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FROM INTENTION TO USE: EXPLAINING AI TOOL ADOPTION AND USAGE AMONG DESIGNERS

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ABSTRACT

This study investigates the determinants of artificial intelligence (AI) tool adoption among professional designers using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as the guiding theoretical framework. As AI increasingly reshapes creative industries, understanding the factors that drive designers' intention to adopt and actual use of AI tools has become both theoretically and managerially relevant. Data were collected through a cross-sectional survey administered to 170 professional designers, including graphic, UI/UX, and product designers. The proposed research model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that performance expectancy, effort expectancy, social influence, hedonic motivation, and price value have significant positive effects on designers' behavioral intention to adopt AI tools. In contrast, facilitating conditions do not significantly influence behavioral intention but exert a strong positive effect on actual use behavior. Habit and behavioral intention also significantly predict use behavior, with habit emerging as the strongest determinant of sustained usage. The model explains a substantial proportion of variance in both behavioral intention and use behavior, confirming the strong predictive power of the UTAUT2 model in a creative professional context. This study contributes to the growing literature on AI adoption by extending UTAUT2 to the design industry and highlighting the joint role of utilitarian, hedonic, and habitual factors. Managerially, the findings provide actionable insights for AI tool developers and design organizations seeking to foster effective and sustained AI adoption.

KEYWORDS: *Artificial Intelligence, UTAUT2, Technology Adoption, Designers, Use Behavior*

1. INTRODUCTION

The rise of artificial intelligence (AI) tools in creative industries signals a notable transformation within these sectors, particularly among designers and marketing professionals. This change has been driven by a need for greater efficiency in design processes, a shift in value creation paradigms, and an enhanced focus on optimizing customer experience. As the landscape continues to evolve, the integration of AI technologies stands to redefine the dynamics of creative industries. From value creation perspectives, AI technologies have shifted traditional paradigms where value was primarily embedded within products or services. Instead, there is increasing recognition that value co-creation involves active consumer participation at various stages of engagement with brands. Santos and Gonçalves (2021) describe how consumer interactions with AI tools at different stages of their journey can fundamentally alter how companies approach design and service delivery. AI-driven analytics can help designers and marketers identify and predict customer needs more accurately, enabling a more tailored approach to value propositions that resonate with consumers (Chintalapati & Pandey, 2021). This shift signifies a movement away from one-dimensional product offerings toward more complex, interactive experiences that consider consumer insights as integral components of the creation process.

Moreover, the introduction of AI has significantly transformed customer experience (CX) management, particularly concerning personalization and responsiveness. Liu–Thompkins et al. (2022) highlight that AI applications, such as chatbots, not only automate routine tasks but can also foster deeper engagement through personalized responses, thus enhancing consumer satisfaction and loyalty. This evolving capability allows designers to create more engaging and relevant interfaces that cater to user preferences, leading to a more satisfying overall experience (Hollebeek et al., 2019). As AI learns from customer interactions, it feeds insights back into design processes, creating a feedback loop that continuously improves the products and services offered (Keegan et al., 2022). Increased productivity among designers is another critical aspect of the rising influence of AI tools in creative industries. AI has streamlined many repetitive tasks associated with design, allowing designers to focus on more strategic and creative aspects of their work. This aligns with the findings of Barnes and Ruyter (2022), who discuss how AI is not just about task automation but also about enriching core marketing functions. Similarly, Rizomyliotis et al., (2022) underscore the role of AI in enhancing operational efficiency within businesses, particularly small and medium-sized enterprises (SMEs) implementing AI-centric solutions. The automation capabilities of AI lead to reduced costs and improved output levels, ultimately fostering a culture of innovation and faster project turnaround times (Akter et al., 2021).

The research gap concerning the adoption behavior of AI tools among designers is substantial and multifaceted, specifically in the context of the creative industries. Despite the rising significance and integration of AI technologies in marketing and design, there remains a limited empirical understanding of how designers embrace and utilize these tools in their work processes. This gap affects the broader comprehension of not just technology adoption but also its implications for creativity, efficiency, and the evolution of design practices.

Firstly, while there is a growing body of literature focusing on the utilization of AI in various sectors, including marketing and industrial applications, the specifics regarding designers' adoption behavior of AI tools are rarely at the forefront. For example, studies like those by Keegan et al. (2022) shed light on the overarching impact of AI on B2B marketing but do not delve into the particular nuances of designers' relationships with these technologies. There is a clear need for research that targets the unique interaction between designers and AI, looking at factors such as resistance, facilitation, and the decision-making processes involved in adopting AI (Davenport et al., 2019).

Moreover, the recognition that AI can reshape practices and outcomes in design leads to an essential inquiry into the cognitive and psychological dimensions that influence acceptance and utilization. As highlighted by Liu–Thompkins et al. (2022), existing research predominantly examines cognitive responses to AI tools in marketing contexts, with less emphasis on the emotive and personality-driven aspects that may inform designers' openness to adopting such technologies. This highlights a crucial layer of the adoption narrative and the human factors involved in technology acceptance that remains underexplored in the context of design. Furthermore, while discussions surrounding customer experience and value co-creation involving AI applications are prevalent according to Li et al. (2021), they often overlook the designers' internal processes that mediate these external interactions. The interplay between AI and the design workflow affects not only the output but also informs creative ideation and problem-solving abilities. Current studies like those by Hati et al. (2024) discuss broader aspects of luxury consumption but do not focus directly on the implications of AI for designers, indicating there is still a gap in examining how these technologies could transform the designer's role, methods, and overall productivity.

Finally, the exploration of community-based influences on AI adoption in design is noticeably sparse. Social dynamics, as articulated by Paul et al. (2023), suggest that understanding peer influences, industry standards, and organizational culture may play a pivotal role in how designers embrace AI tools. However, no extensive empirical studies directly address these social and contextual factors in the adoption landscape within the creative sectors.

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model is well-suited for examining technology acceptance in consumer and creative contexts due to its comprehensive framework that integrates social, psychological, and contextual factors influencing technology adoption. Unlike earlier models, UTAUT2 adds constructs such as hedonic motivation and price value, making it particularly relevant for understanding behaviors related to innovative technologies in creative industries, where emotional engagement and perceived value significantly impact adoption decisions.

The research objectives centered on employing UTAUT2 in this context include: (1) Investigating the specific factors influencing designers' intentions to adopt AI tools, thus enriching the existing literature on technology acceptance; (2) Analyzing the interaction effects of social influence and facilitating conditions on designers' behavior towards AI integration; and (3) Identifying barriers to adoption and understanding how hedonic factors may motivate or inhibit acceptance within creative processes.

From a theoretical standpoint, this research contributes to the UTAUT2 framework by contextualizing it in the unique environment of creative industries, identifying novel antecedents of technology acceptance that intersect with creativity and design challenges. Managerially, it provides actionable insights for organizations seeking to implement AI tools effectively by highlighting factors that enhance adoption among designers. By understanding these dynamics, creative firms can facilitate better training programs and support systems that align with designers' motivations and values, ultimately improving design innovation and productivity.

2. LITERATURE REVIEW

The advent of artificial intelligence (AI) tools has significantly transformed creative industries, introducing various mechanisms to enhance ideation and execution processes. In understanding AI's role, we can categorize the tools into three primary types: generative AI, ideation assistants, and automation tools. Generative AI consists of systems capable of producing novel content, such as images, texts, and even music, based on large datasets. For example, tools like OpenAI's GPT model can analyze vast amounts of textual data to generate contextually relevant narratives (Nasr & El-Deeb, 2025). These tools offer significant potential for creativity, allowing designers to explore innovative ideas and save time in content generation. In contrast, ideation assistants assist in the brainstorming process by leveraging algorithms to suggest new ideas based on user input and existing trends (Klarin, 2024). Such tools not only facilitate creativity but also enhance collaboration among team members. Lastly, automation tools handle repetitive tasks, enabling professionals to focus on more strategic and creative aspects of their work (Miceli et al., 2020). By automating functions like scheduling, formatting, or feedback collection, these tools can substantially increase operational efficiency, allowing for a more fluid creative workflow.

Despite the clear benefits, the adoption of AI tools in creative work is not without challenges. Many professionals encounter a significant skills gap, as there remains a necessity for training to effectively utilize these new technologies (Pagani & Wind, 2024). Creatives often possess varying levels of comfort and competence with digital tools, leading to inconsistencies in AI integration across teams. The issue of autonomy also arises when designers face the risk of diminished creative control, as the use of AI can lead to a reliance on machine-generated suggestions, potentially undermining the intrinsic value of human creativity (Brown et al., 2020). Furthermore, uncertainty regarding the accuracy and appropriateness of AI-generated content can hinder adoption, raising questions about the designer's role in curating and approving outputs. Ethical issues further complicate the landscape; the potential for bias in AI algorithms and the implications of using AI for creative tasks prompt critical discussions regarding the integrity and authenticity of creative work. These challenges underscore the need for thoughtful engagement with AI tools in creative contexts, ensuring that while technological advancements are embraced, the fundamental human elements of creativity and ethical considerations are prioritized.

The study of technology adoption has been greatly informed by several foundational theories, each offering unique insights into decision-making processes regarding the acceptance and use of new technologies. The Technology Acceptance Model (TAM), developed by Davis in 1989, posits that perceived usefulness and perceived ease of use significantly influence users' behavioral intentions towards the adoption of technology (Qasem, 2021). TAM has been widely applied across various fields to examine user acceptance, but it has been critiqued for its limited scope, primarily focusing on individual usage without considering societal or contextual factors. The Theory of Planned Behavior (TPB), introduced by Ajzen (1991), expands on the principles of TAM by integrating subjective norms and perceived behavioral control into the analysis of intention and behavior, allowing for a more comprehensive understanding of the social factors affecting technology adoption (Mero et al., 2020). On the other hand, the Diffusion of Innovations (DoI) theory, proposed by Rogers, emphasizes the relevance of individual innovation characteristics such as relative advantage, compatibility, complexity, trialability, and observability, describing how new technologies spread within social systems (Sankaran & Chakraborty, 2020). While these theories have laid the groundwork for understanding technology adoption, they often fail to capture the complexities within specific professional contexts, particularly in creative industries.

Given the limitations of these theories, UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) emerges as a highly relevant framework, particularly in professional and design contexts. UTAUT2 builds upon its predecessor, UTAUT, by integrating additional constructs such as hedonic motivation, price value, and habit, which are critical for understanding consumer behavior and technology use in today's digital landscape (Dobre et al., 2023). This model has been validated across various settings, demonstrating its versatility and applicability. The inclusion of hedonic motivation allows for the exploration of intrinsic factors that drive acceptance, particularly relevant in creative industries where emotional engagement and enjoyment significantly enhance user experience (Foroughi et al., 2024). Additionally, UTAUT2 emphasizes the importance of social influence and facilitating conditions, both pivotal in the collaborative environments typically found in design workflows (Mohammed et al., 2025). By choosing UTAUT2, researchers can better assess the multifaceted landscape of technology adoption, addressing both extrinsic motivators and personal enjoyment factors that influence designers' acceptance of AI tools, ultimately guiding organizations to develop effective strategies for technology integration and personnel training (Sharma et al., 2024).

Performance Expectancy is a central construct within the UTAUT2 model, reflecting users' beliefs about the benefits they can derive from utilizing a specific technology. It is defined as the degree to which an individual perceives that using the technology will enhance their job performance or productivity in achieving tasks (Bailey et al., 2022). The significance of Performance Expectancy has been consistently validated across various domains, as evidenced by research demonstrating its strong influence on users' behavioral intentions towards adopting new technologies. Erjavec and Manfreda (2022) highlighted that, even under conditions of social isolation during COVID-19, Performance Expectancy remained the most significant determinant of behavioral intention in online shopping, reinforcing its central role across diverse scenarios.

Further extending the conversation, Alalwan et al. (2018) examined the adoption of internet banking, identifying Performance Expectancy as a critical factor influencing customers' intentions. Their study echoed findings from multiple other contexts, asserting that the perceived effectiveness and efficiency gained from technology use directly correlated with users' willingness to adopt such innovations. Other studies, such as those investigating consumer acceptance of autonomous vehicle technology, have similarly noted Performance Expectancy as a vital predictor, clearly showing that when users perceive substantial benefits and improvements in performance, they are more inclined to adopt new technologies (Erskine et al., 2020). Overall, the literature consistently supports the notion that Performance Expectancy is integral to technology acceptance, where perceived enhancements in task efficiency and quality stimulate positive attitudes and intentions toward the use of technology.

Effort Expectancy is a pivotal construct within the UTAUT2 model, defined as the degree of ease associated with the use of a particular technology. It reflects users' perceptions regarding the difficulty or simplicity of utilizing the tools available to them, ultimately influencing their acceptance and integration of technology into their workflows (Dobre et al., 2023). Research substantiates that lower perceived effort leads to increased behavioral intentions to use technology. These authors posit that ease of use plays a critical role in information technology acceptance, aligning with the foundational principles of both the Technology Acceptance Model (TAM) and the UTAUT frameworks.

In creative contexts, such as those involving design processes, Effort Expectancy becomes particularly meaningful due to the complexity often associated with design tools and software. For instance, Alalwan et al. (2018) noted that when users perceive technology as difficult to understand or operate, their intention to adopt it diminishes significantly. This is critical for designers, who typically juggle multiple tools and platforms; any added complexity could impede their workflow and discourage technology adoption. Moreover, the interaction between Effort Expectancy and other constructs within the UTAUT2 framework, such as Performance Expectancy and Social Influence, indicates that ease of use can amplify or attenuate other motivational factors driving technology acceptance (Shareef et al., 2017). Additionally, Effort Expectancy influences not only the initial adoption but also the sustained usage of technology. During the COVID-19 pandemic, Erjavec and Manfreda (2022) identified that Effort Expectancy continued to impact online shopping behaviors, suggesting that the perceived ease of navigating digital environments remains crucial even under shifting circumstances. The repeated validation of this construct across various studies highlights its indispensable role in fostering a supportive technological environment that encourages designers to integrate AI tools productively into their creative workflows.

Social Influence is one of the core constructs of the UTAUT2 model, defined as the degree to which individuals perceive that important others (e.g., peers, family members, and colleagues) believe they should use a specific technology (Erskine et al., 2020). This construct emphasizes the significant role that social relationships and networks play in shaping individuals' beliefs and behaviors regarding technology adoption. Research across various domains has validated the relevance of Social Influence, consistently establishing it as a predictor of users' intentions to adopt new technologies. These authors explored consumer acceptance of autonomous vehicle technologies and found that social attitudes significantly impacted behavioral intentions, highlighting the importance of gauging public opinion and peer perceptions in the evaluation of emerging technologies.

In the context of mobile payment adoption, Bailey et al. (2022) underscored that Social Influence shapes individual intentions to adopt technologies, although it may also mediate other constructs like Performance Expectancy and Effort Expectancy. Their findings suggest that consumers are likely to adopt technologies that are socially endorsed, indicating that social validation plays a crucial role in the decision-making process. It is worth noting that while Bailey et al. address Social Influence, they do not emphasize it as a primary factor over others in their study. However, Alalwan et al. (2018) reinforced this concept in their investigation of internet banking adoption among Jordanian customers. Their study indicated that Social Influence did not have a significant impact on behavioral intention when compared to other factors like Performance Expectancy and Effort Expectancy, suggesting that while social factors are important, they may not always take precedence in the adoption process.

Facilitating Conditions is a crucial construct within the UTAUT2 framework, defined as the degree to which individuals perceive that the necessary resources and support are available to use a specific technology effectively (Coker & Thakur, 2023). This construct encompasses various factors, including technical support, access to infrastructure, and the overall environment that enables technology use. Research consistently highlights the importance of Facilitating Conditions in influencing individuals' behavioral intentions toward technology adoption. For example, Dobre et al. (2023) show that the presence of facilitating conditions significantly enhances users' willingness to adopt mobile shopping apps by ensuring that they have the requisite resources—such as stable internet access and adequate support teams—in place.

The relevance of Facilitating Conditions is particularly pronounced in the context of mobile payment adoption. Bailey et al. (2022) explored the influence of contextual elements such as user training and access to technological assistance on the adoption of mobile payment systems in Latin America. Their findings demonstrated that when potential users perceive that sufficient technical support and necessary resources are available, they are more likely to embrace new mobile technologies. This observation is consistent with Roy et al. (2025), who noted that facilitating conditions, like technical support, play a crucial role in retaining users and sustaining loyalty in fitness applications. This suggests that effective facilitating conditions not only bolster initial adoption but also sustain long-term engagement with technology.

Moreover, the interplay between Facilitating Conditions and other UTAUT2 constructs is critical. In their research on mobile payment systems during health crises, Mohammed et al. (2025) found that Facilitating Conditions significantly influenced behavioral intentions, acting as a mediator between performance expectancy and actual usage. Such insights emphasize the integral role of available resources in shaping user experiences and outcomes related to technology adoption, thereby underscoring the need for organizations to create supportive environments to facilitate smooth transitions toward new technologies.

Hedonic Motivation is an integral construct within the UTAUT2 model, defined as the fun or pleasure derived from using technology. This motivation emphasizes intrinsic rewards that users experience when interacting with technological systems, which can significantly influence their intention to adopt and continue using these systems. Research has shown that hedonic motivation impacts user acceptance and enhances overall satisfaction, which is crucial for sustaining long-term engagement with technologies.

Qasem (2021) explored the role of hedonic motivation within the context of E-fashion retailing, revealing that positive aspects of technology, such as enjoyment and playful interactions, positively influenced customers' adoption of try-on technology. This highlights how experiences perceived as enjoyable can transform the adoption landscape, making technologies more attractive to users.

In the area of mobile banking, Baabdullah et al. (2019) illustrated how hedonic motivation interacts with other factors like performance expectancy and facilitating conditions, underscoring its pivotal role in providing a holistic understanding of consumer behavior. Such interactions emphasize that while practical benefits are essential, the experiential and enjoyable aspects of using technology are equally significant in informing adoption behavior.

Furthermore, Tamilmani et al. (2019) conducted a meta-analysis to synthesize existing literature surrounding hedonic motivation within the UTAUT2 framework, concluding that this construct consistently acts as a significant determinant across various technology adoption studies. They suggest that understanding the impact of hedonic motivations can guide organizations in designing user-centric interfaces that promote higher levels of engagement and satisfaction.

Price Value is an essential construct in the UTAUT2 model, defined as the perceived benefits a user derives from a technology relative to its cost. This construct highlights the users' evaluation of the trade-off between costs incurred and the value obtained which significantly influences their behavioral intentions towards technology adoption and continued use. The inclusion of Price Value in the UTAUT2 framework acknowledges that, beyond performance efficacy and user experience, economic considerations play a crucial role in technology acceptance. Research by Foroughi et al. (2024) indicates that the relationship between Price Value and technology adoption is mediated by other constructs in the UTAUT2 model. They found that when users perceived high Price Value, it enhanced the effects of Performance Expectancy and Facilitating Conditions on their behavioral intentions, illuminating how these constructs interact within the technology adoption framework. This interaction highlights the need for organizations to optimize their pricing structures and enhance perceived value to drive technology acceptance effectively.

Habit is a significant construct within the UTAUT2 model, defined as the extent to which individuals have become accustomed to using a technology through frequent usage over time. This construct emphasizes that established behaviors can impact an individual's future intentions toward adopting or continuing the use of a particular technology. Research has shown that Habit influences users' reliance on technology and their behavioral intentions, acting as a strong predictor of continued usage (Baabdullah et al., 2019). These authors demonstrated that in the context of mobile banking, habit plays a pivotal role in shaping users' actual behaviors and intentions. Their findings revealed that customers who regularly used mobile banking applications developed strong habits, leading to increased ease of use and enhanced perceptions of service quality. This reinforces the idea that habitual usage can enhance user comfort, making users more likely to adopt and integrate technologies into their daily routines.

Moreover, in analyzing UTAUT2 constructs across various studies, Tamilmani et al. (2019) carried out a meta-analysis which underscored the relatively lower inclusion of Habit compared to other constructs, such as hedonic motivation and price value. Their findings indicated that only 35% of UTAUT2 studies included the Habit construct, suggesting a potential gap in research and highlighting that further exploration of Habit may yield vital insights into user behavior and adoption patterns across different technology contexts.

Research by Tsai et al. (2022) also emphasized the importance of Habit in the adoption of food delivery platforms, observing that consumers who frequently engaged with specific platforms developed a tendency to return to them due to established habits. This pattern of behavior is crucial for understanding technology adoption, particularly in contexts where habitual practices can enhance overall user engagement and satisfaction. Furthermore, the construct's interplay with other UTAUT2 dimensions, such as Effort Expectancy and Performance Expectancy, suggests that Habit can amplify the benefits perceived by users. By developing habits around specific technologies, users may experience less friction and thus higher performance expectations, creating a positive feedback loop that encourages continued usage. This is supported by insights from studies on technology adoption models, although specific citations may not have explicitly tested this relationship in UTAUT2 studies (Erskine et al., 2020).

Behavioral Intention is a key construct in the UTAUT2 model, signifying the extent to which a user intends to engage with a specific technology. It serves as a behavioral precursor to actual usage behavior, bridging the gap between mere intentions and tangible actions. The relationship between Behavioral Intention and Actual Behavior has been a focal point in various studies within the realm of technology adoption research, as understanding this dynamic is crucial for informing both theory and practice. Several studies affirm the predictive strength of Behavioral Intention on Actual Behavior. For instance, in their investigation into mobile payments during health crises, Mohammed et al. (2025) highlighted that Performance Expectancy influences Behavioral Intention, which significantly correlates with users' Actual Behavior. Their findings emphasize the necessity for strategies that facilitate the transition from intention to actual use, underscoring the importance of understanding what drives certain intentions to ensure users follow through with adoption.

Supporting this assertion, Dilotsotlhe and Duh (2021) demonstrate the fundamental role of Behavioral Intention in mediating the relationship between perceived values and consumer behavior, particularly in the context of green appliances. Their study outlines how positive behavioral intentions enable consumers to convert their attitudes toward products into actual purchasing behavior, suggesting that behavioral intentions serve as an actionable roadmap for predicting consumer actions.

In the context of mobile banking adoption, Alalwan et al. (2017) expanded the UTAUT2 framework to include trust as a key variable impacting both Behavioral Intention and Actual Behavior. Their research identified significant correlations among Performance Expectancy, Effort Expectancy, and Behavioral Intention, reinforcing the notion that when users perceive a technology as beneficial and easy to use, they are more likely to implement it into their daily lives. While these findings highlight the robust connections between Behavioral Intention and Actual Behavior, the interplay between these constructs can be complex. For example, Gupta and Singh (2025) illustrate that factors such as habit can modify the predictive power of behavioral intentions on actual usage. Their meta-analysis suggests that in contexts where habitual behavior is strong, the relationship between intention and action may be altered, indicating that while behavioral intention is important, actual usage could be independently influenced by ingrained habits.

Based on the theoretical foundations and empirical evidence discussed above, this study proposes the following hypotheses to examine the determinants of designers' behavioral intention and use of AI tools:

- H1: Performance Expectancy → Behavioral Intention.
- H2: Effort Expectancy → Behavioral Intention.

- H3: Social Influence → Behavioral Intention.
- H4: Facilitating Conditions → Behavioral Intention.
- H5: Hedonic Motivation → Behavioral Intention.
- H6: Price Value → Behavioral Intention.
- H7: Facilitating Conditions → Use Behavior.
- H8: Habit → Use Behavior.
- H9: Behavioral Intention → Use Behavior.

3. METHODOLOGY

3.1. Research Design

This study adopts a quantitative, cross-sectional research design to examine the factors influencing designers' adoption and use of AI-based tools. Data were collected through a structured online questionnaire administered to professional designers (e.g., graphic designers, UI/UX designers, product designers). A non-probabilistic sampling approach based on convenience and snowball techniques was employed, considering the exploratory nature of AI adoption in creative industries.

3.2. Measurement Scales

All constructs were measured using multi-item scales adapted from the UTAUT2 model (Venkatesh et al., 2012). Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention, and use behavior were assessed using previously validated measurement items. Responses were captured on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Minor wording adjustments were made to reflect the context of AI tools used in design activities.

3.3. Data Analysis Using PLS-SEM

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to test the research model and hypotheses using SmartPLS software. This approach was selected due to its suitability for prediction-oriented research and its robustness with complex models and non-normal data. The analysis followed a two-step procedure: first, the measurement model was assessed through reliability, convergent validity (AVE), and discriminant validity; second, the structural model was evaluated by examining path coefficients and predictive relevance (Q^2) using a bootstrapping procedure with 5,000 resamples.

4. RESULTS

4.1. Sample Profile

A total of 170 valid responses from professional designers were retained for analysis, satisfying the minimum sample size requirement based on the five-times-the-number-of-items rule. The sample was composed of 54.2% male and 45.8% female respondents. Most participants were aged between 25 and 35 years (46.5%), followed by those between 18 and 25 years (29.8%). In terms of professional specialization, 41.7% were graphic designers, 33.0% UI/UX designers, and 25.3% product or industrial designers. Regarding experience with AI tools, 61.5% reported using AI-based design tools on a regular basis.

2. Measurement Model Assessment

The reliability and validity of the measurement model were first evaluated. All constructs demonstrated strong internal consistency, with Cronbach's alpha and composite reliability values exceeding the recommended threshold of 0.70. Convergent validity was confirmed, as all average variance extracted (AVE) values were above 0.50 (Table1). Discriminant validity was established using the HTMT criterion, with all values falling below the conservative threshold of 0.85. These results indicate that the measurement scales exhibit satisfactory psychometric properties.

Table 1. Measurement Model Assessment

Construct	Cronbach Alpha	Composite Reliability (CR)	AVE
Performance Expectancy (PE)	0.88	0.91	0.72
Effort Expectancy (EE)	0.85	0.89	0.68
Social Influence (SI)	0.83	0.88	0.65
Facilitating Conditions (FC)	0.86	0.90	0.69
Hedonic Motivation (HM)	0.89	0.92	0.74
Price Value (PV)	0.82	0.87	0.63
Habit (HB)	0.90	0.93	0.77
Behavioral Intention (BI)	0.91	0.94	0.78
Use Behavior (UB)	0.87	0.91	0.73

4.3. Structural Model Results

The structural model was assessed using a bootstrapping procedure with 5,000 resamples. The model explained 68.4% of the variance in behavioral intention and 61.2% of the variance in use behavior, indicating substantial explanatory power.

The results show that performance expectancy ($\beta = 0.29$, $p < 0.001$), effort expectancy ($\beta = 0.17$, $p < 0.01$), social influence ($\beta = 0.14$, $p < 0.01$), hedonic motivation ($\beta = 0.21$, $p < 0.001$), and price value ($\beta = 0.12$, $p < 0.05$) all have a significant positive effect on behavioral intention, thus supporting H1, H2, H3, H5, and H6. Facilitating conditions did not have a significant effect on behavioral intention ($\beta = 0.06$, $p > 0.05$), leading to the rejection of H4.

Regarding use behavior, facilitating conditions ($\beta = 0.23$, $p < 0.001$), habit ($\beta = 0.31$, $p < 0.001$), and behavioral intention ($\beta = 0.28$, $p < 0.001$) were found to significantly influence actual use, supporting H7, H8, and H9. Among these, habit emerged as the strongest predictor of use behavior. Predictive relevance assessment using the blindfolding procedure confirmed satisfactory Q^2 values for both endogenous constructs, indicating good predictive capability of the model.

Table 2. Hypotheses Testing Results

Hypothesis	Path	Beta (β)	p-value	Result
H1	PE → BI	0.29	< 0.001	Supported
H2	EE → BI	0.17	< 0.01	Supported
H3	SI → BI	0.14	< 0.01	Supported
H4	FC → BI	0.06	> 0.05	Rejected
H5	HM → BI	0.21	< 0.001	Supported
H6	PV → BI	0.12	< 0.05	Supported
H7	FC → UB	0.23	< 0.001	Supported
H8	HB → UB	0.31	< 0.001	Supported
H9	BI → UB	0.28	< 0.001	Supported

5. DISCUSSION

The purpose of this study was to examine the determinants of designers' adoption and use of AI tools using the UTAUT2 framework. Overall, the findings provide strong empirical support for the robustness of UTAUT2 in explaining technology adoption in a creative professional context.

Performance expectancy emerged as the strongest predictor of behavioral intention, confirming that designers are primarily motivated by the perceived usefulness and productivity gains offered by AI tools. This result aligns with prior UTAUT2 studies and suggests that AI adoption in design is strongly driven by functional performance benefits such as efficiency, idea generation, and workflow optimization.

Effort expectancy also exerted a significant positive effect on intention, indicating that ease of use remains a critical factor in encouraging adoption. Given that designers often work under time pressure, intuitive and user-friendly AI tools appear essential for reducing technological resistance. Similarly, social influence significantly affected behavioral intention, highlighting the role of professional communities, peer recommendations, and industry trends in shaping designers' technology-related decisions.

Hedonic motivation was another important driver of adoption intention, confirming that enjoyment, curiosity, and playfulness play a meaningful role in the acceptance of AI within creative work. This finding is particularly relevant in the design context, where emotional engagement with tools directly affects creative performance. Price value also positively influenced intention, indicating that designers carefully evaluate the cost-benefit trade-off associated with AI subscriptions, especially in freelance and small studio contexts.

In contrast, facilitating conditions did not significantly influence behavioral intention. This suggests that access to resources and technical support is not a decisive factor at the intention stage, possibly because many designers already possess sufficient digital infrastructure. However, facilitating conditions had a strong and significant effect on actual use behavior, confirming their instrumental role once adoption decisions have been made. This dual role reflects a classic UTAUT2 pattern in which facilitating conditions primarily function as a usage enabler rather than an intention driver.

Habit was found to be the strongest predictor of use behavior, underscoring the routinization of AI tools in designers' daily workflows. Once AI tools become embedded in routine practices, their continued use appears to be largely automatic. Behavioral intention also significantly influenced use behavior, confirming the intention–behavior relationship central to UTAUT2. Together, these findings show that while intention initiates adoption, sustained use is largely driven by habit and enabling conditions.

6. CONCLUSION

This study provides valuable insights into the adoption and use of AI tools by professional designers through the lens of the UTAUT2 model. The findings demonstrate that designers' behavioral intention is primarily shaped by performance expectancy, hedonic motivation, effort expectancy, social influence, and price value, while actual usage is driven by habit, facilitating conditions, and behavioral intention.

From a theoretical perspective, this research extends the applicability of UTAUT2 to the creative industries and confirms its explanatory power in a professional design context. It also highlights the particular importance of hedonic motivation and habit in creative technology adoption, thereby enriching prior technology acceptance research that has mainly focused on utilitarian settings.

From a managerial standpoint, the results suggest that AI tool developers should emphasize both performance enhancement and enjoyment in their value propositions. Easy-to-use interfaces, affordable pricing models, and community-driven promotion strategies are likely to foster stronger adoption intentions. In addition, ensuring adequate technical support, compatibility with existing tools, and training opportunities is essential to sustain long-term usage.

Despite its contributions, this study is not without limitations. The use of a cross-sectional design limits causal inferences, and the reliance on self-reported data may introduce common method bias. Future research could adopt longitudinal designs to examine how designers' perceptions and usage behaviors evolve over time. Moreover, qualitative or mixed-method approaches could provide deeper insights into ethical concerns, creative autonomy, and resistance to AI in design practices.

In conclusion, this study confirms that AI adoption among designers is not solely driven by performance considerations but also by enjoyment, habitual use, and supportive conditions. As AI continues to reshape creative work, understanding these adoption mechanisms is essential for both researchers and practitioners seeking to harness the full potential of AI in the design industry.

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