The Application of Generative AI Among Photographers: Formation and Influencing Factors of Behavioral Intention

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ABSTRACT

Generative Artificial Intelligence (GAI) is reshaping photographic workflows, yet photographers' adoption decisions remain incompletely understood. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), we surveyed 97 photographers and tested a structural equation model with partial least squares (PLS-SEM). Performance expectancy ($\beta = 0.279$, $p < 0.05$) and social influence ($\beta = 0.528$, $p < 0.001$) significantly increase behavioral intention, whereas effort expectancy and facilitating conditions show no direct effect. Facilitating conditions, however, enhance intention indirectly through effort expectancy and social influence, underscoring the importance of resource support and peer validation. Empirically, the study clarifies which levers most effectively encourage Generative AI uptake in photography. Conceptually, it extends UTAUT by demonstrating that socio-psychological dimensions—perceived authorship, identity, and community alignment—can outweigh functional considerations in creative domains, offering actionable guidance for future promotion strategies.

Keywords: Generative AI, Photographers, UTAUT, SmartPLS, Behavioral Intention

1. Introduction

1.1 Research Background and Motivation

The development of Generative AI has accelerated rapidly, reshaping workflows and creative processes in various sectors, particularly within the creative industries. As noted in the World Economic Forum's "Future of Jobs Report" [1], machines and algorithms are projected to perform more than half of all work-related tasks by 2025, resulting in both the creation of 133 million new jobs and the elimination of approximately 75 million traditional roles. This evolution presents significant challenges for professions that rely heavily on manual and creative labor.

In the context of photography, the creative process—including ideation, scene design, execution, and post-production—demands substantial investment of time and expertise. Generative AI technologies now offer highly efficient and flexible tools that transform traditional photography workflows, but also introduce new challenges related to professional adaptation and the integration of technology with creative values.

1.2 Research Objectives

According to the "State of the Photography Industry Report" released by Zenfolio in April [2], the application of AI in photography has grown markedly. The adoption rate of Generative AI among photographers increased by 12% compared to the previous year, and the proportion of photographers who have never used AI dropped from 46% to 18%. Approximately half of all photographers now incorporate AI tools into their workflows, although only 2% rely solely on AI-generated images.

In this context, AI technologies are redefining professional practice in photography by enhancing efficiency and creative flexibility. However, the widespread acceptance of AI by photographers is still subject to multiple influencing factors, including individual attitudes toward technology, expectations regarding its effectiveness, learning barriers, and access to resources.

This study focuses on the acceptance of Generative AI among photographers, utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) as a theoretical foundation [3]. The research aims to examine how facilitating conditions, effort expectancy, and performance expectancy influence the intention to use Generative AI tools. The UTAUT model posits that behavioral intention to use technology is primarily affected by four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions.

The main objectives of this research are as follows:

1. To analyze the adoption of Generative AI tools among photographers and to understand current application trends in the field of photography.
2. To assess the impact of Generative AI tools on creative efficiency, artistic expression, and market competitiveness, clarifying both the value and challenges of these technologies.
3. To examine photographers' psychological and behavioral patterns using the UTAUT model, identifying key factors influencing the adoption of Generative AI tools.

Through a questionnaire survey, this study investigates photographers' attitudes, needs, behaviors, and perceptions regarding the use of Generative AI tools, thereby providing insights into their acceptance and evaluation of these emerging technologies.

1.3 Scope and Limitations

This research employs an online questionnaire distributed via Google Forms, targeting professionals with experience using Generative AI imaging tools. The questionnaire link was shared through relevant Facebook communities, with the formal survey period spanning from November 15 to December 15, 2024. The survey population consists of photographers who have experience using Generative AI software, aiming to analyze the factors affecting their continued intention to use such tools.

It is important to note that, due to the reliance on online community sampling and a participant pool largely concentrated in the northern region, the sample may not be fully representative of all photographers. As a result, the generalizability of the findings is subject to certain limitations and should be interpreted with caution.

1.4 Research Gap and Study Focus

While Generative AI has rapidly advanced and gained attention across various domains such as education, enterprise, and design, existing empirical research on its application within the field of photography—particularly among professional photographers—remains scarce. Prior studies grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) have primarily investigated key determinants of technology adoption, yet have seldom addressed the unique psychological dimensions encountered by creative professionals, such as creative anxiety and role ambiguity arising from the use of AI-generated content. Furthermore, the influence of peer recognition and community culture, which are crucial in the creative industries, has not been sufficiently explored in the context of technology acceptance.

In addition, although prior UTAUT-based research has emphasized the direct effects of constructs such as effort expectancy and facilitating conditions on behavioral intention, limited attention has been paid to their indirect or mediating roles. This has resulted in a fragmented understanding of how these constructs interact within a broader acceptance framework.

To address these gaps, the present study focuses on photographers as a creative professional group and develops an integrated structural model that incorporates both psychological and contextual factors. By combining the UTAUT model with insights from creativity research, this study investigates not only the direct predictors of usage intention but also the mediating pathways through which external conditions and social dynamics influence adoption behavior. The findings aim to deepen the theoretical comprehension of AI adoption in creative fields and provide actionable insights for the promotion of Generative AI tools in professional photography workflows.

2. Literature Review

2.1 Overview of Generative AI Technologies and Applications

Generative AI refers to a class of deep learning technologies capable of generating new content—such as text, images, or music—based on diverse and complex prompts, including language, instructions, or questions. The core technology behind Generative AI originates from the development of Generative Adversarial Networks (GANs) proposed by Goodfellow et al [4], which introduced a competitive training framework between a generator and a discriminator to produce highly realistic outputs.

Recent advancements have led to the emergence of diffusion models (e.g., Stable Diffusion) and large language models (LLMs) such as GPT-4 [5] ,and the text-to-video model SORA [6]. Diffusion models offer greater control and the ability to iteratively generate high-quality images, making them highly applicable in artistic creation and image synthesis. LLMs, by leveraging multimodal learning, can generate not only text but also images and cross-modal creative content, expanding the scope and capabilities of Generative AI.

These innovations are transforming not only the technical landscape but also how creativity is conceptualized and practiced within creative industries [7]. In fact, Generative AI is no longer simply a tool that augments human labor—it is becoming an autonomous collaborator in the creative process.

For instance, co-creative workflows involving Generative AI are enabling designers, musicians, and writers to iterate, refine, and evolve their ideas through "mutual learning" loops between human and AI systems [8]. This transformation marks a paradigmatic shift from using software as passive design tools to engaging with Generative AI as active creative agents.

Main Application Areas

Generative AI has found applications across various creative and technical fields, including:

- Image Generation: Artistic creation, advertising design, and product prototyping (e.g., DALL-E, Midjourney).
- Video Generation and Editing: Marketing videos, virtual character animation, and educational videos (e.g., Runway ML, Synthesia).
- Multimodal Generation: Integration of text, images, and speech, with significant breakthroughs in intelligent assistants and human–computer interaction (e.g., OpenAI's GPT-4 and the text-to-video model Sora).
- Publishing and Content Creation: Generative AI tools now assist in tasks such as automated editing, content summarization, and article drafting, providing benefits like cost reduction, audience customization, and efficiency in workflows [7].
- Music and Literary Production: Music composition systems (e.g., MusicLM) and AI poets challenge traditional notions of authorship and originality, producing creative works that often pass Turing-style indistinguishability tests from human-made content [9].
- Furthermore, Generative AI's creative outputs—especially in visual arts and text—are increasingly accepted by major institutions and audiences. The acquisition of Refik Anadol's Unsupervised series by the Museum of Modern Art (MoMA) in New York exemplifies how Generative AI-generated works are gaining legitimacy and cultural value [9]. As a result, distinctions between human and machine creativity are blurring, prompting reevaluation of what constitutes creative authorship, artistic labor, and aesthetic value.

2.2 Development and Application of Generative AI in Photography

Generative AI models, trained on vast datasets, can autonomously generate new content—including images, text, and videos—enabling innovative tools and workflows for photographers.

2.2.1 Pre-production: intelligent scene design and planning

In the early stages of photography, Generative AI serves as a crucial tool for enhancing creativity and proposal efficiency:

- Recent advances in Generative AI enable creators across fields—from architects to photographers—to swiftly create virtual scene mockups from text prompts. For example, Adobe Firefly demonstrates how architectural designers can rapidly visualize concepts, a capability equally valuable in advertising, pre-visualization, and cinematic production planning [10].
- Composition and Scene Suggestions: By analyzing large image datasets, Generative AI can provide composition recommendations that align with the intended theme or style.
- Lighting Simulation: AI can simulate the effects of different weather or lighting conditions on a scene, supporting optimal shooting time selection.

- Visual Inspiration Generation: In creative discussions, Generative AI can rapidly produce visual references. For example, Adobe Firefly enables users to create high-quality design drafts from simple descriptions, streamlining creative direction [6].
- In creative industries, Generative AI serves as both an ideation tool and a communication facilitator, significantly improving individual productivity and enabling iterative group planning. For example, design teams can prompt Generative AI during meetings to rapidly generate visual variations of staging concepts or moodboards, reducing iteration time from days to minutes [11].

2.2.2 Shooting: real-time generation and assistance

Generative AI also supports the shooting stage:

- Intelligent background generation and replacement are increasingly feasible due to developments in Generative AI. Tools like Runway ML enable real-time background substitution, cutting production costs. Runway's AI models have even been used for effects .
- Multimodal Content Support: Advanced multimodal models such as GPT-4 and SORA can produce supplementary materials (e.g., illustrations, captions) on demand, facilitating synchronized creation within production teams.
- In live creative environments, Generative AI enables real-time collaboration, allowing visual, audio, and technical teams to test creative decisions on the spot. This supports simultaneous decision-making during shooting, rather than sequential trial and error, thus redefining collaborative workflows in production [11].

2*.2.3 Post-production: automated enhancement and creative processing*

In post-production, Generative AI offers powerful optimization and creative tools:

- Image enhancement and restoration are increasingly supported by AI algorithms capable of automatically denoising images, correcting color balance, and enhancing fine details, thereby improving overall image quality and processing efficiency. As demonstrated in the International Journal of Modern Engineering and Management Research (2024), such capabilities can significantly streamline digital workflows. For instance, the Generative AI features in Adobe Photoshop apply these techniques to enable fast and effective image repair and quality improvement [13].
- Style Transfer and Creative Effects: Photographers can apply artistic styles (e.g., vintage, cartoon) to images using Generative AI , meeting diverse client requirements.
- Batch Generation and Management: AI streamlines large-scale image processing by enabling automatic tagging and bulk generation, improving photographers' workflow efficiency.
- Moreover, Generative AI allows professionals to extend their creative and operational roles beyond traditional boundaries. Designers and photographers can now produce presentation-ready slide visuals and layout drafts, using AI to prototype ideas directly rather than relying on multiple production intermediaries [11].
- However, challenges remain, such as difficulty in achieving consistent visual styles across AI outputs and the limited readiness of 3D and video AI tools for high-quality production needs. These limitations currently restrict full automation in high-end photographic or cinematic post-

production [14].

Overall, Generative AI is revolutionizing traditional photography workflows by providing flexible, efficient, and creative tools at every stage of production.

2.3 Psychological Factors Affecting Creative Professionals' Use of Generative AI

2.3.1 Technology acceptance in the creative class

Florida [15] introduced the concept of the "creative class," which encompasses professionals such as artists, designers, media, and technology workers. These individuals value creativity, autonomy, and self-expression. Their acceptance of technology is not merely driven by convenience or efficiency, but also by whether the tool enhances their personal style, strengthens professional identity, or deepens creative output.

For photographers, the use of Generative AI is often evaluated in terms of its ability to expand creative possibilities, support expressive composition, or provide compelling visual resources for client proposals. When Generative AI is perceived as an extension of the creative process, willingness to adopt it increases. Conversely, if AI is seen as threatening originality or diminishing professional value, it may provoke resistance [15]. Thus, understanding photographers' values and creative motivations is essential for analyzing technology adoption in this field.

In a cross-cultural comparative study, it was found that the perception of whether AI supports or undermines personal creative identity varies significantly across cultural contexts. For instance, U.S. artists often embrace Generative AI when it is framed as a tool to support individual expression, whereas creatives in Japan and China exhibit more ambivalence, citing concerns over authenticity and control [16]. This suggests that technology acceptance in the creative class is also influenced by broader socio-cultural attitudes toward authorship and machine agency.

2.3.2 Interaction between Intrinsic Motivation and Creative Environment

Amabile's [17] Componential Theory of Creativity highlights three critical components: domain-relevant skills, creative-thinking skills, and intrinsic motivation, the latter being the core driver of creative behavior. When the external environment and tools support this motivation, creativity is more likely to flourish.

In the context of Generative AI, if AI tools provide inspiration, visual sketches, or creative direction, they may be embraced as resources that enhance intrinsic motivation and sustain creative passion. However, if the tools are overly restrictive or produce formulaic results, they may diminish a sense of control and creative engagement. Therefore, the design of Generative AI tools for creative professionals should emphasize flexibility and freedom of expression to enhance psychological acceptance.

A recent systematic review further reinforces this point by emphasizing that creative professionals are more likely to adopt Generative AI when it is perceived as augmenting their personal vision rather than replacing it. In particular, the experience of "creative flow"—a deeply immersive mental state—depends heavily on systems that respect user autonomy and support self-guided exploration [9].

Building on this, Bender [18] argues that the true reward of creative work often lies in the process itself. For many practitioners, solving narrative or visual problems is inherently fulfilling. If Generative AI automates these core problem-solving tasks without engaging the creator's input, it may unintentionally diminish the very motivation it aims to support. Thus, meaningful AI integration should focus on amplifying—rather than bypassing—the creator's cognitive and emotional investment.

2.3.3 Role ambiguity and creative anxiety in the age of Generative ai

Guzman and Lewis [19] have observed that the widespread adoption of AI in media industries has caused significant shifts in both production processes and professional identity. Generative AI blurs the lines of authorship and originality, raising both psychological and ethical issues. For photographers, the capacity of AI to produce highly realistic or creative images may be perceived as a challenge to professional value and uniqueness. If audiences or clients cannot distinguish between human and AI-created work, or if they believe that AI can "replace" photographers, this may lead to anxiety and reduced confidence among creative professionals [19]. To foster positive acceptance, it is crucial to emphasize the collaborative nature of AI, ensuring that photographers retain creative control and ownership.

Recent literature suggests that creative workers' anxiety is not solely economic but deeply tied to fears of losing autonomy, recognition, and the sense of dignity in their craft [18]. Drawing on the concept of "meaningful work," Bender [18] argues that Generative AI must be integrated in ways that amplify human creative strengths, rather than subsume them. Otherwise, the risk is not just professional displacement, but a broader erosion of the psychological rewards that sustain long-term creative engagement.

2.4 Generative AI's Disruptive Potential: Opportunities and Challenges in Creative Industries

As Generative AI continues to evolve, its implications for the creative industries have grown increasingly complex. Amankwah-Amoah et al. [7] provide a comprehensive framework that positions Generative AI not as a mere productivity tool, but as a transformative force that redefines creative workflows, business models, and human-AI collaboration. While sectors such as advertising, publishing, software development, and graphic design benefit from increased efficiency, content customization, and accelerated production, the challenges—ranging from job displacement to ethical dilemmas around authenticity and authorship—remain acute. Their conceptual framework emphasizes the delicate balance between automation and the human touch, which is especially vital in domains driven by emotional resonance and aesthetic value.

Building upon this framework, other scholars have underscored domain-specific implications. For example, in visual journalism, the deployment of text-to-image AI tools has sparked concerns over misinformation, algorithmic bias, and erosion of photojournalistic trust [14]. Thomson et al. report that visual editors across newsrooms express a cautious optimism—recognizing the potential of AI for illustration and efficiency, yet wary of reputational risks and the undermining of visual truth claims in journalism.

Beyond journalism, research has noted that Generative AI models challenge traditional notions of creative labor. Some scholars argue that such tools, when embedded in creative workflows, may lead to the devaluation or even disappearance of human creative input, especially in mass media production environments where automation is prioritized [18]. This aligns with broader concerns about AI-enabled disintermediation and the precarious nature of cultural work in digital economies [11].

Cultural context also plays a critical role in shaping public and practitioner attitudes toward Generative AI. A cross-national comparison of artistic communities in the U.S., Japan, and China reveals diverging perceptions of AI's legitimacy and value in creative expression. While American participants were more willing to embrace AI as an experimental partner, Japanese respondents often stressed the importance of human craftsmanship and authenticity, and Chinese artists expressed concerns over censorship and data training ethics [16].

Lastly, a systematic review by Heigl [9] and a complementary analysis by Heigl [9] suggest that while Generative AI offers rich opportunities for co-creativity, ideation, and personalization, it simultaneously risks reinforcing dominant aesthetic norms due to training data limitations. These works call for further research into inclusive design, algorithmic transparency, and hybrid human-AI creativity models.

Together, these studies portray a rapidly shifting creative landscape—one where Generative AI holds the promise of augmenting imagination and expression, yet also poses existential questions about authorship, originality, and labor. As the creative industries move forward, the key lies not only in technological adoption, but also in ethical governance, cultural sensitivity, and interdisciplinary collaboration.

2.5 Theoretical Foundation: Unified Theory of Acceptance and Use of Technology (UTAUT)

In the early 19th century, economists began to investigate the relationships between consumers' intentions to use products, their behaviors, and related influencing factors. In 1985, Davis developed the first comprehensive acceptance model, which later evolved into the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT).

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. [3], aims to explain and predict users' acceptance of new technologies. UTAUT integrates eight different models of technology acceptance and behavioral theories, including the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). UTAUT proposes four core constructs—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—along with four moderators: Gender, Age, Experience, and Voluntariness of Use. These factors collectively explain behavioral intention and actual technology usage.

Performance expectancy refers to the degree to which users believe that technology will improve their job performance and is considered the most significant predictor of behavioral intention. Effort expectancy relates to the perceived ease of use; technologies that are easier to use are more likely to be adopted. Social influence measures the extent to which users perceive that important others believe they should use the technology. Facilitating conditions reflect users' perceptions of the availability of resources and infrastructure to support technology use, which has a direct effect on actual usage. Empirical research shows that UTAUT explains up to 70% of variance in behavioral intention and about 50% in actual use across different contexts.

Recent empirical studies have extended UTAUT to examine the adoption of emerging technologies such as Generative AI. For example, a 2024 study applying UTAUT to Korean enterprises revealed that effort expectancy and social influence significantly influenced behavioral intention to adopt Generative AI systems, whereas performance expectancy and facilitating conditions showed no significant impact [20]. This suggests that in the early stages of adoption, ease of use and social encouragement may outweigh perceived performance gains or infrastructural readiness. Moreover, the study identified moderating effects of age and work experience, highlighting the necessity of tailored AI adoption strategies across employee demographics [20].

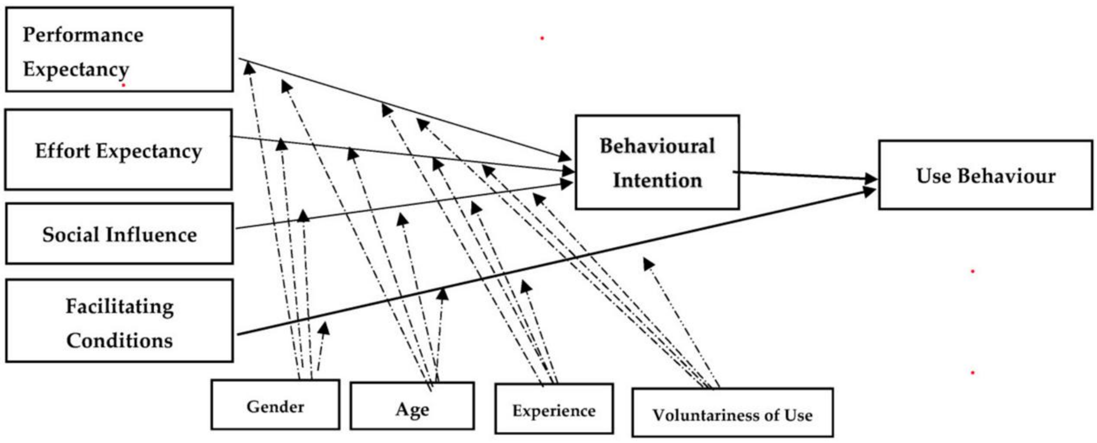

Figure 1. The Unified Theory of Acceptance and Use of Technology (UTAUT) Framework
Source: Adapted from Venkatesh et al. (2003)

Table 1. Representative UTAUT-Based Studies on Generative AI Acceptance

Author(s)	Year	Title
Kim, Y., Blazquez, V., & Oh, T.	2024	Determinants of Generative AI System Adoption and Usage Behavior in Korean Companies: Applying the UTAUT Model
Wang, Zheng, & Wang	2024	Exploring Factors Influencing Artists' Adoption of Generative AI Using the UTAUT Model
Chang	2022	Factors Affecting the Intention to Use AI-Generated Image Software
Lin	2023	Examining Employees' Acceptance of Generative AI with the UTAUT Framework
Yen	2024	Attitude Survey on AI Generation Tools among Digital Media Students and Workers
Chu	2023	A Study on Teachers' Use of Generative AI Systems Based on the Technology Acceptance Model

Source: By author.

2.6 Summary

The UTAUT model provides a comprehensive theoretical foundation for examining technology acceptance in various domains, including creative industries. It highlights the importance of performance benefits, usability, social influence, and supporting conditions in shaping users' intentions and behaviors regarding new technologies. Numerous studies have applied UTAUT to the adoption of Generative AI among creative professionals, providing empirical evidence and analytical frameworks for this study.

3. Research Design

3.1 Research Framework

This study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT). The primary independent variables include performance expectancy, effort expectancy, and facilitating conditions, while the main dependent variable is behavioral intention to use Generative AI tools. The research model examines whether these core factors influence photographers' intention and subsequent behavior regarding the adoption of Generative AI tools.

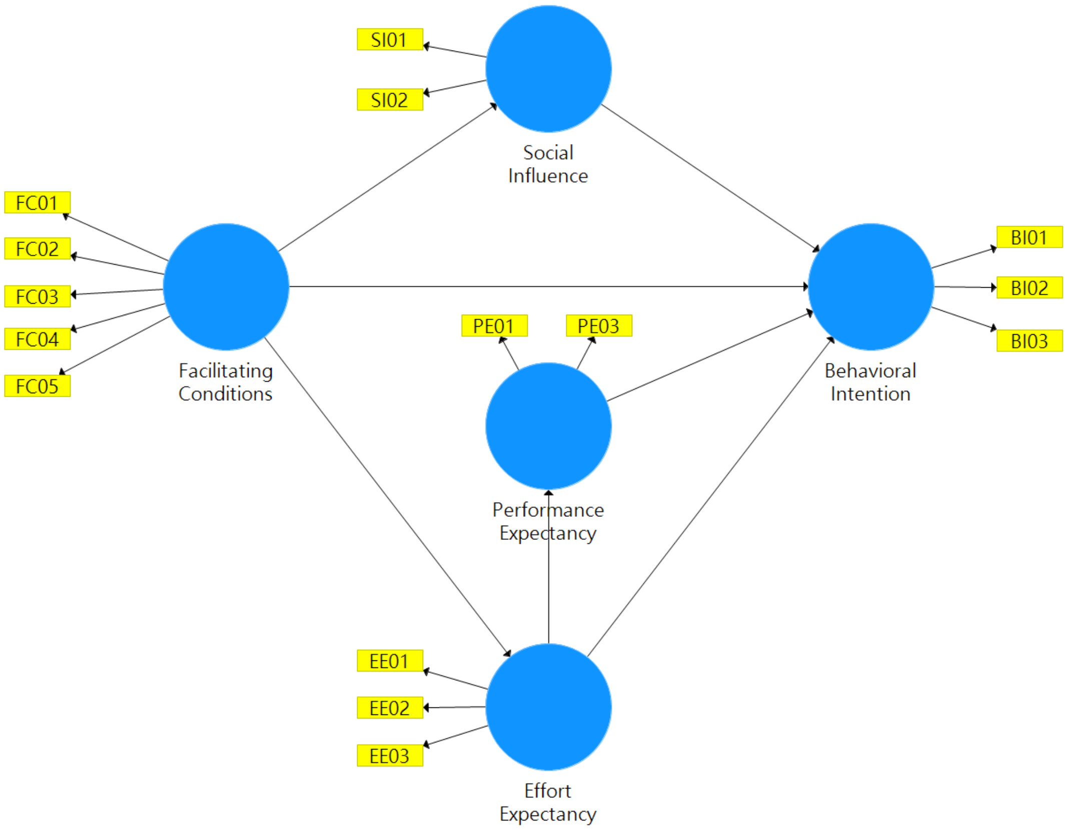

Figure 2. Research Framework
Source: By author.

3.2 Research Hypotheses

Based on empirical and theoretical analysis, this study establishes and tests a set of hypotheses to clarify the relationships among the main constructs in the research model. The following hypotheses are proposed:

- H1: Facilitating conditions have a positive effect on behavioral intention.
- H2: Facilitating conditions have a positive effect on effort expectancy.
- H3: Facilitating conditions have a positive effect on social influence.
- H4: Effort expectancy has a positive effect on performance expectancy.
- H5: Performance expectancy has a positive effect on behavioral intention.
- H6: Social influence has a positive effect on behavioral intention.
- H7: Effort expectancy has a positive effect on behavioral intention.

3.3 Analytical Tool: SmartPLS

To test the structural equation model (SEM), this study employed SmartPLS 4 software to conduct Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis [21]. Compared to covariance-based SEM (such as AMOS), PLS-SEM is more suitable for studies with smaller sample sizes and complex models, offering stronger predictive capabilities and greater flexibility in model validation [21][22].

The reliability and validity of the reflective measurement models were evaluated through indicators such as outer loadings, composite reliability (CR), and average variance extracted (AVE) [23][24][25]. Discriminant validity was further confirmed using the Fornell-Larcker criterion and the HTMT ratio [26]. For the structural model, the relationships among latent variables were assessed by examining path coefficients, t-values, and p-values to test the hypotheses [26][27]. Bootstrap analysis was performed to examine mediation and total effects, thereby enhancing the statistical robustness of the model [21].

Model fit was evaluated using the standardized root mean square residual (SRMR), a widely used index of model adequacy. Following Hu and Bentler’s (1999) recommendations, an SRMR value of 0.08 or lower was considered indicative of good model fit [28]. The application of SmartPLS facilitates not only the validation of the UTAUT framework in the context of Generative AI adoption, but also clearly demonstrates the direct and indirect effects among constructs [21].

3.4 Research Questions

This study aims to explore the adoption of Generative AI technologies in the field of photography using the UTAUT framework. To focus on the research objectives, two primary research questions are formulated:

1. What are the key factors influencing photographers’ intention to use Generative AI tools?
2. Does the UTAUT model reveal any mediating mechanisms that indirectly enhance or suppress the effects of these constructs on behavioral intention?

4. Results and Discussion

4.1 Descriptive Statistics

A total of 97 valid responses were collected via the online survey, targeting photographers with experience using Generative AI tools. The demographic analysis indicates that the majority of respondents were between 22 and 39 years old, with a higher proportion of male participants (approximately 60%) compared to females (about 40%). Most participants had backgrounds in communication and media or design and visual arts, accounting for 34.18% and 18.99% of the sample, respectively.

4.2 Reliability and Validity Analysis

Standardized path coefficients (β) and significance levels (p-values) are displayed for each relationship. Only significant paths are represented by solid lines. The measurement and structural model validity are supported by established criteria [29].

The measurement model was evaluated using SmartPLS 4 to ensure the reliability and validity of each construct. As shown in Table 2, all indicator outer loadings exceeded 0.70, except BI03 (0.66), indicating good indicator reliability. Cronbach's α and composite reliability (CR) values for each construct were above 0.7, and average variance extracted (AVE) values exceeded 0.5, demonstrating sound internal consistency and convergent validity.

Table 2. Summary of Reliability and Convergent Validity Coefficients (n = 97)

Variable	Item	Factor Loading	Cronbach's α	Composite Reliability (ρA)	Composite Reliability (ρc)	Average Variance Extracted (AVE)
Behavioral Intention	BI01	0.80	0.677	0.714	0.817	0.60
	BI02	0.85				
	BI03	0.66				
Effort Expectancy	EE01	0.90	0.791	0.81	0.877	0.705
	EE02	0.83				
	EE03	0.79				
Facilitating Conditions	FC01	0.87	0.846	0.855	0.891	0.622
	FC02	0.86				
	FC03	0.72				
	FC04	0.73				
	FC05	0.74				

Performance Expectancy	PE01	0.91	0.756	0.76	0.891	0.804
	PE02	0.89				
Social Influence	SI01	0.90	0.784	0.785	0.903	0.823
	SI02	0.91				

Source: By author.

Discriminant validity was assessed using the Fornell-Larcker criterion and the HTMT ratio. For all constructs, the square root of the AVE exceeded the inter-construct correlations, and all HTMT values were below 0.9, confirming satisfactory discriminant validity. [30][31]

Table 3. Fornell-Larcker Criterion Coefficient Summary (n = 97)

	BI	EE	FC	PE	SI
BI	0.775				
EE	0.438	0.84			
FC	0.45	0.674	0.789		
PE	0.544	0.481	0.531	0.896	
SI	0.669	0.565	0.569	0.499	0.907

Source: By author.

The reliability and convergent validity of each construct were assessed using Cronbach's alpha [25], composite reliability (CR), and average variance extracted (AVE). As shown in Table 3, all outer loadings exceeded 0.7, Cronbach's alpha and CR values were above 0.7, and AVE values were above 0.5, indicating mostly satisfactory reliability and convergent validity. Most constructs showed Cronbach's α and composite reliability (CR) > .70; the BI construct's α was .677, though ρA and CR met the recommended thresholds, so overall internal consistency is acceptable.

Table 4. Discriminant Validity: HTMT Ratio (n = 97)

	BI	EE	FC	PE	SI
BI					
EE	0.58				
FC	0.57	0.82			
PE	0.69	0.61	0.66		
SI	0.90	0.72	0.70	0.65	

Note: HTMT ratios (< 0.90 indicate adequate discriminant validity).

Source: By author.

Discriminant validity was evaluated using the Fornell-Larcker criterion. As presented in Table

4, the square root of the AVE for each construct exceeded its correlations with other constructs, confirming adequate discriminant validity within the measurement model. [30]

4.3 Structural Equation Model and Hypothesis Testing

Partial Least Squares Structural Equation Modeling (PLS-SEM) was performed using SmartPLS 4 to test the direct and indirect effects of UTAUT constructs on behavioral intention. The results are summarized in Table 5.

- Performance expectancy exhibited a significant positive effect on behavioral intention ($\beta = 0.279$, $p = 0.023$), supporting H5.
- Social influence also had a strong positive effect ($\beta = 0.528$, $p < 0.001$), supporting H6.
- Effort expectancy ($\beta = 0.009$, $p = 0.945$) and facilitating conditions ($\beta = -0.004$, $p = 0.976$) did not show significant direct effects on behavioral intention, thus H1 and H7 were not supported.
- Facilitating conditions significantly influenced both effort expectancy ($\beta = 0.674$, $p < 0.001$; H2) and social influence ($\beta = 0.569$, $p < 0.001$; H3).
- Effort expectancy significantly affected performance expectancy ($\beta = 0.481$, $p < 0.001$; H4).

The explanatory power for behavioral intention was moderate, with an R^2 value of 0.507. The SRMR =0.081, which is within the ≤ 0.10 threshold commonly considered acceptable for PLS-SEM (Hair et al., 2022).

Table 5. Path Coefficients and Hypothesis Testing Results

Hypothesis	Path	β	*p*-value	Supported
H1	FC → BI	-0.004	0.976	No
H2	FC → EE	0.674	<0.001	Yes
H3	FC → SI	0.569	<0.001	Yes
H4	EE → PE	0.481	<0.001	Yes
H5	PE → BI	0.279	0.023	Yes
H6	SI → BI	0.528	<0.001	Yes
H7	EE → BI	0.009	0.945	No

Note: FC = Facilitating Conditions; EE = Effort Expectancy; SI = Social Influence; PE = Performance Expectancy; BI = Behavioral Intention.
Source: By author.

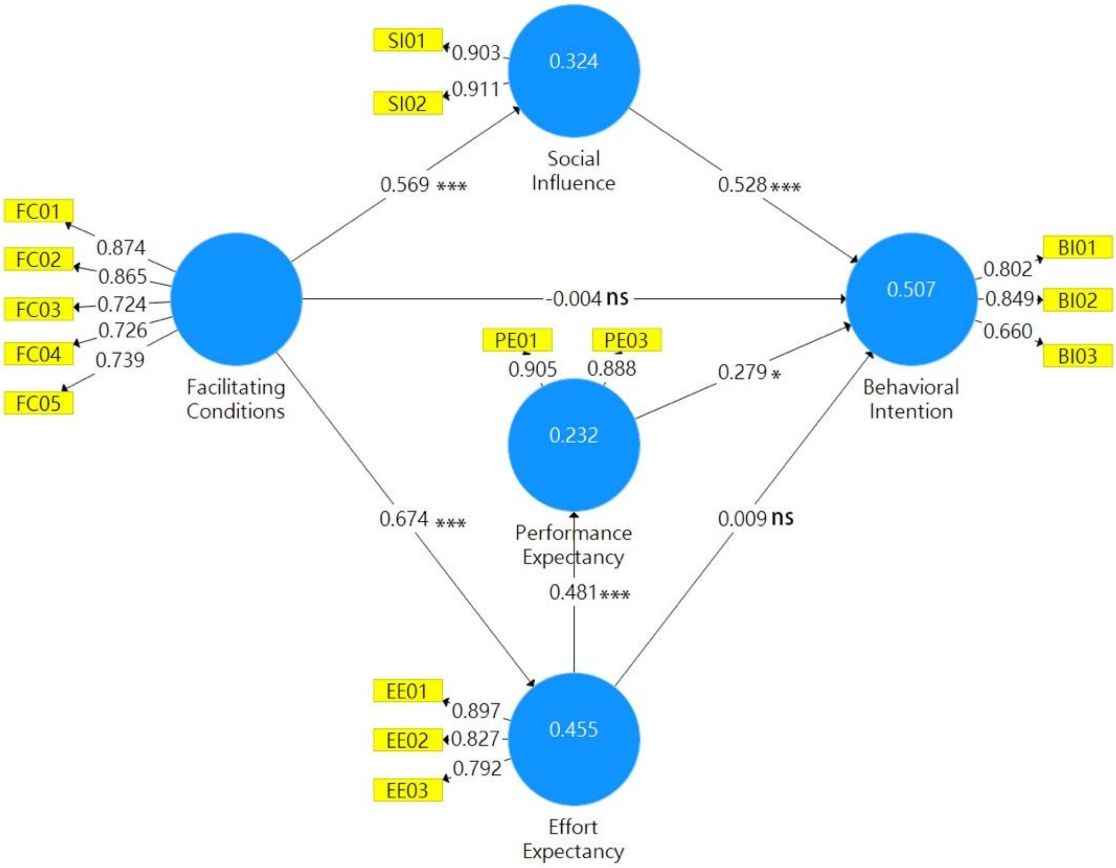

Figure 3. The Validated Structural Model of the Study

Source: By author.

4.4 Mediation Analysis

Mediation effects were examined using bootstrapping analysis in SmartPLS. Although facilitating conditions did not have a significant direct effect on behavioral intention, it exerted significant indirect effects through social influence ($\beta = 0.300$, $p < 0.001$) and through the serial pathway of effort expectancy and performance expectancy ($\beta = 0.324$, $p < 0.001$). Effort expectancy also demonstrated an indirect effect on behavioral intention via performance expectancy ($\beta = 0.134$, $p = 0.040$). These findings underscore the importance of indirect mechanisms, where resource support and operational ease enhance perceived effectiveness and social approval, thereby strengthening behavioral intention.

4.5 Discussion

This study provides important empirical evidence on the adoption of Generative AI among photographers, leveraging the Unified Theory of Acceptance and Use of Technology (UTAUT) as a theoretical framework. The findings not only confirm core UTAUT predictions but also offer unique insights into technology acceptance in creative industries, particularly within the context of rapidly evolving AI tools.

4.5.1 Performance-driven adoption in creative workflows

Consistent with the UTAUT model, performance expectancy emerged as a significant driver of behavioral intention. Photographers who perceived Generative AI tools as beneficial for improving creative efficiency, output quality, or market competitiveness demonstrated a markedly higher willingness to use such tools. This performance-oriented mindset reflects the demands of the photography industry, where visibility of results and speed of response are crucial for professional success. The ability of AI to accelerate post-production, automate routine tasks, and provide new creative possibilities reinforces its perceived value among practitioners.

4.5.2 The critical role of social influence and community dynamics

Social influence was identified as the strongest direct predictor of behavioral intention, highlighting the importance of professional communities and peer validation in technology diffusion. Positive recommendations and visible adoption of AI tools by key opinion leaders, peer groups, or influential figures create a ripple effect, accelerating wider acceptance. This finding resonates with the decentralized consensus mechanism often observed in creative fields, where community-driven trends can rapidly shape norms and best practices.

4.5.3 Effort expectancy and the "low-barrier" technology phenomenon

Unlike traditional UTAUT findings, effort expectancy did not significantly predict behavioral intention in this context. This can be attributed to the high usability of mainstream Generative AI tools (e.g., Midjourney, Canva AI), which feature intuitive graphical interfaces and require minimal technical expertise. As a result, the perceived ease of use has become an implicit baseline—a "satisficed" or "taken-for-granted" condition—rather than a differentiating factor in technology adoption decisions. This suggests that, in scenarios where usability is nearly universal, its predictive power for intention is diminished.

4.5.4 Facilitating conditions as indirect enablers

Although facilitating conditions did not directly affect behavioral intention, their impact was significant through indirect paths, specifically via effort expectancy and social influence. Resource support, training accessibility, and system reliability foster greater confidence, positive expectations, and enhanced community identity, thus indirectly encouraging adoption. This underscores the importance of maintaining robust support infrastructure, even when tools are easy to use.

4.5.5 Professional identity, creative control, and ai anxiety

Beyond the structural model, the results highlight the psychological complexities unique to creative professionals. Many photographers' acceptance or resistance to Generative AI is not merely a matter of functional benefit, but also relates to deeper concerns about authorship, creative control, and professional identity. The blurred lines between human and AI-generated content can provoke anxiety regarding originality and role displacement, as discussed by Guzman and Lewis (2024). Addressing these concerns requires ongoing emphasis on the collaborative nature of AI—as a creative assistant rather than a replacement—and supporting photographers in maintaining ownership and control over their creative processes.

4.5.6 Cultural and contextual considerations

The findings further illustrate how local professional cultures and digital literacy influence technology acceptance. The study's sample, largely drawn from digitally savvy and community-oriented photographers in Taiwan, may have contributed to the high baseline for effort expectancy and the pronounced role of social influence. For international generalization, it is necessary to account for industry-specific, regional, or cultural differences in both tool accessibility and community structure.

4.5.7 Implications for practice and future research

For practitioners and developers, these findings suggest that successful promotion of Generative AI in photography should focus not only on showcasing practical benefits but also on fostering positive community narratives and role models. Training, case sharing, and peer-driven learning environments can further facilitate acceptance.

For researchers, the study highlights the value of extending technology acceptance models to include creative satisfaction, self-efficacy, and anxiety about technological replacement. Future research could benefit from longitudinal designs, cross-industry comparisons, and mixed-methods approaches to capture the evolving and multi-faceted nature of AI adoption in creative professions.

In summary, this study demonstrates that, while core UTAUT constructs remain relevant, the psychological, cultural, and community factors play an increasingly prominent role in technology acceptance within creative domains. The performance benefits of AI, the influence of professional networks, and nuanced attitudes toward creative control and authorship must all be considered for a comprehensive understanding of Generative AI adoption among photographers.

5. Conclusions

5.1 Main Findings

This study investigated the application of Generative AI among photographers, utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical foundation. By integrating the constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions, the study analyzed their influence on behavioral intention to adopt Generative AI tools. Data were collected through a questionnaire survey of 97 photographers with experience using Generative AI imaging software and analyzed using SmartPLS 4.

The main findings are as follows:

- Performance expectancy and social influence were identified as the most significant factors directly affecting photographers' intention to use Generative AI tools. When photographers perceived that Generative AI could enhance creative efficiency and professional performance, or when they received positive opinions from peers and professional communities, their willingness to adopt the technology increased substantially.
- Effort expectancy and facilitating conditions did not have significant direct effects on behavioral intention. However, facilitating conditions positively influenced both effort expectancy and social influence, while effort expectancy further enhanced performance expectancy. This indicates that resource availability and operational support play important intermediary roles in shaping positive attitudes toward AI adoption.

- The structural model demonstrated moderate explanatory power ($R^2 = 0.507$) and satisfactory fit (SRMR = 0.081. While slightly above the 0.08 'good' threshold (Hu & Bentler, 1999), it remains within the ≤ 0.10 range commonly considered acceptable for PLS-SEM applications [21].

5.2 Theoretical and Practical Implications

5.2.1 Theoretical implications

The findings highlight that the drivers of technology adoption among creative professionals differ from those in other industries. For photographers, the perceived performance benefits and peer influence are particularly crucial. The results support the extension of UTAUT into creative fields and suggest that the relative ease of use and resource availability become less influential when Generative AI tools are intuitive and highly accessible.

5.2.2 Practical implications

- Promoting Success Stories and Community Influence: Given the significant role of social influence, it is recommended that AI tool developers and photography educators leverage professional communities, opinion leaders, and social media platforms to share positive use cases and encourage technology diffusion.
- Enhancing Training and Resource Accessibility: Although effort expectancy was not a direct predictor, providing practical tutorials, hands-on workshops, and user support can reduce uncertainties and resistance, fostering a positive attitude toward adoption.
- Clarifying the Collaborative Role of AI: To alleviate concerns about replacement or devaluation, stakeholders should emphasize the role of AI as a creative assistant rather than a threat to professional identity.

5.3 Research Limitations

This study, while offering important empirical insights, is subject to several limitations:

5.3.1 Sampling bias:

The use of convenience sampling via online communities resulted in a sample predominantly drawn from photographers located in northern Taiwan with relatively high levels of digital literacy. This sampling approach may restrict the generalizability of the findings to the broader population of photographers, particularly those in different regions or with less technological experience.

5.3.2 Lack of strict occupational screening:

Although participants were required to have experience using Generative AI tools, the study did not rigorously control for variables such as years of professional experience, area of specialization, or employment status. As a result, the sample was heterogeneous, which may dilute the explanatory power of certain constructs and limit the interpretability of subgroup differences.

5.3.3 Self-reported data and social desirability bias:

All data were collected using self-administered questionnaires, which are inherently subject to social desirability bias and subjective reporting. Respondents may have overstated their positive attitudes or willingness to adopt AI tools, leading to more optimistic results than would be observed in actual professional practice.

5.3.4 Temporal limitation and rapid technological change:

The research was conducted during the fourth quarter of 2024. Given the fast-paced evolution of Generative AI technologies and adoption trends, the findings may only reflect attitudes and practices at a specific moment in time, thus limiting the long-term applicability of the conclusions.

5.3.5 Ceiling effects in effort expectancy:

The study observed low variance in effort expectancy, likely because mainstream Generative AI tools are widely regarded as highly user-friendly. This ceiling effect may have reduced the predictive power of effort expectancy within the model, especially in contexts where ease of use is considered an industry standard.

In light of these limitations, future research is encouraged to utilize more diverse and representative samples, adopt stratified or purposive sampling methods, employ mixed-methods or longitudinal designs, and remain attentive to the ongoing development of AI technologies within creative industries.

5.4 Directions for Future Research

Building on the findings and limitations of this study, several recommendations are proposed for future research and practical application:

5.4.1 Stratified sampling and occupational differentiation:

Future studies should employ stratified sampling strategies and clearly define subgroups within the photography profession (e.g., commercial, artistic, event, or news photographers). This would enhance the external validity of findings and allow for comparative analysis of technology acceptance

5.4.2 Processes across different professional roles.

Extension of the Theoretical Model:It is recommended that future research incorporates additional psychological constructs—such as creative satisfaction, professional self-efficacy, and anxiety about technological replacement—into the technology acceptance framework. This would enrich the explanation of behavioral intention formation, particularly in creative industries where identity and

5.4.3 Job security are salient concerns.

Mixed-Methods and Qualitative Approaches:Combining quantitative surveys with qualitative methods, such as in-depth interviews, focus groups, or case studies, can provide deeper insights into photographers' emotional responses, creative challenges, and shifting perceptions of AI in practice. Such approaches would supplement the narrative depth that cannot be fully captured by self-administered questionnaires.

5.4.4 Longitudinal and cross-industry comparisons:

Longitudinal research designs are encouraged to observe changes in attitudes and behaviors toward Generative AI over time, tracking the integration of technology throughout different phases of professional adaptation. Additionally, comparative studies across creative domains—such as illustration, graphic design, and video editing—can help identify both universal and domain-specific factors influencing AI adoption.

5.4.5 Emphasizing training, community influence, and practical support:

Practitioners, tool developers, and educators should focus on providing hands-on training, sharing successful use cases, and fostering community engagement to reduce uncertainty and resistance among photographers. Leveraging the influence of professional communities, key opinion leaders, and peer networks can significantly promote the diffusion and positive perception of Generative AI technologies.

5.4.6 Clarifying the collaborative role of ai:

To address potential concerns about professional replacement or devaluation, it is important to position AI tools as creative assistants rather than threats to professional identity. Industry and educational stakeholders should emphasize the complementary nature of AI—highlighting its role in supporting inspiration, efficiency, and creative exploration—thereby guiding professionals to embrace technology proactively.

By addressing these directions, future research can provide a more nuanced and comprehensive understanding of Generative AI adoption among photographers and offer actionable strategies for industry and education stakeholders to support sustainable and confident technology integration.

5.5 Concluding Remarks and Future Research

This study provides a comprehensive examination of the factors influencing photographers' intention to adopt Generative AI tools, grounded in the UTAUT framework. The findings confirm that performance expectancy and social influence are the most influential determinants of behavioral intention, emphasizing that perceived creative utility and peer validation play critical roles in shaping adoption behavior among creative professionals. Although effort expectancy and facilitating conditions do not directly predict usage intention, their significant indirect effects suggest that usability and environmental support still matter—primarily by enhancing perceived performance and reinforcing social norms.

The results also highlight that acceptance of Generative AI is not merely a function of technical capability or interface simplicity; instead, it is deeply intertwined with users' creative identities, sense of authorship, and professional positioning. Notably, some users, despite perceiving tools as easy to operate, remain hesitant to adopt them due to concerns over the dilution of their artistic style or the ambiguity of their professional role—echoing concerns raised in [19] about the psychological tensions AI introduces in creative workflows.

Looking ahead, future research should further explore these sociopsychological dimensions through qualitative and longitudinal designs, enabling a deeper understanding of how attitudes evolve over time and differ across creative disciplines. Comparative studies across visual fields—such as photography, illustration, animation, and design—could uncover shared adoption patterns and context-specific challenges. Additionally, incorporating variables such as creative autonomy, originality anxiety, and perceived control will help refine existing acceptance models to better reflect the realities of creative work in an AI-augmented environment. Through this integrated approach, future research can better inform the responsible and empowering implementation of Generative AI in the creative industries.

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Conflicts of Interest

The author confirms that there are no conflicts of interest.

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