Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 4, 24-31
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i4.5933

User perceptions and intentions to continue using generative AI tools in the design process

Jhonghee Kim[1], Hyungjoon Kim[2*]
[1]Samsung Art & Design Institute, South Korea.
[2]Joongbu University, South Korea; hjkim1@joongbu.ac.kr (H.K.).

Abstract: The integration of generative AI into the design process enhances creativity and optimizes workflows, yet research on user engagement and experiential factors is limited. This study addresses the gap by developing a conceptual model that analyzes designers' perceptions of AI-assisted workflows, adoption attitudes, and sustained usage intentions. Using an extended Technology Acceptance Model (TAM), a survey was conducted with professionals actively employing generative AI tools. The findings indicate that innovativeness, self-efficacy, perceived enjoyment, and service quality significantly impact perceived usefulness and ease of use, influencing intentions to sustain AI adoption. This research offers insights into the long-term integration of generative AI in design, contributing to both academic discourse and practical applications while informing future research on AI-enhanced design methodologies.

Keywords: *Generative AI, Intention to continuous use, Perceived ease of use, Perceived usefulness, Personal innovativeness, Self-efficacy.*

1. Introduction

Recent advancements in artificial intelligence have enabled AI-driven systems to analyze large datasets, recognize patterns, and generate optimal design solutions [1, 2]. Generative AI technologies assist in complex design tasks that traditionally depend on human expertise, providing efficient and intelligent problem-solving capabilities [3]. Designers increasingly use tools like Midjourney, Stable Diffusion, and DALL-E for creating posters, brand identities, and typography, while ChatGPT aids in drafting design descriptions and refining creative expression [4, 5]. As generative AI adoption in design workflows expands, studying its impact becomes crucial.

Despite growing use, research on the adoption and sustained utilization of generative AI tools in design is still limited [6]. This study addresses this gap by developing a research model and hypotheses to examine user perceptions, attitudes, and continued usage intentions. Utilizing an extended Technology Acceptance Model (TAM), a structured survey was conducted with professionals actively using AI-assisted design tools. The findings provide theoretical and practical insights into designers' perceptions of AI integration, adoption behaviors, and long-term engagement with these technologies. This study contributes to both academic research and professional practice, guiding future advancements in AI-integrated design environments.

2. Literature Review

2.1. Theoretical Background

This study is based on the Technology Acceptance Model (TAM), developed by as a framework for predicting technology adoption behaviors [7]. TAM has been widely applied for over three decades to understand acceptance, rejection, and continued use of emerging technologies [8, 9]. Its relevance

History: Received: 23 January 2025; Revised: 25 March 2025; Accepted: 31 March 2025; Published: 3 April 2025
* Correspondence: hjkim1@joongbu.ac.kr

demonstrates its effectiveness in explaining user perceptions and intentions regarding information technologies, making it suitable for studying generative AI adoption in design.

2.2. Extended Technology Acceptance Model (TAM)

TAM identifies perceived usefulness (PU), perceived ease of use (PEU), and attitude toward use (ATT) as key factors influencing behavioral intention (BI) to adopt technology. ATT captures cognitive and affective evaluations, PEU reflects perceived user-friendliness, and PU indicates the perceived ability to enhance efficiency and productivity. The model proposes that PU and PEU shape ATT, which subsequently influences BI and actual usage behavior.

Despite its broad application, TAM has faced criticism for two main reasons. First, it has been deemed limited in considering macro-level influences, such as sociocultural and organizational factors [10]. Second, it is criticized for overemphasizing extrinsic motivators while neglecting intrinsic factors like engagement and enjoyment [11]. To address these concerns, Fagan, Neill and Wooldridge introduced an integrated model incorporating external variables for a more comprehensive understanding of technology adoption [12].

This study extends TAM by integrating personal innovativeness, self-efficacy, perceived enjoyment, and service quality to enhance its predictive power regarding technology adoption and behavioral variations [13]. This extension offers a deeper understanding of user experiences in adopting generative AI tools in design processes, contributing to the discourse on AI-driven creative methodologies.

2.3. Personal Innovativeness in user's Perception

Personal innovativeness in information technology (IT) denotes an individual's willingness to experiment with and adopt new technologies [14]. This trait indicates a tendency for novelty-seeking and significantly affects perceived usefulness (PU) and perceived ease of use (PEU) in technology adoption [13, 15]. Evidence shows that personal innovativeness directly enhances perceived utility and convenience in various contexts, including mobile Internet services and metaverse learning [16, 17]. It is broadly defined as the inclination to adopt new products ahead of the majority Foxall, et al. [18] with studies confirming its positive impact on attitudes and intentions toward technology [19]. Individuals with higher innovativeness are more likely to recognize technological benefits and integrate tools into their work [20].

Hypothesis 1: Personal innovativeness positively affects perceived ease of use of generative AI tools in the design process.

Hypothesis 2: Personal innovativeness positively affects perceived usefulness of generative AI tools in the design process.

2.4. Self-Efficacy in user's Perception

According to Bandura [21] self-efficacy reflects an individual's confidence in completing tasks. In technology use, it pertains to the belief in effectively operating technical systems and utilizing AI tools Bandura [21] and Rahman, et al. [22]. Bandura [21] Social Cognitive Theory posits that self-efficacy strengthens with success through experience. Individuals interested in AI exhibit higher self-efficacy Latikka, et al. [23] enhancing their engagement with technology [24]. AI technologies promote self-efficacy by providing personalized learning experiences and feedback Chen, et al. [25] while AI-driven assessments facilitate progress tracking and skill improvement [26].

Hypothesis 3: Self-efficacy positively affects perceived ease of use of generative AI tools in the design process.

Hypothesis 4: Self-efficacy positively affects perceived usefulness of generative AI tools in the design process.

2.5. Enjoyment in user's Perception

Enjoyment is a multifaceted emotion that motivates individuals toward success in complex tasks [27]. In the context of AI usage, it encompasses the satisfaction derived from interactions with AI technologies and serves as a key determinant of behavioral intention [27, 28]. Positive experiences with technology foster favorable attitudes, enhancing user engagement [29]. This often leads to a state of flow, where users feel immersed and intrinsically motivated [30]. Over time, interaction with AI cultivates excitement and a sense of mastery, encouraging exploration of new opportunities [31].

Hypothesis 5: Enjoyment positively affects perceived ease of use of generative AI tools in the design process.

Hypothesis 6: Enjoyment positively affects perceived usefulness of generative AI tools in the design process.

2.6. Perceived Service Quality

AI-driven tools ensure consistent service quality by minimizing fatigue, frustration, and errors, resulting in reliable and standardized performance [32]. This reliability fosters user trust and commitment to AI-assisted services [33]. Users experience self-expansion, extension, restriction, and reduction when interacting with AI tools [34]. Research emphasizes that satisfaction, acceptance, trust, and continued engagement are critical for AI adoption [35]. Factors such as information accuracy, service reliability, perceived enjoyment, usefulness, and ease of use significantly enhance user satisfaction and ongoing utilization [36]. Additionally, emotional attachment to AI tools influences trust, commitment, and satisfaction [36]. While AI also enhances brand perception and user satisfaction [37].

Hypothesis 7: Service quality positively affects perceived ease of use of generative AI tools in the design process.

Hypothesis 8: Service quality positively affects perceived usefulness of generative AI tools in the design process.

2.7. Perceived Usefulness, Ease of use, and Intention to use

The Technology Acceptance Model (TAM) is a widely accepted framework for understanding the adoption of emerging technologies [38]. It posits that behavioral intention and actual usage are primarily driven by perceived usefulness (PU) and perceived ease of use (PEU) [42]. PU reflects the belief that technology enhances productivity, while PEU indicates that it is user-friendly and effortless [7]. These factors significantly shape user acceptance; individuals are more likely to adopt technologies deemed beneficial and intuitive [39]. When users view a technology as efficient and easy to integrate, their propensity to adopt and engage with it rises. Prior studies confirm that PU and PEU are critical predictors of technology adoption across multiple digital applications [40].

Hypothesis 9: Perceived usefulness positively affects intention to use generative AI tools in the design process again.

Hypothesis 10: Perceived ease of use positively affects intention to use generative AI tools in the design process again.

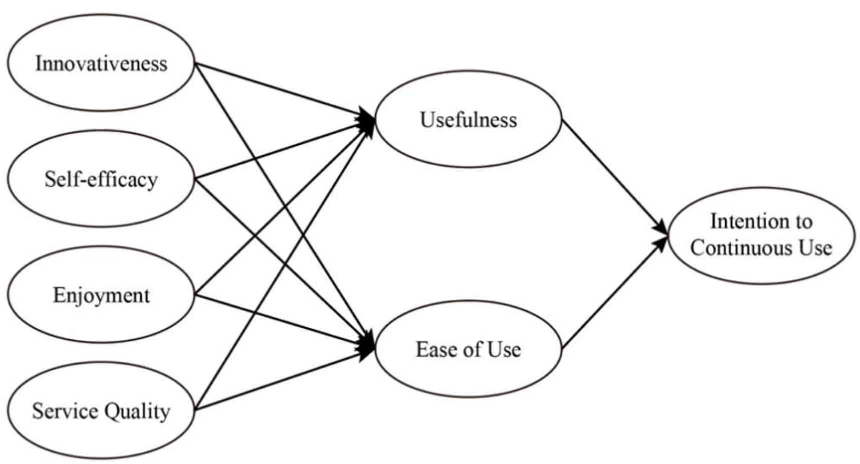

Figure 1.
Research model.

3. Methodology

3.1. Participants

This study conducted an online survey with 327 designers in Korea to explore the continued usability of generative AI tools, specifically within the context of Asian cultures. Targeting designers who are current employees and graduates from the design university affiliated with the researcher, the study aims to provide insights into user experiences with generative AI.

3.2. Measurement Instrument

The questionnaire, grounded in the extended Technology Acceptance Model (TAM), encompassed seven constructs: personal innovativeness, self-efficacy, enjoyment, service quality, perceived usefulness, perceived ease of use, and intention to continue use. Each item was rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Items were meticulously crafted based on established literature to ensure validity.

Table 1.
Demographic variables of respondents.

Gender			**Age**			**Work Experience**		
Group	**Frequency**	**Percentage (%)**	**Group**	**Frequency**	**Percentage (%)**	**Group**	**Frequency**	**Percentage (%)**
male	101	30.90%	20s	140	41.30%	1~2 yrs	103	31.50%
female	226	69.10%	30s	152	43.10%	3~4 yrs	21	6.40%
			40s	50	15. 0%	3~5 yrs	78	23.90%
			50s and above	2	0.60%	5~7 yrs	58	17.70%
						More than 7 yrs	67	20.50%

3.3. Procedures

A reliability analysis was performed on the questionnaire items, showing that the Cronbach's alpha coefficients for all scales exceeded 0.7. Consequently, these items were retained for constructing the final scale and subsequent analysis. Multiple regression and hierarchical regression analyses were employed to verify the hypotheses.

4. Results

As presented in Table 2, the multiple regression analysis revealed significant effects on perceived usefulness from self-efficacy, perceived enjoyment, and service quality, while personal innovativeness did not show a significant effect. Conversely, personal innovativeness, self-efficacy, and service quality significantly influenced perceived ease of use, with perceived enjoyment showing no significant impact.

These findings indicate support for hypotheses 1, 3, 4, 6, 7, and 8, while hypotheses 2 and 5 were not supported. Additionally, as detailed in Table 3, both perceived usefulness and perceived ease of use significantly affected users' intention to continue using generative AI tools, along with a direct significant effect from perceived enjoyment, thus supporting hypotheses 9 and 10.

Table 2.
Results of multiple regression analysis on usefulness and ease of use.

Independent Variables	Dependent Variables					
	Ease of use			Usefulness		
	β	t	p	β	t	p
Personal Innovativeness	0.201	4.349	0.000	0.037	0.757	0.449
Self-efficacy	0.373	7.203	0.000	0.151	2.753	0.006
Enjoyment	0.022	0.435	0.664	0.240	4.568	0.000
Service Quality	0.364	8.010	0.000	0.495	10.280	0.000
Model	R^2 = 0.728 (F=215.40, p<0.001)		R^2 = 0.695 (F=183.03, p<0.001)		R^2 = 0.695 (F=183.03, p<.001)	

Table 3.
Stepwise regression analysis results for continued use intention.

Model		β	t	p	ΔR^2	F	p
1	Perceived Usefulness	0.418	7.085	0.000	0.459	137.562	0.000
	Perceived Ease of Use	0.312	5.289	0.000			
2	Personal Innovativeness	0.051	0.863	0.389	0.121	23.067	0.000
	Self-Efficacy	0.117	1.676	0.095			
	Enjoyment	0.474	7.420	0.000			
	Perceived Service Quality	-0.054	-0.790	0.430			

5. Discussion

5.1. Theoretical and Practical Implications

The proposed model offers a structured analysis of factors influencing users' intentions to continue using AI-driven technologies. Findings indicate that innovativeness, self-efficacy, enjoyment, and service quality significantly impact perceptions of usefulness and ease of use, which in turn influence continued engagement. This aligns with the extended Technology Acceptance Model (TAM) framework, highlighting the role of both cognitive and affective factors in technology adoption.

5.2. Impact of Innovativeness and Self-Efficacy on Technology Perception

The results underscore that innovativeness and self-efficacy are key to shaping user perceptions of usefulness and ease of use. Users exhibiting higher technological openness perceive AI tools as more beneficial, while increased self-efficacy enhances perceptions of ease of use. This supports prior research suggesting that technological self-efficacy is a predictor of adoption behavior in digital environments.

5.3. Role of Enjoyment and Service Quality

Affective and service-related elements also significantly contribute to user experience and retention. Enjoyment enhances perceived usefulness and ease of use, indicating that users who find intrinsic pleasure in using the system are more likely to incorporate it into their workflows. Similarly, high service quality fosters user trust and continuous use intention, emphasizing the need for hedonic features and reliable system performance to ensure long-term adoption.

5.4. Mediating Role of Usefulness and Ease of use

Our findings confirm that perceived usefulness and ease of use mediate the relationship between user attributes (innovativeness, self-efficacy, enjoyment, and service quality) and continued usage intention. Notably, ease of use directly influences perceived usefulness, reinforcing the TAM hypothesis that more user-friendly systems are viewed as more valuable. This suggests that enhancing user interface design and reducing operational complexity is essential for optimizing perceived system value.

5.5. Implications for Technology Adoption and Design

The study offers practical implications for AI system developers and digital service providers. First, fostering user innovativeness and self-efficacy through educational initiatives can improve adoption rates. Second, integrating features that enhance enjoyment and maintaining high service quality can promote long-term user engagement. Finally, ensuring that AI tools remain intuitive and functionally relevant is critical for maximizing adoption and ongoing use.

5.6. Limitations and Suggestions for Future Research

This study focused on designers aged 20 to 50 in South Korea, examining factors affecting the continuous use of generative AI tools within this cultural context. The impact of cultural differences on usage intentions emerged as a key area for further investigation. Future research should explore the moderating effects of cultural factors through cross-cultural studies, examining how generative AI adoption varies across different cultural and economic environments to provide broader insights into global usage trends.

6. Conclusion

The findings of this study empirically validate the extended Technology Acceptance Model (TAM), demonstrating that a combination of cognitive, affective, and service quality factors significantly influences users' intentions to continue using AI-driven technologies. By addressing usability challenges and enhancing user experiences, developers can maximize engagement and foster sustainable technology adoption. However, as AI technologies evolve, understanding external influences and behavioral shifts over time will be crucial for their long-term integration. Future research should investigate the dynamics of user behavior and external factors influencing technology adoption, alongside the examination of cultural differences to refine AI-driven strategies. A comprehensive understanding of these elements will enhance the adaptability and inclusivity of AI innovations, providing valuable insights for policymakers and industry leaders in building user-centric and ethically responsible AI ecosystems.

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.

References

[1] T. Qiu, D. Yang, H. Zeng, and X. Chen, "Understanding graphic designers' usage behavior of generative artificial intelligence tools," *Kybernetes*, 2024.
[2] T. B. Kristiansen, K. Kristensen, J. Uffelmann, and I. Brandslund, "Erroneous data: the Achilles' heel of AI and personalized medicine," *Frontiers in Digital Health*, vol. 4, p. 862095, 2022.
[3] P. Manickam *et al.*, "Artificial intelligence (AI) and internet of medical things (IoMT) assisted biomedical systems for intelligent healthcare," *Biosensors*, vol. 12, no. 8, p. 562, 2022.
[4] J. A. Silverman, S. A. Ali, A. Rybak, J. B. van Goudoever, and N. S. Leleiko, "Generative AI: Potential and pitfalls in academic publishing," vol. 77, ed: LWW, 2023, pp. 573-574.
[5] P. Hacker, A. Engel, and M. Mauer, "Regulating ChatGPT and other large generative AI models," in *In Proc. of the 2023 ACM conference on fairness, accountability, and transparency (FAccT'23). Chicago, 2023, pp. 1112-1123*, 2023.
[6] C. Akverdi and G. E. Baykal, "Generative ai tools in design fields: opportunities and challenges in the ideation process," in *In Adjunct Proceedings of the 2024 Nordic Conference on Human-Computer Interaction (NordiCHI'13). Uppsala, 2024, pp. 1-5*, 2024.
[7] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS quarterly*, pp. 319-340, 1989.

[8] G. Liu and C. Ma, "Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model," *Innovation in Language Learning and Teaching*, vol. 18, no. 2, pp. 125-138, 2024.
[9] M. Salahshour Rad, M. Nilashi, and H. Mohamed Dahlan, "Information technology adoption: a review of the literature and classification," *Universal Access in the Information Society*, vol. 17, pp. 361-390, 2018.
[10] S. Y. Park, "An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning," *Journal of educational technology & society*, vol. 12, no. 3, pp. 150-162, 2009.
[11] V. Venkatesh, "Creation of favorable user perceptions: Exploring the role of intrinsic motivation," *MIS quarterly*, pp. 239-260, 1999.
[12] M. H. Fagan, S. Neill, and B. R. Wooldridge, "Exploring the intention to use computers: An empirical investigation of the role of intrinsic motivation, extrinsic motivation, and perceived ease of use," *Journal of Computer Information Systems*, vol. 48, no. 3, pp. 31-37, 2008.
[13] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Management science*, vol. 46, no. 2, pp. 186-204, 2000.
[14] W. Wu and L. Yu, "How does personal innovativeness in the domain of information technology promote knowledge workers' innovative work behavior?," *Information & Management*, vol. 59, no. 6, p. 103688, 2022.
[15] P. Patil, K. Tamilmani, N. P. Rana, and V. Raghavan, "Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal," *International Journal of Information Management*, vol. 54, p. 102144, 2020.
[16] J. Lu, J. E. Yao, and C.-S. Yu, "Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology," *The journal of strategic Information Systems*, vol. 14, no. 3, pp. 245-268, 2005.
[17] A. S. Al-Adwan, N. Li, A. Al-Adwan, G. A. Abbasi, N. A. Albelbisi, and A. Habibi, "Extending the technology acceptance model (TAM) to Predict University Students' intentions to use metaverse-based learning platforms," *Education and Information Technologies*, vol. 28, no. 11, pp. 15381-15413, 2023.
[18] G. R. Foxall, R. E. Goldsmith, and S. Brown, "Consumer psychology for marketing," *(No Title)*, 1998.
[19] Y. Hwang and Y. Wu, "Methodology for visual communication design based on generative AI," *International journal of advanced smart convergence*, vol. 13, no. 3, pp. 170-175, 2024.
[20] C. Sagnier, E. Loup-Escande, D. Lourdeaux, I. Thouvenin, and G. Valléry, "User acceptance of virtual reality: an extended technology acceptance model," *International Journal of Human–Computer Interaction*, vol. 36, no. 11, pp. 993-1007, 2020.
[21] A. Bandura, *Self-efficacy: The exercise of control*. Macmillan, 1997.
[22] M. S. Rahman, M. Ko, J. Warren, and D. Carpenter, "Healthcare Technology Self-Efficacy (HTSE) and its influence on individual attitude: An empirical study," *Computers in Human Behavior*, vol. 58, pp. 12-24, 2016.
[23] R. Latikka, T. Turja, and A. Oksanen, "Self-efficacy and acceptance of robots," *Computers in Human Behavior*, vol. 93, pp. 157-163, 2019.
[24] K. Renninger, "Working with and cultivating the development of interest, self-efficacy, and self-regulation," *Innovations in educational psychology: Perspectives on learning, teaching and human development*, pp. 107-138, 2010.
[25] X. Chen, H. Xie, D. Zou, and G.-J. Hwang, "Application and theory gaps during the rise of artificial intelligence in education," *Computers and Education: Artificial Intelligence*, vol. 1, p. 100002, 2020.
[26] J.-M. Dewaele and P. D. MacIntyre, "Foreign language enjoyment and foreign language classroom anxiety: The right and left feet of the language learner," *Positive psychology in SLA*, vol. 215, no. 236, pp. 9781783095360-010, 2016.
[27] J. Hamari, M. Sjöklint, and A. Ukkonen, "The sharing economy: Why people participate in collaborative consumption," *Journal of the association for information science and technology*, vol. 67, no. 9, pp. 2047-2059, 2016.
[28] S.-A. A. Jin, "Leveraging avatars in 3D virtual environments (Second Life) for interactive learning: The moderating role of the behavioral activation system vs. behavioral inhibition system and the mediating role of enjoyment," *Interactive Learning Environments*, vol. 19, no. 5, pp. 467-486, 2011.
[29] J. J. Wu and Y. S. Chang, "Towards understanding members' interactivity, trust, and flow in online travel community," *Industrial Management & Data Systems*, vol. 105, no. 7, pp. 937-954, 2005.
[30] Y. Lu, T. Zhou, and B. Wang, "Exploring Chinese users' acceptance of instant messaging using the theory of planned behavior, the technology acceptance model, and the flow theory," *Computers in human behavior*, vol. 25, no. 1, pp. 29-39, 2009.
[31] Y. Li, Y. Song, Y. Sun, and M. Zeng, "When do employees learn from artificial intelligence? The moderating effects of perceived enjoyment and task-related complexity," *Technology in Society*, vol. 77, p. 102518, 2024.
[32] X. Liao, X. Zhang, Z. Wang, and H. Luo, "Design and implementation of an AI-enabled visual report tool as formative assessment to promote learning achievement and self-regulated learning: An experimental study," *British Journal of Educational Technology*, vol. 55, no. 3, pp. 1253-1276, 2024.
[33] Y. Ruan and J. Mezei, "When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type," *Journal of Retailing and Consumer Services*, vol. 68, p. 103059, 2022.

[34] T. P. Novak and D. L. Hoffman, "Relationship journeys in the internet of things: a new framework for understanding interactions between consumers and smart objects," *Journal of the Academy of Marketing Science*, vol. 47, pp. 216-237, 2019.
[35] F. Linwei and T. S. Yun, "Workflow for Anamorphic 3D Advertising based on Image Distortion," *International Journal of Internet, Broadcasting and Communication*, vol. 16, no. 3, pp. 170-183, 2024.
[36] M. Ashfaq, J. Yun, S. Yu, and S. M. C. Loureiro, "I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents," *Telematics and informatics*, vol. 54, p. 101473, 2020.
[37] M. Chung, E. Ko, H. Joung, and S. J. Kim, "Chatbot e-service and customer satisfaction regarding luxury brands," *Journal of business research*, vol. 117, pp. 587-595, 2020.
[38] J. van Niekerk, P. M. Delport, and I. Sutherland, "Addressing the use of generative AI in academic writing," *Computers and Education: Artificial Intelligence*, vol. 8, p. 100342, 2025.
[39] L. Truc, "Empowering tomorrow: Unleashing the power of e-wallets with adoption readiness, personal innovativeness, and perceived risk to client's intention," *Journal of Open Innovation Technology Market and Complexity*, vol. 10, no. 3, p. 100322, 2024.
[40] R. K.-J. Yeh and J. T. Teng, "Extended conceptualisation of perceived usefulness: Empirical test in the context of information system use continuance," *Behaviour & Information Technology*, vol. 31, no. 5, pp. 525-540, 2012.