

Influence of users' perceived self-efficacy and perception of generative artificial intelligence chatbots' problem-solving ability on chatbots' value and intention to continue using them

Shih-Tse Wang

wsh2008@dragon.nchu.edu.tw

National Chung Hsing University

Yun-Xiu Cai

National Chung Hsing University

Research Article

Keywords: generative artificial intelligence, chatbot, perceived self-efficacy, problem-solving ability, hedonic and utilitarian value, continued usage intention

Posted Date: September 9th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10736501/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

Since GAI chatbots have grown dramatically in recent years, retaining users remains a critical issue for GAI chatbot marketers. Building on Perceived Value Theory, this paper empirically tests a research model that incorporates antecedents of perceived value (utilitarian and hedonic value) from two trait perspectives, i.e., individual characteristics (users' self-efficacy) and technology characteristics (the GAI chatbots' problem-solving ability), to examine factors that affect user intention to continue using chatbots. This study collected 612 valid responses from individuals who had used GAI chatbots and analyzed the data using partial least squares structural equation modeling. The results show that users' perceptions of their self-efficacy and the problem-solving ability of GAI chatbots contribute to their perceptions of chatbots' utilitarian and hedonic value, which, in turn, promote the intention to continue using chatbots. The extended perceived value model and these findings can help GAI chatbot marketers develop efficient GAI development and communication strategies by clarifying how users' perceptions of their self-efficacy and the problem-solving ability of GAI chatbots influence their perceived utilitarian and hedonic value of the chatbots and their intention to continue using them.

1. Introduction

Generative artificial intelligence (GAI) efficiently meets users' demands by generating content in various formats—such as videos, images, text, and code—in response to users' requests (Sánchez-Ruiz et al., 2023). GAI chatbots—such as OpenAI's ChatGPT, Google's Gemini, and Anthropic's Claude—are successful GAI applications. These chatbots have been trained using large language models (LLMs), robust artificial intelligence systems that process massive amounts of text data (e.g., billions of web pages) through complex transformer architectures. Since LLMs understand word relationships, GAI can produce responses in text, code (like ChatGPT and Gemini), and images (such as DALL-E and Midjourney) based on prompts (Brizuela & Merchan 2023). This innovation is transforming how companies, institutions, and individuals engage with technology (Ruggeri et al., 2025).

The GAI chatbot industry has seen a rapid rise in popularity, attracting a large user base. Leading companies such as Google (Gemini), Meta AI (ImageBind), LaMDA, and Runway (Gen-2 model) have invested heavily in this field. As competition among GAI chatbots grows, attracting and keeping users becomes a key challenge for marketers. Studies have identified various factors affecting ongoing use of GAI chatbots, including task-technology fit (Hu et al., 2025), perceived benefits (Khreis et al., 2025), information quality (Qi et al., 2025), perceived usefulness and ease of use (Hu et al., 2025; Saxena & Doleck 2023; Wang et al., 2026; Thi Thuy et al., 2024), performance expectations (Baig & Yadegaridehkordi 2025; Holzmann et al., 2025; Zhu et al., 2026), confirmation of expectations (Hsu, 2025), perceived personalization (Khreis et al., 2025), perceived enjoyment (Wang et al., 2026), user satisfaction (Baig & Yadegaridehkordi 2025; Hu et al., 2025; Meah & Qin 2024; Qi et al., 2025; Thi Thuy et al., 2024), technical self-efficacy (Khreis et al., 2025), effort expectancy (Holzmann et al., 2025), trust (Li et al., 2026), ethical judgment (Holzmann et al., 2025), and influences from social factors and supportive conditions (Baig & Yadegaridehkordi 2025; Hu et al., 2025).

In recent years, Perceived Value Theory (PVT) has gained popularity for analyzing the factors that influence users' intentions and behaviors. It proposes a logical link between perceived customer value and consumption intentions (Yang et al., 2023). According to PVT, perceived value is a holistic assessment of a subject's overall utility from the user's perspective (Chen et al., 2025). Liu et al. (2025) noted that consumers' perceived GAI values can be divided into perceived utilitarian value, which relates to functionality, and perceived hedonic value, which pertains to emotional satisfaction. Both emotional and functional factors are important when evaluating technologies, and user intentions to engage with GAI are influenced by both types of value (Hong et al., 2024). Researchers emphasize that offering both utilitarian and hedonic value is strongly associated with the intention to continue using GAI (Liu et al., 2025; Kim & Baek, 2024).

However, little research has focused on the factors affecting GAI's hedonic and utilitarian value. A review of the literature reveals that Liu et al. (2025) are the only ones to investigate how heuristic factors (like anthropomorphism and likability) and systematic factors (such as perceived intelligence and AI compatibility) influence students' willingness to continue using GenAI based on its hedonic and utilitarian benefits. Their research shows that AI features such as intelligence and compatibility mainly determine perceived utilitarian value, while hedonic value is driven by anthropomorphism and likability. Despite these insights, the underlying factors shaping users' perceived hedonic and utilitarian value of GAI remain a significant and unresolved issue.

Each user's value assessment is subjective (Elshaer et al., 2025) and shaped by users' characteristics. Research shows that individuals' technological self-efficacy shapes how they perceive the value of technological products (Thoumrungroje & Suprawan, 2024). Self-efficacy is a personal characteristic rooted in a person's subjective self-image (Ekman et al., 2024) and is generally defined as the belief in one's ability to perform the specific sequences of behavior required to operate the system (Sun & Bhattacharjee, 2014). Although self-efficacy is a critical factor in users' assessment of systems (Li et al., 2026), little research has examined how users' self-efficacy affects their perceived utilitarian and hedonic value of an object, particularly in the GAI context.

On the other hand, characteristics of AI tools, such as reliably providing accurate and context-aware solutions, help users trust the system's dependability and competence, thereby increasing its perceived value (Ngo et al., 2026). Problem-solving technology has been employed to leverage GAI (Hamtini & Assaf 2024). People use AI systems for their learning, predictive, and problem-solving capabilities (Arar et al., 2025). GAI chatbots can assist with problem-solving across various topics (Dalgıç et al., 2024), including content creation, research, coding, and image and video generation. Although studies have shown that rule-based chatbots with problem-solving capabilities in the retail industry can satisfy and delight customers (Jasom et al., 2022), the influence of users' perceptions of the GAI's problem-solving feature on their evaluations of the chatbots' utilitarian and hedonic value remains underexplored.

In summary, both hedonic and utilitarian values play key roles in evaluating technologies, yet the antecedent factors that shape users' perceived hedonic and utilitarian value of GAI remain unclear. This

study, therefore, extends PVT by examining how user characteristics, such as self-efficacy, and technology characteristics, such as the problem-solving capabilities of GAI chatbots, influence users' assessments of hedonic and utilitarian value. These perceptions, in turn, affect users' intent to continue using GAI chatbots. Our research questions are: 1. How does users' self-efficacy influence their perceived utilitarian and hedonic value of these chatbots? 2. How does the perceived problem-solving ability of GAI chatbots impact their perceived GAI values? The study aims to provide new insights into users' behavioral psychology and marketing related to GAI, particularly by extending PVT to explore the antecedents of hedonic and utilitarian value from user characteristics (such as self-efficacy) and technology characteristics (like problem-solving skills). This helps clarify the psychological factors driving continued GAI chatbot use, which can assist GAI marketers in developing more effective GAI development and communication strategies.

2. Literature Review

2.1 *GAI chatbots*

Based on core models like LLMs, GAI encompasses a range of AI systems that have become a disruptive force in data-driven innovation (Qiao et al., 2022). Recent systems utilize a multimodal approach, capable of processing and generating various media formats such as text, images, audio, video, and 3D virtual reality simulations (Bussell et al., 2023). GAI chatbots, like ChatGPT (launched by OpenAI in November 2022), are designed to follow prompts and deliver detailed responses (Ouyang et al., 2022). These chatbots facilitate character-based interactions without spatial or temporal limitations (Karri & Kumar, 2020), setting them apart from rule-based chatbots (Bozkurt & Sharma, 2024). Rule-based chatbots operate under predefined rules stored in lookup tables (Alnaeem, 2025; Wang & Lin, 2000) or using Prolog-like rules (Biermann et al., 1997), which restrict their ability to understand inputs and generate novel responses, limiting open-ended conversations and adaptation to new information. Conversely, GAI chatbots can sustain long, open-ended dialogues (Jeon & Lee, 2023) and adapt their responses based on input rather than fixed answers (Traymbak et al., 2024). Their main functions include providing information tailored to users' needs (Chung et al., 2020) and creating diverse content—such as text, images, audio, code, and videos (Kanbach et al., 2024)—to address questions across various topics (Dalgıç et al., 2024). GAI refers to a technology that uses deep learning models to generate human-like content, including text or images, in response to complex inputs like language prompts, instructions, and questions (Liu et al., 2025).

2.2 **User's self-efficacy perception and perceived problem-solving ability of GAI chatbots**

Perceived self-efficacy generally refers to an individual's belief in their capacity to accomplish tasks within a specific context (Kyaw & Soe 2024). In this study, it pertains to a person's confidence in solving general problems (Wu et al., 2025; Yang & Zhou 2022). Those with high perceived self-efficacy consistently pursue their goals, persevering through challenges until they attain the desired results or

performance levels (Kyaw & Soe 2024). People with greater perceived self-efficacy tend to possess the skills needed to handle complex tasks (Malik & Rao 2019). Research shows that perceived self-efficacy significantly affects the acceptance and use of technology (Wang et al., 2015; Wang et al., 2013). For instance, it is critical to the sustained use of app-based services (Malik & Rao 2019).

Conversely, AI technologies aid problem-solving and reasoning by proposing approaches to challenges and assessing outcomes (Dalgıç et al., 2024). AI technologies that support users are linked to enhanced problem-solving skills (Yuan et al., 2022). Perceived problem-solving ability of AI refers to beliefs about AI's competence, which foster rational trust, lead users to believe AI can genuinely help them reach their goals, and diminish skepticism (Ding et al., 2023). In this study, the perceived problem-solving ability of GAI chatbots is based on the user's objective evaluation of the chatbots' problem-solving skills.

2.3 Perceived Value Theory (PVT)

The idea of 'value' has long been a fundamental part of economic theory, stemming from classical models such as exchange and utility theory (Hao et al., 2025). PVT suggests that an individual's motivation to act depends on how they perceive the potential benefits or returns of that action (Wei et al., 2025). Consumer-perceived value describes how consumers assess goods based on a specific concept (Wang et al., 2024). It is relevant in many contexts, including both physical products and intangible services (Hao et al., 2025), and is a key factor influencing consumer purchasing decisions (Wang & Yu, 2016). Perceived value involves the user's cognitive evaluation of a product and mainly indicates the product's value or utility to the user during a particular activity (Wang et al., 2023). The overall product value, representing consumers' comprehensive assessment of these features, underpins their purchasing choices (Han et al., 2025).

Hedonic value is an emotional component reflecting the perceived benefit of an option's capacity to evoke feelings or emotional states, such as relaxation and joy (Dam, 2025). Hedonic value centers on enjoyment and emotional rewards, including fun, entertainment, and pleasure (Liu et al., 2025). By contrast, utilitarian value denotes the degree to which a technology's characteristics and cost align with the user's anticipated benefit, and it is recognized when the predicted criteria are met (Dam, 2025). Thus, it is typically associated with rational judgments (Liu et al., 2025) and can be evaluated from two distinct angles, 1) a product's functional performance (Vo et al., 2024) or 2) price-quality ratios (Yuan et al., 2022). In our study, it refers to an overall assessment of value that incorporates quality and value-for-money (Wang & Yu, 2016).

3. Research Framework and Hypothesis

3.1 Effect of perceived self-efficacy on perception of GAI chatbots' hedonic value

Perceived self-efficacy, indicating individuals' confidence in their ability to leverage AI for goal achievement (Latikka et al., 2021), influences their performance outcomes (Kim et al., 2016). In this

study, self-efficacy specifically refers to a person's belief in their problem-solving capabilities. Confidence in technology use shapes how users perceive its applications—higher self-efficacy correlates with more positive evaluations (Lewis & Loker, 2014). One research suggests that self-efficacy also affects emotional responses to tasks (Kim et al., 2016). Additionally, perceived hedonic value describes how enjoyable, pleasurable, and satisfying a technology or service appears (Li et al., 2021; Vo et al., 2024). Yuen et al. (2021) found that greater perceived self-efficacy leads to positive outcomes like increased pleasure. It is also suggested that hedonic value improves through smooth, effortless interactions that foster enjoyment and flow during use (Can et al., 2025). Users with strong problem-solving skills tend to perform better on tech-related tasks (Klingenberg et al., 2025) and respond more independently to system feedback (Lai & Lin, 2025), resulting in more seamless and enjoyable interactions with GAI chatbots. Based on these points, this study proposes the following hypothesis:

H1: Users' perceived self-efficacy positively influences their perception of GAI chatbots' hedonic value.

3.2 Effect of perceived self-efficacy on perception of GAI chatbots' utilitarian value

Perceived utilitarian value is a consumer's evaluation of a technology's functional benefits and costs, including quality and value for money (Wang & Yu 2016; Lin & Lu 2015). AI chatbots provide answers to users' questions and are thus considered valuable tools (Zhang et al., 2024a). Researchers have suggested that individuals with high self-efficacy are more likely to perceive a product or service as valuable (Yuen et al., 2021; Cao et al., 2022). Given that higher self-efficacy leads to more positive assessments of a technology (Lewis & Loker 2014), users with higher self-efficacy may place greater value on GAI chatbots in terms of quality and value for money. On the basis of these insights, this study proposed the following hypothesis:

H2: Users' perceived self-efficacy positively influences their perception of GAI chatbots' utilitarian value.

3.3 Effect of perceived problem-solving ability of GAI chatbots on perception of chatbots' hedonic value

Users' perception of value is reflected in the characteristics of technical products or services (Liu et al., 2025). Prior research has also indicated that one of the most essential features a service chatbot should have is the ability to engage in problem-solving with customers, and that a chatbot with problem-solving abilities enables users to be pleased and delighted with the chatbot (Jasom et al., 2022). Because GAI provides flexible explanations and problem-solving techniques (Vyas & Bhardwaj 2026), when GAI chatbots achieve such important outcomes, this leads to the user's subjective experience of pleasure (Mahmoud Sayed et al., 2024). On the basis of these insights, this study proposes the following hypothesis:

H3: The perceived problem-solving ability of GAI chatbots positively influences perceptions of their hedonic value.

3.4 Effect of perceived problem-solving ability of GAI chatbots on perception of their utilitarian value

GAI chatbots can provide information, analyze data, compose content, draw conclusions, offer suggestions, and solve problems (Saxena & Doleck 2023). Research indicates that GAI chatbots help users solve problems, enabling them to collect more detailed information about the topic (Dalgıç et al., 2024). This highlights their role in influencing users' cognitive evaluation of the service and how users perceive AI's problem-solving effectiveness, which in turn boosts their overall assessment of its utility (Ngo et al., 2026). Thus, when users recognize the problem-solving capabilities of GAI chatbots, they may view them as valuable tools worth their time. On the basis of this discussion, this study proposed the following hypothesis:

H4: The perceived problem-solving ability of GAI chatbots positively influences perception of the chatbots' utilitarian value.

3.5 Effects of perceived hedonic and utilitarian value on continued usage intention

Yu et al. (2013) demonstrated that perceived hedonic value positively influences behavioral intention. Additionally, Hong et al. (2017) and Ozturk et al. (2016) reported that perceived the hedonic value of a product or service is strongly correlated with the intention to continue using that product or service. Furthermore, Kim and Oh (2011) found that the perceived utilitarian value of information systems positively influences users' intention to continue using them. Ozturk et al. (2016) found a significant positive effect of perceived utilitarian value on the continued use of mobile hotel booking technology. Researchers have found that users who perceive both hedonic and utilitarian value in using a GAI chatbot are likely to continue using it (Liu et al., 2025; Kim & Baek 2024). On the basis of this discussion, this study proposed the following hypotheses:

H5: Perceived hedonic value positively influences the intention to continue using a GAI chatbot.

H6: Perceived utilitarian value positively influences the intention to continue using a GAI chatbot.

The research framework is illustrated in Fig. 1.

4. Methodology

4.1 Data collection

This study conducted an anonymous online survey in Taiwan from March to April 2024, distributed through Taiwanese social media forums and groups, including those on Facebook and LINE. Potential participants were approached on the social media platforms listed above. At the beginning of the survey, respondents were informed of (1) the academic research aims and objectives and thanked for their

valuable responses to improve overall data quality; (2) that participation was voluntary and that respondents could withdraw from the study at any time; and (3) that responses were anonymous and did not include individual identifiers, so they could not be traced back to any individual. The participant survey and completed questionnaires showed that written informed consent was received from all participants. The research protocol was not reviewed by an institutional review board because the study maintained participant anonymity and voluntary participation, thus safeguarding their autonomy. In addition, to prevent multiple submissions in anonymous data collection, we checked whether IP addresses were the same. The results indicate that no submissions came from the same IP address. The survey targeted individuals who used GAI chatbots; potential respondents were filtered by asking them the question, "Do you use GAI chatbots?" After invalid samples were excluded, 612 valid questionnaires remained. The respondents were instructed to base their responses on their experiences with the GAI chatbot they used most frequently. Of the respondents, 541 (88.4%) used ChatGPT, 26 (4.2%) used Google Gemini, 21 (3.4%) used Microsoft Bing, and 15 (2.5%) used Claude. The sample comprised 313 women (51.1%) and 299 men (48.9%). Most respondents (384 individuals, 62.8%), were aged between 20 and 29 years, 129 (21.1%) were between 30 and 39 years, and 51 (8.3%) were between 40 and 49 years. Regarding educational attainment, 378 respondents (61.8%) held a college degree, and 216 (35.3%) had a master's degree or higher. Thus, more than 90% of respondents possessed at least a college degree.

4.2 Measurements

The measurement scales were adapted from those validated in other studies. In this study, users' self-efficacy is operationally defined as the score reflecting users' perceived problem-solving ability, with items phrased as "I can solve problems." The self-efficacy measure was adapted from Gao et al. (2015) and comprised three items. The problem-solving ability of GAI is operationally defined by performance or scores that assess users' subjective beliefs in the GAI chatbot, including "believe" and "trust" that the GAI chatbot can solve problems and is consistent with their expectations. The construct of perceived problem-solving ability was adapted from Heppner and Baker (1997) and was measured using four items. Perceived hedonic value is the degree to which users derive value from the interesting, enjoyable, pleasant, and entertaining aspects of using a GAI chatbot, whereas perceived utilitarian value is the degree to which users view GAI as a means to an end, focusing on good value for the money. The measures for perceived hedonic value and perceived utilitarian value were adapted from Wang (2022) and consisted of four and three items, respectively. Finally, continuance usage intention is defined as a user's subjective probability or willingness to continue using GAI after initial adoption, specifically by evaluating the decision to continue using GAI. The continuance usage intention measure was adapted from Wang (2012) and comprised three items. Some of the scales were modified to fit the context of our study, which focuses on GAI. Because the original scales were in English but the study was conducted in Taiwan, which uses Chinese, the study employed a back-translation method to validate that the Chinese version is consistent with the original English version. In addition, before the questionnaire was formally distributed, it was pretested with 10 graduate students. Based on their feedback and suggestions, this study revised the wording and sentence structure without altering the meaning of the question items.

This process also ensured the reliability, clarity, and consistency of the measures used in this study. Responses were assessed using a 7-point Likert scale with endpoints ranging from 1 (strongly disagree) to 7 (strongly agree).

5. Data Analysis and Results

5.1 Common Method Bias (CMB)

To evaluate the risk of common method bias (CMB) in self-reported data, which can affect data validity and hypothesis testing (Zhang et al., 2024b), we employed Harman's one-factor test to assess whether CMB posed a significant issue (Wu et al., 2018). A serious CMB threat typically results in the first factor explaining 50% or more of the variance (Podsakoff et al., 2003). We used the 17 observed variables in the factor analysis. Harman's one-factor test indicated that CMB was unlikely to be a concern, with the first factor accounting for only 40.15% of the variance. In addition, we used SmartPLS 3.2.9 to execute Partial Least Squares Structural Equation Modeling (PLS-SEM), and the variance inflation factors (VIFs) were used to detect collinearity and CMB. The PLS-SEM analysis showed that all VIFs were < 1.567 , below the threshold of 3.3 (Wen et al., 2024), confirming that CMB was not a concern.

5.2 Internal reliability and convergent validity

Internal reliability and convergent validity of the latent variables are established when outer loadings exceed 0.6 (Riaz et al., 2023), CR exceeds 0.7, and AVE exceeds 0.5 (Fornell & Larcker 1981). The values are presented in Table 1. In this study, outer loadings ranged from 0.77 to 0.95, exceeding the 0.6 threshold. Additionally, CR ranged from 0.88 to 0.94, exceeding the 0.7 threshold, and AVE ranged from 0.65 to 0.84, exceeding the 0.5 threshold. Thus, all values satisfied their respective criteria, and the measurements exhibited satisfactory internal reliability and convergent validity.

Table 1
Descriptive Statistics of Measurements

Constructs	Item	Outer Loading	CR	AVE
Self-efficacy	I believe I can solve some problems easily.	0.90	0.91	0.77
	I believe I can solve problems.	0.91		
	I believe I can solve some problems without much effort.	0.82		
Problem-solving ability of GAI chatbots	Even if I initially have no solutions, I believe most problems can be solved using the GAI chatbot	0.81	0.88	0.65
	I trust that decisions made through the use of the GAI chatbot can solve problems	0.84		
	Using the GAI chatbot can yield solutions to problems	0.80		
	The GAI chatbot can solve most problems if I invest sufficient time and effort.	0.77		
Perceived hedonic value	Using the GAI chatbot is interesting.	0.88	0.93	0.76
	Using the GAI chatbot is enjoyable.	0.92		
	Using the GAI chatbot is pleasant.	0.90		
	Using the GAI chatbot is highly entertaining.	0.77		
Perceived utilitarian value	GAI chatbots are worth continuing to learn and use.	0.90	0.92	0.79
	GAI chatbots are worth investing time and effort to use.	0.91		
	GAI chatbots are valuable.	0.86		
Continue usage intention	I plan to continue using the GAI chatbot.	0.94	0.94	0.84
	I will continue to use the GAI chatbot.	0.95		
	In the future, I will regularly use the GAI chatbot.	0.86		

Source: Results of the present study

5.3 Discriminant validity

Discriminant validity, a subcategory of construct validity, assesses the separation among latent constructs. The Fornell and Larcker criterion (1981) was used to establish discriminant validity, requiring that the square root of each construct's AVE exceed its correlations with other constructs. In Table 2, all

square roots of the AVE values exceeded their correlations with other constructs, confirming adequate discriminant validity. Table 3 presents the results of the Heterotrait–Monotrait ratio of correlations (HTMT) test, with each deattenuated correlation below 0.85 (Kwabena et al., 2025), confirming that discriminant validity is achieved.

Table 2
Discriminant Validity (Fornell-Larcker test)

Variable	SE	PSA	PHV	PUV	CUI
Self-efficacy (SE)	0.88				
Problem-solving ability of GAI chatbot (PSA)	0.18	0.81			
Perceived hedonic value (PHV)	0.32	0.37	0.87		
Perceived utilitarian value (PUV)	0.32	0.33	0.60	0.89	
Continued usage intention (CUI)	0.30	0.31	0.50	0.70	0.92

Gray dots represent the squared AVE values of each construct, whereas the other values represent the correlation coefficients of each variable.

Source: Results of the present study

Table 3
Discriminant Validity (HTMT test)

Variable	SE	PSA	PHV	PUV	CUI
Self-efficacy (SE)					
Problem-solving ability of GAI chatbot (PSA)	0.22				
Perceived hedonic value (PHV)	0.37	0.42			
Perceived utilitarian value (PUV)	0.36	0.39	0.67		
Continued usage intention (CUI)	0.34	0.36	0.54	0.80	
Source: Results of the present study					

5.4 Structural Model Hypothesis Tests

Model fit for the PLS-SEM was assessed using the standardized root mean square residual (SRMR) and the normed fit index (NFI). An acceptable fit is indicated by SRMR values below 0.08 and NFI values above 0.85 (Lin et al., 2024). In this study, the SRMR was 0.059 and the NFI was 0.853, indicating acceptable fit. A bootstrapping analysis with 5,000 resamples was conducted to evaluate the structural model's hypotheses (Hair et al., 2022). The results, shown in Table 4, confirmed that all hypotheses were supported at $p < .001$. In addition, effect sizes (f^2) were assessed to determine the predictive power of the hypotheses, with values of > 0.02 , 0.15 , and 0.35 representing small, medium, and large effect sizes,

respectively (Cohen, 1988). As shown in Table 4, the f^2 values indicated that the model's hypotheses had small to large effect sizes. Moreover, the model explained 20.1% of the variance in perceived hedonic value, 17.6% of the variance in perceived utilitarian value, and 50.7% of the variance in continued usage intention.

Table 4
Results of Hypothesis Tests

Hypothesis	Path Coefficient	t-Value	f^2 effect	Finding
H1: Self-efficacy → Perceived hedonic value	0.27	6.76***	0.085	supported
H2: Self-efficacy → Perceived utilitarian value	0.26	6.97***	0.081	supported
H3: Problem-solving ability of GAI chatbots → Perceived hedonic value	0.32	7.76***	0.122	supported
H4: Problem-solving ability of GAI chatbots → Perceived utilitarian value	0.28	6.31***	0.095	supported
H5: Perceived hedonic value → Continue usage intention	0.12	3.46***	0.019	supported
H6: Perceived utilitarian value → Continue usage intention	0.63	19.57***	0.517	supported
Source: Results of this study				

6 Discussion

Extending PVT, this study examined the antecedents of users' perceived utilitarian and hedonic value of GAI chatbots, focusing on the user characteristic (i.e., users' self-efficacy) and GAI's technological characteristics (i.e., problem-solving capabilities). The results showed that users' perceived self-efficacy and the perceived problem-solving ability of GAI chatbots significantly influenced their perceived hedonic and utilitarian value. Consequently, perceived hedonic and utilitarian value significantly influenced their intention to continue using these chatbots.

6.1 Theoretical and practical implications

This study's findings provide insights into the factors influencing the continued intention to use GAI chatbots. The study demonstrated that perceived hedonic value and perceived utilitarian value positively influence continued usage intention, a finding consistent with those of previous studies (i.e., Liu et al., 2025; Kim & Baek 2024). While both hedonic and utilitarian values are important in evaluating technologies, it remains unclear which factors influence users' perceived hedonic and utilitarian value of GAI. This study extends PVT by examining whether user characteristics, such as self-efficacy, and GAI's technological characteristics, such as problem-solving ability, shape perceptions of these values and whether these perceptions may influence users' intention to continue using GAI chatbots. Our findings

reveal that users' perceived self-efficacy and perceived GAI chatbots' problem-solving ability positively influence perceptions of chatbots' hedonic and utilitarian value. Thus, this study extends PVT by examining the antecedents of perceived hedonic and utilitarian value from the perspectives of user characteristics (i.e., users' self-efficacy) and technology characteristics (i.e., the problem-solving capabilities of GAI chatbots). This study contributes to the literature by aligning work on PVE and extends the theory by incorporating the antecedent factors, including user characteristics and technology characteristics.

The paper outlines several practical implications based on the findings. The present study indicates that perceived hedonic and utilitarian value influence the intention to continue using GAI chatbots, with utilitarian value having a considerably stronger influence on this intention than hedonic value. To enhance user retention, GAI chatbot marketers should place greater emphasis on the value and worth of GAI chatbots in their GAI development and communication strategies. In their communication strategy, GAI chatbot marketers must shift from explaining what GAI is (features or characteristics) to what it delivers for the user (value and benefits). Focus on the "why" rather than the "what." Features are technical facts; benefits are the meaningful results. Clearly identify the specific challenges or problems users face and position GAI as the solution to those challenges or problems. They can also provide evidence by showing potential savings in money, time, or resources (e.g., "saves 5 hours of manual entry per week"). In addition, GAI chatbot marketers should strive to design GAI chatbots that clearly demonstrate their value and worth through savings in money, time, or resources in their GAI development strategies.

Furthermore, the findings reveal that users' self-efficacy significantly influences their perceptions of these chatbots' hedonic and utilitarian value. This suggests that GAI marketers can increase users' perceived hedonic and utilitarian value of GAI by boosting users' confidence in their problem-solving ability. To build users' confidence, GAI marketers should consider shifting users' mindsets from fear to curiosity and providing them with structured tools to succeed with GAI. Specifically, they can build users' confidence by breaking down large, overwhelming problems into smaller, actionable steps and offering user assistance with its use in their GAI development strategies. In addition, we found that the perception of GAI chatbots' problem-solving ability significantly influences perceptions of their hedonic and utilitarian value. Therefore, to enhance users' perceptions of chatbots' hedonic and utilitarian value, GAI chatbot marketers should promote the problem-solving capabilities of GAI chatbots. For example, they should communicate that even when a user initially has no solutions, most problems can still be solved with the GAI chatbot, which will assist step by step. They should also strive to design GAI that increases user trust, ensuring that decisions made through the use of the GAI chatbot can provide appropriate content or answers to solve their problems, yielding solutions if they invest sufficient time and effort.

6.2 Limitations and future research

This study has some limitations. First, in the absence of population surveys on GenAI user profiles in Taiwan, the results are derived from 612 responses mainly from younger users (83.9% aged 20–39) and

well-educated individuals (90% with at least a college degree). Future research could explore other countries or user groups to improve validity. Second, the sample is predominantly ChatGPT users (88.4%), with fewer than 5% responses for Claude, Gemini, and Bing. Consequently, the findings mainly reflect ChatGPT users' perceptions and may not be generalizable to all GAI chatbots. The theoretical framework focused on "GAI chatbots" in general, with practical insights aimed at "GAI chatbot marketers" broadly. This could limit the applicability of the results across various GAI chatbot applications. Further research should examine different GenAI platforms to validate these findings. Third, This study considered perceived problem-solving ability using a single dimension. However, Harefa and Purba (2020) classified problem-solving ability into four dimensions: transforming, answering, interpreting, and verifying capabilities. Therefore, follow-up studies can extend the present study's framework by using multiple dimensions. Investigating the multiple dimensions of problem-solving ability could provide valuable insights. Fourth, a person with a higher degree of digital literacy can more easily obtain, analyze, and evaluate information from technological applications (Dalgıç et al., 2024). Thus, researchers should consider including digital literacy as an antecedent of self-efficacy to extend this study's research framework.

6.3 Conclusion

The study extended the perceived value model by integrating two trait perspectives, i.e., individual characteristics (users' self-efficacy) and technology characteristics (the GAI chatbots' problem-solving ability). The results show that users' perceptions of their self-efficacy and of the GAI chatbots' problem-solving ability contribute to their perceptions of chatbots' utilitarian and hedonic value, which, in turn, promote the intention to continue using chatbots. Given that numerous GAI chatbot apps have been developed and the number of such apps has grown dramatically, competition among GAI chatbot marketers is fierce. To increase the competitiveness of their GAI app service, GAI chatbot marketers must understand the antecedents of continued usage intention to develop promotion and communication strategies for attracting and retaining users.

Declarations

Ethics statement

Because our anonymous surveys do not collect personal data and pose minimal risk, we did not need to submit the research plan for review to an institutional review board. We carefully crafted the protocol in accordance with the American Psychological Association's Ethical Guidelines for Research with Human Subjects. Ethical considerations were integrated throughout the process—participants were informed that participation was voluntary and that they could withdraw at any time; that their data would be used solely for academic purposes; and that responses would remain anonymous and no personal information would be collected. Informed consent was obtained from all participants, ensuring transparency and respect throughout.

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contribution

Conceptualization: Wang and Cai; Data curation: Cai; Formal analysis: Wang and Cai; Methodology: Wang and Cai; Supervision: Wang; Validation: Wang and Cai; Writing – original draft: Cai; Writing – review & editing: Wang. All authors have read and approved the final version of the manuscript.

Data availability:

The data are available at Figshare. (<https://dx.doi.org/10.6084/m9.figshare.28381769>)

References

1. Alnaeem, L. A. (2025). Potentials and challenges of using ChatGPT in language learning: EFL learners' perceptions. *Theory and Practice in Language Studies*, 15(5), 1437–1445. <https://doi.org/10.17507/tpls.1505.08>
2. Arar, K. H., Özen, H., Polat, G., & Turan, S. (2025). Artificial intelligence, generative artificial intelligence and research integrity: A hybrid systemic review. *Smart Learning Environments*, 12(1), e44. <https://doi.org/10.1186/s40561-025-00403-3>
3. Baig, M.I., Yadegaridehkordi, E. (2025). Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education. *International Journal of Educational Technology in Higher Education*, 22(1), 1–24. <https://doi.org/10.1186/s41239-025-00506-4>
4. Biermann, A. W., Guinn, C., Fulkerson, M. S., Keim, G. A., Liang, Z., Melamed, D. M., & Rajagopalan, K. (1997). Goal-oriented multimedia dialogue with variable initiative. In *Foundations of Intelligent Systems: 10th International Symposium, ISMIS'97* Charlotte, North Carolina, USA October 15–18, 1997 Proceedings 10 (pp. 1–16), Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-63614-5_1
5. Bozkurt, A., & Sharma, R. C. (2024). Are we facing an algorithmic renaissance or apocalypse? Generative AI, ChatBots, and emerging human-machine interaction in the educational landscape. *Asian Journal of Distance Education*, 19(1), 1–12.

6. Bussell, C., Ehab, A., Hartle-Ryan, D., & Kapsalis, T. (2023). Generative AI for immersive experiences: Integrating text-to-image models in VR-mediated co-design workflows. In *International Conference on Human-Computer Interaction* (pp. 380–388), Cham: Springer Nature Switzerland.
https://doi.org/10.1007/978-3-031-36004-6_52
7. Can, G., Elif, K., & Ioannis, A. (2025). The role of collaborative consumption in the servitization of digital service platforms. *Management & Marketing*, 20(4), 60–85. <https://doi.org/10.2478/mmcks-2025-0027>
8. Cao, J., Li, J., Wang, Y., & Ai, M. (2022). The impact of self-efficacy and perceived value on customer engagement under live streaming commerce environment. *Security and Communication Networks*, 2022, 1–13. <https://doi.org/10.1155/2023/9868043>
9. Chen, J., Wu, X., Luo, Y., & Liu, K. (2025). The impact mechanism of social network information on tourism travel: an empirical analysis based on internet celebrity cities. *Humanities and Social Sciences Communications*, 12, e1623. <https://doi.org/10.1057/s41599-025-05892-8>
10. Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, 117, 587–595.
<https://doi.org/10.1016/j.jbusres.2018.10.004>
11. Cohen, J. E. (1988). *Statistical power analysis for the behavioural sciences*, (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.
12. Dalgiç, A., Yaşar, E., & Demir, M. (2024). ChatGPT and learning outcomes in tourism education: The role of digital literacy and individualized learning. *Journal of Hospitality, Leisure, Sport & Tourism Education*, 34, 100481. <https://doi.org/10.1016/j.jhlste.2024.100481>
13. Dam, T. C. (2025). The influence of utilitarian value, hedonic value, and online review on consumers' satisfaction, trust, and repurchasing intention in e-commerce platforms. *Innovative Marketing*, 21(2), 105–118. [https://doi.org/10.21511/im.21\(2\).2025.09](https://doi.org/10.21511/im.21(2).2025.09)
14. Ding, L., Li, T., Jiang, S., & Gapud, A. (2023). Students' perceptions of using ChatGPT in a physics class as a virtual tutor. *International Journal of Educational Technology in Higher Education*, 20(1), e63. <https://doi.org/10.1186/s41239-023-00434-1>
15. Ekman, A., Pennbrant, S., Sterner, A., Forsberg, E., Hedén, L., Nunstedt, H., ... Hallgren, J. (2024). Health promoting resources and lifestyle factors among higher education students in healthcare and social work programmes: A survey with a longitudinal multicentre design. *BMC Public Health*, 24, 1–11. <https://doi.org/10.1186/s12889-024-20506-9>
16. Elshaer, I. A., Azazz, A. M., S., Sameh, F., Abdulaziz, A., Fathy, E. A., & Fouad, A. M. (2025). From asymmetry to satisfaction: The dynamic role of perceived value and trust to boost customer satisfaction in the tourism industry. *Tourism and Hospitality*, 6(2), e68.
<https://doi.org/10.3390/tourhosp6020068>
17. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.
<https://doi.org/10.2307/3151312>

18. Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems*, 115(9), 1704–1723. <https://doi.org/10.1108/IMDS-03-2015-0087>
19. Hao, X., Xu, J., & Wang, Y. (2025). How generative AI shapes user perceived value and adoption intention in digital museum experiences. *Heritage Science*, 13(1), e608. <https://doi.org/10.1038/s40494-025-02194-9>
20. Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)*, Sage, Thousand Oaks, CA.
21. Hamtini, T., & Assaf, A. J. (2024). Exploring the efficacy of GenAI in grading SQL query tasks: A case study. *Cybernetics and Information Technologies*, 24(3), 102–111. <https://doi.org/10.2478/cait-2024-0027>
22. Han, Z., Zhao, D., Sun, F., & Zhu, H. (2025). A study on the diffusion model of new energy passenger vehicles with consideration of product value. *PLoS One*, 20(5), e0323316. <https://doi.org/10.1371/journal.pone.0323316>
23. Harefa, N., & Purba, L. S. L. (2020). Problem solving skills improvement and the impact on students' learning outcomes: learning based e-project. In *Journal of Physics: Conference Series* (Vol. 1567, No. 2, p. 022038), IOP Publishing. <https://doi.org/10.1088/1742-6596/1567/2/022038>
24. Heppner, P. P., & Baker, C. E. (1997). Applications of the problem-solving inventory. *Measurement and Evaluation in Counseling and Development*, 29(4), 229–241. <https://doi.org/10.1080/07481756.1997.12068907>
25. Holzmann, P., Gregori, P., & Schwarz, E. J. (2025). Students' little helper: Investigating continuous-use determinants of generative AI and ethical judgment. *Education and Information Technologies*, 30(17), 24991–25011. <https://doi.org/10.1007/s10639-025-13708-0>
26. Hong, J. W., Fischer, K., Kim, D., Cho, J. H., & Sun, Y. (2024). I am not your typical chatbot: Hedonic and utilitarian evaluation of open-domain chatbots. *International Journal of Human–Computer Interaction*, 41(14), 8963–8974. <https://doi.org/10.1080/10447318.2024.2416016>
27. Hsu, L. (2025). From experience to adoption: Modelling EFL learners' GenAI continuance through linear and configurational approaches. *European Journal of Education*, 60(2), e70108. <https://doi.org/10.1111/ejed.70108>
28. Hu, Y., Yu, X., Hu, Y., & Li, K. (2025). Determinants of continuance intention to use GAI in academic research among graduate students: Findings from PLS-SEM and fsQCA. *Education and Information Technologies*, 30(14), 20289–20315. <https://doi.org/10.1007/s10639-025-13565-x>
29. Jasom, A., Srisangkajorn, T., & Limarunothai, W. (2022). How chatbot e-services motivate communication credibility and lead to customer satisfaction: The perspective of Thai consumers in the apparel retailing context. *Innovative Marketing*, 18(3), 13–25. [https://doi.org/10.21511/im.18\(3\).2022.19](https://doi.org/10.21511/im.18(3).2022.19)
30. Jeon, J., & Lee, S. (2023). Large language models in education: A focus on the complementary relationship between human teachers and ChatGPT. *Education and Information Technologies*, 28(12),

15873–15892. <https://doi.org/10.1007/s10639-023-11834-1>

31. Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M. & Lahmann, A. (2024). The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, 18(4), 1189–1220. <https://doi.org/10.1007/s11846-023-00696-z>
32. Karri, S. P. R., & Kumar, B. S. (2020). Deep learning techniques for implementation of chatbots. In *2020 International Conference on Computer Communication and Informatics (ICCCI)*, pp. 1–5, IEEE. <https://doi.org/10.1109/ICCCI48352.2020.9104143>
33. Khreis, S. H. A., Elkhwesky, Z., Sabiote-Ortiza, C., Parvez, M. O., & Al-Azab, M. (2025). Antecedents influencing the sustained intention to utilize generative artificial intelligence chatbots within the domains of hospitality and tourism. *Geo Journal of Tourism and Geosites*, 61(3), 1505–1518. <https://doi.org/10.30892/gtg.61310-1520>
34. Kim, B., & Oh, J. (2011). The difference of determinants of acceptance and continuance of mobile data services: A value perspective. *Expert Systems with Applications*, 38(3), 1798–1804. <https://doi.org/10.1016/j.eswa.2010.07.107>
35. Kim, H.-W., Chan, H. C., & Gupta, S. (2016). Examining information systems infusion from a user commitment perspective. *Information Technology & People*, 29(1), 173–199. <https://doi.org/10.1108/ITP-09-2014-0197>
36. Kim, J. S., & Baek, T. H. (2024). Motivational determinants of continuance usage intention for generative AI: an investment model approach for ChatGPT users in the United States. *Behaviour & Information Technology*, 44(12), 3080–3096.
37. Klingenberg, M., Diaz, C., & Rojas, M. P. (2025). Factors associated with technology learning and STEM vocations in high school-the case of technovation Chile. *The Educational Review*, 9(5), 475–489. <https://doi.org/10.26855/er.2025.05.001>
38. Kwabena, N. T., Chovancová Miloslava, Bludo, G. Y., & Aloysius, S. (2025). Navigating the digital transformation path: The role of digital leadership and technological capability through the dynamic capability model. *Management & Marketing*, 20(3), 48–64. <https://doi.org/10.2478/mmcks-2025-0011>
39. Kyaw, W. M. M., & Soe, A. T. (2024). Leadership styles, self-Efficacy, and innovative work behaviour of software developers. *The South East Asian Journal of Management*, 18(1), 105–129. <https://doi.org/10.21002/seam.v18i1.1544>
40. Lai, C.-H., & Lin, C.-Y. (2025). Analysis of learning behaviors and outcomes for students with different knowledge levels: A case study of intelligent tutoring system for coding and learning (ITS-CAL). *Applied Sciences*, 15(4), e1922. <https://doi.org/10.3390/app15041922>
41. Latikka, R., Savela, N., Koivula, A., & Oksanen, A. (2021). Attitudes toward robots as equipment and coworkers and the impact of robot autonomy level. *International Journal of Social Robotics*, 13(7), 1747–1759. <https://doi.org/10.1007/s12369-020-00743-9>
42. Lewis, T. L., & Loker, S. (2014). Technology usage intent among apparel retail employees. *International Journal of Retail & Distribution Management*, 42(5), 422–440.

<https://doi.org/10.1108/IJRDM-07-2012-0067>

43. Li, J., Hudson, S., & So, K. K. F. (2021). Hedonic consumption pathway vs. acquisition-transaction utility pathway: An empirical comparison of Airbnb and hotels. *International Journal of Hospitality Management*, 94, 102844. <https://doi.org/10.1016/j.ijhm.2020.102844>
44. Li, X., Chao, W., Kang, X., Han, C., Pang, Y., Ji, X., .. Bai, X. (2026). Exploring key psychological factors influencing virtual fitting room adoption among individuals with physical disabilities. *Scientific Reports*, 16(1), e4309. <https://doi.org/10.1038/s41598-025-29428-x>
45. Li, X., Liu, H., Zhou, T., Hu, C., & Ramayah, T. (2026). Generative artificial intelligence heuristic cues, trust and continuous intention of CBeC platform and the moderating role of information overload. *Scientific Reports*, 16(1), e3161. <https://doi.org/10.1038/s41598-025-32935-6>
46. Lin, K.-Y., & Lu, H.-P. (2015). Predicting mobile social network acceptance based on mobile value and social influence. *Internet Research*, 25(1), 107–130. <https://doi.org/10.1108/IntR-01-2014-0018>.
47. Lin, P. M., Wilson Au, W. C., & Baum, T. (2024). Service quality of online food delivery mobile application: An examination of the spillover effects of mobile app satisfaction. *International Journal of Contemporary Hospitality Management*, 36 (3), 906–926. <https://doi.org/10.1108/IJCHM-09-2022-1103>
48. Liu, Y., Zhang, Z., & Wu, Y. (2025). What drives Chinese university students' long-term use of GenAI? Evidence from the heuristic-systematic model. *Education and Information Technologies*, 30, 14967–15000. <https://doi.org/10.1007/s10639-025-13403-0>
49. Luthans, F., & Peterson, S. J. (2002). Employee engagement and manager self-efficacy: Implications for managerial effectiveness and development. *The Journal of Management Development*, 21(5), 376–387. <https://doi.org/10.1108/02621710210426864>
50. Mahmoud Sayed, M. A., Khaled Zaki, A. W., & Amr Mohamed, M. A. (2024). Generative AI and media content creation: Investigating the factors shaping user acceptance in the Arab Gulf states. *Journalism and Media*, 5(4), 1624–1645. <https://doi.org/10.3390/journalmedia5040101>
51. Malik, G., & Rao, A. S. (2019). Extended expectation-confirmation model to predict continued usage of ODR/ride hailing apps: role of perceived value and self-efficacy. *Information Technology & Tourism*, 21(4), 461–482. <https://doi.org/10.1007/s40558-019-00152-3>
52. Meah M. R., & Qin, H. (2024). ChatGPT: Advocacy or opposition through mixed methods. *Journal of Computer Information Systems*. 1–16. <https://doi.org/10.1080/08874417.2024.2372036>
53. Ngo, T. T. A., Chau, H. K. L., Tran, N. P. N., & Bui, C. T. (2026). The impact of AI-powered service on customer continuance usage intention in E-retailing: An extended expectation confirmation model. *Acta psychologica*, 262, 106095. <https://doi.org/10.1016/j.actpsy.2025.106095>
54. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
55. Qiao, H., Liu, V., & Chilton, L. (2022). Initial images: using image prompts to improve subject representation in multimodal AI-generated art. In *Proceedings of the 14th Conference on Creativity*

- and Cognition, 15–28. <https://doi.org/10.1145/3527927.3532792>
56. Qi, J., Ji'an Liu, & Xu, Y. (2025). The role of individual capabilities in maximizing the benefits for students using GenAI tools in higher education. *Behavioral Sciences*, 15(3), e328. <https://doi.org/10.3390/bs15030328>
57. Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies*, 27(6), 7893–7925. <https://doi.org/10.1007/s10639-022-10925-9>
58. Ozturk, A. B., Nusair, K., Okumus, F., & Hua, N. (2016). The role of utilitarian and hedonic values on users' continued usage intention in a mobile hotel booking environment. *International Journal of Hospitality Management*, 57, 106–115. <https://doi.org/10.1016/j.ijhm.2016.06.007>
59. Paciello, M., Corbelli, G., & D'Errico, F. (2023). The role of self-efficacy beliefs in dealing with misinformation among adolescents. *Frontiers in Psychology*, 14, 1155280. <https://doi.org/10.3389/fpsyg.2023.1155280>
60. Riaz, M., Wu, J., Sherani, M., Sher, A., Boamah, F. A., & Zhu, Y. (2023). An empirical evaluation of the predictors and consequences of social media health-misinformation seeking behavior during the COVID-19 pandemic. *Internet Research*, 33(5), 1871–1906. <https://doi.org/10.1108/INTR-04-2022-0247>
61. Ruggeri, M., Sorin, A., & Savastano, M. (2025). Navigating AI sustainability: A life cycle assessment approach toward viable future solutions. *Management & Marketing*, 20(4), 145–155. <https://doi.org/10.2478/mmcks-2025-0037>
62. Saxena, A., & Doleck, T. (2023). A structural model of student continuance intentions in ChatGPT adoption. *Eurasia Journal of Mathematics, Science and Technology Education*, 19(12), e2366. <https://doi.org/10.29333/ejmste/13839>
63. Shamim, K., Misra, S.C. (2025). Leveraging AI to drive online impulse buying: a SOBC perspective. *International Journal of Retail & Distribution Management*, 53(10–11), 1040–1056. <https://doi.org/10.1108/IJRDM-07-2024-0334>
64. Sun, Y., & Bhattacharjee, A. (2014). Looking inside the “It Black Box”: Technological effects on it usage. *The Journal of Computer Information Systems*, 54(2), 1–15. <https://doi.org/10.1080/08874417.2014.11645681>
65. Thi Thuy, A. N., Tran, T. T., An, G. K., & Phuong, T. N. (2024). ChatGPT for educational purposes: Investigating the impact of knowledge management factors on student satisfaction and continuous usage. *IEEE Transactions on Learning Technologies*, 17, 1367–1378. <https://doi.org/10.1109/TLT.2024.3383773>
66. Thourungroje, A., & Suprawan, L. (2024). Investigating M-payment intention across consumer cohorts. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(1), e431. <https://doi.org/10.3390/jtaer19010023>
67. Traymbak, S., Sharma, M., Anand, A., & Shukla, A. (2024). Chatbot technology in the education sector: a bibliometrics analysis using VOS viewer. *International Journal of System Assurance*

- Engineering and Management*, 1–12. <https://doi.org/10.1007/s13198-023-02230-6>
68. Vo, D.-T., Hoang, A. P., Dang-Pham, D., & Nguyen, L.V.T. (2024). Exploring value co-destruction process in customer interactions with AI-powered mobile applications. *Pacific Asia Journal of the Association for Information Systems*, 16(1), 51–73.
69. Vyas, H., & Bhardwaj, R. G. (2026). Comparative evaluation of ChatGPT and DeepSeek for competitive programming: International collegiate programming contest case. *International Journal of Intelligent Systems*, 2026(1), e14. <https://doi.org/10.1155/int/7757033>
70. Wang, C.-H. M. (2012). Determinants and consequences of consumer satisfaction with self-service technology in a retail setting. *Managing Service Quality: An International Journal*, 22(2), 128–144. <https://doi.org/10.1108/09604521211218945>
71. Wang, C., Du, Y., & Zou, B. (2026). Learners' acceptance and use of multimodal artificial intelligence (AI)-Generated content in AI-Mediated informal digital learning of English. *International Journal of Applied Linguistics*, 36(1), 927–940. <https://doi.org/10.1111/ijal.12827>
72. Wang, C., Harris, J., & Patterson, P. (2013). The roles of habit, self-efficacy, and satisfaction in driving continued use of self-service technologies: A longitudinal study. *Journal of Service Research*, 16(3), 400–414. <https://doi.org/10.1177/1094670512473200>
73. Wang, E. S. T. (2022). Influences of innovation attributes on value perceptions and usage intentions of mobile payment. *Journal of Electronic Commerce Research*, 23(1), 45–58.
74. Wang, E. S. T., & Yu, J.-R. (2016). Effect of product attribute beliefs of ready-to-drink coffee beverages on consumer-perceived value and repurchase intention. *British Food Journal*, 118(12), 2963–2980. <https://doi.org/10.1108/BFJ-03-2016-0128>
75. Wang, F., Wang, K., Han, Y., & Cho, J. H. (2024). Influences of design-driven FMCG on consumers' purchase intentions: A test of S-O-R model. *Humanities & Social Sciences Communications*, 11(1), e852. <https://doi.org/10.1057/s41599-024-03362-1>
76. Wang, H., Hall, N. C., and Rahimi, S. (2015). Self-efficacy and causal attributions in teachers: Effects on burnout, job satisfaction, illness, and quitting intentions. *Teaching and Teacher Education*, 47, 120–130. <https://doi.org/10.1016/j.tate.2014.12.005>
77. Wang, H. M., & Lin, Y. C. (2000). Goal-oriented table-driven design for dialogue manager. In *Sixth International Conference on Spoken Language Processing*. (ICSLP 2000). 2: 599–602. Beijing, China. <https://doi.org/10.21437/ICSLP.2000-340>
78. Wang, Y., Lu, L., Zhang, R., Ma, Y., Zhao, S., & Liang, C. (2023). The willingness to continue using wearable devices among the elderly: SEM and FsQCA analysis. *BMC Medical Informatics and Decision Making*, 23, 1–13. <https://doi.org/10.1186/s12911-023-02336-8>
79. Wei, H., Yao, J., & Wang, F. (2025). The effect of government publicity and guidance on farmers' ecological environment governance participation behavior—The mediating effect of environmental literacy and perceived value. *PLoS One*, 20(7), e0328274. <https://doi.org/10.1371/journal.pone.0328274>

80. Wen, B., Kurniasari, F., & Elissa, D. L. (2024). Elucidating drivers of repurchase intention in the e-marketplace through the lens of online trust-building mechanisms. *Innovative Marketing*, 20(1), 212–226. [https://doi.org/10.21511/im.20\(1\).2024.18](https://doi.org/10.21511/im.20(1).2024.18)
81. Wu, J., Law, R., & Liu, J. (2018). Co-creating value with customers: a study of mobile hotel bookings in China. *International Journal of Contemporary Hospitality Management*, 30(4), 2056–2074. <https://doi.org/10.1108/IJCHM-08-2016-0476>
82. Wu, J., Zhang, Q., Gan, X., Liu, X., Hu, J., & Wang, Y. (2025). The relationship between digital literacy and innovative behavior among chinese medical students: The chain mediating roles of diversity experience and creative self-efficacy. *BMC Medical Education*, 25(1), e1194. <https://doi.org/10.1186/s12909-025-07799-z>
83. Yang, H., & Zhou, D. (2022). Perceived organizational support and creativity of science-technology talents in the digital age: The effects of affective commitment, innovative self-efficacy and digital thinking. *Psychology Research and Behavior Management*, 15, 2421–2437. <https://doi.org/10.2147/PRBM.S378141>
84. Yang, H., Zhang, P., & Liu, H. (2023). The influence of the brand image of green agriculture products on China's consumption intention–The mediating role of perceived value. *PloS One*, 18(10), e0292633. <https://doi.org/10.1371/journal.pone.0292633>
85. Yu, J., Zo, H., Kee Choi, M., & Ciganek, P. A. (2013). User acceptance of location-based social networking services: An extended perspective of perceived value. *Online Information Review*, 37(5), 711–730. <https://doi.org/10.1108/OIR-02-2020-0058>
86. Yuen, K. F., Saidi, M. S. B., Bai, X., & Wang, X. (2021). Cruise transport service usage post COVID-19: The health belief model application. *Transport Policy*, 111, 185–196. <https://doi.org/10.1016/j.tranpol.2021.08.002>
87. Zhang, S., Zhao, X., Zhou, T., & Kim, J. H. (2024a). Do you have AI dependency? the roles of academic self-efficacy, academic stress, and performance expectations on problematic AI usage behavior. *International Journal of Educational Technology in Higher Education*, 21(4), 1–14. <https://doi.org/10.1186/s41239-024-00467-0>
88. Zhang, Y., Cham, T., Pek, C. K., & Leong, C. (2024b). Is face and information availability important in green purchasing among young consumers? *Humanities & Social Sciences Communications*, 11(1), e878. <https://doi.org/10.1057/s41599-024-03377-8>
89. Zhu, W., Li, T., & Li, Q. (2026). The power of beliefs: How generative artificial intelligence (GenAI) influences academic performance. *Acta Psychologica*, 263, e106218. <https://doi.org/10.1016/j.actpsy.2026.106218>

Figures

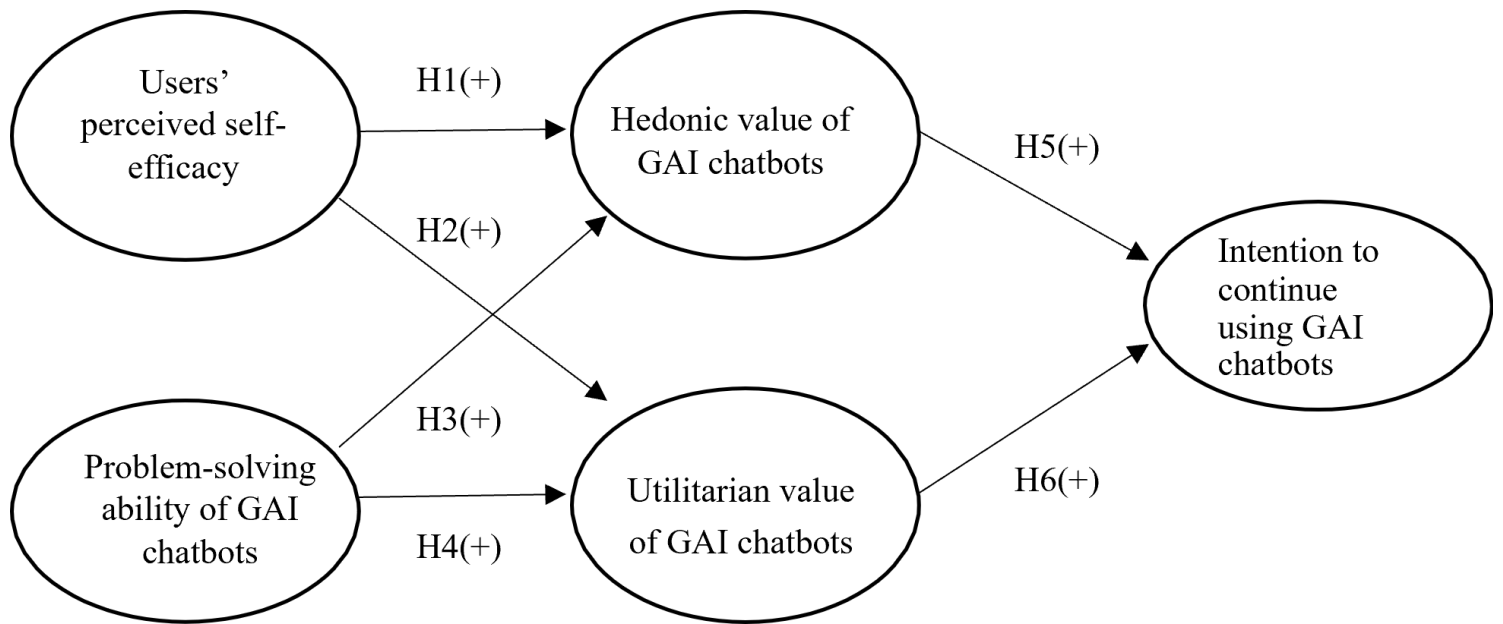


Figure 1

Conceptual Research Framework

Source: Created by the authors for this study