety exacerbates individuals' perceived uncertainty about the future, prompting them to actively seek knowledge as a way to reduce anxiety stemming from the unknown and to enhance their ability to adapt to future changes.

Consumer decision theory further explains how anxiety influences individuals' purchasing behaviors. This theory emphasizes that emotional states play a crucial role in consumer decisions, with anxiety often increasing individuals' willingness to engage in consumption, particularly for products or services that help alleviate emotional distress [19]. Research by Yu et al. [20] has shown that individuals experiencing heightened anxiety are more likely to engage in compensatory consumption behaviors, such as purchasing nostalgic products or investing in self-improvement, to restore psychological comfort. Similarly, in the context of AI anxiety, individuals may feel an urgent need to invest in knowledge acquisition, purchasing knowledge-related products to strengthen their sense of control over future uncertainties.

Therefore, behavioral decision theory and consumer decision theory together provide a comprehensive theoretical foundation for explaining how AI anxiety influences individuals' willingness to pay for knowledge. While behavioral decision theory explains how individuals actively acquire information under uncertainty to regain control, consumer decision theory illustrates how anxiety-driven emotional responses enhance the likelihood of making purchases. Taken together, these theories suggest that AI anxiety increases individuals' demand for knowledge and motivates them to engage in knowledge payment as a means of reducing uncertainty and enhancing their future adaptability.

Based on the theoretical foundation outlined above, This study posits that AI anxiety significantly positively influences individuals' willingness to pay for knowledge, with its impact manifesting in two key ways: First, AI anxiety heightens individuals' awareness of their knowledge limitations, prompting them to seek knowledge resources to reduce their perceived uncertainty about the future and to improve their ability to adapt to technological changes. Second, the emotional stress caused by anxiety further strengthens individuals' purchasing tendencies, making them more likely to purchase knowledge-related products as a way to gain psychological reassurance and a sense of control over their future.

Thus, we propose the following hypothesis:

H1 AI anxiety significantly positively influences the willingness to pay for knowledge.

The mediating role of perceived value

The Perceived Value Theory posits that consumers assess the overall value of a product or service by weighing its benefits against its costs during the decision-making process [21]. Perceived value encompasses three dimensions: functional value, emotional value, and epistemic value. Functional value involves the psychological satisfaction generated through the product's practical functions (e.g., quality, price). Emotional value reflects the emotional states triggered during product use, while epistemic value is related to knowledge acquisition or skill enhancement [22, 23]. In consumer decisions research, perceived value is recognized as a critical determinant of purchase intention [24]. When consumers perceive a product or service as highly valuable, their willingness to purchase significantly increases. Consequently, perceived value plays a pivotal role in individual consumption decisions and has garnered substantial attention in academic discourse.

In the context of knowledge payment, the role of perceived value is particularly pronounced. Given the intangibility and experience-dependent nature of knowledge products, consumers typically evaluate their perceived value based on content quality, learning benefits, and practical applicability [25]. Empirical studies indicate that a higher perceived value of knowledge payment products significantly enhances consumers' willingness to pay [26]. Therefore, understanding the factors that influence perceived value is crucial for explaining consumer behavior in the knowledge payment domain.

AI anxiety, a psychological response to the uncertainties associated with artificial intelligence (AI) advancements, affects individuals' evaluation of the value of knowledge products, thereby shaping their purchasing behavior. During the decision-making process, individuals assess whether a product contributes to their personal and professional goals [27]. Particularly in the face

of uncertainty, they are more inclined to select products that can mitigate future risks and enhance their competencies.

Given their heightened sensitivity to issues such as job displacement and skill obsolescence, individuals experiencing AI anxiety are more likely to perceive knowledge payment products as an effective means of coping with these challenges. As a result, their perceived value of knowledge products increases accordingly. Furthermore, emotional states significantly influence how individuals evaluate product value [28]. In anxious states, individuals are more likely to focus on products that offer long-term benefits and risk reduction, leading them to attribute a higher value to these products. AI anxiety amplifies individuals' perception of future uncertainty, making them more inclined to recognize knowledge payment products as highly valuable [29]. Such products are perceived as a means to enhance skills, reduce cognitive burden, and alleviate concerns about AI-driven transformations. Consequently, individuals with AI anxiety tend to assess the value of knowledge products more favorably compared to those without such anxiety.

Perceived value is not only influenced by AI anxiety but also plays a crucial role in shaping individuals' willingness to pay for knowledge. When individuals believe that knowledge products provide substantial learning benefits and long-term career competitiveness, their purchase intention significantly increases. This mechanism positions perceived value as a bridge between AI anxiety and willingness to pay for knowledge—AI anxiety elevates individuals' valuation of knowledge products, and a higher perceived value, in turn, strengthens their willingness to pay. Thus, perceived value serves as a mediating mechanism, through which AI anxiety enhances individuals' perception of knowledge product value, ultimately increasing their likelihood of engaging in knowledge payment.

Based on the above discussion, this study proposes the following hypothesis:

H2 Perceived value mediates the relationship between AI anxiety and willingness to pay for knowledge.

The moderating role of self-efficacy

The Self-Efficacy Theory posits that an individual's behavioral choices are influenced not only by external objective factors but also by their intrinsic self-perception. Specifically, an individual's belief in their own abilities plays a critical role in shaping their decisions and behaviors. More precisely, self-efficacy significantly influences task selection, as individuals with high self-efficacy are more inclined to engage in challenging tasks, whereas those with low self-efficacy tend to avoid challenges [10].

Within the frameworks of Self-Efficacy Theory and Behavioral Decision Theory, self-efficacy not only impacts individuals' task selection, effort levels, and approaches to challenges but also plays a crucial role in risk assessment, learning behavior, and purchasing decisions [30]. Individuals with high self-efficacy exhibit greater confidence when confronting challenges, whereas those with low self-efficacy, due to heightened risk perception, are more likely to withdraw from such activities [31]. In the context of knowledge acquisition and learning, self-efficacy significantly affects individuals' learning strategy preferences. Individuals with high self-efficacy tend to engage in self-directed learning to enhance their competencies, whereas those with low self-efficacy are more dependent on external resources, such as paid knowledge products [32, 33].

Regarding the relationship between AI anxiety and willingness to pay for knowledge, self-efficacy serves as a negative moderator. When individuals experience uncertainty and anxiety associated with AI technology, they often seek to enhance their skills through knowledge payment as a strategy to mitigate potential career displacement risks. However, individuals with high self-efficacy generally exhibit greater confidence in their ability to acquire and apply knowledge [34]. They are more likely to leverage free resources or engage in self-directed learning to enhance their competitiveness rather than rely on paid knowledge products. Consequently, when faced with AI anxiety, individuals with high self-efficacy are less likely to increase their willingness to pay for knowledge due to anxiety. Instead, they tend to explore self-learning avenues or utilize free educational resources. This suggests that self-efficacy attenuates the positive relationship between AI anxiety and willingness to pay for knowledge.

Based on this, the following hypothesis is proposed:

H3 Self-efficacy negatively moderates the impact of AI anxiety on the willingness to pay for knowledge.

Perceived value is a crucial determinant of consumers' willingness to pay. Within the framework of Perceived Value Theory, individuals' evaluation of the value of knowledge products is influenced by their learning capabilities. Those with high self-efficacy tend to believe that they can acquire knowledge independently [35, 36], leading them to perceive lower value in paid knowledge products. Conversely, individuals with low self-efficacy, who rely more on external resources, tend to attribute higher value to paid knowledge products.

Thus, when individuals experience AI anxiety, those with high self-efficacy are more likely to depend on their own capabilities rather than paid products, thereby reducing their perceived value of such offerings. In contrast, individuals with low self-efficacy are more likely to perceive paid knowledge products as effective tools to

alleviate anxiety, thus enhancing their perceived value of these products. This indicates that self-efficacy negatively moderates the effect of AI anxiety on perceived value.

Based on this, the following hypothesis is proposed:

H4 Self-efficacy negatively moderates the effect of AI anxiety on perceived value.

In summary, the conceptual model proposed in this study is illustrated in Fig. 1.

Study 1

Pilot experiment

The pilot experiment of this study aims to examine the differences in AI anxiety experienced by individuals exposed to two sets of experimental materials. To achieve this, we utilized the Credamo data collection platform, leveraging its large sample pool of millions to distribute and collect the questionnaires. The platform randomly administered the experimental scenarios, with all participants randomly assigned to either the AI anxiety group or the neutral emotion group, where they read the corresponding emotional induction materials. Emotional induction was employed to elicit anxiety, adapted from Velten [37]. The materials for inducing anxiety were as follows:

AI Anxiety: Imagine you are a data analyst, and your company has recently introduced an AI system capable of automating most data analysis tasks. Although the company has not mentioned any layoff plans, you notice that this AI system is significantly more efficient, completing tasks faster and more accurately than you can. You worry that, as AI technology progresses, your skills may become irrelevant. You attempt to learn new skills related to AI, but find them more challenging than you expected. This leads to feelings of anxiety and uncertainty about your ability to keep up with this technological change and the future job prospects that accompany it.

Neutral Emotion: Imagine you are a data analyst. Your daily work involves processing routine company data to ensure accuracy and generate reports. Recently,

the company has been operating normally, with no significant changes or adjustments. You go about your tasks methodically each day, occasionally discussing project progress with colleagues. The work environment is stable, and your responsibilities proceed as planned.

After reading the emotional induction materials, participants were required to complete a measurement questionnaire for AI anxiety to verify the effectiveness of the emotional manipulation. The questionnaire consisted of 6 items adapted from Wang and Wang [15] (Cronbach's $\alpha = 0.93$). Participants rated their agreement with statements such as "I feel anxious about not keeping up with advances in AI technology/products" and "I worry that AI technology/products will replace humans" on a 7-point Likert scale. The average score was calculated, with higher scores indicating greater levels of AI anxiety. The specific items of the scale are provided in Table 1.

A total of 80 participants were recruited for the study. After excluding questionnaires with incorrect answers to the attention-check questions, 75 valid questionnaires were retained, with 37 participants in the AI anxiety group, 38 in the neutral emotion group, 29 males, and 46 females. An independent samples *t*-test was conducted to analyze the data, and the results indicated successful manipulation of AI anxiety ($M_{\text{AI anxiety group}} = 5.01$, $SD = 1.20$; $M_{\text{neutral emotion group}} = 3.62$, $SD = 1.42$, $t(73) = 4.57$, $p < 0.001$). Therefore, the emotional induction materials used in this experiment will be applied to the main experiment 1.

Formal experiment

This experiment aims to verify the main effect of the study and the mediating effect of perceived value, specifically that AI anxiety positively influences knowledge payment (H1) and that perceived value mediates the impact of AI anxiety on the willingness to pay for knowledge (H2).

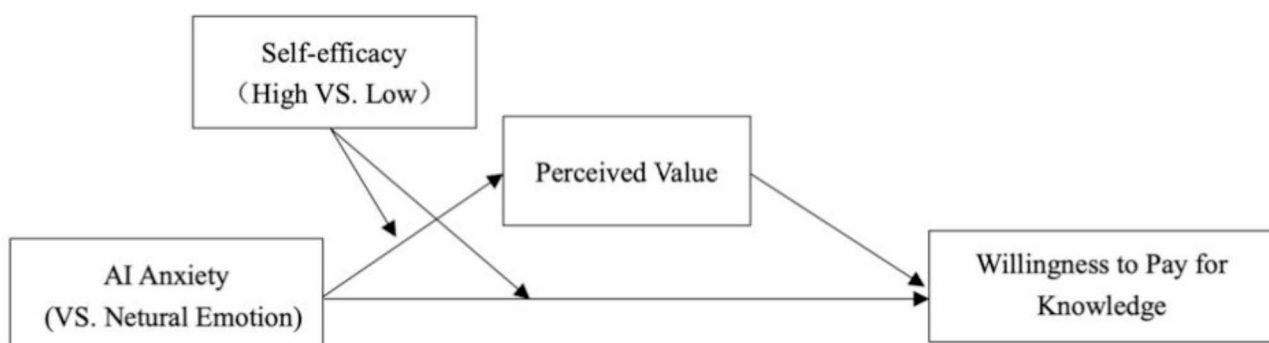


Fig. 1 Conceptual model

Table 1 Measurements

	Items	Reference
Manipulation Check for AI Anxiety	Learning to use AI technologies/products makes me feel anxious.	Wang and Wang [15]
	I feel anxious about not keeping up with advances in AI technology/products.	
	I worry that AI technology/products will replace humans.	
	I am concerned that the widespread use of humanoid robotics will take away people's jobs.	
Perceived Value	I find humanoid AI technology/products (e.g., humanoid robots) frightening.	Kuo et al. [39]
	I find humanoid AI technology/products (e.g., humanoid robots) threatening.	
	Compared to spending a lot of time learning and mastering AI technology, directly purchasing knowledge payment products (such as AI courses or AI-related reading materials) is valuable.	
	Compared to spending significant effort searching for and filtering free knowledge related to AI technology, directly purchasing knowledge payment products (such as AI courses or AI-related reading materials) is valuable.	
Willingness to Pay for Knowledge	I believe that purchasing knowledge payment products (such as AI courses or AI-related reading materials) is worth the investment.	Kim et al. [40]
	I would continue to purchase knowledge payment products related to AI (such as AI courses or AI-related reading materials).	
	If AI-related knowledge payment products (such as AI courses or AI-related reading materials) meet my needs, I would consider purchasing them.	
	When others ask me whether AI-related knowledge payment products (such as AI courses or AI-related reading materials) are worth purchasing, I would recommend them.	
Self-Efficacy Manipulation Check	I feel capable of learning and mastering AI technology.	Schwarzer et al. [41]
	I am confident that I can effectively apply AI technology.	
	I am confident that I can solve the problems I encounter.	

Participants

Experiment 1 recruited 308 participants through the Credamo online platform. After excluding 11 participants who failed attention checks, a final sample of 297 participants was retained. The sample size was calculated using GPower Version 3.1 [38]. An independent samples *t*-test was chosen in GPower with a significance level of $\alpha = 0.05$, a statistical power of $1 - \beta = 0.8$, and an expected medium effect size of 0.25. The results indicated that at least 60 participants are needed per group. The final sample of 297 participants resulted in 148–149 individuals per group, meeting the required sample size for the experiment. The age distribution of the participants was 48.48% aged 21–30, 33.33% aged 31–40, and 44.7% male. In terms of educational background, 0.6% had a middle school education or lower, 3.7% had a high school education, 10.1% had a college diploma, 70.3% had a bachelor's degree, and 14.4% had a master's degree or higher.

Experimental materials

(1) AI Anxiety and Neutral Emotion.

To elicit emotional states, we employed an emotional induction method adapted from Velten [37]. The materials used for AI anxiety and neutral emotion induction were the same as those implemented in the pilot Experiment 1, as they were designed to simulate real-world occupational scenarios involving AI-driven technological advancements while maintaining neutrality in the control condition. Given their demonstrated effectiveness in the pilot Experiment and their strong relevance to the research context, these materials were considered appropriate for use in the formal experiment.

(2) Manipulation Check for AI Anxiety.

The manipulation check for AI anxiety consisted of 6 items, adapted from Wang and Wang [15] (Cronbach's $\alpha = 0.92$ in this study). After reading the stimulus materials, participants rated their agreement with statements such as "I feel anxious about not keeping up with advances in AI technology/products" and "I worry that AI technology/products will replace humans" using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), shown in Table 1. The average score of the entire scale was calculated, with higher scores indicating higher levels of AI anxiety.

(3) Perceived Value Scale.

Perceived value was measured using 3 items, adapted from Kuo et al. [39] (Cronbach's $\alpha = 0.833$ in this study). Items included statements like "Compared to spending a lot of time learning and mastering AI technology, directly purchasing knowledge payment products (such as AI courses or AI-related reading materials) is valuable." (see Table 1). Each item was rated on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). The overall average score was calculated, with higher scores indicating higher perceived value.

(4) Willingness to Pay for Knowledge Scale.

Willingness to pay for knowledge was also measured using 3 items, adapted from Kim et al. [40] (Cronbach's $\alpha = 0.835$ in this study). Example items included "I would continue to purchase knowledge payment products related to AI (such as AI courses or AI-related reading materials)." Each item was rated on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). The overall average score was calculated, with higher scores indicating a greater willingness to pay for knowledge. Detailed items and their descriptions can be found in Table 1.

Experiment design and procedure

Experiment 1 employed a one-factor between-subjects design (AI Anxiety vs. Neutral Emotion), with the dependent variable being the willingness to pay for knowledge and the mediating variable being perceived value.

The experimental procedure was as follows: First, participants were randomly assigned to either the AI anxiety group or the neutral emotion group using the built-in randomization function of the Credamo data collection platform. This platform automatically distributes participants across conditions in a fully randomized manner, ensuring that each participant had an equal probability of being allocated to either group, thereby reducing selection bias. Once assigned to their respective groups, participants received emotion induction materials. After reading the emotional induction materials, participants completed the measurement items related to AI anxiety to verify the success of the manipulation. Subsequently, participants filled out the perceived value scale, the willingness to pay for knowledge scale, and two attention check questions [42]. The first question reads: "This question is to check whether you are answering attentively. Please select 1," while the second question is: "This question is to check whether you are answering attentively. Please enter: 'Hello' (only enter the content within the

quotation marks)." Finally, participants provided demographic information.

Results

Manipulation check

The results of the independent samples t-test indicated a significant group difference in AI anxiety, with the AI anxiety group scoring significantly higher than the neutral group ($M_{\text{AI anxiety group}} = 5.02$, $SD = 1.41$; $M_{\text{neutral emotion group}} = 3.46$, $SD = 1.33$, $t(295) = 9.76$, $p < 0.001$), confirming that the manipulation of AI anxiety was successful.

Main effect

The independent samples t-test results regarding willingness to pay for knowledge showed that the AI anxiety group had a higher willingness to pay compared to the neutral emotion group ($M_{\text{AI anxiety group}} = 5.69$, $SD = 0.83$; $M_{\text{neutral emotion group}} = 4.96$, $SD = 1.17$, $t(295) = 6.18$, $p < 0.001$). These results indicate that AI anxiety positively affects individuals' willingness to pay for knowledge, thus supporting H1.

To examine the potential impact of gender on willingness to pay for knowledge, a two-way ANOVA was conducted with AI anxiety (VS. neutral emotion) and gender as independent variables, and willingness to pay for knowledge as the dependent variable. The results revealed a significant main effect of AI anxiety on willingness to pay for knowledge ($F(1, 293) = 31.98$, $p < 0.001$, $\eta^2 = 0.09$), while the main effect of gender was not significant ($F(1, 293) = 0.145$, $p = 0.703$, $\eta^2 = 0.01$). Moreover, the interaction effect of AI anxiety and gender on willingness to pay for knowledge was not significant ($F(1, 293) = 0.05$, $p = 0.819$, $\eta^2 = 0.01$), indicating that willingness to pay for knowledge does not vary by gender, thus eliminating gender as a confounding factor in the experiment.

Mediating effect

The mediation effect of perceived value was tested using Model 4 from the PROCESS plugin [44]. When willingness to pay for knowledge was the dependent variable, the direct effect of AI anxiety on willingness to pay was significant ($\beta = 0.44$, $p < 0.001$, $t = 4.50$, $SE = 0.09$, $LLCI = 0.24$, $ULCI = 0.63$), confirming H1. After incorporating the mediator, perceived value, into the model, the positive predictive effect of AI anxiety on perceived value was significant ($\beta = 0.46$, $p < 0.001$, $t = 4.13$). Additionally, perceived value significantly predicted willingness to pay for knowledge ($\beta = 0.57$, $p < 0.001$, $t = 12.43$). The indirect effect of AI anxiety on willingness to pay for knowledge through perceived value was significant (indirect effect = 0.26, $SE = 0.06$, $LLCI = 0.13$, $ULCI = 0.40$, not including 0), indicating that perceived value significantly mediates the relationship between AI anxiety and

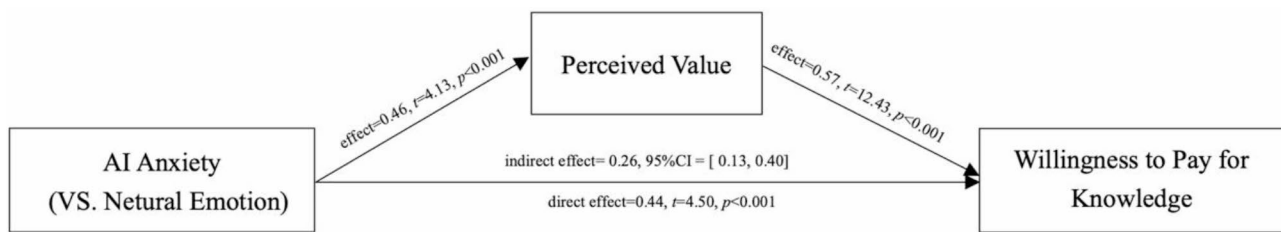


Fig. 2 Mediating Effect in Study 1

willingness to pay for knowledge, thus supporting H2, as illustrated in Fig. 2.

Study2

Pilot experiment

The purpose of Pilot Experiment 2 is to test the effectiveness of the manipulation of self-efficacy as a moderator variable. This experiment utilized the event recall method and administered the questionnaires through the Credamo data collection platform. Participants were randomly assigned to different experimental groups via the platform, where they read the corresponding manipulation materials for their group and completed the event recall task.

Self-efficacy was induced through recall manipulation based on Bandura [43]. The text materials were as follows:

High Self-Efficacy Group: “Please recall and describe a successful and fulfilling experience in detail. For example, a time when you achieved an award or successfully completed a challenging task. Please try to remember the context, the actions you took, and how you felt after succeeding.”

Low Self-Efficacy Group: “Please recall and describe a frustrating and disappointing experience in detail. For example, a time you failed an exam or did not meet an important goal. Please try to remember the context, what you attempted, and how you felt after the failure.”

After reading the materials and completing the event recall task, participants were required to complete a self-efficacy measurement questionnaire to assess the effectiveness of the manipulation. The self-efficacy manipulation check consisted of 3 items adapted from Schwarzer et al. [41] (Cronbach’s $\alpha = 0.85$). Participants rated statements such as “I feel capable of learning and mastering AI technology” and “I am confident that I can solve problems I encounter.” The average score was calculated, with higher scores indicating greater self-efficacy. The specific items of the scale are provided in Table 1.

A total of 82 participants were recruited for the study. After excluding questionnaires with incorrect answers to the attention-check questions, 78 valid questionnaires were retained, with 41 participants in the high self-efficacy group, 37 in the low self-efficacy group, 35 males,

and 43 females. An independent samples *t*-test was conducted to analyze the data, and the results indicated successful manipulation of self-efficacy ($M_{\text{high self-efficacy group}} = 5.89$, $SD = 0.83$; $M_{\text{low self-efficacy group}} = 4.77$, $SD = 1.05$, $t(76) = 5.26$, $p < 0.001$). Therefore, the event recall method used will be continued in the formal Experiment 2.

Formal experiment

The purpose of this study is to examine the moderating effect of self-efficacy on the relationship between AI anxiety and willingness to pay for knowledge (H3), as well as its moderating effect on the relationship between AI anxiety and perceived value (H4). A 2×2 (AI anxiety vs. neutral emotion) \times self-efficacy (high vs. low) between-subjects experimental design was employed.

Participants

Experiment 2 recruited 520 participants through the Credamo online platform, excluding 14 participants who answered attention-check questions incorrectly, resulting in a final sample of 506 participants. Using G*Power 3.1, with a medium effect size of 0.25, statistical power of $1 - \beta = 0.80$, and a significance level of $\alpha = 0.05$, a sample size estimation for the 2×2 design indicated that at least 40 participants were needed per group, totaling 160 participants. The current study’s sample of 506 participants had group sizes ranging from 126 to 128, meeting the experimental requirements. The age distribution was as follows: 21–30 years (43.08%), 31–40 years (41.30%), with males comprising 41.84%. In terms of education level, 0.4% had junior high school or lower, 3.3% had high school education, 8.3% had an associate degree, 68.9% had a bachelor’s degree, and 17.7% had a master’s degree or higher.

Experimental materials

(1) AI Anxiety and Neutral Emotion

The emotional induction method used in Study 2 was identical to that in Study 1, adapted from Velten [37].

(2) AI Anxiety Manipulation Check Scale

The AI anxiety manipulation check scale used in Study 2 was identical to that in Study 1. The scale consisted of 6 items adapted from Wang and Wang [15]. Detailed items and their descriptions can be found in Table 1. The scale demonstrated excellent reliability in this study (Cronbach's $\alpha = 0.935$).

(3) Self-Efficacy

Self-efficacy was induced using a recall manipulation method based on Bandura [43]. The materials used for self-efficacy induction were identical to those employed in the pilot Experiment 2, where participants were instructed to recall and describe past experiences of either success or failure to enhance or diminish their self-efficacy perceptions. Given their demonstrated effectiveness in the pilot Experiment and their strong theoretical foundation, these materials were deemed appropriate for application in the formal experiment.

(4) Self-Efficacy Manipulation Check Scale

The self-efficacy manipulation check consisted of three items adapted from Schwarzer et al. [41] (Cronbach's $\alpha = 0.91$). After reading the stimulus materials, participants rated statements such as "I feel capable of learning and mastering AI technology" and "I am confident that I can solve problems I encounter" using a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). The average score was calculated, with higher scores indicating greater self-efficacy.

(5) Perceived Value Scale

The Perceived Value Scale utilized in Study 2 was identical to the one employed in Study 1, consisting of 3 items adapted from Kuo et al. [39]. A detailed description of the items can be found in Table 1. The scale exhibited excellent reliability in this study (Cronbach's $\alpha = 0.891$).

(6) Willingness to Pay for Knowledge Scale

The Willingness to Pay for Knowledge Scale used in Study 2 was the same as that applied in Study 1, comprising three items adapted from Kim et al. [40]. Detailed descriptions of the items are provided in Table 1. The scale demonstrated strong reliability in this study (Cronbach's $\alpha = 0.915$).

Experimental design and procedure

Participants were randomly assigned to either the AI anxiety group or the neutral emotion group and received the corresponding emotion induction materials. After reading the materials, they completed the AI anxiety measurement to evaluate the success of the manipulation. Next, participants proceeded to the self-efficacy manipulation task, where they were instructed to read the self-efficacy manipulation materials and complete the event recall task. Subsequently, they completed a self-efficacy measurement questionnaire to assess the effectiveness of the manipulation. Following this, participants responded to the perceived value scale, the willingness to pay for knowledge scale, and two attention check questions [42]. The first question reads: "This question is to check whether you are answering attentively. Please select 1," while the second question is: "This question is to check whether you are answering attentively. Please enter: 'Hello' (only enter the content within the quotation marks)." Participants then provided demographic information.

Results

Manipulation check

The results of the manipulation check indicated significant group differences in AI anxiety, with the AI anxiety group scoring significantly higher than the neutral group ($M_{\text{AI anxiety group}} = 5.01$, $SD = 1.36$; $M_{\text{neutral emotion group}} = 3.52$, $SD = 1.35$, $t(504) = 12.34$, $p < 0.001$). This confirms the success of the AI anxiety manipulation. Additionally, the high self-efficacy group demonstrated significantly higher scores compared to the low self-efficacy group, indicating successful manipulation of self-efficacy ($M_{\text{high self-efficacy group}} = 5.43$, $SD = 1.12$; $M_{\text{low self-efficacy group}} = 4.95$, $SD = 1.43$, $t(504) = 4.23$, $p < 0.001$).

Main effect

The independent samples t-test results for willingness to pay for knowledge showed that the AI anxiety group had a significantly higher willingness to pay compared to the neutral emotion group ($M_{\text{AI anxiety group}} = 5.45$, $SD = 1.22$; $M_{\text{neutral emotion group}} = 4.41$, $SD = 1.46$, $t(504) = 8.68$, $p < 0.001$). These results indicate that AI anxiety positively affects individuals' willingness to pay for knowledge, thereby confirming H1.

Main effect and moderation effect

A two-way ANOVA was conducted to examine the moderating effect of self-efficacy on the relationship between AI anxiety and willingness to pay for knowledge. When willingness to pay was the dependent variable, the main effect of AI anxiety was significant ($F(1, 502) = 78.59$, $p < 0.001$, $\eta^2 = 0.13$), and the main effect of self-efficacy was also significant ($F(1, 502) = 21.33$, $p < 0.001$, $\eta^2 = 0.04$).

The interaction between the two variables was significant ($F(1, 502) = 6.96, p < 0.01, \eta^2 = 0.01$). Simple effects analysis revealed that in the AI anxiety group, participants with high self-efficacy had a significantly lower willingness to pay compared to those with low self-efficacy ($M_{\text{high self-efficacy group}} = 5.02, SD = 1.43; M_{\text{low self-efficacy group}} = 5.87, SD = 0.78; t = -5.13, d = 0.64, p < 0.001$). In the neutral emotion group, there was no significant difference in willingness to pay between low and high self-efficacy participants ($M_{\text{high self-efficacy group}} = 4.30, SD = 1.46; M_{\text{low self-efficacy group}} = 4.53, SD = 1.45; t = -1.40, d = 0.17, p = 0.16$). Therefore, H3 is supported (See Fig. 3).

Mediation effect

The mediation effect of perceived value was tested using Model 4 from the PROCESS plugin [44]. When willingness to pay for knowledge was the dependent variable, the direct effect of AI anxiety on willingness to pay for knowledge was significant ($\beta = 0.64, p < 0.001, t = 6.18, SE = 0.10, LLCI = 0.43, ULCI = 0.84$), confirming H1.

After incorporating the mediator variable, perceived value, into the model, the positive predictive effect of AI anxiety on perceived value was significant ($\beta = 0.51, p < 0.001, t = 6.01$). Additionally, the positive predictive effect of perceived value on willingness to pay for knowledge was significant ($\beta = 0.53, p < 0.001, t = 14.87$). Thus, the indirect effect of AI anxiety on willingness to pay for knowledge through perceived value was significant (indirect effect = 0.27, $SE = 0.05, LLCI = 0.18, ULCI = 0.38$, not including 0), indicating that perceived value significantly mediates the relationship between AI anxiety and willingness to pay for knowledge, further validating H2.

Moderating effect of self-efficacy on perceived value

Given that the independent variable (AI anxiety) and the moderating variable (self-efficacy) are categorical variables, while the mediator variable (perceived value) is continuous, a two-way ANOVA was employed to examine the moderating effect of self-efficacy on perceived value. The results showed a significant interaction

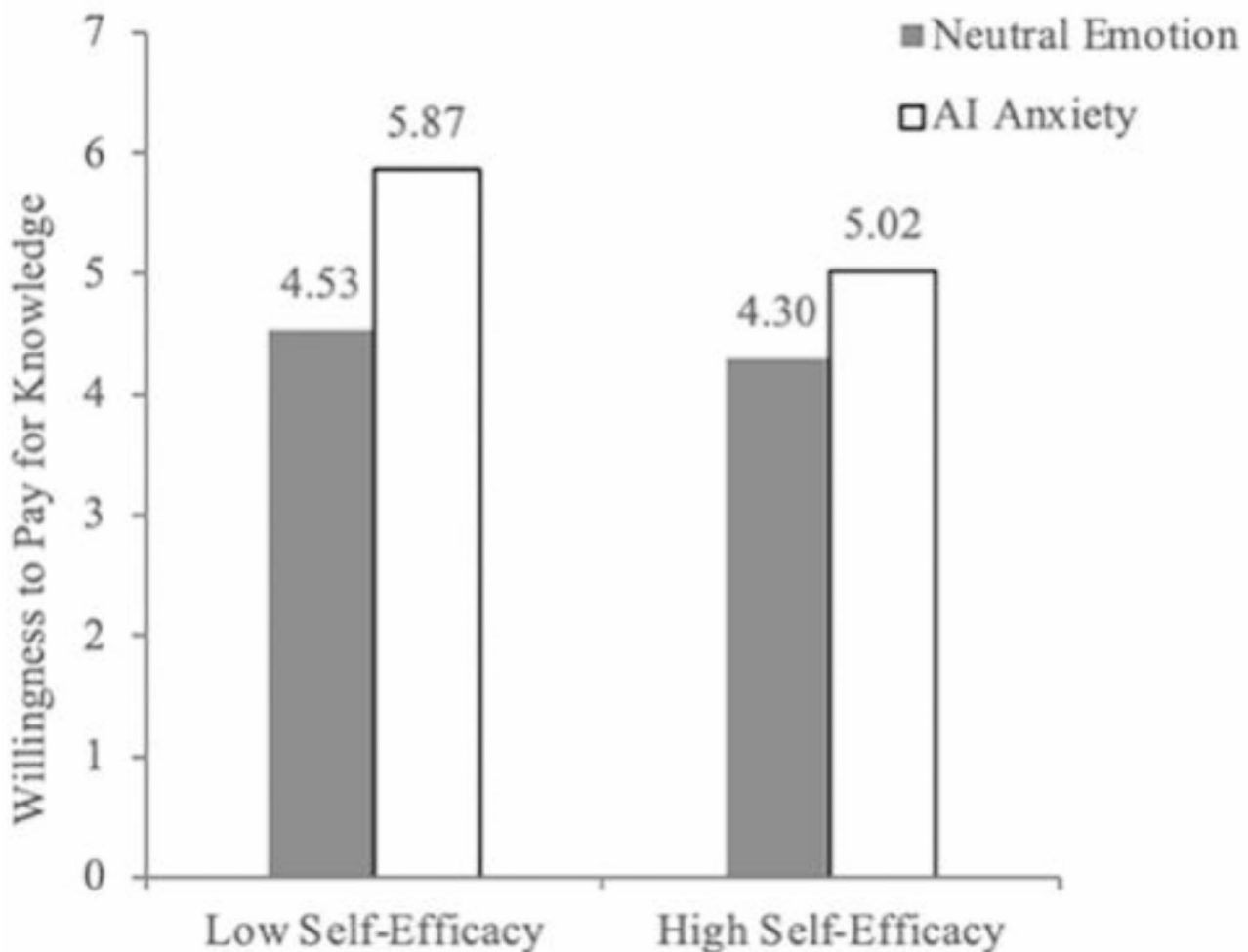


Fig. 3 Moderating role of self-efficacy in the relationship between AI anxiety and the willingness to pay for knowledge

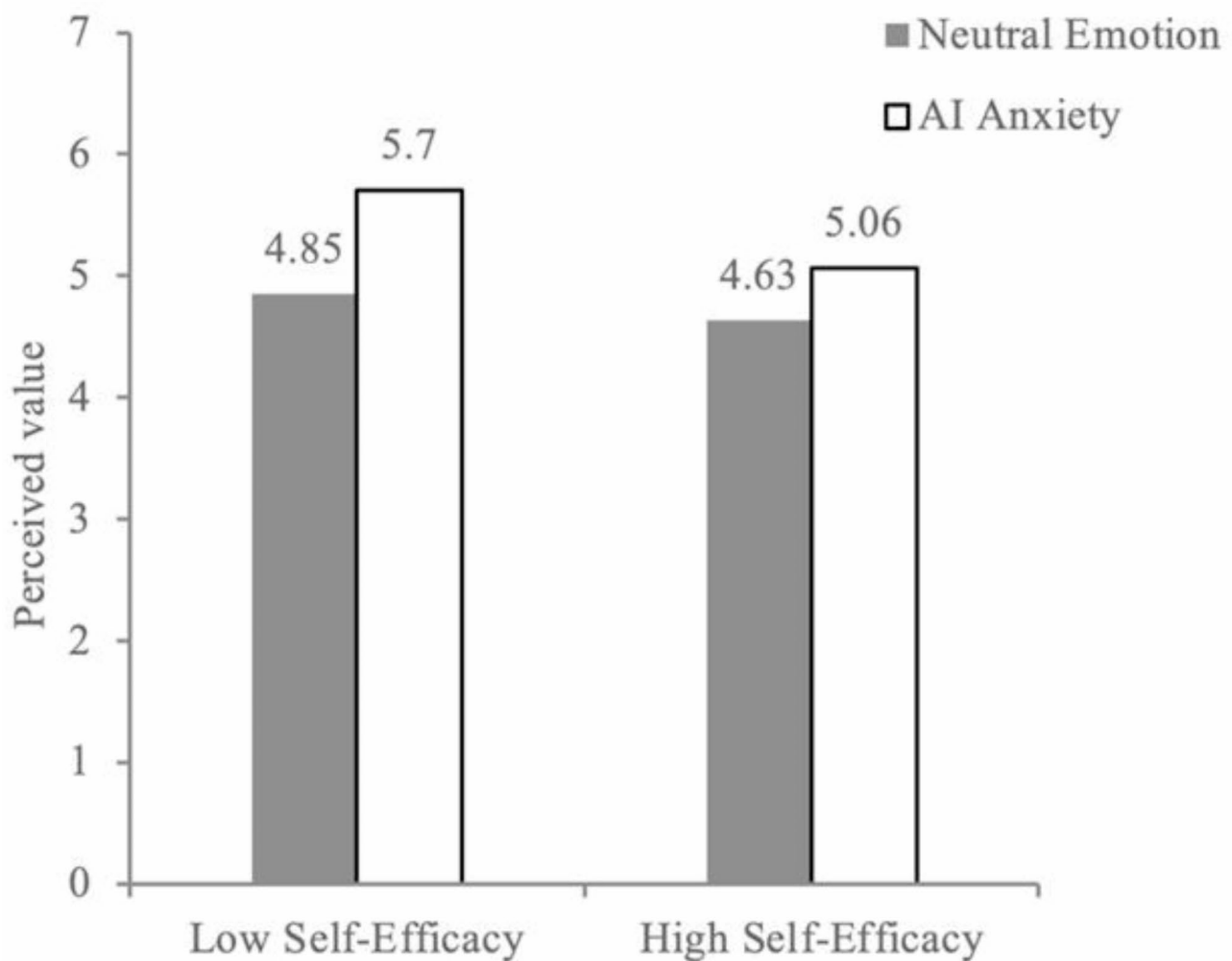


Fig. 4 Moderating role of self-efficacy in the relationship between AI anxiety and perceived value

between the two ($F(1, 502)=4.16, p<0.05, \eta^2 = 0.01$). Specifically, in the AI anxiety group, participants with high self-efficacy had significantly lower perceived value than those with low self-efficacy ($M_{\text{high self-efficacy group}} = 5.06, SD=1.25; M_{\text{low self-efficacy group}} = 5.70, SD=0.81; t = -4.35, d=0.54, p<0.001$). In the neutral emotion group, there was no significant difference in perceived value between low and high self-efficacy participants ($M_{\text{high self-efficacy group}} = 4.63, SD=1.32; M_{\text{low self-efficacy group}} = 4.85, SD=1.26; t = -1.47, d=0.18, p=0.14$). This indicates that compared to consumers with high self-efficacy, individuals with low self-efficacy tend to perceive greater value in knowledge payment products when facing AI anxiety (See Fig. 4), supporting H4.

Subsequently, the interactive effect of AI anxiety and self-efficacy on willingness to pay for knowledge through perceived value was tested. With willingness to pay for knowledge as the dependent variable, AI anxiety as the independent variable, self-efficacy as the moderator, and perceived value as the mediator, moderated mediation

analysis was conducted using PROCESS (Model 8, 5000 bootstraps) [44]. The results revealed that perceived value mediates the interaction between AI anxiety and self-efficacy in affecting willingness to pay for knowledge (indirect effect = $-0.25, SE=0.12, LLCI=-0.51, ULCI=-0.01$, not including 0). Further analysis showed that, when self-efficacy is high, the indirect effect of perceived value is significant (indirect effect = $0.25, SE=0.09, LLCI=0.06, ULCI=0.44$, not including 0); when self-efficacy is low, the indirect effect of perceived value is also significant (indirect effect = $0.50, SE=0.09, LLCI=0.33, ULCI=0.70$, not including 0). This further validates H2 and H4.

General discussion

This study explores the mechanisms and boundary conditions of the impact of AI anxiety on users' willingness to pay for knowledge in the context of artificial intelligence, drawing from theories of behavioral decision, consumer decision, and perceived value. Two experiments were conducted to test the relevant hypotheses.

Experiment 1 aimed to validate the main effect and the mediation effect by constructing a mediation model based on the theory of perceived value, revealing how AI anxiety influences users' willingness to pay for knowledge through perceived value. The results show that AI anxiety has a significant positive effect on willingness to pay for knowledge, and perceived value plays a partial mediating role in this relationship. Experiment 2 further examined the moderating role of self-efficacy, finding that high self-efficacy weakens the influence of AI anxiety on willingness to pay, while low self-efficacy strengthens this effect.

Theoretical contributions

This study investigates the relationship between AI anxiety and willingness to pay for knowledge, contributing to a deeper understanding of how anxiety-related emotions shape consumer behavior. While prior research on anxiety has primarily focused on work stress and job insecurity [44–47], the broader implications of anxiety induced by emerging technologies like AI on consumer purchasing behavior have largely been overlooked.

These findings provide new insights into Behavioral Decision Theory and Consumer Decision Theory by illustrating how emotional states influence cognitive evaluations and subsequent decision-making processes in consumption contexts. While Behavioral Decision Theory emphasizes the role of uncertainty and cognitive biases in decision-making, this study extends its application to anxiety-driven consumer choices, demonstrating that AI-induced anxiety can amplify perceived risks and shift preferences toward external knowledge resources. Similarly, from the perspective of Consumer Decision Theory, which focuses on how consumers evaluate options and assign value to products, this study highlights how AI anxiety affects individuals' perceived value assessments, leading them to justify expenditures on knowledge products as a form of risk mitigation.

These findings offer a fresh research pathway for understanding how AI technology influences individual consumption decisions, broadening the scope of studies on the behavioral effects of AI anxiety. Furthermore, this study empirically validates the mediating role of perceived value between AI anxiety and willingness to pay for knowledge, uncovering the psychological mechanism through which individuals rationalize their consumption decisions in anxiety-inducing situations by enhancing perceived value. While perceived value has been extensively applied in consumer behavior research [48], this study extends its application to the unique context of AI anxiety, illustrating how individuals mitigate uncertainty and fear associated with technological advancements by increasing the perceived value of informational products. This highlights the pivotal mediating role of perceived value in addressing AI-induced anxiety.

By embedding perceived value within the framework of AI anxiety, this study deepens theoretical insights into how emotional states influence cognitive evaluations and subsequent consumer behaviors. This contribution not only refines the conceptualization of perceived value theory but also underscores its relevance in anxiety-inducing contexts, such as those driven by rapid technological changes. Moreover, it lays a theoretical foundation for future research to explore the interplay among emotions, value perceptions, and consumer purchasing behavior in other contexts characterized by uncertainty or disruption.

Additionally, this study extends self-efficacy theory by examining its role in shaping consumer behavior under AI-induced anxiety. While self-efficacy is traditionally regarded as a positive resource that helps individuals cope with challenges [49, 50], this study reveals its nuanced role in the context of AI-induced anxiety, particularly its potential negative moderating effect. The findings indicate that individuals with high self-efficacy, due to their strong confidence in their abilities, may exhibit reduced reliance on external resources (e.g., knowledge payment products). This behavior stems from their tendency to depend more on internal resources, perceiving themselves as capable of solving problems independently and, consequently, evaluating external resources as less necessary. Conversely, individuals with lower self-efficacy are more inclined to seek external support, regarding knowledge payment products as essential tools to address AI-related uncertainties and compensate for their lack of confidence. This divergence underscores the complex interplay between self-efficacy and anxiety-driven consumer behavior.

By situating self-efficacy within the framework of AI-induced anxiety and consumer purchasing behavior, this study extends its theoretical boundaries. While previous studies have predominantly framed self-efficacy as a mechanism for reducing stress and improving performance, this research identifies its context-dependent nature. In high-anxiety scenarios (e.g., uncertainty caused by rapid technological advancements), individuals with high self-efficacy are more likely to rely on internal resources, such as self-directed learning or leveraging existing skills, and less likely to depend on external resources. This behavioral tendency reduces their demand for knowledge payment products, resulting in distinct consumption patterns compared to those with lower self-efficacy.

By incorporating self-efficacy into the theoretical model, this study enriches the understanding of individual-level moderators in consumer behavior. These findings suggest that future research should investigate the contextual boundaries of self-efficacy, particularly in scenarios where technological change triggers anxiety.

and uncertainty. Furthermore, exploring other individual difference variables (e.g., adaptability, innovativeness) in similar contexts may yield valuable insights into their potential moderating effects.

In conclusion, This study provides a comprehensive theoretical framework for understanding the relationship between AI anxiety, perceived value, and self-efficacy in shaping consumer behavior. By integrating insights from Behavioral Decision Theory and Consumer Decision Theory, this research enhances our understanding of how emotions influence cognitive evaluations and purchasing decisions. Additionally, it extends self-efficacy theory by demonstrating its dual role in moderating anxiety-driven consumer behavior, revealing its impact beyond traditional performance-based outcomes. These findings contribute to a more nuanced understanding of how psychological traits shape consumer responses to technology-induced anxiety, offering new directions for future research on individual differences, perceived value, and consumer behavior in anxiety-inducing contexts.

Practical implications

As AI technology rapidly advances, users are increasingly experiencing anxiety when faced with technological changes [51]. This study reveals the positive impact of AI anxiety on the willingness to pay for knowledge, indicating that users often turn to knowledge payment to enhance their skills and cope with technological challenges in uncertain situations. Knowledge payment platforms can capitalize on this trend by designing specialized content, such as AI-related training courses or skill development programs, to meet users' needs in addressing AI anxiety and increase their willingness to pay.

The study also shows that perceived value plays a mediating role between AI anxiety and willingness to pay for knowledge, suggesting that platforms can enhance users' purchase motivation by increasing the perceived value of their products. Specifically, in the context of AI, platforms can improve users' perceived value of knowledge payment products by showcasing real-world applications of AI technology, offering personalized learning paths, and clearly communicating learning benefits, thereby increasing users' trust and willingness to pay.

Moreover, the study finds that users with high self-efficacy are more inclined to cope with AI anxiety through self-directed learning, while users with low self-efficacy rely more on knowledge payment products. Thus, knowledge payment platforms can offer personalized services based on users' self-efficacy levels. For high self-efficacy users, platforms can provide more free resources and self-directed learning tools [52]. For low self-efficacy users, platforms can introduce guided learning projects and supportive learning services to help increase their

reliance on knowledge products and their willingness to pay.

Beyond knowledge payment platforms, these findings also offer valuable insights for industries integrating AI technologies. As AI adoption expands across sectors such as healthcare, finance, education, and manufacturing, organizations must address AI-related anxiety as a key factor influencing both consumer and employee adaptation. Companies implementing AI-driven automation can collaborate with knowledge platforms to offer AI training programs, ensuring employees perceive upskilling as valuable rather than intimidating, which can facilitate a smoother transition to AI-enhanced workflows. Similarly, businesses integrating AI into customer service, retail, and digital platforms can enhance consumer trust by effectively communicating AI's benefits, thereby reducing hesitation toward AI-driven services and improving user adoption rates. Furthermore, industries facing rapid AI adoption can establish learning ecosystems where professionals from various sectors gain access to curated AI-related content, fostering a workforce that is more adaptable to technological change. By proactively addressing AI-related anxiety, organizations can not only ease technological transitions but also maximize the benefits of AI adoption across multiple sectors.

Finally, the study provides policymakers with strategies to address the anxiety associated with the development of AI technology. As AI becomes more widespread, societal concerns about AI anxiety are increasing. This study finds that AI anxiety not only affects users' emotions but also significantly impacts their learning and consumption behaviors. Policymakers can promote AI-related educational programs, particularly offering learning support to low self-efficacy groups, to help them better cope with the anxiety brought by technological changes, ultimately increasing society's acceptance of AI technology.

Through these practical implications, this study provides actionable insights for knowledge payment platforms, AI-integrating industries, and policymakers, helping them better understand and manage AI anxiety while facilitating the successful adoption of AI technologies across different sectors.

Limitations and future directions

Limitations

This study, through two experiments, tested the influence of AI anxiety on the willingness to pay for knowledge. The sample used in the experiments primarily came from specific groups, which may not fully reflect the behavioral characteristics of all users. This limitation could affect the generalizability of the findings. Moreover, cultural disparities in AI perceptions may play a crucial role in shaping how individuals experience AI anxiety and, consequently, their willingness to invest in knowledge. In

societies where AI is perceived as a significant threat to employment [53], individuals may experience heightened AI anxiety and a stronger inclination to pay for knowledge as a coping mechanism. Conversely, in cultures where AI is seen as an opportunity for economic growth and personal development, individuals may exhibit lower levels of AI anxiety, which could result in weaker motivation to engage in knowledge payment. Given that this study primarily focused on a single cultural context, the findings may not be fully generalizable across different cultural settings. Future research should employ cross-cultural comparisons to explore how cultural variations influence AI-related consumer behavior.

Beyond cultural influences, potential sample biases may have also shaped the results. Factors such as technological literacy, education level, and economic background may impact how individuals perceive AI-related risks and their willingness to pay for knowledge. For instance, individuals with higher technological literacy may feel more confident in self-learning, thus relying less on paid knowledge resources, while those with lower technological familiarity may perceive structured knowledge payment products as essential tools for skill acquisition. Similarly, financial constraints may affect individuals' purchasing decisions, with those facing economic pressure being less likely to invest in knowledge products despite experiencing high AI anxiety. Future research should integrate more diverse and representative samples to ensure the robustness of the findings.

Although the experimental design was rigorous, there may be a gap between the experimental context and actual knowledge payment scenarios. The contextual limitations of the experiment may not fully replicate users' behavioral patterns on real knowledge payment platforms. Future research could consider conducting more field-based, long-term studies that closely simulate real environments, observing users' longitudinal behavioral changes on actual knowledge payment platforms to improve the ecological validity of the research.

Additionally, this study mainly focused on the effects of AI anxiety, perceived value, and self-efficacy on the willingness to pay for knowledge. However, other potential factors, such as social support and economic pressure, may also play important roles in the relationship between AI anxiety and willingness to pay for knowledge. Individuals with strong social support networks may rely on guidance from their professional and personal networks, reducing their dependency on paid knowledge products. Conversely, those lacking social support may perceive knowledge payment as a necessary alternative to acquiring information and skills. Similarly, economic constraints may affect individuals' investment decisions [54, 55], as those facing financial hardships may be less likely to pay for knowledge despite experiencing AI-related

anxiety. Future research could introduce these variables and construct more comprehensive theoretical models to better explain the underlying mechanisms behind knowledge payment behavior.

Future research directions

This study reveals the moderating role of self-efficacy in the relationship between AI anxiety and willingness to pay for knowledge. Future research could explore how other individual differences—such as personality traits, socioeconomic status, and cognitive flexibility—shape responses to AI anxiety. For example, individuals with higher openness to experience may perceive AI anxiety as an opportunity for learning, whereas those with lower openness may be more risk-averse, leading to reduced investment in knowledge. This will provide theoretical support for businesses to develop more precise user segmentation and personalized marketing strategies.

As the pace and impact of AI technology dissemination vary globally, future research could conduct cross-cultural comparative studies to examine whether there are significant differences in the impact of AI anxiety on knowledge payment willingness across different cultural contexts. Cross-cultural studies can reveal the role of culture in technological adoption and anxiety responses, offering more broadly applicable insights for the global promotion of technology and user behavior management. Given that individuals' perceptions of AI are shaped by both cultural norms and technological exposure, these factors may influence whether AI is seen as a threat or an opportunity, ultimately shaping their willingness to invest in knowledge as a coping mechanism.

Moreover, AI anxiety may change dynamically over time as individuals gradually adapt to technology. Future research could undertake longitudinal studies to examine the trajectory of anxiety changes as individuals have prolonged exposure to and adapt to AI technology, as well as the sustained impact of these changes on the willingness to pay for knowledge. This would provide more in-depth insights for knowledge payment platforms to develop long-term user cultivation strategies.

In summary, although this study provides important theoretical frameworks and empirical support for understanding the mechanism by which AI anxiety influences knowledge payment willingness in the context of artificial intelligence, it has certain limitations in terms of sample diversity, experimental contexts, and the scope of variables covered. Future research should aim to deepen the understanding of the relationship between AI anxiety and consumer behavior by expanding samples, introducing more real-world contexts, and considering more potential variables.

Acknowledgements

The authors thank the participants for their support to this study.

Author contributions

Conceptualization, J.C. and J.S.; methodology, M.H. and J.S.; validation, M.H.; formal analysis, J.C.; investigation, M.H. and J.S.; resources, J.C. and J.S.; data curation, M.H.; writing—original draft preparation, M.H.; writing—review and editing, J.S.; visualization, J.C.; supervision, J.C.; project administration, J.S.; funding acquisition, J.C. All authors have read and agreed to the published version of the manuscript.

Funding

This research was supported by The Special Project for Rural Cadres Residency under the “Great Earth Thesis” program at Guizhou University of Finance and Economics in 2022, Project Number: 2023ZCGBA04; National Social Science Fund, Western Project(21XZ002);The Ministry of education of Humanities and Social Science project (19YJCZH054).

Data availability

The Data generated during the current study are available from the corresponding author on request.

Declarations

Ethics approval and consent to participate

The data used in this study have been submitted and approved by the Guizhou university of finance and economics Ethics Committees on research involving humans. Informed consent was obtained from all participants of the study. This study followed the Declaration of Helsinki.

Consent for publication

Not Applicable.

Competing interests

The authors declare no competing interests.

Received: 29 September 2024 / Accepted: 18 February 2025

Published online: 06 March 2025

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