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Exploring the Factors Influencing Continuance Intention to Use AI Drawing Tools: Insights from Designers

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Abstract: With the continuous evolution of artificial intelligence technology, AI drawing tools have emerged as highly esteemed instruments in the modern design industry. These tools, owing to their exceptional performance and innovative features, offer creators an unprecedented artistic experience. However, the factors influencing designers' continuance intention to use AI drawing tools remain ambiguous. This study is grounded in the expectation–confirmation model–information systems continuance (ECM-ISC) model, which is further refined and hypothesized in light of the characteristics of AI drawing tools. Using structural equation modeling, we analyzed 398 valid questionnaire responses. The results elucidated the relationships of key constructs, such as perceived usefulness, perceived ease of use, satisfaction, expectation confirmation, perceived playfulness, perceived switching cost, subjective norms, and perceived risk, on designers' continuance intention. Notably, perceived ease of use, traditionally considered vital, did not result in a significant influence on continuance intention or perceived usefulness in this research. This insight offers new perspectives for AI drawing tool developers and designers, suggesting that while pursuing user friendliness, broader considerations affecting user decisions should be taken into account. This study not only enriches the theoretical framework but also provides valuable guidance for the practical field.

Keywords: AI drawing tools; designers; continuance intention; ECM-ISC

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1. Introduction

Generative artificial intelligence (GAI) has emerged as a pivotal branch within the AI domain, focusing on producing novel and original content. The advancements in artificial-intelligence-generated content (AIGC) technology have demonstrated significant potential across various fields, profoundly altering human–computer interactions and approaches to complex problem solving. These advancements owe much to breakthroughs in deep learning and neural networks. For instance, the generative adversarial network (GAN) proposed by Goodfellow et al. [1] has greatly empowered the AIGC sector, enabling computers to generate high-quality images, audio, and text. Furthermore, OpenAI's GPT-3 model has underscored the immense potential of AIGC in text generation, exhibiting capabilities to draft articles, code, and even craft poetry [2]. Serving as a tangible application of AIGC, artificial intelligence (AI) drawing tools offer not only unprecedented creative instruments for artists and designers but also herald an era of boundless possibilities. As technology continuously evolves, we can anticipate that AI drawing tools will persistently shape and enrich our creative realms.

In the design realm, the application of AIGC has garnered widespread attention and research. The continuous evolution of this technology provides designers with novel tools and methods, heralding revolutionary shifts throughout the design process. Within the design industry, AIGC applications are predominantly centered on automated design, rapid prototyping, and personalized design. By employing AIGC technology, designers can swiftly produce a multitude of design sketches, thus accelerating the iterative process of ideation. Additionally, AIGC aids designers in generating design solutions tailored to individual user needs, offering a more personalized user experience [3].

As a significant offshoot of AIGC, AI drawing tools have witnessed rapid development in recent years, with platforms like Deep Art, Prisma, and DALL●E able to autonomously generate high-quality artistic creations based on user inputs. The foundational principles of these tools typically rest on deep learning and neural networks, particularly generative adversarial networks (GANs) [1]. GANs produce images virtually indistinguishable from genuine data through two competing networks: the generator and discriminator. In the design arena, this signifies that AI can fabricate novel design sketches or complete artistic pieces based on given parameters or samples [4]. Additionally, some advanced AI painting tools integrate other technologies, such as natural language processing, enabling designers to guide AI in generating specific images or designs through simple descriptions [5]. The role of AI drawing tools can be perceived as a potent "concept generator" within the designer's creative conceptualization process [6]. According to research by Brisco, Hay, and Dhami [7], contemporary text-to-image AIs, such as Midjourney, DALL●E 2, and Disco Diffusion, have been explored for their potential to supplant designers in the design process. These tools can not only swiftly generate images from text prompts but, in certain instances, the images they create are almost indistinguishable from those crafted by humans using computer graphics software.

Expectation–confirmation theory (ECT) has been extensively applied in research concerning technology acceptance and usage [8]. ECT emphasizes the impact of the congruence between user expectations and actual usage experience on the continuing use of technology [9]. The ECM-ISC further extends this theory, incorporating additional variables and relationships, offering a more comprehensive framework for our investigation [10]. To delve more holistically into designers' continuance intention towards AI drawing tools, we introduced five new variables: perceived ease of use, perceived playfulness, perceived switching cost, perceived risk, and subjective norms. These variables respectively depict the designers' experience when using the tool, its allure, the costs of transitioning from other tools to AI drawing tools, potential privacy risks posed by the tool, and the influence of external factors on the designers' intention to use. This study aims to gain a deeper understanding of the factors influencing designers' continuance intention to use AI drawing tools, thereby propelling continuous growth in practical applications. The findings of our research can offer novel insights and implications for both academic pursuits and practices in related domains.

2. Literature Review

Recently, the rapid development of AI drawing tools has unlocked unprecedented creative possibilities for designers. These tools have shown immense potential not only in technological advancement and educational applications but also in enhancing user experience and strengthening human–computer collaboration, becoming indispensable aids in the design industry. However, to ensure their continuous and effective use, it is crucial to deeply understand and address the challenges designers face during their usage. These challenges include, but are not limited to, enhancing the tools' usability and reliability and better integrating them into designers' daily workflows. Going forward, research and development teams must intensify their efforts to explore innovative applications of AI drawing tools, while ensuring that these tools meet the complex needs and expectations of users, thereby driving ongoing progress and innovation in the design field.

AI drawing tools have not only demonstrated rapid technological progress but have also provided new means for artistic creation. AI-Sketcher, utilizing deep learning technology, has significantly improved the quality of sketches, showcasing the vast potential of AI in the realm of artistic creation [11]. Furthermore, the application of AI technology in the automation of water treatment and desalination processes, though not directly related to drawing tools, has exhibited AI's capability to solve complex problems across multiple domains. This cross-disciplinary technological advancement offers new possibilities for the future innovation of AI drawing tools [12].

AI drawing tools have also been widely adopted in the educational sector, where their role extends beyond enhancing students' design skills to include fostering an understanding and application of AI technology. Polak, Schiavo, and Zancanaro [13] highlighted the potential of AI educational tools in improving students' digital competencies. Moreover, the use of AI in transportation and smart city domains [14] not only further validates the educational value of AI technology but also encompasses a comprehensive understanding of its future societal and environmental impacts. This underscores the importance of AI application in education, which focuses not only on the cultivation of technical skills but also on the awareness of its implications for the future.

The user experience of AI drawing tools not only impacts the creative process of designers but also plays a crucial role in the tools' continuous using intention and development. The study by Bitkina, Kim, Park, Park, and Kim [15] investigated the effects of system failures on operator stress levels, highlighting the importance of reliability and user-friendliness in the design of AI tools. Additionally, although the focus of the research by [16] was not on drawing tools, their discussion on the application of AI in software engineering provides valuable insights into how to enhance the user experience of AI tools, particularly in solving complex problems and automating task processing.

The collaborative relationship between designers and AI tools is increasingly considered a key to driving innovation. The research by Gmeiner, Yang, Yao, Holstein, and Martelaro [17] delved into the challenges designers face while learning to collaborate with AI design tools, emphasizing the importance of enhancing interactivity and communication efficiency. On the other hand, the study by De la Vall and Araya [18] explored the potential advantages and challenges of AI language learning tools. Although their focus differs, their discussion on how to design more effective human–computer collaboration interfaces offers significant insights for the user interface design of AI drawing tools.

Through the above literature review, we can conclude that the extensive application and potential impact of AI drawing tools in the design field offers powerful creative support and new ways of working for designers. With the ongoing development of AI technology, these tools are expected to further drive design innovation, providing designers with greater creative freedom and a wider range of expression possibilities.

3. Theoretical Background and Research Hypothesis

3.1. Key Variables in ECM-ISC Model

In exploring designers' continuance intention towards AI drawing tools, we adopted the ECM-ISC Model as our theoretical framework to investigate the relationships among various key variables. The origins of ECM-ISC can be traced back to the ECT [8], initially proposed by Oliver to delve into consumer satisfaction and repurchase intentions. Subsequently, this theoretical framework was extensively adopted and developed by researchers in the information systems field, culminating in the ECM-ISC model to elucidate the pivotal factors influencing information system user behavior.

The ECM-ISC model highlights the pivotal role of variables such as satisfaction, confirmation, and perceived usefulness in the continuing use of information systems. This model focuses on the match between user expectations and actual using experiences and how this congruence influences the intention to continue using the system through satisfaction and perceived usefulness [19]. For instance, in specific technological domains like mobile health services (mHealth), the ECM-ISC model takes into account the comprehensive impact of technological characteristics, individual differences, and environmental factors on the intention to continue use [20].

In the design field, particularly in the application of AI drawing tools, the ECM-ISC model provides researchers with a theoretical framework to better understand the key driving factors behind designers' continuing usage of these tools. By evaluating designers' confirmation of expectations, perceived usefulness, and satisfaction after using AI drawing tools, it is possible to delve into how these factors interact to either facilitate or hinder designers' intention to continue using these tools.

The application of the ECM-ISC model is not limited to the aforementioned areas; it has also been extensively used to study the continuous using behavior of users in various information systems, such as online learning [21] and fitness applications [22], demonstrating its wide applicability and significant impact across different research contexts. In the model of the continuous usage of information systems, satisfaction is explicitly regarded as a key factor influencing users' continuous intentions to use technology [9]. Several studies have highlighted the positive relationship between satisfaction and the intention to continue use. For instance, the research by Ashfaq, Yun, and Yu indicates that users are more likely to continue using a technology or service if they are satisfied with it, even in the presence of alternatives [23]. Joo, Park, and Shin also found a positive correlation between satisfaction and the continuous usage intention in their respective research contexts [24].

Perceived usefulness is also widely considered to be a key factor affecting users' continuance intention. Davis [25] emphasized the decisive role of perceived usefulness in users' acceptance and use of new technologies, which has been further confirmed in the study by Hamid et al. [26]. The expectation confirmation describes the degree of matching between the actual performance of the product or service and the user's expectations. Bhattacherjee et al. [27] pointed out that users tend to be more satisfied when their expectations are met, which has also been confirmed in other studies [28–30].

The following hypotheses are proposed based on the above discussion:

Hypothesis 1 (H1). *Satisfaction has a significant positive impact on continuance intention.*

Hypothesis 2 (H2). *Perceived usefulness has a significant positive impact on continuance intention.*

Hypothesis 3 (H3). *Perceived usefulness has a significant positive impact on satisfaction.*

Hypothesis 4 (H4). *Expectation confirmation has a significant positive impact on satisfaction.*

Hypothesis 5 (H5). *Expectation confirmation has a significant positive impact on perceived usefulness.*

3.2. Perceived Playfulness

In addition to the variables included in the ECM-ISC model, this study also introduces a new variable, "perceived playfulness". Perceived playfulness plays an important role in exploring the designers' acceptance of AI drawing tools. Especially in the field of design, playfulness may be one of the intrinsic motivations to enhance designers' intention to use AI tools [31]. Studies have shown that playfulness plays a key role in technology acceptance.

As derivatives of artificial intelligence technology, AI drawing tools offer users vivid creative experiences, such as exploring various artistic styles and creating unique art pieces. These experiences have drawn attention to the users' perceived playfulness. When users initially experience AI drawing tools, if their expectations are not fully met, their perceived playfulness and perceived usefulness of the tool may be lowered, leading to disappointment. From a theoretical perspective, perceived playfulness can be seen as a part of a user's intrinsic motivation [25], whereas perceived usefulness is more of a reflection of extrinsic motivation [32]. These two motivations jointly influence user behavior. Therefore, it is reasonable to speculate that expectation confirmation not only affects extrinsic motivation but also has an impact on the intrinsic perceived playfulness.

Perceived playfulness describes the pleasure and interest users experience when using a particular technology or service. It can be defined as the degree of enjoyment a user feels when using a certain technology or tool [33]. Studies indicate that perceived playfulness significantly influences users' intentions to use and their satisfaction levels [34]. In the design industry, designers might become more engaged due to the playfulness of AI drawing tools. Perceived playfulness could influence designers' decisions and actions through emotional responses, such as pleasure and satisfaction, encouraging them to more actively adopt new technologies [35]. Several studies support the notion that perceived playfulness positively impacts satisfaction [36,37].

The following hypotheses are proposed based on the above discussion:

Hypothesis 6 (H6). *Expectation confirmation has a significant positive impact on perceived playfulness.*

Hypothesis 7 (H7). *Perceived playfulness has a significant positive impact on continuance intention.*

Hypothesis 8 (H8). *Perceived playfulness has a significant positive impact on satisfaction.*

3.3. Perceived Ease of Use

Perceived ease of use plays a crucial role in the adoption of AI drawing tools. Its intuitive user interface and simplicity of operation are favored by designers. This feature allows designers to easily generate high-quality images through a few simple steps, not only optimizing the design process but also ensuring that the output images meet professional standards and quality requirements.

Numerous studies have confirmed that the perceived ease of use decisively influences whether users will continue to use a tool and whether they will recommend it to others. For instance, in their research on mobile banking applications, Yuan and colleagues found that the ease of use of an application is a core factor in users' decisions to continue its use [38]. This principle is equally applicable to the adoption of AI drawing tools, where designers also consider their ease of use as an important factor in their choice.

Further research has also revealed a positive correlation between perceived ease of use and perceived usefulness. For instance, a study by Jiang and colleagues on the virtual try-on feature in a mobile shopping environment showed that users' perceived ease of use significantly enhanced their perceived usefulness of the feature [39]. Therefore, incorporating perceived ease of use as a key variable in research is crucial for understanding how the convenience of AI drawing tools affects designers' perceptions of their usefulness and, in turn, influences their intention to continue using these tools.

The following hypotheses are proposed based on the above discussion:

Hypothesis 9 (H9). *The perceived ease of use of AI drawing tools has a significant positive influence on designers' intention to continue using them.*

Hypothesis 10 (H10). *The perceived ease of use of AI drawing tools has a significant positive influence on designers' evaluations of their perceived usefulness.*

3.4. Subjective Norms

In this study, subjective norms are defined as designers' attitudes and expectations towards their social and professional groups. These attitudes and expectations reflect their subjective perception that adopting AI drawing tools in their field or social circle is a welcomed, accepted, or encouraged behavior. The concept of subjective norms was initially mentioned in the theory of reasoned action and was further extended in the theory of planned behavior [40]. When designers face the choice of whether to use a specific AI drawing tool, their decisions are often strongly influenced by the community or team they belong to. For instance, if the prevailing view in a design team is that a certain technology has significant advantages, designers might be more inclined, driven by social expectations, to adopt that technology [41]. Additionally, when designers trust positive evaluations of a particular technology from their peers or authorities in the industry, it further boosts their confidence and acceptance of that technology [42]. Such social influence and trust may encourage designers to be more inclined to adopt and use the technology.

Subjective norms also positively influence perceived usefulness and ease of use. Aji et al. [43] indicated that subjective norms significantly influenced users' perceived usefulness, perceived ease of use, and behavioral intentions regarding electronic currency. Moreover, Bonn et al. [44] emphasized the social influence on online purchasing behavior, where subjective norms, as a crucial factor, had a significant positive impact on perceived usefulness and ease of use. In the AI domain, Shamsi et al. [45] explored students' use of AI voice assistants, where subjective norms were considered a key driving factor influencing their usage.

We proposed the following hypotheses according to the above discussion:

Hypothesis 11 (H11). *Subjective norms have a significant impact on designers' continuance intention.*

Hypothesis 12 (H12). *Subjective norms have a significant impact on designers' perceived usefulness.*

Hypothesis 13 (H13). *Subjective norms have a significant impact on designers' perceived ease of use.*

3.5. Perceived Risk

Perceived risk plays a pivotal role in technology adoption and is defined as the anticipation and apprehension of potential adverse consequences by users when considering adopting or using a specific technology [46]. In the realm of AI-generated art and creativity, especially with the rapid advancement of AI drawing tools, their boundless creative potential has garnered widespread attention. However, as the legal frameworks and market conditions pertaining to these tools continue to evolve, designers have expressed concerns regarding the privacy and security risks associated with using AI drawing tools [47]. These apprehensions encompass potential data breaches or misuse when supplying personal information and artworks to these tools. Moreover, for artworks generated by AI drawing tools, designers may be wary of issues related to copyrights, originality, and potential infringement risks [48]. On a macro level, the higher the risk perception of AI drawing tools among users, the lower their intent might be to continue using this technology [49]. Song et al. [50] corroborated this result in their study on AI customer service. This underscores the significance of perceived risk as a crucial determinant in the designers' continuance intention to use AI drawing tools.

If the community exhibits a positive stance towards a technology and encourages its use, individuals may perceive lower associated risks and are thus more likely to persist in using that technology. Conversely, if there are expressed concerns or an emphasis on the potential risks of a technology within the community, an individual's risk perception may increase, consequently affecting their intent to use.

In addition, subjective norms also play a key role in perceived risk. According to Silva et al. [51], when users believe that a technology is considered "normal" or "acceptable" in their community, their perceived risk of the technology may be reduced. This suggests that the attitudes and perceptions within the design community are pivotal in influencing the continued usage of AI drawing tools. If their community is positive about a technology and encourages its use, individuals may perceive a lower risk and are more likely to continue using the technology. On the contrary, if the community expresses concern about a technology or highlights its potential risks, the individual's perceived risk may increase, thus affecting their intention to use the technology. This notion is further supported by Chi et al. [52], who explored how perceived risk affects users' intent to continue use.

Based on the above discussion, we propose the following hypotheses:

Hypothesis 14 (H14). *Subject norms have a significant negative impact on designers' perceived risk of AI drawing tools.*

Hypothesis 15 (H15). *Perceived risk has a significant negative impact on designers' continuance intention.*

3.6. Perceived Switching Cost

In the context of technology acceptance and use, the perceived switching costs are a crucial factor that users must consider when contemplating moving from one product or service to another. This concept encompasses not only economic costs but also investments of time, effort, and emotion [53]. Within the framework of this study, the perceived switching costs specifically refer to the various costs designers anticipate when transitioning from traditional design tools or methods to AI drawing tools. Existing research has revealed a positive connection between the perceived switching costs of AI tools and their perceived usefulness [54], indicating that designers are more likely to recognize the value of transitioning to AI tools when they perceive the costs of moving from traditional tools to be lower, thereby increasing the perceived usefulness of AI tools.

Furthermore, the perceived switching costs also have a significant impact on designers' perceptions of the ease of use of AI tools. When designers consider the process of transitioning from other tools to AI tools as straightforward and stress free, they are more inclined to perceive AI tools as easy to use. This finding has been confirmed in multiple studies; for example, Joo and colleagues, in their research on students' use of K-MOOCs, found a close relationship between technology acceptance, satisfaction, and the intention to continue use. They further emphasized that when students perceive the costs of switching to new technology as low, they are more likely to consider the technology both easy to use and useful [55].

Moreover, Gupta's research underscores the positive impact of cognitive absorption, perceived usefulness, and information quality on the intention to continue use, indirectly indicating that when users perceive the costs of switching from traditional tools to new technology as low, their intention to continue use may increase [56]. The study by Lin and Lee, which explored the effects of perceived intelligence and perceived anthropomorphism on user satisfaction and the intention to continue use, provides insights on how to enhance the intention to continue use by increasing the perceived usefulness and reducing the perceived switching costs [57]. This implies that when designers perceive the costs of transitioning from traditional design tools to AI drawing tools as low, their intention to continue to use these tools will increase. The theoretical and existing research discussion shows the importance of reducing the perceived switching costs in technology acceptance and continuous use intentions, as well as understanding how these costs influence designers' intention to continue using AI drawing tools.

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

Hypothesis 16 (H16). *Designers' perceived usefulness of AI drawing tools has a significant positive influence on their perceived switching cost.*

Hypothesis 17 (H17). *Designers' perceived ease of use of AI drawing tools has a significant positive influence on their perceived switching costs.*

Hypothesis 18 (H18). *Designers' perceived switching costs of AI drawing tools has a significant positive influence on their intention to continue using them.*

3.7. Research Hypotheses

Based on the ECM-ISC model, this study aims to explore designers' intentions to continue using AI drawing tools and the factors influencing their intentions. Integrating expectation confirmation theory (ECT) with the theoretical foundation of the information system continuance model, we have constructed a comprehensive hypothetical model to delve into designers' usage behaviors and attitudes. Based on the hypotheses proposed above, the hypothetical model developed in this study is illustrated in Figure 1. The variables included in the hypothetical model and their operational definitions are presented in Table 1.

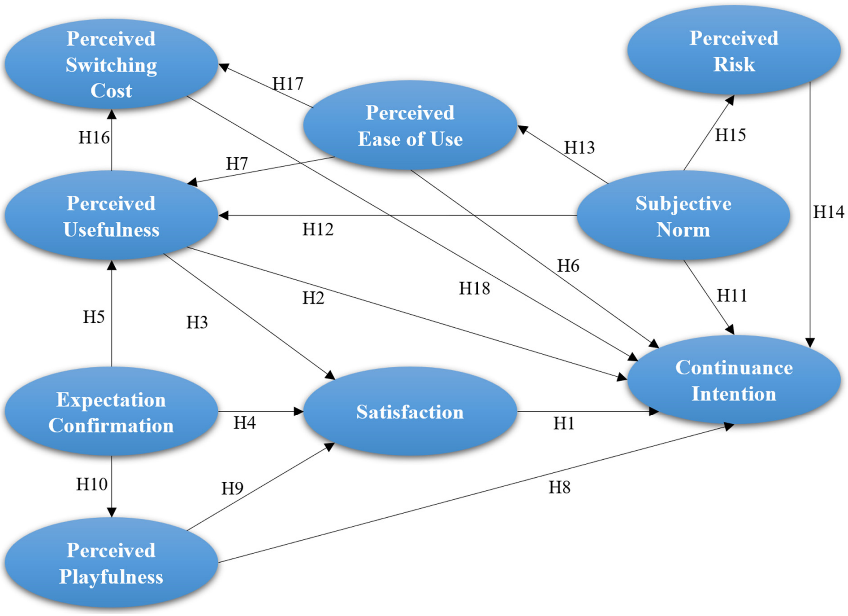

Figure 1. Hypothetical model.

Table 1. Variables in the hypothetical model and their definitions.

Variables	Operational Definitions
Perceived usefulness (PU)	Perceived usefulness refers to users' belief that using AI drawing tools to assist design can significantly enhance their work efficiency, convenience, and the degree to which they obtain inspiration. This concept is based on users' subjective evaluation of the actual benefits and performance improvements that AI drawing tools can provide during the assisted design process.
Perceived ease of use (PeoU)	Perceived ease of use describes the degree of effort users believe is required to learn and use AI drawing tools for design-related tasks. It involves users' evaluation of the clarity, comprehensibility of the AI drawing tool's interface, and the simplicity of the overall usage process.
Satisfaction (SA)	Satisfaction reflects users' overall perception of fulfillment after using AI drawing tools to assist design. It is based on a comprehensive evaluation of the tool's performance, the extent to which it meets needs, and the level of enjoyment experienced during use.
Expectation confirmation (EC)	Expectation confirmation is the perception of the match between users' actual experience and their prior expectations after using AI drawing tools. This concept focuses on users' evaluation of the design assistance outcomes provided by AI drawing tools exceeding their expectations.
Perceived playfulness (PP)	Perceived playfulness refers to the fun and pleasure users experience when using AI drawing tools to assist design. It highlights the aspect of AI drawing tools as innovative technology that, beyond practicality, can also add elements of enjoyment and entertainment value to the design process.
Perceived switching cost (PSC)	Perceived switching cost involves users' assessment of the anticipated difficulties, time consumption, and level of effort required to integrate AI drawing tools into their existing design workflows. This reflects the various potential costs users perceive when considering replacing old tools with AI drawing tools.
Continuance intention (CI)	Continuance intention refers to users' intention to keep using AI drawing tools in the future. This includes users' expectations to maintain or even increase their current frequency of use.
Subjective norms (SN)	Subjective norms refer to the perceived support or expectation from significant others (such as friends, family, leaders, or colleagues) regarding the use of AI drawing tools to assist design. This concept reflects the role of social influence in the user's decision-making process.
Perceived risk (PR)	Perceived risk is the assessment of potential negative consequences that users worry about when using AI drawing tools to assist design, such as a decrease in innovation ability, a reduction in autonomous design capability, or the risk of design work leakage.

4. Research Design and Methods

4.1. Questionnaire Design

The questionnaire was designed based on a literature review, utilizing validated and well-established scales to ensure reliability and validity. The questionnaire is divided into two main parts: the first part collects respondents' basic information, including gender, age, and professional background and the second part focuses on behavioral measurement, covering key constructs such as satisfaction, perceived usefulness, expectation confirmation, perceived playfulness, perceived ease of use, subjective norms, perceived risk, and perceived switching cost. All items use a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), aiming to assess designers' attitudes and perceptions from multiple perspectives in detail. To reduce order effects, some items are presented in a random order. The scales for the behavioral measurement part are shown in Table 2.

Table 2. Measurement scales for constructs.

Constructs	Coding	Item Content	Source
Perceived usefulness	PU1	Using AI drawing tools for design assistance plays a significant role in inspiring me.	[25]
	PU2	Using AI drawing tools for design assistance is highly convenient for me.	
	PU3	With AI drawing tools assisting in design, I can easily complete my work.	
Perceived ease of use	PEoU1	The interaction with AI drawing tools is clear and intuitive.	[25]
	PeoU2	Using AI drawing tools doesn't require much mental effort on my part.	
	PeoU3	I find it easy to use AI drawing tools for design-related tasks.	
Satisfaction	SA1	Overall, I am satisfied with using AI drawing tools for design assistance.	[9]
	SA2	I feel delighted when using AI drawing tools for design assistance.	
	SA3	AI drawing tools meet my needs, which makes me very happy.	
Expectation confirmation	EC1	The experience I gain from using AI drawing tools for design assistance exceeds my expectations.	[9]
	EC2	The benefits provided by AI drawing tools surpass my expectations.	
	EC3	AI drawing tools greatly inspire my designs.	
Perceived playfulness	PP1	I find it fascinating to use AI drawing tools.	[28]
	PP2	I thoroughly enjoy the process of using AI drawing tools for design assistance.	
	PP3	Using AI drawing tools for design assistance brings me ease and pleasure.	
Perceived switching costs	PSC1	Integrating AI drawing tools into my original design workflow to replace some of my previous tools is not bothersome.	[58]
	PSC2	Incorporating AI drawing tools into my original design workflow doesn't increase the complexity.	
	PSC3	Using AI drawing tools in my current design workflow doesn't consume more of my time and energy.	
Continuance intention	CI1	In the future, I plan to continue using AI drawing tools to replace some of my past tools.	[9]
	CI2	I am more inclined to continue using AI drawing tools in the future.	
	CI3	In the future, I intend to maintain or even increase the frequency of using AI drawing tools.	

Table 2. *Cont.*

Constructs	Coding	Item Content	Source
Subjective norms	SN1	People important to me believe I should use AI drawing tools to assist in design.	[59]
	SN2	My friends have supported me in using AI drawing tools to assist in design.	
	SN3	In work and study, leaders and teachers asked me to use AI drawing tools to assist in design.	
Perceived risk	PR1	I am concerned that prolonged use of AI drawing tools might diminish my design innovation capabilities.	[60]
	PR2	I am concerned that prolonged use of AI drawing tools might reduce my independent design capabilities.	
	PR3	I am concerned that prolonged use of AI drawing tools might lead to the leakage of my design works.	

4.2. Pre-Test and Questionnaire Revision

Before the formal data collection procedure, a pre-test was conducted with a small group of designers and design students as the target group. Based on the feedback from the pre-test, minor revisions were made to the expression of the questionnaire, improving its readability and the accuracy of the measurement.

4.3. Sampling and Data Collection

Data collection was conducted from July to September 2023 through an online questionnaire platform (the online questionnaire was used merely for the convenience of data collection and processing; we still contacted each respondent and obtained informed consent), targeting practicing designers and design students. Through professional design social forums and collaboration with design schools, the diversity and breadth of the sample were ensured. The introduction part of the questionnaire detailed the eligibility criteria for participating in this study, specifically stating that participants needed to be practicing designers or students in design disciplines with experience using AI drawing tools. To improve the response rate and the enthusiasm of respondents, each respondent received appropriate compensation, a strategy that also helped to enhance the representativeness of the sample. This survey received 453 responses, with 398 valid questionnaires retained after screening, resulting in a validity rate of 87.86%. This sample size meets the recommended standard for structural equation modeling (SEM) analysis, which is that the sample size should be more than ten times the number of items analyzed. All data were processed anonymously and in strict compliance with ethical standards. The basic information of the sample of valid responders is presented in Table 3.

4.4. Data Processing and Methods

The collected data underwent preprocessing, including cleaning and handling missing values and outliers. This study used structural equation modeling (SEM) for path analysis to validate the research hypotheses and the model fit. Before conducting path analysis, we performed a reliability analysis to test the internal consistency of the constructs, exploratory factor analysis to identify the underlying factor structure of the measurement items, and confirmatory factor analysis to test the validity and applicability of the scale structure. The reason for using SEM analysis is its ability to effectively handle complex relationships between variables, including direct and indirect effects. The analysis process utilized statistical software such as SPSS (24) and AMOS (24), ensuring the accuracy and validity of the analysis.

Table 3. Demographic of respondents.

	Category	Frequency	Ratio (%)
Group	Professional designers	242	60.80
	Students	156	39.20
Gender	Male	205	51.51
	Female	193	48.49
Age	18–24	90	22.61
	25–30	105	26.38
	31–40	111	27.89
	41–50	46	11.56
	51–60	46	11.56
Design discipline	Product design	71	17.84
	Industrial design	63	15.83
	Visual communication design	48	12.06
	Environmental art design/architecture design	54	13.57
	Fashion and apparel Design	51	12.81
	Digital media design	78	19.60
	Other design disciplines	33	8.29
Total		398	100.0

5. Data Analysis

5.1. Normality Test

Before conducting the measurement and structural model analysis, the normality of each variable was tested. Data are considered to be normally distributed when the values of kurtosis and skewness are within $|10|$ and $|3|$, respectively [61]. According to these criteria, the kurtosis and skewness values of the data collected in this study meet these standards, as shown in Table 4. Based on these results, all available data are considered to be relatively normally distributed and suitable for further analysis.

Table 4. Results of normality test.

Construct	Item	Max	Min	Mean	S. D.	Median	Kurtosis	Skewness
Perceived Usefulness	PU1	1.000	7.000	4.480	1.913	5.000	−0.962	−0.326
	PU2	1.000	7.000	4.455	1.842	5.000	−0.873	−0.387
	PU3	1.000	7.000	4.545	1.886	5.000	−0.938	−0.346
Perceived Ease of Use	PEoU1	1.000	7.000	4.508	1.863	5.000	−0.890	−0.375
	PEoU2	1.000	7.000	4.565	1.919	5.000	−0.994	−0.350
	PEoU3	1.000	7.000	4.440	1.909	5.000	−0.970	−0.340
Satisfaction	SA1	1.000	7.000	4.465	1.899	5.000	−0.930	−0.334
	SA2	1.000	7.000	4.598	1.892	5.000	−0.942	−0.364
	SA3	1.000	7.000	4.523	1.930	5.000	−0.958	−0.423

Table 4. *Cont.*

Construct	Item	Max	Min	Mean	S. D.	Median	Kurtosis	Skewness
Expectation Confirmation	EC1	1.000	7.000	4.490	1.783	4.000	−0.852	−0.253
	EC2	1.000	7.000	4.573	1.835	5.000	−0.831	−0.402
	EC3	1.000	7.000	4.585	1.768	5.000	−0.843	−0.318
Perceived Playfulness	PP1	1.000	7.000	4.688	1.926	5.000	−0.932	−0.470
	PP2	1.000	7.000	4.691	1.918	5.000	−0.948	−0.460
	PP3	1.000	7.000	4.611	1.910	5.000	−0.934	−0.403
Perceived Switching Cost	PSC1	1.000	7.000	4.746	1.784	5.000	−0.717	−0.477
	PSC2	1.000	7.000	4.560	1.692	5.000	−0.679	−0.341
	PSC3	1.000	7.000	4.646	1.738	5.000	−0.683	−0.391
Continuance Intention	CI1	1.000	7.000	4.585	1.833	5.000	−0.773	−0.454
	CI2	1.000	7.000	4.573	1.881	5.000	−0.785	−0.420
	CI3	1.000	7.000	4.646	1.805	5.000	−0.658	−0.485
Subjective Norm	SN1	1.000	7.000	4.802	1.945	5.000	−0.886	−0.530
	SN2	1.000	7.000	4.560	1.807	5.000	−0.694	−0.501
	SN3	1.000	7.000	4.696	1.818	5.000	−0.697	−0.447
Perceived Risk	PR1	1.000	7.000	3.399	1.928	3.000	−0.973	0.342
	PR2	1.000	7.000	3.528	1.904	3.000	−0.931	0.353
	PR3	1.000	7.000	3.327	1.920	3.000	−0.962	0.458

5.2. Reliability Test

The reliability analysis is the first step in the study and aims to assess the reliability of each construct in the questionnaire and ensure the reliability of the measurement tool. In this study, we used Cronbach's α coefficient to assess the internal consistency of each construct. The results of the reliability analysis are shown in Table 5. The Cronbach's α for each construct is greater than 0.8, and the Cronbach's α when any item is deleted is not higher than the current result. This demonstrates that the data reliability is high and that the data have good internal consistency and are suitable for further analysis.

Table 5. Results of reliability test.

Construct	Item	Corrected Item-to-Total Correlation	Cronbach's α if Item Deleted	Cronbach's α
Perceived Usefulness	PU1	0.757	0.839	0.880
	PU2	0.777	0.821	
	PU3	0.768	0.829	
Perceived Ease of Use	PEoU1	0.773	0.832	0.882
	PEoU2	0.785	0.821	
	PEoU3	0.756	0.846	
Satisfaction	SA1	0.739	0.843	0.875
	SA2	0.754	0.830	
	SA3	0.788	0.798	

Table 5. *Cont.*

Construct	Item	Corrected Item-to-Total Correlation	Cronbach's α if Item Deleted	Cronbach's α
Expectation Confirmation	EC1	0.706	0.816	0.855
	EC2	0.737	0.787	
	EC3	0.736	0.788	
Perceived Playfulness	PP1	0.761	0.832	0.879
	PP2	0.751	0.841	
	PP3	0.784	0.811	
Perceived Switching Cost	PSC1	0.726	0.773	0.846
	PSC2	0.722	0.778	
	PSC3	0.692	0.805	
Continuance Intention	CI1	0.758	0.819	0.873
	CI2	0.745	0.831	
	CI3	0.765	0.813	
Subjective Norm	SN1	0.755	0.796	0.864
	SN2	0.740	0.810	
	SN3	0.731	0.818	
Perceived Risk	PR1	0.765	0.835	0.881
	PR2	0.774	0.827	
	PR3	0.768	0.832	

5.3. Explorative FACTOR analysis

In this study, we employed exploratory factor analysis (EFA) to assess the structural validity of the hypothetical model. We conducted the EFA on 27 items using the maximum variance rotation method, with the results presented in Table 6. The cumulative variance explained reached 80.618%, which means that by extracting nine factors, we can explain 80.618% of the information in the 27 items. The extracted variance percentages (i.e., the amount of information extracted) for these nine factors are as follows: 9.486%, 9.408%, 9.175%, 9.137%, 8.981%, 8.921%, 8.892%, 8.797%, and 7.819%. The distributions of variance extracted from each construct are even, indicating that the results of the factor analysis have satisfactory information content and interpretability. Notably, the nine factors extracted correspond to the nine dimensions set in the hypothetical model, which suggests that our questionnaire possesses good structural validity, with each item aligning with its respective construct. The results of EFA provide a reliable foundation for further data analysis.

Table 6. Results of explorative factor analysis.

Construct	Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
Perceived Usefulness	PU1	0.143	0.843	0.092	0.075	0.036	0.170	0.202	0.103	0.064
	PU2	0.111	0.813	0.120	0.108	0.177	0.091	0.118	0.128	0.221
	PU3	0.027	0.808	0.127	0.177	0.167	0.122	0.100	0.184	0.151
Perceived Ease of Use	PEoU1	0.099	0.157	0.115	0.834	0.151	0.127	0.143	0.092	0.128
	PEoU2	0.183	0.126	0.167	0.823	0.173	0.157	0.070	0.149	0.096
	PEoU3	0.111	0.086	0.206	0.753	0.124	0.069	0.282	0.150	0.222
Satisfaction	SA1	0.099	0.174	0.777	0.145	0.140	0.159	0.155	0.186	0.110
	SA2	0.121	0.059	0.783	0.145	0.187	0.186	0.087	0.138	0.239
	SA3	0.111	0.121	0.837	0.179	0.090	0.113	0.192	0.155	0.068

Table 6. *Cont.*

Construct	Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
Expectation Confirmation	EC1	0.106	0.043	0.117	0.123	0.127	0.099	0.174	0.803	0.226
	EC2	0.089	0.251	0.126	0.137	0.186	0.130	0.202	0.764	0.083
	EC3	0.151	0.177	0.263	0.124	0.167	0.140	0.095	0.769	0.080
Perceived Playfulness	PP1	0.116	0.158	0.129	0.117	0.797	0.140	0.142	0.208	0.150
	PP2	0.214	0.104	0.121	0.170	0.776	0.077	0.168	0.164	0.175
	PP3	0.114	0.144	0.182	0.186	0.783	0.198	0.203	0.113	0.147
Perceived Switching Cost	PSC1	0.160	0.198	0.126	0.216	0.178	0.190	0.116	0.220	0.725
	PSC2	0.114	0.202	0.198	0.232	0.174	0.199	0.158	0.107	0.729
	PSC3	0.230	0.150	0.158	0.071	0.201	0.272	0.197	0.147	0.680
Continuance Intention	CI1	0.163	0.166	0.191	0.118	0.111	0.777	0.056	0.238	0.189
	CI2	0.092	0.143	0.128	0.188	0.175	0.811	0.186	0.063	0.116
	CI3	0.189	0.119	0.165	0.065	0.118	0.764	0.223	0.096	0.266
Subjective Norm	SN1	0.116	0.154	0.150	0.182	0.201	0.163	0.758	0.203	0.089
	SN2	0.126	0.155	0.126	0.147	0.108	0.162	0.774	0.226	0.180
	SN3	0.136	0.157	0.175	0.145	0.201	0.132	0.787	0.067	0.131
Perceived Risk	PR1	−0.830	−0.040	−0.118	−0.117	−0.183	−0.036	−0.129	−0.124	−0.159
	PR2	−0.845	−0.081	−0.011	−0.158	−0.094	−0.203	−0.107	−0.066	−0.147
	PR3	−0.842	−0.149	−0.176	−0.076	−0.104	−0.139	−0.095	−0.116	−0.060
Eigenvalue (Rotated)		2.561	2.540	2.477	2.467	2.425	2.409	2.401	2.375	2.111
% of Variance (Rotated)		9.486	9.408	9.175	9.137	8.981	8.921	8.892	8.797	7.819

5.4. Confirmative Factor Analysis

In this study, we employed confirmatory factor analysis (CFA) to assess the convergent validity and discriminant validity of the research model. We focused on factor loadings, composite reliability (CR), and average variance extracted (AVE) to ascertain good convergent validity. Typically, if the factor loadings and CR values are both greater than 0.7 and the AVE value is above 0.5, then the scales are deemed to have good convergent validity [62,63]. As shown in Table 7, the factor loadings, CR values, and AVE values in this study all meet the recommended criteria, suggesting that the related scales exhibit good convergent validity in the model, which implies that the measurement items in the model are highly correlated with the constructs they belong to; thus, the model possesses good convergent validity.

To evaluate the discriminant validity, we referred to the study by Fornell and Larcker [63]. Following their approach, we compared the square root of the AVE values for each construct with its correlations with other constructs. If the square root of each construct's AVE is greater than its correlations with other constructs, then the scale possesses good discriminant validity. As illustrated in Table 8, numbers on the diagonal line, highlighted in bold, represent the square root of the AVE values for each construct. These square root values are greater than the correlation values between the construct and any other construct, thereby confirming good discriminant validity among the constructs in the model. Moreover, we utilized the HTMT (heterotrait–monotrait ratio) method for discriminant validity verification. As shown in Table 9, the numbers in the table represent the HTMT values between pairs of constructs. If the HTMT value is smaller than 0.85, it indicates discriminant validity between pairs of constructs. All the HTMT values in the table are within the standard range, indicating that the scales possess good discriminant validity.

Table 7. Results of convergent validity test.

Construct	Item	UnStd.	*S.E.*	*p*	Std.	AVE	CR
Perceived Usefulness	PU1	1.000	-	-	0.817	0.709	0.880
	PU2	1.014	0.054	0.000	0.860		
	PU3	1.024	0.055	0.000	0.848		
Perceived Ease of Use	PEoU1	1.000	-	-	0.836	0.714	0.882
	PEoU2	1.057	0.054	0.000	0.858		
	PEoU3	1.032	0.054	0.000	0.841		
Satisfaction	SA1	1.000	-	-	0.818	0.703	0.876
	SA2	1.020	0.055	0.000	0.836		
	SA3	1.070	0.056	0.000	0.860		
Expectation Confirmation	EC1	1.000	-	-	0.775	0.663	0.855
	EC2	1.111	0.067	0.000	0.836		
	EC3	1.064	0.064	0.000	0.831		
Perceived Playfulness	PP1	1.000	-	-	0.829	0.708	0.879
	PP2	0.987	0.053	0.000	0.822		
	PP3	1.042	0.053	0.000	0.872		
Perceived Switching Cost	PSC1	1.000	-	-	0.816	0.648	0.847
	PSC2	0.943	0.054	0.000	0.812		
	PSC3	0.940	0.056	0.000	0.787		
Continuance Intention	CI1	1.000	-	-	0.837	0.696	0.873
	CI2	0.991	0.055	0.000	0.808		
	CI3	1.007	0.052	0.000	0.856		
Subjective Norm	SN1	1.000	-	-	0.846	0.680	0.864
	SN2	0.905	0.049	0.000	0.824		
	SN3	0.889	0.050	0.000	0.804		
Perceived Risk	PR1	1.000	-	-	0.838	0.711	0.881
	PR2	1.003	0.052	0.000	0.851		
	PR3	0.999	0.053	0.000	0.841		

Table 8. Results of discriminant validity test (Fornell and Larcker criterion).

Construct	PU	PEoU	SA	EC	PP	PSC	CI	SN	PR
Perceived Usefulness	0.842								
Perceived Ease of Use	0.402	0.845							
Satisfaction	0.393	0.482	0.838						
Expectation Confirmation	0.454	0.441	0.497	0.814					
Perceived Playfulness	0.430	0.487	0.467	0.504	0.841				
Perceived Switching Cost	0.508	0.526	0.511	0.513	0.560	0.805			
Continuance Intention	0.437	0.431	0.487	0.447	0.469	0.605	0.834		
Subjective Norm	0.460	0.499	0.480	0.508	0.528	0.526	0.497	0.825	
Perceived Risk	−0.319	−0.388	−0.360	−0.369	−0.422	−0.464	−0.420	−0.392	0.843

Table 9. Results of discriminant validity test (HTMT Ratio).

Construct	PU	PEoU	SA	EC	PP	PSC	CI	SN	PR
Perceived Usefulness	-								
Perceived Ease of Use	0.457	-							
Satisfaction	0.449	0.548	-						
Expectation Confirmation	0.523	0.508	0.575	-					
Perceived Playfulness	0.490	0.553	0.533	0.581	-				
Perceived Switching Cost	0.590	0.609	0.594	0.602	0.649	-			
Continuance Intention	0.499	0.491	0.557	0.518	0.536	0.704	-		
Subjective Norm	0.528	0.571	0.551	0.590	0.605	0.616	0.572	-	
Perceived Risk	0.362	0.440	0.410	0.425	0.480	0.537	0.480	0.450	-

5.5. Path Analysis

Path analysis is the final data analysis step in this study, employing structural equation modeling (SEM) to validate the hypotheses and relationships of the hypothetical model. In this research, path analysis is used to investigate the direct and indirect relationships between various constructs, as well as their influence on designers' continuance intention. The model fit indices are presented in Table 10, with all indices meeting the criteria for the appropriate model fit. The results of the path analysis are illustrated in Table 11 and Figure 2. Except for H2, H7, H9, and H10, all other hypotheses are supported, which suggests that perceived usefulness, perceived playfulness, and perceived ease of use do not have a significant impact on continuance intention. Perceived usefulness also does not have a significant impact on perceived usefulness. However, the pathways for the other hypotheses all show significant relationships.

Table 10. Model fit indices.

Indices	χ^2/df	RMSEA	CFI	NNFI	TLI	IFI	PGFI	PNFI	PCFI	SRMR
Judgement criterion	<3	<0.10	>0.9	>0.9	>0.9	>0.9	>0.5	>0.5	>0.5	<0.1
Results	2.546	0.062	0.922	0.933	0.933	0.708	0.777	0.810	0.0997	2.546

Note: The reference literature for the judgement criteria is [64–70].

Furthermore, Table 12 reveals the direct and indirect effects of factors such as the perceived switching cost (PSC), subjective norms (SN), perceived usefulness (PU), perceived playfulness (PP), perceived risk (PR), satisfaction (SA), and perceived ease of use (PEoU) on the continuance intention. PSC shows the strongest direct positive effect (β = 0.443), highlighting the importance of switching costs in maintaining the continuance intention. SN and PU exerted a strong positive total effect on the continuance intention through their significant indirect effects, which are at 0.408 and 0.241, respectively. This indicates that social influence and the practicality of the tool are key factors in promoting continuance intention. Although PP had a weaker direct effect (β = 0.063), its indirect effects and total effects were 0.036 and 0.100, respectively, with significances of 0.002 and 0.048, suggesting that PP indirectly influences the continuance intention positively through other factors, emphasizing its important role in attracting designers to continue using AI drawing tools. PR and PEoU showed a direct negative effect and a positive influence through indirect paths, respectively, indicating that whereas risk perception may directly hinder the intention to use, PEoU can indirectly promote continuance intention by enhancing other factors.

Table 11. Results of path analysis.

Hypotheses	Path Analysis			UnStd.	Std.	*S.E.*	*p*	Support
H1	SA	→	CI	0.155	0.174	0.052	0.001	yes
H2	PU	→	CI	0.028	0.030	0.065	0.578	no
H3	PU	→	SA	0.152	0.145	0.063	0.025	yes
H4	EC	→	SA	0.451	0.394	0.092	0.000	yes
H5	EC	→	PU	0.367	0.334	0.082	0.000	yes
H6	EC	→	PP	0.728	0.635	0.064	0.000	yes
H7	PP	→	CI	0.056	0.063	0.050	0.170	no
H8	PP	→	SA	0.209	0.209	0.066	0.002	yes
H9	PEoU	→	CI	−0.067	−0.071	0.069	0.284	no
H10	PEoU	→	PU	0.118	0.116	0.067	0.054	no
H11	SN	→	CI	0.168	0.185	0.075	0.003	yes
H12	SN	→	PU	0.259	0.264	0.087	0.002	yes
H13	SN	→	PEoU	0.604	0.631	0.053	0.000	yes
H14	SN	→	PR	−0.495	−0.498	0.056	0.000	yes
H15	PR	→	CI	−0.117	−0.128	0.049	0.003	yes
H16	PU	→	PSC	0.353	0.421	0.046	0.001	yes
H17	PEoU	→	PSC	0.376	0.439	0.048	0.000	yes
H18	PSC	→	CI	0.491	0.443	0.087	0.001	yes

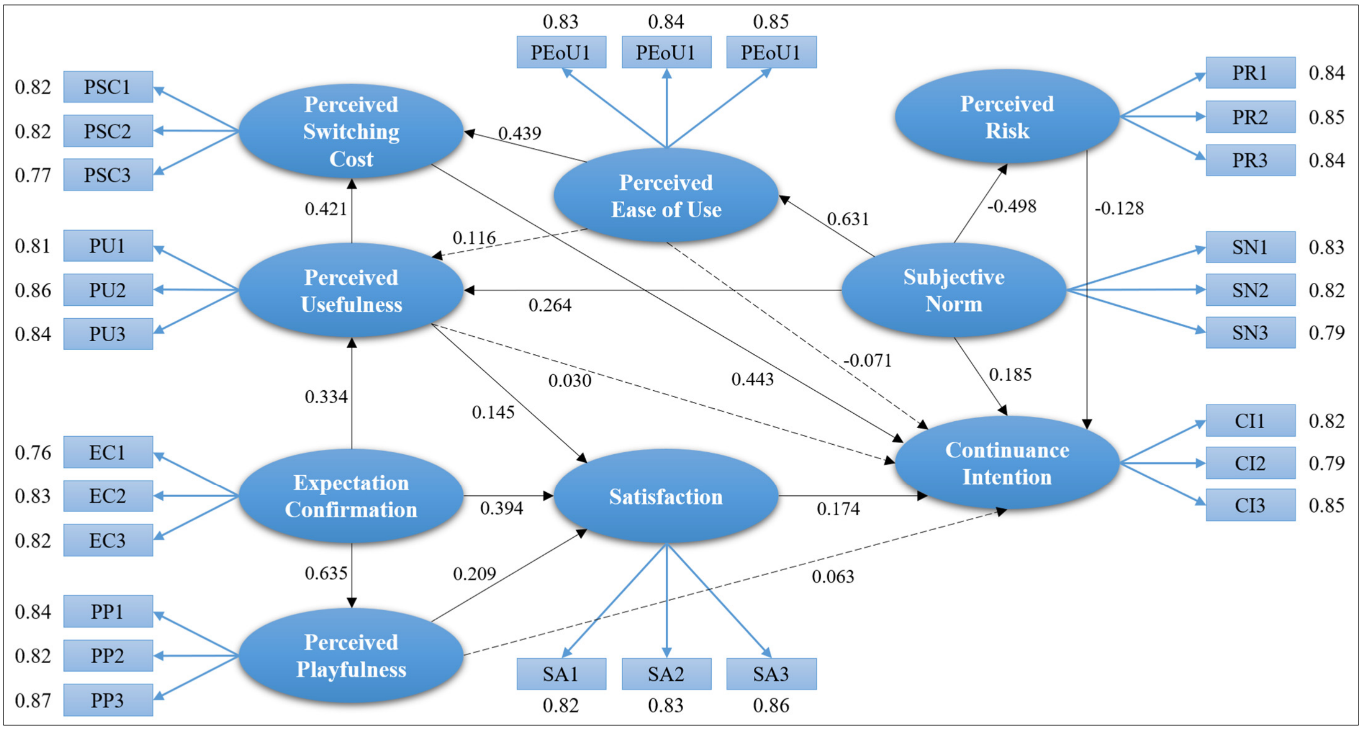

Figure 2. Results of path analysis.

Table 12. Results of direct effect, indirect effect, and total effect on continuance intention.

Relationship Path			Direct Effect		Indirect Effect		Total Effect	
			β	B–C Sig.	β	B–C Sig.	β	B–C Sig.
PP	→	CI	0.063	0.170	0.036	0.002	0.100	0.048
SN	→	CI	0.185	0.003	0.223	0.000	0.408	0.000
PR	→	CI	−0.128	0.003	/	/	−0.128	0.003
SA	→	CI	0.174	0.001	/	/	0.174	0.001
PSC	→	CI	0.443	0.001	/	/	0.443	0.001
PU	→	CI	0.030	0.578	0.211	0.001	0.241	0.000
PEoU	→	CI	−0.071	0.284	0.222	0.000	0.151	0.013

6. Discussion

This study uses structural equation modeling to test the hypothetical model of the designers' intention to continue using AI drawing tools. The empirical analysis results provide the following key findings:

6.1. The Application of Expectation Confirmation Theory in Design Industry

Expectation confirmation theory has traditionally been used to explain consumers' repurchase behavior, especially in terms of satisfaction and loyalty [8]. In this study, ECT-ISC is employed as the theoretical framework to investigate designers' intention to continue using AI drawing tools. What makes this application unique is that it transcends the consumer market and extends to the design creativity industry, a field centered on innovation and individualized needs [71].

The results of the data analysis strongly support the key hypotheses of ECT in the design context. Firstly, the influence of satisfaction on continuance intention has been confirmed (H1 is supported), which is consistent with the original model in [8], which emphasized the central role of consumer satisfaction in repurchase decisions. However, in the realm of AI-assisted design, a designer's "satisfaction" is derived not only from the functional performance of a product but also from how it fosters creative expression and innovation [72]. This satisfaction is multi-dimensional, as it encompasses acknowledgment of the tool's utility (such as timesaving and efficiency improvements) and the fulfillment of artistic and personal expression.

If a tool meets or exceeds these expectations, designers may not only feel satisfied with it, they might also perceive it as having tangible value to their creative work.

Secondly, the significant influence of expectation confirmation on satisfaction (H4 is supported) and perceived usefulness (H5 is supported) reveals the central role of the consistency between expectations and actual experiences in forming satisfaction and perceived usefulness [73]. This is especially important in the design industry, as a designer's expectations of a tool are based not only on its functionality but also on whether they can inspire new creative thinking or offer unique design solutions. If a tool meets or exceeds these expectations, designers are not only satisfied with it but may consider it to be of practical value to their creative work. If a tool meets or exceeds these expectations, designers will feel satisfied and also believe that it has practical value for their creative work.

6.2. Non-Significant Impact of Perceived Usefulness on the Intention to Continue Use

Upon conducting an in-depth analysis of the impact of PU on the continuance intention, it was discovered that, although traditional models consider PU as a core factor, in the specific context of AI drawing tool adoption, the direct impact of PU on the CI is not significant (H2 is not supported). However, it influences CI indirectly through PSC and SA. This finding challenges our traditional understanding of technology acceptance models and suggests that we need to consider user experience from multiple dimensions [74,75].

The data analysis results reflect that users may believe that although AI drawing tools do have their usefulness, switching from current tools to new ones might involve learning costs, time investment, and potential workflow interruptions. If these switching costs are perceived as high, it could hinder users' intention to continue using the tool, even if they consider it useful. Additionally, it indicates that users' satisfaction might be a more direct driving force affecting their continuance intention. This means that even if users find AI drawing tools useful, their actual satisfaction with the tool (including its performance, user experience, etc.) will directly determine whether they are willing to continue using the tools.

Our research not only expands the understanding of technology acceptance and continuance usage theories but also provides new perspectives and strategic recommendations for the design and marketing of technological products like AI drawing tools. Although the direct impact of PU on the continuance intention is not significant, the mediating role of PSC and SA reveals a more complex pathway of influence. This finding reminds us that multiple interacting factors need to be considered in understanding and promoting the process of technology acceptance and continuance intention.

6.3. The Role of Perceived Ease of Use Redefined in AI Drawing Tools

In the process of constructing structural equation models, this study introduced the concept of PEoU, which, in other domains, is often a key factor driving user acceptance and the adoption of new technologies. However, this study found that in the specific context of designers using AI drawing tools, the impact of PEoU on users' continuance intention seems to have diminished (neither Hypothesis 9 nor Hypothesis 10 were supported). This finding compels us to reconsider how ease of use for AI drawing tools is applied and understood in the design field, especially when the tools involve artistic creation and expression. The study speculates that the underlying reasons for the decreased influence of perceived ease of use may involve the following factors:

6.3.1. The Tension between Creative Challenges and the Simplicity of Technology

Designers often seek novel and challenging creative processes, which may stand in opposition to the ease of use of technology. For designers, the allure of a tool lies not only in its ability to reduce workload or simplify tasks but more importantly in how it fosters innovative thinking, offers unique solutions, or supports new forms of expression [76]. Therefore, an excessive emphasis on ease of use can be perceived as sacrificing creative potential, which in turn could affect designers' intention to continue using the tool.

6.3.2. The Mismatch between High Skill Levels and Expectations of Ease of Use

It is observed that designers typically possess high technical skill levels and a deep understanding of tools, which alters their expectations and evaluation of ease of use. Within professional domains, the complexity of a tool is not always seen as a disadvantage and may be thought of as necessary to provide greater control and flexibility. Therefore, designers might not favor continued usage of a tool merely because it is "easy to use".

6.3.3. Subjective- and Emotion-Driven Artistic Creation

Unlike other fields, design and artistic creation are often highly personalized and driven by emotion. The decision to use a specific tool may not be based solely on its practicality but also on whether it aligns with the designer's personal style, values, and expressive intentions. This emotional and subjective assessment can transcend conventional considerations of ease of use, thereby redefining the parameters of tool acceptance.

6.3.4. Specific Dynamics within Design Field

In the design field, innovation and exploratory features are often more critical than functionality and efficiency. Designers tend to evaluate whether tools can assist them in exploring new styles, techniques, or perspectives, rather than just their intuitiveness or ease of use. This field-specific dynamic may explain why PEoU becomes less relevant in this context [77]. The findings prompt us to reconsider the application of PEoU within the continuous usage model. Across different cultural and industry contexts, the factors influencing users' continuance intention may vary, necessitating the consideration of more intrinsic and context-related factors. For tools involving creativity and expressiveness, such as AI drawing tools, the continuous usage model may need further expansion to incorporate individuals' artistic inclinations, creative needs, and profession-specific expectations.

Moreover, this also suggests that researchers and practitioners need to move beyond the traditional concept of ease of use to fully appreciate the complex needs and motivations of users (in this case, designers). Developers of AI drawing tools, in the development and promotion of such tools, should take into account these unique user characteristics, emphasizing the tools' capabilities in fostering creativity, providing personalized experiences, and enabling artistic exploration [76], rather than focusing solely on their ease of use.

6.4. The Role of Perceived Playfulness in Enhancing Satisfaction with AI Drawing Tools

When investigating designers' intention to continue using AI drawing tools, we noted a significant phenomenon: PP (Hypothesis 8) plays a crucial role in enhancing user satisfaction, with a standardized coefficient of 0.209 and a p-value of less than 0.01 indicating a significant impact. However, PP (Hypothesis 7) did not significantly affect designers' intention to continue use. This finding challenges our previous understanding that playfulness would directly promote usage intention. Instead, it suggests that playfulness might indirectly influence usage intention by improving satisfaction. The following section will further analyze how PP affects designers' intention to use AI drawing tools:

6.4.1. The Intrinsic Drivers of Satisfaction: The Multidimensional Role of Perceived Playfulness

Perceived playfulness is not merely a simple experiential factor but a complex, multidimensional construct that enhances designers' satisfaction on both the psychological and practical levels.

Psychologically, PP engages designers' intrinsic motivations, sparking their curiosity and desire to explore [78]. The nonlinear, unrestricted creative environment provided by AI drawing tools activates designers' creative thought processes, offering a sense of freedom and excitement not typically afforded by traditional drawing tools. The fulfillment of curiosity and exploratory desires directly correlates with user satisfaction, as designers who find pleasure and interest in using the tools are more likely to provide positive feedback.

On a practical level, PP enhances satisfaction by increasing experimentation and interaction. When designers experiment with new techniques and styles using AI drawing tools, each creation becomes a unique experience. This experimental nature not only allows designers to expand their skills and styles but also offers immediate feedback and a sense of achievement. Over time, this positive feedback loop contributes to increased satisfaction and long-term user loyalty.

Furthermore, PP is linked to social interaction [79]. As designers create with AI tools, they tend to share their creative processes and outcomes, establishing connections with peers and audiences. The increased social interaction provides social support and recognition, further enhancing the pleasure of using the tools.

In summary, PP significantly enhances satisfaction through its comprehensive impact on designers' intrinsic motivations, experimental interactions, and social engagements. This multidimensional fulfillment transforms AI drawing tools into platforms for creative expression and social interaction, deepening designers' overall satisfaction with the tools.

6.4.2. The Connection between Satisfaction and Continued Intention to Use and the Transformative Role of Perceived Playfulness

Research indicates that satisfaction plays a crucial mediating role in analyzing designers' intention to continue using AI drawing tools [80]. PP influences their continuance intention indirectly by enhancing user satisfaction. This section will thoroughly examine how PP is transformed into the intention to continue use.

Satisfaction reflects a comprehensive evaluation based on user experience, including the degree of pleasure, fulfillment, and whether expectations were met while using the tool. In the context of AI drawing tools, PP provides a unique and appealing user experience that may be absent in traditional drawing tools or software. By fulfilling designers' creative needs and curiosity, PP boosts their overall satisfaction, which then translates into a motivation for continued usage.

The intention to continue using a tool is not merely based on its functionality or performance efficiency but is deeply rooted in a deeper emotional connection of satisfaction. Higher levels of satisfaction can motivate designers to continue exploring and using AI drawing tools, even if these tools may have functional limitations. This suggests that designers' loyalty and continued usage are not just rational decisions but are closely linked to emotional fulfillment and psychological engagement.

This finding offers significant insights for the design and practice of AI drawing tools. Developers should consider how to integrate playfulness into the user experience and promote continuous usage by enhancing satisfaction. The design of tools should not focus solely on functionality but also on providing an environment that inspires creativity, encourages exploration, and supports self-expression.

In the product lifecycle, the intention for continued usage is crucial for maintaining the product's activity and success. Perceived playfulness, by increasing user satisfaction, fosters long-term engagement and use of the tool. Designers' intention to continue using AI drawing tools stems from their satisfaction with the unique experiences provided by these tools, which may intensify over time as they accumulate more positive experiences related to their use.

The link between PP enhancing satisfaction and the intention to continue using AI drawing tools reveals the complexity of user behavior. It not only highlights the importance of improving user satisfaction but also emphasizes the need to focus on the multidimensional aspects of users' emotional and psychological experiences when developing tools. By deeply understanding these factors, more human-centered, appealing, and enduring products can be designed.

6.5. Perceived Switching Costs: Striking a Balance between Traditional Tools and AI Drawing Tools

Regarding designers' adoption of AI painting tools, the perceived switching costs emerge as an indispensable factor. This not only pertains to financial outlays but also encompasses time, effort, and emotional investments. The results from this study reveal a positive relationship between the perceived switching costs and perceived usefulness (H16 is supported), as well as between the perceived switching costs and perceived ease of use (H17 is supported). These findings are crucial for understanding the practical challenges designers face when adopting AI drawing tools. The following is a discussion on the difficulties designers encounter when using AI drawing tools and the strategic considerations proposed to address these challenges.

6.5.1. Learning and Adaptation

For designers, adopting new tools entails investing time and effort into learning how to use them effectively [81], which involves not just mastering new technical skills but also adapting to potentially altered workflows and modes of creative expression. Even if AI drawing tools may offer long-term benefits, the short-term learning curve and the adaptation process can pose a challenge.

6.5.2. Emotional Investment and Brand Loyalty

Designers often develop emotional attachments to tools they have used over extended periods. Such attachment is not solely based on the functionality of the tools but also encompasses familiarity, emotional memories tied to past projects, and loyalty to specific brands or products [82]. Consequently, transitioning to new AI painting tools can evoke feelings of loss and uncertainty.

6.5.3. Strategic Consideration

From our analysis and understanding of the challenges designers face when using AI drawing tools, we believe that providers of AI drawing tools and leaders of design teams might consider adopting a phased strategy, gradually integrating new tools or features into workflows. This can alleviate the immediate pressure of switching, allowing designers to gradually adapt to the new workflow while minimizing the disruption to work and the risk of reduced productivity. Furthermore, we believe that offering comprehensive training and ongoing technical support to designers is crucial in reducing the barriers to switching. Not only can this help designers quickly master new tools but it can also alleviate the uncertainty and stress of the transition by demonstrating the organization's commitment to employee growth and development.

6.6. The Trade-Offs of Perceived Switching Cost and the Importance of Finding a Balance between Traditional Tools and AI Drawing Tools

Switching costs not only involve financial investments but also time, effort, and emotional investments. The study reveals a positive relationship between PU, PEoU, and PSC, with PSC significantly impacting continuance intention. Understanding the challenges faced by designers in adopting AI drawing tools is crucial. Below are the difficulties faced by designers when using AI drawing tools and considerations for future strategies.

6.6.1. Perceived Switching Costs: Striking a Balance between Traditional Tools and AI Drawing Tools

For designers, adopting new tools means dedicating time and energy to learn how to use them effectively. This includes mastering new skills and adapting to potentially changing workflows and modes of creative expression. Although AI drawing tools may offer long-term benefits, the short-term learning curve and adaptation process can still pose a challenge.

6.6.2. Perceived Switching Costs: Striking a Balance between Traditional Tools and AI Drawing Tools

Designers often develop a deep emotional attachment to the tools they have used over a long period. This attachment is not just based on the tool's functionality but also on emotional memories of familiarity with the tool and loyalty to specific brands or products. Therefore, switching to new AI drawing tools can trigger feelings of loss and uncertainty.

6.6.3. Perceived Switching Costs: Striking a Balance between Traditional Tools and AI Drawing Tools

After analyzing the difficulties encountered by designers with AI drawing tools, we suggest that AI drawing tool providers and design team leaders consider adopting a gradual strategy, introducing new tools or features into the workflow step by step. This approach can alleviate the pressure of an immediate switch, allowing designers more time to adapt to the new system and reducing the risk of work interruptions and productivity declines.

Furthermore, providing comprehensive training and ongoing technical support is crucial for reducing the barriers to switching. This not only helps designers quickly master new tools but also alleviates the uncertainty and stress during the transition by demonstrating the organization's commitment to employee growth and development.

7. Conclusions

This study employs a structural equation modeling approach to investigate the factors influencing designers' intention to continue using AI drawing tools. The results offer strategic guidance for the development and optimization of AI drawing tools to cater to the specific needs of designers and enhance their user experience. This study identified key indicators that influence designers' intention to continue using AI drawing tools and employed a structural equation model to validate the critical factors affecting their adoption and usage through a literature review. Based on the analysis results from the model, the study draws the following conclusions:

This study unveils several key factors and their path relationships that influence designers' intention to continue using AI drawing tools. These factors include perceived usefulness, perceived ease of use, satisfaction, expectation confirmation, perceived playfulness, perceived switching costs, subjective norms, and perceived risk.

It is crucial to focus on users' satisfaction to encourage designers' continued usage of AI drawing tools. Both the functional performance of the tools and their capabilities in fostering creativity and innovation should be carefully improved to ensure users' satisfaction. Moreover, expectation confirmation plays a pivotal role in shaping users' satisfaction and perceived usefulness, which underscores the importance of consistency between users' expectations of tool performance and their actual experiences.

Perceived playfulness plays an indispensable role in determining whether designers intend to continue to use AI drawing tools. Compared to traditional usability and functionality factors, the intrinsic motivations (such as seeking pleasure and satisfaction) for using design assistance tools might be more significant in the fields of art and design. Subjective norms and perceived risk also demonstrate a notable impact, emphasizing the importance of peer recommendations, industry standards, and potential risks in the decision-making process. However, the perceived ease of use did not show the anticipated impact on the designers' intention to continue using AI drawing tools, which prompted us to rethink the role of ease of use in the design industry and its role in meeting designers' needs.

Based on these findings, we suggest that developers of AI drawing tools should not only pay attention to the technical performance of the tools but also the intrinsic needs and motivations of designers. To better serve designers, developers should focus on providing platforms that can inspire creativity, promote personalized expression, and enhance job playfulness. Additionally, broader user acceptance evaluation criteria should also be taken into account, including users' emotional reactions, the quality and originality of creative outcomes, and how the tool strengthens users' artistic expression and personal growth.

7.1. Theoretical Contribution

Through in-depth structural equation modeling analysis, this study significantly advanced our understanding of the factors influencing designers' continued use of AI drawing tools. By expanding and optimizing the ECM-ISC model, this research not only identified the importance of traditional factors such as perceived usefulness, satisfaction, and expectation confirmation but also revealed the significant impact of new dimensions like perceived playfulness, perceived switching costs, subjective norms, and perceived risk on the continuance intention. Particularly, the reassessment of the impact of perceived ease of use showed that it did not directly affect the continuance intention in this study, challenging conventional wisdom and offering a new perspective for the design and promotion of AI drawing tools. This study not only enriches the theoretical knowledge base regarding technology acceptance and continuous use but also provides valuable insights for practitioners, guiding them on how to better meet designers' needs and promote the continued development and innovation of AI drawing tools.

7.2. Practical Contribution

This study holds significant practical implications for the acceptance and use of AI drawing tools, offering profound insights for designers and developers. Firstly, by deeply understanding the motivations and challenges of designers using AI tools, it provides developers with crucial information to design products that better meet user needs, thereby broadening the market. Secondly, optimizing AI drawing tools to meet the specific expectations of designers not only enhances their work efficiency and creative output but also promotes technological innovation and development within the entire creative industry, pushing the creative sector towards higher levels of innovation. These findings emphasize the importance of targeted development and continuous optimization of AI tools in stimulating creativity and enhancing design practices.

7.3. Limitations and Future Research

While this study offers valuable insights and strategies concerning the adoption and usage of AI drawing tools, it does come with certain research limitations. Future studies could make improvements and delve deeper in the following aspects. For instance, the respondents in this study primarily hail from specific regions, which might not fully represent the needs and preferences of designers from various geographical and cultural backgrounds. Future research could expand the sample size to encompass designers from a broader range of countries and regions to obtain more comprehensive and diverse data. Moreover, while the study proposes a series of improvement strategies for AI drawing tools based on designers' needs, the actual effectiveness of these strategies has not been validated. Future studies could employ user tests and interface evaluations, among other methods, to assess the real-world impact and feasibility of these strategies.

For future research, we recommend adopting interdisciplinary approaches that encompass cognitive psychology, human–computer interaction, art psychology, etc., to thoroughly understand the psychological processes and emotional needs of designers when using AI drawing tools. As designers' tool needs and preferences might evolve with time and technological advancements, future studies could engage in more extended observations and tracking to grasp these changing trends. It is essential to focus on the diversity of designers from various backgrounds, in terms of differences in gender, culture, and education level, to ensure that the improvement strategies for AI drawing tools cater to the needs of different groups, realizing genuinely user-centric and inclusive design.

In summary, although this study has certain limitations, it lays the foundation for future research and points out several directions worth further exploration. We hope that future studies, building on this foundation, can delve deeper into the genuine needs and emotional experiences of designers, providing more robust support for the improvement and development of AI drawing tools.

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