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Is Everyone an Artist? A Study on User Experience of AI-Based Painting System

Junping Xu [1], Xiaolin Zhang [2], Hui Li [3], Chaemoon Yoo [1] and Younghwan Pan [1,*]

[1] Department of Smart Experience Design, Kookmin University, Seoul 02707, Republic of Korea; xjp1110@kookmin.ac.kr (J.X.); chaemoonyoo10@kookmin.ac.kr (C.Y.)
[2] College of Art and Design, Guangdong University of Technology, Guangzhou 510006, China; colleenzhang@gdut.edu.cn
[3] College of Fine Arts, Guangxi Normal University, Guilin 541006, China
* Correspondence: peterpan@kookmin.ac.kr; Tel.: +82-2-910-4943

Abstract: Artificial Intelligence (AI) applications in different fields are developing rapidly, among which AI painting technology, as an emerging technology, has received wide attention from users for its creativity and efficiency. This study aimed to investigate the factors that influence user acceptance of the use of AIBPS by proposing an extended model that combines the Extended Technology Acceptance Model (ETAM) with an AI-based Painting System (AIBPS). A questionnaire was administered to 528 Chinese participants, and validated factor analysis data and Structural Equation Modeling (SEM) were used to test our hypotheses. The findings showed that Hedonic Motivation (HM) and Perceived Trust (PE) had a positive effect (+) on users' Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), while Previous Experience (PE) and Technical Features (TF) had no effect (−) on users' Perceived Usefulness (PU). This study provides an important contribution to the literature on AIBPS and the evaluation of systems of the same type, which helps to promote the sustainable development of AI in different domains and provides a possible space for the further extension of TAM, thus helping to improve the user experience of AIBPS. The results of this study provide insights for system developers and enterprises to better motivate users to use AIBPS.

Keywords: AI-Based Painting Systems (AIBPS); Technology Acceptance Model (TAM); behavioral intentions; user experience; Structural Equation Modeling (SEM)

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1. Introduction

Artificial Intelligence (AI) is rapidly developing and is becoming more widely used as computer technology and algorithms continue to advance. The International Data Corporation (IDC) reports that global spending on AI will more than double between 2023 and 2026, with spending exceeding USD 300 billion [1]. Since the end of the 20th century, applied research on AI has been widely used in various fields as an interdisciplinary approach, subtly transforming industries such as automotive, finance, healthcare, retail, journalism, media, education, gaming, online assistants, payments, art, and smart homes [2,3], and previous scholars have related AI art through literature and case studies [4,5]. Examples include the AI video content generation system Runway, the AI image processing system Toolkit, the AI automatic social media posting system Repurpose IO, the AI music system Amper Music, and the AI art image system Dall-E2.

AI art is widely used in the field of AI-Generated Content (AIGC) [6], and various related systems have been developed to facilitate and enhance the capabilities of users [7]. The chatbot product Chat GPT, based on AIGC, has surpassed 100 million active users in only two months since its launch, making it the fastest-growing application in history [8]. Scholars have prospectively discussed the potential of AI art technology applications [9–11]. Deng explores the application of AI in art design [12]; Liu analyzes the relationship between the integration of traditional and AI painting [13]; Köbis and Mossink experimentally assess whether users distinguish AI-generated poetry [14]; De Mantaras, RL, and Arcos, J.L study the relationship between AI and music [15]; and Jeon studies film creation through an AI-generated system that generates stories, narratives, images, and sounds in films using AI [16]. Therefore, the application of AI in the field of art is promising, and more AI will be applied to art creation in the future.

Driven by AI art, the application of AI in the field of painting continues to mature and develop [13]. AIBPS can generate paintings by learning and simulating the process of human painting [5], and can also generate a large number of images and works in a short time [17]. Therefore, more and more artists and designers are applying it to practical creations. In 2022, the first prize winner of the Colorado State Fair Art Competition, "Théâtre D'opéra Spatial", made headlines with a painting by designer Jason M. Allen using the AIBPS Midjourney [18]. However, according to the interview, he generated images more than 800 times through the AI system and repeatedly performed tests to obtain satisfactory work, meaning the system did not directly generate the expected satisfactory work. Academics also continue to discuss user acceptance regarding AI-generated paintings, such as whether AI-generated paintings are art [19,20], whether users accurately recognize AI-generated paintings [21], whether AI is imaginative [5], whether AI can create artistic paintings autonomously [22], whether AI-generated art can be considered human-created works like "Art", and whether users accept AI-generated paintings. Therefore, user acceptance and behavioral intentions towards AIBPS may be a real issue, as it can directly affect user engagement and sustained usage. If users do not accept and use AIBPS, this may lead to lower user retention, lower user activity, and reduced revenue for AIBPS [23]. Thus, AI is widely used in fields such as art creation and design, and research is needed to optimize user acceptance and behavioral intentions to improve its effectiveness.

The Technology Acceptance Model (TAM) is the most prevalent theory used to evaluate user acceptance of new AI technologies [24] and was first proposed by Davis [25]. TAM is now widely used in different aspects of new technologies and confirmed that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) have a significant impact on user acceptance. Researchers have continuously upgraded and extended TAM based on TAMs such as TAM2, TAM3, UTAUT, UTAUT 2, etc. [26–32]. Moreover, the Robotic Architectural Technology Acceptance Model (RATAM), a new high-tech acceptance theory model for AI robot architecture design contexts, provides new insights into the future development of AI in architectural design [33].

Due to AI-Based Painting Systems (AIBPS) being an emerging technology, scholars have predominantly focused on comparing algorithms and functionalities across different systems, with limited research on users' specific experiences, attitudes, and acceptance when using AIBPS. Despite the crucial importance of user acceptance and usage for the successful application of AIBPS, there is a lack of empirical research that applies Extended Technology Acceptance Model (ETAM) to systematically explore the factors influencing users' acceptance and usage of AIBPS. Therefore, this study aims to fill the existing research gap and provide research directions for further in-depth exploration of user acceptance of AIBPS. By investigating and analyzing the factors influencing user acceptance and usage of AIBPS, this study will offer valuable insights into the development and application of this field. Therefore, this study aims to explore the factors that influence users' acceptance and behavioral intentions toward AIBPS using an extended TAM framework, and extends previous discussions on AIBPS to help evaluate and improve the experience and effectiveness of using the technology in practical applications. In general, this study aims to answer the following questions. (1) What are the factors that influence users' acceptance and use of AIBPS? (2) What are the relationships among the influencing factors? (3) How can the development and improvement of AIBPS features used by users be facilitated in response to these factors?

The research framework of this paper is as follows: Section 2, which reviews AIBPS and technology acceptance models, presents the research model and hypotheses of this paper and explores the determinants that influence the acceptance and use of AIBPS. In Section 3, we collect user data through questionnaire surveys and analyze them. Section 4 evaluates the measurement model and Structural Equation Model. In Section 5, we present our discussion and realizations. In Section 6, the conclusions of this paper are summarized. Section 7 discusses the limitations of the study and future directions. It is hoped that these findings will help system developers better understand users' preferences and acceptance of AIBPS, facilitate the development of new features, and thus, guide users to accept and use AIBPS more rationally, and consequently, promote the sustainable development of artistic creativity. Figure 1 shows a workflow diagram of the research methodology in this paper.

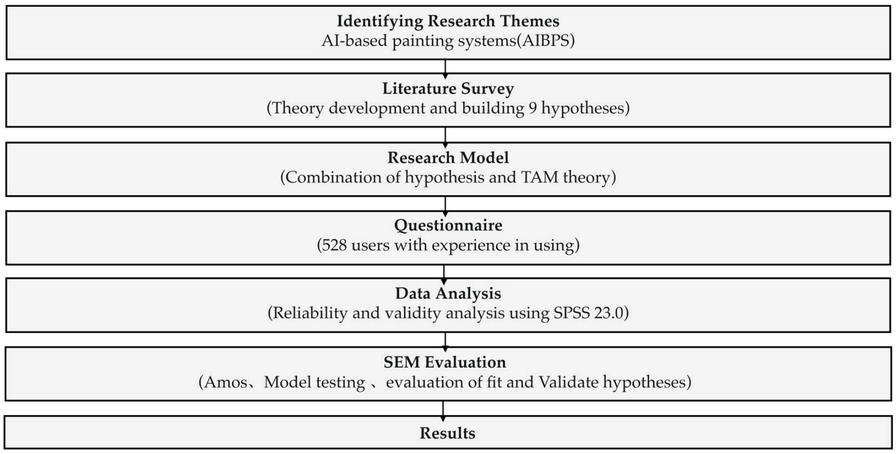

Figure 1. Research methodology.

2. Theoretical Background and Hypothesis Development

2.1. Overview of Artificial Intelligence (AI) in Painting

In recent years, AI techniques have gained popularity in the field of painting art, and the current mainstream AIBPS is based on semantic analysis [34]. This technique uses a huge database of text and images to train a machine-learning model that generates images by learning based on the textual input given by the user [35]. AIBPS uses deep learning algorithms to analyze and learn existing images, enabling the creation of new images. For example, Edmond de Belamy, a generative adversarial network portrait painting produced by the Parisian art collective Obvious in 2018, sold for USD 432,500 at Christie's New York in October 2019 [36]. Existing generative classes of neural networks include Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), Creative Adversarial Networks (AICANs), and Contrastive Language–Image Pre-training Models (CLIPs). The early AIBPS include DeepDream, Prisma, and Dall-E, and the current AIBPS include Disco Diffusion, Dall-E2, Imagen, Midjourney, and Stable Diffusion. Currently, there are two types of generative model of AIBPS on the market: one is diffusion-based and the other is sequence-to-sequence [37]. Therefore, generating high-quality, realistic images that accurately match the text descriptions is still a challenging task for AI systems.

Previous scholars have explored the relationship between AI and painting, such as creativity in AI painting [38], reflections on AI painting techniques [13], the attitudes of art and non-art majors towards AI painting [17], comparing human and AI painting [39], and applying AI painting techniques to cultural and creative products [40]. The art of AI painting incorporates a wide range of techniques and styles, using machine learning to improve the user's painting ability. Whether or not they have or specialize in painting skills, with the help of AIBPS, art major and non-art major users can easily create impressive works [17]. The intervention of AI in the creation of painting art not only brings more possibilities, but also overturns the paradigm of art creation and changes the way we think about viewing and evaluating artworks [39]. Thus, humans and AI can form a good partnership when making art, thus allowing for maximum creativity [38]. Since AI-generated paintings are based on technology, while human-generated paintings are based on emotions, fundamental differences remain in some aspects [41]. More and more users are now interested in the AIBPS creation method; however, whether users are willing to accept this art creation method, what factors contribute to user acceptance, and whether frequent use of AI painting systems will lead to the homogenization of creation, are the topics of this paper's research.

2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is used to explain and predict the adoption of computer technology. Davis argued that for a new technology to be accepted, it is crucial that it be used and easily identified [25]. His research developed and validated new scales for two specific variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) [42]. TAM is also one of the most commonly used models to understand the level of user adoption of emerging and communication technologies [43]. A meta-analysis conducted by some scholars proved that TAM is a valid and robust model and has been widely used [44]. In addition, PU and Attitude toward Using (ATT) directly affect Behavioral Intention (BI), whereas PEOU affects BI by PU directly or indirectly [45]. In the context of this study, users' ATT and BI were higher if they perceived that using AIBPS in their painting creation process was beneficial.

TAM is an important theoretical basis for studying users' acceptance of new technologies. In this model, PU and PEOU are two important influencing factors and they are both influenced by external variables, and many scholars have proposed new models by combining these variables. These models provide system developers with a better way to control user Behavioral Intention (BI) [46]. For example, the Technology Acceptance Model for the Elderly (STAM) explores the acceptance of new technologies among older Hong Kong residents [47]; the Technology–Organization–Environment (TOE) framework combined with TAM examines the factors influencing end-user ATT and BI regarding AI-based technologies in construction companies [28]; and the Learning Behavior Acceptance Model (T-LBAM) explores the intrinsic influences of students' participation in gamified online courses on willingness [26]. It is important to note that there are many influencing factors in TAM, and these factors vary significantly across different research areas. Therefore, in order to better understand the extent to which users accept new technologies, it is essential to thoroughly consider the influence of various external variables on user perception [27]. Several external variables, based on different research subjects, have been identified and incorporated into studies by scholars [26–33]. The inclusion of these external variables helps expand our understanding of user acceptance of new technologies and provides a more comprehensive analysis of the related phenomena. In addition, TAM has been used by many scholars as a theoretical basis for research describing users' ATT and BI regarding new systems or technologies for AI, and the model has been validated in areas such as Smart Banking [48], mobile payments [49], healthcare [50], service delivery [51], learning platforms [52], architecture companies [28], and digital libraries [46].

Although many scholars have applied TAM to the AI field, no scholars have yet combined TAM with the AI art field in an empirical study. The process by which various TAM factors in the AI field influence the acceptance of AIBPS is not clear. Therefore, this study aims to propose an Extended Technology Acceptance Model (ETAM) and combine it with AIBPS to investigate the factors that influence users' acceptance and use of AIBPS. Through this study, we can provide new ideas for applying the ETAM model in the AI field, and also help to promote the development of the AI art field.

2.3. Research Hypotheses

2.3.1. Previous Experience (PE)

Previous Experience refers to the fact that experienced users will find this new technology more useful and easier to use, and will be more likely to use it more often [53]. Although TAM has been shown to be applicable to experienced users, Previous Experience (PE) is still one of the main predictors of users' behavioral intentions [54,55]. In a meta-analysis of 107 papers, scholars identified 152 external variables that influence Perceived

Usefulness (PU) and ease of use, of which they identified Previous Experience (PE) as particularly important [56]. Experienced users are more receptive to new technologies, and thus, Previous Experience (PE) is an important factor influencing users' adoption of new technologies [57]. Studies have shown that experience is one of the most adequate moderating variables in TAM [44]. Therefore, we propose the following hypotheses:

Hypothesis 1 (H1a). *The user's Previous Experience of AIBPS will positively influence their Perceived Usefulness of AIBPS.*

Hypothesis 1 (H1b). *The user's Previous Experience of AIBPS will positively influence their Perceived Ease of Use of AIBPS.*

2.3.2. Technical Features (TF)

Technical Features need to be applicable and easy to use, and compatible with prior art, to reflect the advantages of functionality [28]. Some scholars have argued that AI device-specific technology preferences play an important role in user acceptance of new technologies [58]. Thus, in some cases, users' ATT and BI may vary depending on the Technical Features (TF) of the system and the differences between users [59]. According to previous studies, the Technical Features (TF) of a new technology or device can directly affect the user's PEOU and PU of the system [46,60,61]. Thus, the inclusion of Technical Features as external variables in TAM can help to better understand user acceptance and the adoption of AI painting technology. Consequently, we offer the following hypotheses:

Hypothesis 2 (H2a). *The Technical Features of AIBPS will positively influence users' Perceived Usefulness of AIBPS.*

Hypothesis 2 (H2b). *The Technical Features of AIBPS will positively influence users' Perceived Ease of Use of AIBPS.*

2.3.3. Hedonic Motivation (HM)

Hedonic Motivation refers to the pleasure or expectation of pleasure that an individual obtains through the use of AI devices [51]. Furthermore, previous studies have used hedonism as a major predictor of user behavior regarding technological systems [62]. With the continuous development of AI technologies, Hedonic Motivation (HM) has been widely used in terms of users' acceptance of AI [63,64], involving applications such as smart banking [48] and smart voice assistants [65], and some scholars have shown that Hedonic Motivation (HM) also significantly influences the social presence of AI chat systems, and thus, the intention to use AI chat services [66]. For users, when using AI devices for hedonic motives, these devices can provide benefits by satisfying personal interests and entertainment needs [67]; in other words, hedonic motives are the pleasure or joy derived from using the technology or system and are important determinants of users' acceptance and continued use of the technology [68]. In addition, several related studies have extended the TAM model to include Hedonic Motivation (HM) factors, and one such study proposed the Hedonic Motivation System Adoption Model (HMSAM) [69]. Accordingly, the following hypotheses are proposed:

Hypothesis 3 (H3a). *The user's Hedonic Motivation for AIBPS will positively influence their Perceived Usefulness of AIBPS.*

Hypothesis 3 (H3b). *The user's Hedonic Motivation for AIBPS will positively influence their Perceived Ease of Use of AIBPS.*

2.3.4. Perceived Trust (PT)

Perceived Trust refers to the user's recognition of the reliability and trustworthiness of a system [70]. As people become increasingly dependent on new technologies, trust in new technologies has become increasingly important [71,72]. Perceived Trust (PT), as a predictor of technology acceptance [73,74], is central to explaining the relationship between users' beliefs about new technologies and acceptance behavior [73]. Studies have shown that users' Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) for new technologies have an influential role in their trust [53]. Lockey et al. conducted a literature review survey of AI trust, assessing what is known about AI trust [75], while Choung et al. examined the role of trust in AI voice assistants based on college students [76]; Łapińska et al. investigated the extent to which company employees trust AI [77]; and Jacovi et al. explored the prerequisites, reasons, and goals for human trust in AI, with the aim of designing trustworthy AI products and evaluating their trustworthiness [78]. At the same time, users' trust and reliance on AI decision aids may be fragile [79]. Schnall et al. investigated the relationship between Perceived Trust (PT) and intention to use, as well as between PU and PEOU [80]. As AI technologies become common in various domains, trust has a significant impact on the intention to use AI and plays an important role in the acceptance of AI technologies [81]. For example, Perceived Trust (PT) influences the BI of intelligent healthcare services [81]. Solberg et al. proposed a conceptual model of perceived risk and dependence for AI decision making that helps researchers to study trust in and dependence on AI decision aids [82]. Thus, we propose the following hypotheses:

Hypothesis 4 (H4a). *The user's Perceived Trust of AIBPS will positively influence their Perceived Usefulness of AIBPS.*

Hypothesis 4 (H4b). *The user's Perceived Trust of AIBPS will positively influence their Perceived Ease of Use of AIBPS.*

2.3.5. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

Perceived Usefulness (PU) refers to the extent to which individuals believe that a new technology can improve their efficiency [83] and has also been interpreted as the subjective likelihood of potential users [30]. Perceived Ease of Use (PEOU) refers to the extent to which individuals accept that a new technology can be easily adopted without requiring significant time to learn [39]. Perceived Ease of Use (PEOU) not only affects users' PU, but also affects their Attitude toward Using (ATT) regarding their acceptance of new AI technologies [46]. As the main determinants of users' use and acceptance of new technologies [25], PU and PEOU equally have a positive impact on the Attitude toward Using (ATT) aspect of chat AI robots [84,85]. The development of new systems that are easy to use will become increasingly common in the future, and adherence to or deviation from commonly understood standards of ease of use may have a significant impact on the acceptance of a system [86]. By providing an intuitive user interface, easy-to-understand steps, and a quick feedback mechanism, users can quickly master the use of AIBPS, making it easier for non-professional users to create paintings, while also helping professional users to gain inspiration and improving the efficiency and quality of their creations. Therefore, we offer the following hypotheses:

Hypothesis 5 (H5). *The user's Perceived Usefulness of AIBPS will positively influence their Attitude towards AIBPS.*

Hypothesis 6 (H6). *The user's Perceived Usefulness of AIBPS will positively influence their Behavioral Intention towards AIBPS.*

Hypothesis 7 (H7). *The user's Perceived Ease of Use of AIBPS will positively influence their Perceived Usefulness of AIBPS.*

Hypothesis 8 (H8). *The user's Perceived Ease of Use of AIBPS will positively influence their Attitude towards AIBPS.*

2.3.6. Attitude toward Using (ATT)

The use of new technologies has been shown to depend on users' Attitude toward Using (ATT) and their influence on decision-making [73], and users' ATT is also a determinant of the use of new technologies [51,86–88]. BI depends on a person's ATT regarding the behavior in question. Attitudes and emotions toward the use of AI devices will determine their attitudes toward the use of AI devices in the service delivery process and their willingness to use them in service delivery [51]. In a study by Sánchez-Prieto et al., student users' ATT regarding an AI learning program was a factor in determining whether they actively used the program or not [89]. Therefore, users' decision to use AIBPS may depend on their Attitude toward Using (ATT). As such, we propose the following hypothesis:

Hypothesis 9 (H9). *The user's Attitude toward Using AIBPS will positively influence their Behavioral Intention towards AIBPS.*

2.4. Research Model

This study analyzes the factors that influence users' willingness to use and acceptance of AI painting systems. Expanding on Davis' Technology Acceptance Model (TAM), external variables were derived from the literature survey and prior research analysis. Table 1 outlines our hypotheses.

Table 1. Research hypotheses.

Variables	Hypotheses	Description
Previous Experience (PE)	H1a	The user's Previous Experience of AIBPS will positively influence their Perceived Usefulness of AIBPS.
	H1b	The user's Previous Experience of AIBPS will positively influence their Perceived Ease of Use of AIBPS.
Technical Features (TF)	H2a	The Technical Features of AIBPS will positively influence users' Perceived Usefulness of AIBPS.
	H2b	The technical features of AIBPS will positively influence users' Perceived Ease of Use of AIBPS.
Hedonic Motivation (HM)	H3a	The user's Hedonic Motivation for AIBPS will positively influence their Perceived Usefulness of AIBPS.
	H3b	The user's Hedonic Motivation for AIBPS will positively influence their Perceived Ease of Use of AIBPS.
Perceived Trust (PT)	H4a	The user's Perceived Trust of AIBPS will positively influence their Perceived Usefulness of AIBPS.
	H4b	The user's Perceived Trust of AIBPS will positively influence their Perceived Ease of Use of AIBPS.
Perceived Usefulness (PU)	H5	The user's perceived usefulness of AIBPS will positively influence their Attitude toward Using AIBPS.
	H6	The user's Perceived usefulness of AIBPS will positively influence their Behavioral Intention towards AIBPS.

Table 1. *Cont.*

Variables	Hypotheses	Description
Perceived Ease of Use (PEOU)	H7	The user's Perceived Ease of Use of AIBPS will positively influence their Perceived Usefulness of AIBPS.
	H8	The user's Perceived Ease of Use of AIBPS will positively influence their Attitude toward Using AIBPS.
Attitude toward Using (ATT)	H9	The user's Attitude toward Using AIBPS will positively influence their Behavioral Intention toward Using AIBPS.

Based on the above hypotheses, this study proposes a research model for acceptance behavior toward AIBPS. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude toward Using (ATT) to use, and Behavioral Intention (BI) were taken as basic variables. Four external variables were deduced through a literature survey and previous research analysis: Previous Experience (PE), Technical Features (TF), Hedonic Motivation (HM), and Perceived Trust (PT). According to the characteristics of AIBPS, a research model of AI painting service acceptance is proposed. Figure 2 shows the proposed research model [30].

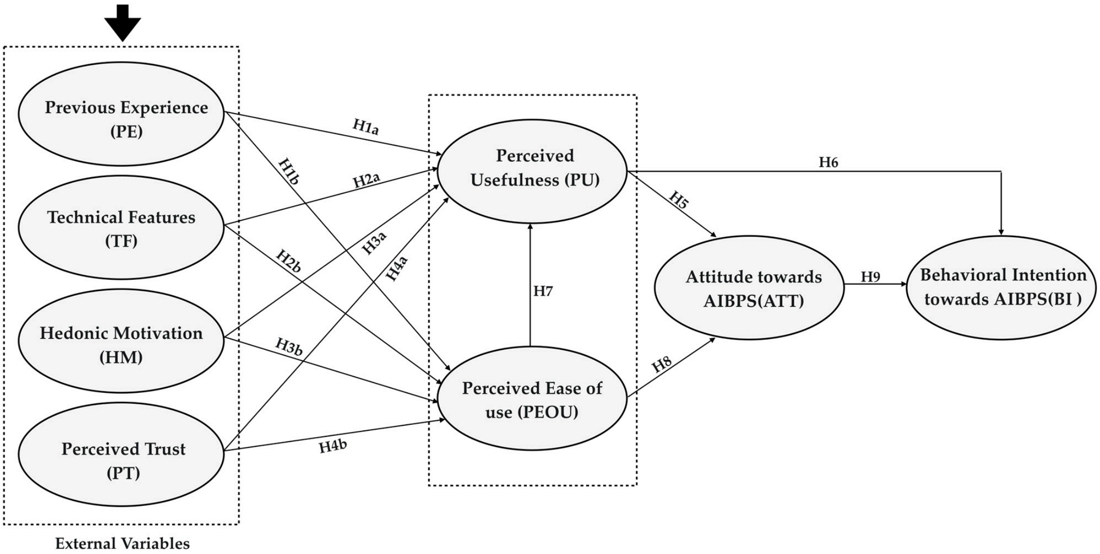

Figure 2. Proposed conceptual model.

3. Methods

3.1. Questionnaire Design

The study's questionnaire was divided into three parts: Section 1 provided a brief description of and introduction to AI painting, as well as relevant images; the second section asked respondents about their gender, age, educational background, frequency of use, and experience level. Section 2 aimed to explore users' willingness to utilize AIBPS, and it contained 8 variables with 4–5 options to measure each, making a total of 34 items. The details and references of the variable item questionnaire are shown in Table 2. To ensure that the questionnaire was accurately represented in terms of clerical wording, substance, and ambiguity, we first sent it to five expert university professors with an average of eight years of experience teaching AI and art for checking. All data submitted by the participants will be kept confidential and used for academic purposes only and will not be shared with third parties, and their identifying information will not be made public. Each user who completed the questionnaire received a WeChat bonus of 5 RMB as a reward to express our appreciation for their time and truthful answers to each question. As a large scale performed better than a small scale in terms of reliability and validity in an empirical study [90], all items in Section 3 were measured on a 7-point Likert scale

(1: “strongly disapprove”, 2: “disapprove”, 3: “somewhat disapprove”, 4: “fair”, 5: “somewhat approve”, 6: “approve”, and 7: “strongly approve”).

Table 2. Questionnaire for variable items and reference.

Variables	Items	Issue	Reference
Perceived Usefulness (PU) (five items)	PU1	Using AIBPS would enable me to accomplish tasks more quickly.	Davis (1989) [25], Venkatesh and Davis (2000) [84], Lee et al. (2003) [84], Chatterjee et al. (2021) [30]
	PU2	Using AIBPS would help me learn a lot more.	
	PU3	Using AIBPS saves time and effort and increases my efficiency.	
	PU4	Using AIBPS would make it easier to do my job.	
	PU5	Using AIBPS would help create new ideas for my work	
Perceived Ease of Use (PEOU) (five items)	PEOU1	Learning to operate AIBPS would be easy for me.	Davis (1989) [25], Lee et al. (2003) [83], Venkatesh et al. (2003) [91], Yousafzai et al. (2007) [92]
	PEOU2	I would find it easy to get AIBPS to do what I want them to do.	
	PEOU3	I would find AIBPS easy to use.	
	PEOU4	My interaction with AIBPS would be clear and understandable.	
	PEOU5	It would be easy for me to become skillful at using AIBPS.	Davis (1989) [25], Davis et al. (1989) [42], Na et al. (2022) [28]
Attitude toward Using (ATT) (four items)	ATT1	Using AIBPS is a good idea.	
	ATT2	I am positively impressed with the ability of the AIBPS.	
	ATT3	I find AIBPS to be valuable systems for creating works.	
	ATT4	I am very satisfied with the artwork generated by AIBPS.	
Behavioral Intention (BI) (four items)	BI1	I find it worthwhile to create with AIBPS.	Davis (1989) [25], Taylor and Todd (1995) [93], Venkatesh et al. (2003) [91], Castiblanco Jimenez et al. (2021) [29]
	BI2	I find it beneficial to create with AIBPS.	
	BI3	I intend to use AIBPS to create in the future.	
	BI4	I would recommend AIBPS to others.	
Previous Experience (PE) (four items)	PE1	It would have been easier to use if I had previous experience with AIBPS.	Gefen et al. (2003) [53], Liu et al. (2010) [94], Abdullah and Ward (2016) [95]
	PE2	If the website had an online guide feature, I would know how to use it better.	
	PE3	By following the step-by-step instructions on the website, it will be easy to operate.	
	PE4	I would have better understood how to use the AIBPS if a friend had first.	
Technical Features (TF) (four items)	TF1	AIBPS can output quality work without the need for mastering the basics of painting.	Castiblanco Jimenez (2020) [96], Wang et al. (2020) [60], Na et al. (2022) [28]
	TF2	AIBPS can provide me with the content I need whenever I need it.	
	TF3	AIBPS create works quickly and in a very short time.	
	TF4	AIBPS can meet the needs of non-professional people	
Hedonic Motivation (HM) (four items)	HM1	I enjoyed interacting with AIBPS.	Alenezi et al. (2010) [97], Venkatesh et al. (2012) [98], Lu et al. (2019) [99]
	HM2	Interacting with AIBPS is fun.	
	HM3	Interacting with AIBPS is entertaining.	
	HM4	The actual interaction process with the AIBPS would be pleasant.	
Perceived Trust (PT) (four items)	PT1	I trust AIBPS to ensure that I can use them properly.	Lee (2005) [100], Lean et al. (2009) [101], Liu and Yang (2018) [102], Vimalkumar et al. (2021) [103]
	PT2	I have more trust in the works created by AIBPS.	
	PT3	I have more trust in the data sources of AIBPS	
	PT4	I have more trust in the privacy protection of AIBPS.	

3.2. Participants and Data Collection

From September to December 2022, a total of 568 completed questionnaires were collected through the online questionnaire platform Questionnaire Star, a Chinese platform specialized in providing online questionnaire services. Some questionnaires were also considered invalid. As the study was conducted among users who had accessed or used AIBPS, the second part on demographics was closed with a skip option, i.e., “You have not accessed or used AIBPS", and in these cases, the questionnaires were considered invalid. According to the questionnaire system, only 6 of the respondents in this study had not been exposed to or used AIBPS, accounting for 0.01% of the total, and a total of 40 invalid questionnaires were removed. In order to reduce the influence of typical technique bias, the questionnaire was set up in such a way that, firstly, it took no less than 120 s to complete, and any questionnaire that took less than 120 s to complete was considered unreliable; secondly, invalid questionnaires, such as those with obvious contradictions and those with the same answer given consecutively, were excluded. Finally, the Harman single factor test [104] was used to test for typical technique bias, and a reshuffled principal component factor analysis was performed on each variable. As shown in Table 3, the first unrotated factor explained 28.927% of the total variance, which is well below the critical threshold of 40%, indicating that the data contained no common method bias (see Table 3).

Table 3. Common method deviation test (Harman single factor test).

NO.	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotating Sum of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative%	Total	% of Variance	Cumulative %
1	9.835	28.927	28.927	9.835	28.927	28.927	3.806	11.196	11.196

The sample size of this study is an important factor for SEM analysis, and too small a sample size may affect the model fit. Therefore, after rigorous screening, 528 valid questionnaires were used in this study for research and analysis, with a valid return rate of 93%. It is worth mentioning that this sample size meets the required sample size for SEM analysis, which is greater than 200 [105]. Additionally, the content of this study was approved by the Academic Ethics Committee of University X in May 2022.

3.3. Demographic Information

In this study, the data of 528 valid samples were analyzed demographically (Table 4), and then, processed using SPSS software. In terms of gender, there were 274 males (51.89%) and 254 females (48.11%). In terms of age, 134 respondents (25.38%) were aged 18–25, 122 respondents (23.11%) were aged 26–30, and 93 respondents (17.61%) were aged 31–40, with these three age groups dominating the sample. In terms of educational background, 214 respondents (40.53%) were below undergraduate, and 251 (47.53%) were undergraduates. In terms of frequency of use, 153 (28.97%) used AIBPS once a day, 267 (50.57%) once a week, 23 (4.36%) once a month, and 85 (16.1%) other. The percentage of users with previous painting experience was 90.72%. The demographic profile of respondents reported in this study was similar to the demographic profile reported in previous technology acceptance studies, and therefore, warrants further statistical analysis.

The results of the study of the AI paintings systems encountered are listed in Table 5, with Dall-E2 having the highest degree of familiarity at 80.68%, followed by Midjourney at 72.16%, Disco Diffusion at 59.28%, Stable Diffusion at 52.27%, WOMBO at 50.57%, and NovelAI at 33.14%. It is worth noting that DALL-E1 was released in 2021 and was known and used by a wide range of users early on, so more users will start using DALL-E2 when it is released, which is one of the reasons for its high percentage of familiarity. Midjourney can be used on the communication software Discord to easily talk to others and obtain paintings, while Disco Diffusion can be run directly in Google Drive and generates paintings with the highest accuracy, making it one of the AIBPS most often used by professional users.

Table 4. Demographic characteristics of the respondents.

Category	Sub-Category	Frequency (n = 528)	Percentage %
Gender	Male	274	51.89
	Female	254	48.11
Age (years)	<18	59	11.17
	18~25	134	25.38
	26~30	122	23.11
	31~40	93	17.61
	41~50	53	10.04
	51~60	40	7.58
	>61	27	5.11
Education level	Below undergraduate	214	40.53
	Undergraduate	251	47.54
	Post-graduate	50	9.47
	Doctor	13	2.46
Frequency of use of AIBPS	At least once a day	153	28.97
	At least once a week	267	50.57
	At least once a month	23	4.36
	Other	85	16.1
Previous painting experience	YES	479	90.72
	NO	49	9.28
Total participants		528	100.00

Table 5. Percentage of exposure to and use of AIBPS.

Items	Percentage (n = 528)
Disco Diffusion	59.28%
Dall-E2	80.68%
Midjourney	72.16%
Stable Diffusion	52.27%
WOMBO	50.57%
NovelAI	33.14%

4. Results

Based on the theory of previous studies, it was suggested that the analysis be conducted in two parts [106]. The first one assesses the measurement model and the second assesses the Structural Equation Model.

4.1. Measurement Model Assessment

To ensure the quality of the data analysis, we performed Confirmatory Factor Analysis (CFA) on the data. The valid sample size for the analysis of these test data was 528, which exceeded the number of analyzed items 10-fold, and the sample size was moderate.

4.1.1. Results of the Reliability and Validity Test

First, we performed a reliability analysis and calculated Cronbach's Alpha (CA) and Composite Reliability (CR). Since the reliability should be greater than at least 0.8 [106], the final values obtained by the test were both greater than 0.8. Therefore, it could be proven that the findings of the variables were reasonable, the items were retained, and the model was reliable. The Convergence Validity was then tested, and the study showed that the average variance (AVE) extracted was to be greater than 0.5 [107,108]. Factor loading analysis measures the correlations between individual variables and factors, which are usually substantial and significant for all items and need to be greater than 0.7 [109]. The significance levels of the current items were all below 0.05, the Average variance Extractions (AVE) of the variables were greater than 0.5, and the standardized factor loading coefficients were all above 0.7. Therefore, the validation factors for the variables were measured at good levels, indicating convergent validity and meeting the requirements for further model analysis (see Table 6).

Table 6. Reliability and validity analysis.

Variables	Items	Standardized Factor Loadings	Cronbach's α	CR	AVE
Perceived Usefulness (PU)	PU1	0.804	0.903	0.903	0.651
	PU2	0.798			
	PU3	0.816			
	PU4	0.805			
	PU5	0.810			
Perceived Ease of Use (PEOU)	PEOU1	0.806	0.887	0.887	0.611
	PEOU2	0.806			
	PEOU3	0.762			
	PEOU4	0.728			
	PEOU5	0.803			
Attitude toward Using (ATT)	ATT1	0.808	0.854	0.855	0.595
	ATT2	0.740			
	ATT3	0.778			
	ATT4	0.759			
Behavioral Intention (BI)	BI1	0.821	0.858	0.859	0.603
	BI2	0.759			
	BI3	0.758			
	BI4	0.767			
Previous Experience (PE)	PE1	0.928	0.964	0.964	0.871
	PE2	0.919			
	PE3	0.939			
	PE4	0.947			
Technical Features (TF)	TF1	0.929	0.952	0.954	0.837
	TF2	0.902			
	TF3	0.915			
	TF4	0.914			
Hedonic Motivation (HM)	HM1	0.841	0.874	0.874	0.635
	HM2	0.770			
	HM3	0.774			
	HM4	0.801			
Perceived Trust (PT)	PT1	0.822	0.868	0.868	0.623
	PT2	0.766			
	PT3	0.776			
	PT4	0.791			

Secondly, KMO and Bartlett's tests were conducted to analyze the overall questionnaire for validity. The results are shown in Table 7. The KMO value for this part of the questionnaire was 0.914 and Bartlett's spherical test chi-square value was 12,816.192, with a degree of freedom of 561 and a significance of 0.000 < 0.05, which indicates that the data passed the validity test and were suitable for subsequent factor analysis.

Table 7. Validity analysis (KMO and Bartlett's test).

Kaiser–Meyer–Olkin Measure of Sampling Adequacy		**0.914**
Bartlett's Test of Sphericity	Approx. chi-square	12,816.192
	df	561
	Sig.	0.000

4.1.2. Discriminant Validity

In this study, two methods were used to evaluate discriminant validity. First, a method of assessing the square root of AVE was conducted to demonstrate that the factors have discriminant validity based on previous research [110], and the square root of AVE for each factor must be greater than the correlation coefficient for each pair of variables [111]. The values of the square root of the AVE for the discriminant validity of this measurement were all higher than the correlation coefficients under the items, indicating that the measurement questions had good discriminant validity (see Table 8).

Table 8. Discriminant validity (Fornell–Larcker criterion).

	PU	PEOU	ATT	BI	PE	TF	HM	PT
PU	0.807							
PEOU	0.390	0.782						
ATT	0.317	0.356	0.772					
BI	0.470	0.489	0.562	0.777				
PE	0.139	0.198	0.189	0.254	0.933			
TF	0.129	0.155	0.140	0.192	0.151	0.915		
HM	0.365	0.402	0.370	0.567	0.206	0.103	0.797	
PT	0.278	0.311	0.321	0.438	0.110	0.096	0.323	0.789

Secondly, this study used the heterotrait–monotrait ratio of validity method, which assesses the correlation between different factors and the consistency within the same factor, with an HTMT value limit of less than 0.85 [112]. Upon measurement, all HTMT values in this study were less than 0.85, indicating that each variable had good discriminant validity. The discriminant validity of the variables is reasonably demonstrated in Table 9.

Table 9. Discriminant validity (HTMT values).

	PU	PEOU	ATT	BI	PE	TF	HM	PT
PU	-							
PEOU	0.435	-						
ATT	0.362	0.409	-					
BI	0.533	0.561	0.655	-				
PE	0.149	0.215	0.209	0.279	-			
TF	0.139	0.169	0.156	0.215	0.158	-		
HM	0.411	0.457	0.428	0.655	0.225	0.114	-	
PT	0.315	0.355	0.373	0.508	0.121	0.108	0.371	-

4.2. Structural Equation Assessment

4.2.1. Model Fit Index

As demonstrated in Table 10, the CMIN/DF value for the model analyzed in this study was 1.843, and the value for the remaining fit indicators NFI was 0.928, IFI was 0.966, TLI was 0.962, CFI was 0.965, GFI was 0.901, and RMSEA was 0.040. All of the fit indicators reached higher than the minimum values recommended by previous studies [113], indicating that the model scales match well. This indicates a good model fit [114], and therefore, the model test results could be analyzed.

Table 10. Recommended and actual values of fit indices.

Fit Index	CMIN/DF	RFI	NFI	IFI	CFI	PCFI	GFI	AGFI	TLI (NNFI)	RMSEA
Recommended value	$\leq$3.0	>0.9	>0.9	>0.9	>0.9	>0.8	>0.9	>0.8	>0.9	<0.08
Measurement model	1.843	0.921	0.928	0.966	0.965	0.885	0.901	0.886	0.962	0.040

4.2.2. Model Path Analysis

The evaluation was conducted using the Structural Equation Modeling (SEM) model, and path analysis was performed using IBM AMOS 25. The results are presented in

Table 11 and Figure 3. Eleven out of thirteen hypotheses were confirmed, indicating a positive influence. Among the four external variables, Previous Experience (PE), Technical Features (TF), Hedonic Motivation (HM), and Perceived Trust (PT), the study found that PE and TFs ultimately had a negative influence on users' PU (-), so hypotheses H1a (PE→PU, β = 0.026, t = 0.616, $p > 0.05$) and H2a (TF→PU, β = 0.060,t = 1.419, $p > 0.05$) were not confirmed. However, PE and TFs eventually positively influenced users' PEOU (+); thus, H1b (PE→PEOU, β = 0.107, t = 2.475, $p < 0.05$) and H2b (TF→PEOU, β = 0.102, t = 2.339, $p < 0.05$) were verified, which is consistent with the results of previous studies.

Table 11. Path coefficients of the Structural Equation Model.

Hypotheses	Relationship	β	Estimate	S.E.	C.R./t-Value	*p*-Value	Significance
H1a	PE→PU	0.026	0.015	0.024	0.616	0.538	Not Supported
H1b	PE→PEOU	0.107	0.057	0.023	2.475	0.013	Supported
H2a	TF→PU	0.060	0.037	0.026	1.419	0.156	Not Supported
H2b	TF→PEOU	0.102	0.058	0.025	2.339	0.019	Supported
H3a	HM→PU	0.254	0.239	0.047	5.054	0.000	Supported
H3b	HM→PEOU	0.377	0.331	0.044	7.594	0.000	Supported
H4a	PT→PU	0.149	0.159	0.050	3.206	0.001	Supported
H4b	PT→PEOU	0.229	0.228	0.047	4.875	0.000	Supported
H5	PU→ATT	0.206	0.170	0.043	3.964	0.000	Supported
H6	PU→BI	0.351	0.343	0.043	7.989	0.000	Supported
H7	PEOU→PU	0.276	0.296	0.057	5.177	0.000	Supported
H8	PEOU→ATT	0.347	0.307	0.049	6.320	0.000	Supported
H9	ATT→BI	0.539	0.638	0.059	10.877	0.000	Supported

β: standard rate, S.E.: standard error, C.R.: critical ratio (t-value), *p*: *p*-value.

HM and PT eventually had a positive influence on both the PU and PEOU of users (+). Thus, hypotheses H3a (HM→PU, β = 0.254, t = 5.054, $p < 0.05$), H3b (HM→PEOU, β = 0.377, t = 7.594, $p < 0.05$), H4a (PT→PU, β = 0.149, t = 3.206, $p < 0.05$), and H4b (PT→PEOU, β = 0.229, t = 4.875, $p < 0.05$) were verified.

In this study, we assumed the following hypotheses: H5 (PU→ATT, β = 0.206, t = 3.964, $p < 0.05$), H6 (PU→BI, β = 0.351, t = 7.989, $p < 0.05$), H7 (PEOU→PU, β = 0.276, t = 5.177, $p < 0.05$), H8 (PEOU→ATT, β = 0.347, t = 6.320, $p < 0.05$), and H9 (ATT→BI, β = 0.539, t = 10.877, $p < 0.05$), which are also consistent with the results of previous studies. The hypotheses were valid and were all verified.

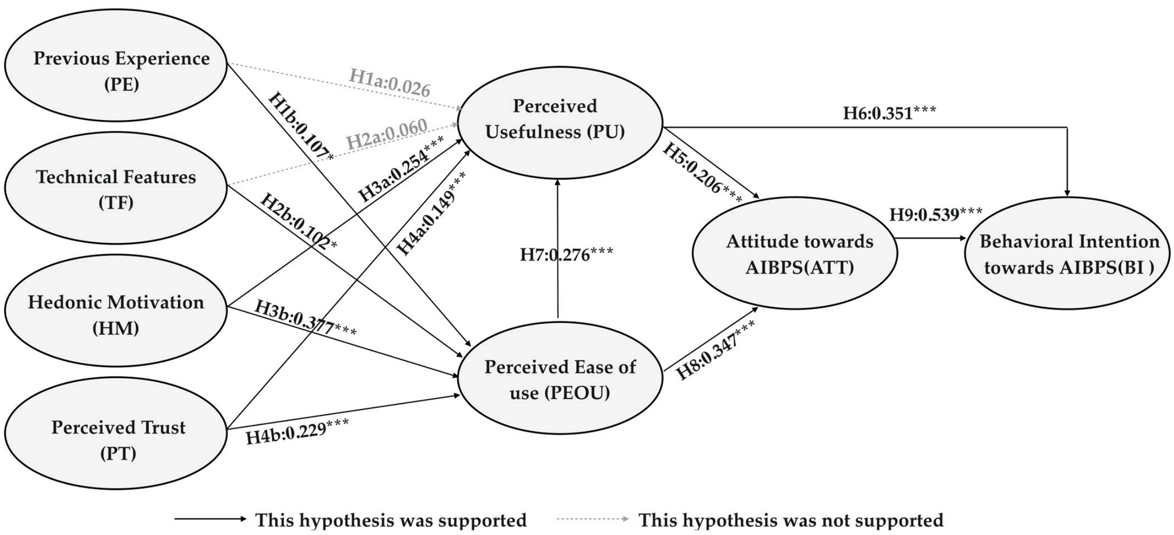

Figure 3. Results of the structural model test. * $p < 0.05$, *** $p < 0.001$.

5. Discussion and Implications

5.1. Discussion

This study aims to investigate the determinants that influence users' acceptance and Behavioral Intention (BI) toward AIBPS. First, the findings indicate that the external variable Previous Experience (PE) has a positive influence on users' Perceived Ease of Use (PEOU), which is consistent with previous research by scholars studying new AI technologies and systems. The same is true of the inclusion of the variable PE in the external variables of the scholars' studies; the difference is that for different subjects, PE interacts with different external variables, thus affecting PU and PEOU [54,55,57], and that Previous Experience (PE), as a variable that can influence users' attitudes and adoption of technology, is more likely to be accepted by experienced users [115]. However, PE has a negative influence on users' Perceived Usefulness (PU). One possible reason is that AIBPS has a simple and easy-to-use user interface and interaction design, and users may be more concerned with the artistic effects generated by the system itself, so PE is not necessary for users. To improve the AIBPS user experience, AIBPS developers can continuously optimize AIBPS by collecting user feedback and requirements and providing tutorials to help users understand AIBPS. In summary, if users have Previous Experience with AIBPS, they are more likely to be satisfied with other AIBPS and willing to use them repeatedly. In addition, developers can customize their AIBPS according to the needs and expectations of their target users.

Second, TFs have a positive influence on users' Perceived Ease of Use (PEOU), according to previous studies confirming that the Technical Features (TFs) of a new technology or device directly affect users' PU and PEOU of that system [46,60,61], thus confirming that TFs have a positive influence on Attitude toward Using (ATT) and Behavioral Intention (BI) regarding new technology [58]. However, TFs have a negative influence on users' PU, which indicates that AIBPS, which generates paintings by simply typing text in a dialog box, has no learning cost for even inexperienced users who have never been exposed to AI painting. However, users cannot be satisfied by the TFs of AIBPS and cannot achieve their expected goals. Therefore, developers can improve the TFs of AIBPS by developing new features, which, in turn, improve the quality of painting generation, the user interface, and the ease of use of the service. In addition, developers can combine advanced algorithms, machine learning, and natural language processing techniques to enhance the capabilities of AIBPS. For the development of AIBPS, this can include an adjustment function of painting parameters, an editing and processing function, a voice recognition function, and a virtual reality function. The editing and processing function allows the user to resize and add filters to their generated paintings, thus enhancing the user's sense of operation and control; the voice recognition function allows the user to control the painting process through voice commands, further improving the interaction and user experience between the user and AI; and the virtual reality function allows users to feel the charm of creating artworks in an immersive way.

Then, Hedonic Motivation (HM) has a positive influence on both the Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) of users, a finding that is also consistent with previous findings obtained by authors studying new AI technologies [48,65,97,116,117]. Specifically, users are hedonically motivated to create art using AIBPS, and AIBPS provides a platform to create paintings without the need for manual painting skills, which further facilitates users' use of the system. Therefore, developers can increase users' enjoyment and motivation, and subsequently improve their BI to use the AIBPS system by providing diverse functionalities and a good user experience. In addition, to enhance users' Hedonic Motivation (HM), system developers can provide a series of painting styles and themes that cater to users' emotional and aesthetic preferences. Meanwhile, in line with the development trend of the Metaverse, developers can create virtual communities or galleries to enable users to share their paintings created through AIBPS with others, and add functions to enable users to receive feedback and support within the virtual community.

Moreover, Perceived Trust (PT) has a positive influence on both the PU and PEOU of users, a result that confirms previous scholars' views [76,118] that trust is particularly important when users try to use AI technologies [119]. The user's consideration of trust is crucial in the use of AI systems. The higher the trust level, the more it helps to promote user acceptance of the AI system's services [50], while PT also predicts PU [76]. McKnight argues that to build initial trust, perceptions of risk must be overcome, which, in turn, increases the willingness to use these new technologies [120]. Therefore, developers can enhance users' PT by protecting the security and privacy of user data, maintaining sufficient transparency, providing a good user feedback mechanism, and offering clear and concise terms of service and privacy policies to ensure that AIBPS quickly fixes and addresses issues and vulnerabilities that arise during the creation process. This lets users know how AIBPS uses their data, ensures that paintings on AIBPS do not infringe on the intellectual property rights of others, and protects the independent copyright of paintings created by users.

Users' Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) have a positive influence on Attitude toward Using (ATT) and Behavioral Intention (BI). Numerous scholars have previously confirmed this result [25,46,82,86]. Previous research applied TAM to new technologies and systems and found that these factors have a positive impact on users' ATT and BI. However, previous studies did not apply TAM to AIBPS. Therefore, this study builds on previous research and finds that these factors are also applicable to AIBPS, and that developers need to focus on the factors (PE, TFs, HM, and PT) that affect users' PU and PEOU, as summarized in this study, in order to better improve users' ATT and BI. The simple interface of AIBPS allows users to understand its functionality intuitively. As a result, users choose to use AIBPS much more efficiently, which leads to a more positive ATT for AIBPS. Studies have shown that the development of new technologies and systems that are easy to use can increase user acceptance, and this trend will become more common in the future [121]. Thus, to increase user satisfaction with AIBPS, it is recommended that similar products offer higher-quality input images, more diverse shortcut keys, and more advanced features, such as generating a combination of multiple artworks, the clearer presentation of descriptive vocabulary, and faster modification modes. In addition, to enhance the user's knowledge, developers can visualize the algorithm process in more detail, including various parameter changes, so that users can understand how the program works. In summary, it is recommended that developers continue to enhance the PU and PEOU of AIBPS by providing better features and an enhanced user experience, thus promoting the development of ATT and BI.

5.2. Implications

The results of this study have important implications. Upon reviewing the application of TAM theory to AIBPS and exploring the applicability of the theory in studying user acceptance of AI technology, our research results show that both users' PU and PEOU of AIBPS have a positive impact on their Attitude toward Using (ATT) and Behavioral Intention (BI), which represents an important theoretical contribution to the existing literature on AIBPS and TAM. As the research on AI applications in fields such as art creation and design is enhanced, factors related to user needs and behavioral habits can be explored to improve the adaptability and practicality of AI in these fields [19,20], reduce user resistance, increase their acceptance and use intentions, and thus, better meet user needs and promote the development of AI technologies in fields such as art creation and design. As a premise for system design and enhancement, these research findings can assist system designers in comprehending users' acceptance of AIBPS and their behavioral intentions.

In terms of relevant policies, attention should be paid to the impact of AIBPS on the arts, culture, and other fields, and relevant policy norms should be introduced to promote its sustainable development. To this end, policymakers can adopt a series of policy measures, such as protecting intellectual property rights, encouraging innovative design, and regulating data use. Enterprises and organizations should strengthen the management and application of AIBPS to ensure that it is legal, standardized, reliable, and secure. In addition, they should pay attention to the users' feedback and evaluation, continuously improve system performance, enhance user experience and satisfaction, and promote the market competitiveness and share of AIBPS, so as to gain more users and profits. Therefore, when developing AIBPS, researchers can refer to TAM and use it to evaluate the user acceptance of AIBPS, so as to improve the efficiency of system design and development, continuously optimize the system's functionality and ease of use, and increase user acceptance of and satisfaction with the system.

6. Conclusions

The aim of this study was to investigate the factors that influence user acceptance and usage of AIBPS. By extending the external variables and incorporating AIBPS as a new technology into the Technology Acceptance Model (TAM), we used Structural Equation Modeling (SEM) to verify the effects of these factors on users' Attitude toward Using (ATT) and Behavioral Intention (BI). AIBPS plays a vital role in improving the quality and creative efficiency of users' paintings, reducing unnecessary human and material costs, and enabling sustainable AI development. It was found that Hedonic Motivation (HM) and Perceived Trust (PT) had a positive influence on users' Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Among them, Hedonic Motivation (HM) had the most significant effect on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), indicating that users enjoy interacting with AIBPS, find the process of AI painting generation interesting, and enjoy the process of creating artworks. Therefore, the facilitators presented in this study should be considered when developing new features. However, the effects of Previous Experience (PE) and Technical Features (TF) on Perceived Usefulness (PU) were not significant, and despite the ease of operation and user comprehension of AIBPS, users were not satisfied with the artwork generated by AI painting and failed to achieve the desired goal. This suggests that system developers should focus on improving user satisfaction in generating paintings. This study highlights the strengths of TAM theory and provides new empirical research on user acceptance and use of AIBPS, as well as important implications for the design and development of new features for the same type of AIBPS. In summary, although the development of AIBPS is still in its early stages, these research findings indicate that it has demonstrated practical value and will play an increasingly important role in the future of art creation and design. At the same time, these studies have raised some issues related to technology acceptance and the user experience of AIBPS, which need to be further explored and addressed in future research.

7. Research Limitations and Future Research

This study has several limitations. First, although a large number of respondents participated in this study, the data were only from the Chinese region and did not have a global scope. Therefore, future studies could consider collecting and comparing data from different countries to expand the impact of the study. Second, this study used an online questionnaire, which makes it difficult to understand users' attitudes comprehensively. Therefore, future studies could use user interviews or discussion groups to gain an in-depth understanding of user needs. In future research, the model can be used to cross-validate and generalize other factors to delve deeper into the AI field, study the pain points of AIBPS users, analyze the applicability of different models, and summarize the differences between the AIBPS creation process and the human painting process. This will contribute to the development of new features for similar AIBPS, improve user experience and satisfaction, and have important theoretical and practical implications.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
TAM	Technology Acceptance Model
SEM	Structural Equation Model
AMOS	Analysis of Moment Structures
GAN	Generative Adversarial Networks
VAE	Variational Autoencoders
CLIP	Contrastive Language–Image Pre-training Models
ML	Machine Learning
PU	Perceived Usefulness
PEOU	Perceived Ease of Use
ATT	Attitude toward Using
BI	Behavioral Intention
PE	Previous Experience
TF	Technical Features
HM	Hedonic Motivation
PT	Perceived Trust

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