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The use of generative AI tools in design work: Motivation and decision-making process of users

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Abstract: As generative AI technologies evolve, more designers are integrating these tools into their workflows. While existing research has examined the use of generative AI in design, few studies have conceptualized user engagement within an integrated model of motivational and behavioral factors. This study explores key constructs—attitudes, subjective norms, perceived behavioral control, intention to use, and actual usage—through the Uses and Gratifications Theory (UGT) and the Theory of Planned Behavior (TPB). Results indicate that designers' attitudes and subjective norms significantly affect their intention to adopt generative AI tools, which in turn influences actual usage. Designers generally hold positive attitudes toward these tools, and external social influences are crucial to their adoption. Finally, enhancing perceived control may further promote adoption and integration into design practices.
Keywords: *Attitudes, Generative AI tools, Intentions, behavior, Perceived behavioral control, Subjective norms.*

1. Introduction

The design industry has been undergoing rapid transformation due to advancements in digital technology, fundamentally altering creative workflows and expanding design methodologies. One of the most significant developments is the increasing incorporation of generative AI tools, enabling designers to integrate AI as collaborative agents in creative processes [1]. A global survey indicates that 25% of designers currently use generative AI, with more than half expressing their intent to adopt these tools in the future [2]. This trend underscores the need for academic and industry discussions on the shift from conventional design practices to AI-assisted methodologies [3]. Understanding this transition is critical, as it is poised to redefine industry standards, reshape creative workflows, and introduce new paradigms in design innovation.

While generative AI adoption has gained momentum, the transition from motivation to actual usage behavior remains insufficiently studied from an empirical perspective [4]. As designers increasingly interact with AI-driven tools, it becomes essential to examine how motivational factors influence engagement with generative AI. The Uses and Gratifications Theory (UGT) provides insights into user motivations, while the Theory of Planned Behavior (TPB) explains the process through which these motivations translate into intentional and actual adoption [5]. By integrating these perspectives, a comprehensive model can be developed to analyze the key determinants of AI adoption in design workflows. Since generative AI applications rely on active user participation, understanding these behavioral patterns is crucial for optimizing human-AI collaboration [6].

Despite the growing body of research on AI-driven design, studies that comprehensively address both motivational and behavioral perspectives remain limited [7]. This study aims to bridge this gap by developing a theoretical framework explains the increasing use of generative AI tools in design. By offering an empirically grounded model, this research contributes to both academic discourse and

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practical applications, providing valuable insights for design professionals, researchers, and industry stakeholders.

2. Literature Review

2.1. Image-generative AI tools

The emergence of user-friendly generative AI technologies, such as DALL·E and Midjourney, has significantly transformed text-to-image synthesis, facilitating applications in visual content creation and digital artistry [8]. Previously, integrating machine learning (ML) into creative fields required specialized knowledge [9]. Now, these platforms allow users to generate refined visuals using natural language commands [10].

Midjourney and Stable Diffusion are leading AI-based image synthesis models known for their accessibility and capabilities. Stable Diffusion is developed by Stability AI, while Midjourney operates independently [11, 12]. Both utilize advanced deep learning techniques, including diffusion models and generative adversarial networks (GANs), to create images based on user prompts. Recently, Vega AI has emerged, enhancing multi-modal generation functionalities and eliminating the need for local deployment. It excels in converting 2D wireframe sketches into fully rendered 3D images.

Effective prompt engineering is crucial for optimizing AI-generated outputs. This discipline focuses on structuring user inputs to enhance human-machine interaction and model performance [13]. Prompts typically include contextual parameters that influence the semantic accuracy and aesthetic quality of generated visuals.

Midjourney is notable for its ability to integrate large language models (LLMs), facilitating the interpretation of abstract concepts into tangible visual elements [14]. In automotive design, for example, it translates consumer emotional responses into distinct morphological features of car designs.

Generative Artificial Intelligence (GAI) is also impacting various fields, including natural language processing, 3D graphics, and video generation [15]. In design-intensive areas such as architecture and product development, GAI enhances ideation, rapid prototyping, and iterative refinement. Its integration into design workflows promotes collaboration between human designers and AI systems, driving innovation and efficiency [16, 17].

2.2. Motivational Use of Generative AI

User motivation is a key factor influencing technology-related decisions and behaviors, driving actions toward specific goals [18]. The Uses and Gratifications (U&G) theory explains that individuals engage with technologies to fulfill psychological needs [19]. This framework reveals motivations behind the adoption and use of various technologies [20, 21]. For instance, Chen, Hsiao, and Li demonstrate that perceived usefulness, enjoyment, and social belonging significantly shape usage habits in location-based mobile applications [22, 23].

In the U&G context, motivation is critical for predicting user behavior [24, 25]. It includes the reasons and goals propelling users toward action. For generative AI tools, motivations are typically categorized as utilitarian and hedonic [26]. Utilitarian motives focus on practical benefits like efficiency, while hedonic motives center on enjoyment and satisfaction derived from technology use [27]. Positive emotions from hedonic gratification enhance attitudes toward AI tools Picot-Coupey, et al. [28] while utilitarian users aim for goal achievement, leading to favorable feelings and future intentions [29]. Studies show that positive attitudes toward generative AI tools often arise from perceived value in product information and interactivity [30, 31].

Experiential value from interacting with generative AI also significantly influences attitudes [32]. This value enhances perceptions of technology, as experiential satisfaction is linked to favorable attitudes [33]. Hsu, Yu, and Chao found that experiential value notably impacts user perceptions [34]. Thus, alongside utilitarian and hedonic motives, experiential intensity is key to user engagement with generative AI tools [35]. Such engagement is derived from immersive experiences that provide deep satisfaction through active participation [36].

Considering the accessible nature of generative AI tools, utilitarian, hedonic, and experiential motives together shape user engagement. Rahman, Khan, and Iqbal found that utilitarian values significantly influence user attitudes more than hedonic values or concerns about trust and privacy [37]. This study integrates these three motivational dimensions—utilitarian, hedonic, and experiential—as antecedents to attitudes toward generative AI tools, exploring their relevance in the m-commerce context.

2.3. Decision-Making Process of Generative AI Tools

The adoption of generative AI tools follows a sequential decision-making process from initial exposure to attitude formation and usage intention. The Uses and Gratifications (U&G) theory addresses psychological motivations, while the Theory of Planned Behavior (TPB) offers insights into behavioral intention. TPB identifies three factors influencing intention: attitude toward behavior, subjective norms, and perceived behavioral control (PBC) [38].

Attitudes stem from an individual's beliefs about the outcomes of behavior, reflecting a predisposition towards usage [39]. These attitudes can be reinforced by psychological satisfaction, boosting adoption likelihood [40]. Subjective norms—social influences from peers and industry trends—also play a critical role in shaping behavioral intention [41]. Research shows that word-of-mouth (WOM) and social persuasion significantly impact technology adoption [42]. Additionally, PBC connects intention to actual behavior, reflecting users' perceptions of control over external constraints [43]. Users may experience a loss of control in complex digital environments, affecting adoption decisions Dabholkar and Sheng [44] however, those with higher technological competence often report greater PBC, facilitating engagement [45].

Behavioral intention serves as a mediator between perceived control and actual behavior; users are more likely to act when they have the intention and confidence to do so [29]. Studies have effectively integrated U&G and TPB to examine technology adoption patterns. For instance, Raza et al. found that social influence, perceived behavioral control, and attitudes significantly affect Facebook usage [46]. Similarly, Chen, Liang, and Cai analyzed motivational and behavioral factors in digital service adoption Chen, et al. [47] while Sun et al. linked continued use of link-sharing tools to intention and subjective norms [48]. This study combines U&G and TPB to provide a comprehensive framework for understanding the decision-making process of generative AI users.

2.4. Hypotheses and Research

This study investigates user motivations and components of planned behavior to predict the adoption and use of generative AI tools among South Korean designers. Prior research has integrated Uses and Gratifications Theory (U&G) with the Theory of Planned Behavior (TPB), enhancing explanatory power by incorporating motivational components from U&G, thus increasing theoretical robustness [46]. While many studies have explored user behavior in technology adoption, they typically focus on either motivational drivers or planned behavior frameworks, rather than integrating both into a comprehensive model. Additionally, previous research often emphasizes external environmental influences while neglecting the impact of internal psychological factors on decision-making.

To address this gap, this study proposes that user motivation to engage with generative AI tools positively influences attitudes toward adoption. Furthermore, attitudes, subjective norms, and perceived behavioral control are posited as key determinants of behavioral intention, which in turn predicts actual usage behavior. Based on these foundations, the following hypotheses are presented:

Hypothesis 1 (H1): Attitudes toward using generative AI tools will positively predict behavioral intention.

Hypothesis 2 (H2): Subjective norms regarding generative AI tools will positively predict behavioral intention.

Hypothesis 3 (H3): Perceived behavioral control will positively predict behavioral intention.

Hypothesis 4 (H4): Perceived behavioral control will positively predict generative AI tool usage behavior.

Hypothesis 5 (H5): Behavioral intention will positively predict generative AI tool usage behavior.

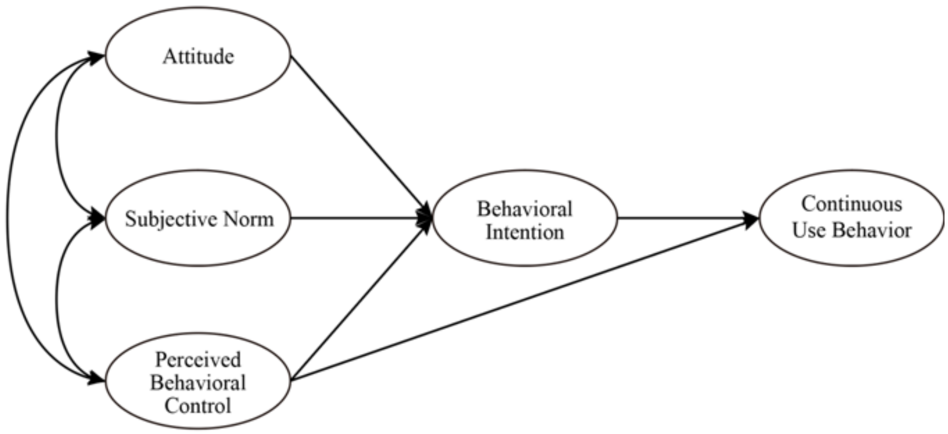

Figure 1.
Research model.

3. Methodology

3.1. Participants

This study utilized an online survey to gather insights from 287 designers regarding their perspectives on generative AI adoption. Administered through an online platform, the survey ensured a diverse participant pool. The majority of respondents were women in their 20s and 30s, with professional experience evenly distributed from 1 to over 7 years.

Table 1.
Demographic variables of respondents.

Gender			Age			Work Experience		
Group	Frequency	Percentage (%)	Group	Frequency	Percentage (%)	Group	Frequency	Percentage (%)
Male	85	29.7%	20s	119	41.6%	1~2 years	88	30.8%
Female	201	70.3%	30s	128	44.8%	3~4 years	18	6.3%
			40s	38	13.3%	3~5 years	71	24.8%
			50s and above	1	0.3%	5~7 years	51	17.8%
						More than 7yrs	58	20.2%

3.2. Measurement

This study measured four exogenous variables and one endogenous variable based on the U&G theory and the TPB. Questionnaire items were adapted to the context of the study, with all constructs assessed using a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5):

Attitudes: Five items were adapted from Amaro and Duarte, and Sun, Law, and Schuckert [49].

Subjective Norms: Three items were derived from Tarkiainen and Sundqvist [49].

Perceived Behavioral Control: Four items were adopted from Basole and Major [1].

User Intention: Four items regarding behavioral intention were sourced from Hsiao and Tang [3].

Continuous Use Behavior: Three items on actual usage of generative AI tools were adapted from Hsiao and Tang [3].

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3.3. Procedures

A reliability analysis was performed on the questionnaire items, resulting in the exclusion of items that undermined reliability to create the final scale for analysis. Multiple regression and stepwise regression analyses were conducted to test the hypotheses.

4. Results

The findings indicate that attitudes, subjective norms, and perceived behavioral control significantly impact behavioral intention, providing empirical support for Hypotheses 1, 2, and 3.

Table 2.
Results of multiple regression analysis on behavioral intention.

Independent Variables	β	t	p	$R2(\Delta R^2$	F	p
Attitude	0.623	11.483	0.000	0.520	102.061	0.000
Subjective Norm	0.111	2.032	0.043			
Perceived Behavioral Control	0.110	2.632	0.009			

The analysis also confirmed that behavioral intention significantly influences continuous usage behavior, supporting Hypothesis 4. Additionally, to assess the direct effect of perceived behavioral control on continuous usage behavior, an analysis was conducted excluding the effects of behavioral intention. Results showed that perceived behavioral control did not have a significant direct effect, leading to the rejection of Hypothesis 5. However, subjective norms were found to have a significant direct effect on continuous usage behavior, underscoring their role in shaping user engagement with generative AI tools.

Table 3.
Stepwise regression analysis results for continuous use behavior.

Analytical Steps	Independent Variables	β	t	p	$R2(\Delta R^2$	F	p
1	Behavioral Intention	0.445	8.378	0.000	0.198	70.190	0.000
2	Attitude	0.100	1.221	0.223	0.051	6.372	0.000
	Subjective Norm	0.204	2.953	0.003			
	Perceived Behavioral Control	-0.085	-1.592	0.112			

5. Discussion

The alternative research model based on the Theory of Planned Behavior (TPB) effectively analyzes factors influencing continuous use behavior of generative AI tools. The findings reveal that attitudes, subjective norms, and perceived behavioral control significantly affect behavioral intention, which is crucial in shaping continuous usage. Notably, while subjective norms have both direct and indirect effects on continuous use, perceived behavioral control did not demonstrate a significant direct impact, indicating its influence is mainly mediated through behavioral intention.

These results align with existing research highlighting the importance of psychological and social factors in technology adoption [39]. The significance of subjective norms emphasizes the role of social influence in AI adoption, while the connection between behavioral intention and continuous use behavior underscores the need to foster motivational drivers for long-term engagement.

5.1. Influence of Attitude and Subjective Norms on Behavioral Intention

The analysis confirms that attitude significantly influences behavioral intention, suggesting users view AI tools as beneficial and enjoyable, which enhances adoption decisions. This finding supports literature indicating that positive perceptions, such as usefulness and ease of use, boost user motivation to integrate AI into workflows.

Additionally, subjective norms strongly impact behavioral intention, highlighting the importance of peer influence, organizational expectations, and social acceptance in users' willingness to use AI tools.

This indicates that perceived endorsement by colleagues and industry trends contributes to higher adoption rates in design and creative fields. The direct effect of subjective norms on continuous use behavior suggests that external encouragement—through industry trends and workplace integration—reinforces sustained engagement. AI developers and service providers should implement community-driven adoption strategies, including AI education and collaborative environments.

In the context of Korean society, subjective norms play a more critical role than perceived behavioral control in shaping behavioral intention and actual behavior, particularly in professional settings. Studies indicate that social expectations significantly influence decision-making beyond individual perceptions of control [50].

5.2. The Role of Perceived Behavioral Control

Contrary to expectations, perceived behavioral control did not significantly affect continuous use behavior, despite influencing behavioral intention. This implies that while users' confidence in using AI tools impacts their intention, it does not independently drive sustained usage. Enhancing user control alone may not ensure long-term engagement; motivational factors like perceived benefits and social validation are crucial for continued usage.

5.3. Behavioral Intention as A Mediator of Continuous Use

The study confirms that behavioral intention mediates the relationship between psychological factors and actual usage behavior, reinforcing findings from the TAM and TPB frameworks. A strong intention increases the likelihood of continued engagement with technology. In the growing context of AI tools in creative industries, fostering a positive user experience is essential for sustaining long-term usage.

5.4. Limitations And Suggestions for Future Research

This study highlights that subjective norms significantly influence designers' continuous use of generative AI tools within the South Korean cultural context, indicating a crucial cultural distinction. In contrast to individualistic Western societies, where perceived behavioral control is a key driver of AI adoption, collectivist cultures like South Korea place greater emphasis on social expectations in shaping usage behavior. This finding underscores the need for further cross-cultural comparative studies examining the role of subjective norms in user experiences and attitudes toward generative AI tools.

Additionally, future research should investigate how subjective norms affect team-based design workflows involving generative AI, particularly in South Korea and in global collaborative settings. Expanding research in these areas may yield deeper insights into culturally adaptive AI integration strategies across design industries worldwide.

6. Conclusion

This study affirms that attitude, subjective norms, and behavioral intention are critical determinants of continuous AI adoption, with perceived behavioral control playing an indirect role. The results emphasize the importance of social influence, especially within collectivist cultural contexts, where subjective norms directly impact user behavior. Unlike individualistic societies that prioritize personal control in AI adoption, this research illustrates the significance of external social expectations in fostering sustained engagement with generative AI tools.

These insights advocate for community-driven adoption strategies and the reinforcement of positive behavioral intentions to ensure the long-term integration of AI into professional design workflows. Moving forward, this research can offer valuable guidance for AI developers, designers, and industry stakeholders in crafting culturally adaptive strategies that enhance user experience and facilitate seamless AI integration in diverse collaborative environments.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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