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Analysis of Microsoft Copilot Acceptance as Artificial Intelligence-Generated Content (AIGC) Using the TAM/TPB Model

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Abstract

The development of Artificial Intelligence-Generated Content (AIGC) technology has brought significant changes to creative work processes, particularly in design. Microsoft Copilot is one implementation of AIGC aimed at enhancing user productivity and efficiency. However, its adoption among designers remains limited due to various psychological, functional, and social considerations. This study aims to analyze the factors influencing user acceptance of Copilot by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), along with external constructs such as trust, functional risk, and emotional risk. Data were collected through a survey of 100 respondents, including design students and professionals, using a 5-point Likert scale questionnaire. The analysis was conducted using the Structural Equation Modeling Partial Least Squares (SEM-PLS) approach. The results indicate that perceived usefulness, perceived ease of use, and subjective norms significantly influence trust, which in turn positively affects the behavioral intention to use Copilot. These findings highlight the critical role of trust as a mediating factor linking perceptions of usefulness and social pressure to the intention to adopt AIGC technologies. This study provides a foundation for developing AI implementation strategies in the creative industry that consider users' psychological aspects.

Keywords: *Acceptance, AI, Creative, Copilot, Designer, Efficiency.*

1. Introduction

The advancement of Artificial Intelligence (AI) technology has significantly impacted various fields, including design [1]. One increasingly popular AI implementation is Copilot, an AI-based system designed to assist designers in enhancing their efficiency and creativity. Copilot enables designers to generate ideas, automate repetitive tasks, and improve productivity by providing data-driven design recommendations [2].

Despite these advantages, the adoption of AI in the design industry still faces challenges regarding user acceptance. Several studies indicate that integrating AI into creative work is not as seamless as expected. Designers who have experimented with AI tools often prefer traditional methods, citing concerns over AI's lack of flexibility and its perceived reduction of originality and creative idealism. Additionally, factors such as trust in AI, ease of use, and social influence play a crucial role in shaping users' intention to adopt such technologies [1].
To understand the factors influencing AI acceptance in design, this study adopts the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) [3]. TAM focuses on how perceived usefulness and perceived ease of use affect users' intentions to adopt technology [4], while TPB adds the dimensions of social norms, trust in AI, and both functional and emotional risks that may influence user decisions [5].

By employing this model, the study aims to explore how these factors contribute to designers' acceptance of Copilot. The findings are expected to provide valuable insights for AI developers in enhancing user trust and comfort, as well as support the design industry in effectively integrating AI into creative workflows.

2. Literature review

2.1. Artificial Intelligence Generated Content (AIGC)

AIGC refers to content generated using advanced Generative AI (GAI) techniques, rather than by human authors. Examples of AIGC include ChatGPT, which is a language model developed by OpenAI to build conversational AI systems, and DALL-E-2, which is capable of generating unique, high-quality images from text descriptions. The AIGC generation process typically consists of two steps: extracting intent information from human instructions and generating content according to the extracted intent. AIGC has been adopted in a variety of industries, including the arts, advertising, and education, and is expected to continue to be a significant area of research in the future [6].

Artificial Intelligence Generated Content (AIGC) is content generated using advanced Generative AI (GAI) techniques, rather than by human authors. AIGC technology has a variety of functions, ranging from generating text, images, videos, to music. The advantages offered by AIGC include efficiency and speed in content creation, cost-effectiveness, content personalization, increased creativity, 24/7 availability, and consistency in content style and quality. However, this technology also has risks, such as potential data privacy violations, replacement of jobs previously performed by humans, market monopolization by large technology companies, and the spread of false information. Considering these advantages and risks, AIGC has become the subject of significant research in various fields, including art, advertising, and education [7].

2.2. Theoretical Framework

2.2.1. Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is a model developed by Fred D. Davis in 1989 to explain and predict user acceptance of information technology. TAM is based on two main constructs: perceived usefulness and perceived ease of use. Perceived Usefulness: The extent to which a person believes that using a particular technology will improve their performance. Perceived Ease of Use: The extent to which a person believes that using a particular technology will be free of effort [4].

The Technology Acceptance Model (TAM) has been widely used to examine various factors that influence the acceptance and adoption of technology in various fields. Among them, TAM has been applied in the context of digital finance, such as research on the adoption of fintech (financial technology) for digital payment systems. This study measures and analyzes the factors that influence user acceptance of the use of fintech in digital payments, such as OVO and Gopay. In addition, other studies have used TAM to evaluate user attitudes towards fintech in various countries, such as Bangladesh and Indonesia, and explore additional variables such as financial literacy, user attitudes, cultural factors, and geographic location. TAM has also been used to deepen understanding of perceptions of data security and privacy in the use of fintech, as well as the effect of ease of use on user intentions to adopt the technology [8].

Although the basic TAM model consists of only two main constructs, namely Perceived Usefulness (PU) and Perceived Ease of Use (PEU), this study combines TAM with TPB (Theory of Planned Behavior), and adds external constructs such as Trust, Functional Risk, and Emotional Risk. This development aims to adapt the model to the context of using generative AI technology such as Copilot in the design world.

2.2.1. Technology Acceptance Model (TAM)

The Theory of Planned Behavior (TPB) is a psychological model developed by Icek Ajzen in 1991 to predict and explain human behavior in various contexts, including technology adoption. This model states that a person's intention to perform a behavior is influenced by three main factors: attitude toward behavior (ATB), subjective norms (SN), and perceived behavioral control (PBC). TPB can explain user behavior in technology adoption by describing how attitudes, subjective norms, and perceived behavioral control affect users' intentions to adopt new technologies. For example, if a user believes that a new technology will provide benefits and improve work efficiency (ATB), then their attitude toward adopting the technology will be positive, thereby increasing their intention to adopt the technology. If the user's social environment (such as friends, coworkers, or superiors) supports the use of the new technology (SN), then the user will feel encouraged to adopt the technology. If users feel that they have the necessary abilities and resources to use the new technology (PBC), they will be more likely to adopt the technology. Thus, attitudes toward behavior, subjective norms, and perceived behavioral control are the main variables in the TPB that influence a person's decision to adopt technology.[5]

Theory of Planned Behavior (TPB) has been widely used to examine various factors that influence individual intentions and behaviors in various fields. In the context of the use of Pay Later services by millennials, TPB identifies millennials' motivations, perceptions, and financial control related to the risks of using Pay Later. This study shows that ease of access, flexibility, and promotional incentives from Pay Later motivate millennials to use it. In addition, social pressure from relatives, the environment, and social media also influence this motivation, along with their belief in control over Paylater use. However, millennials are also aware of risks such as spontaneous purchases, financial difficulties, and defaults, which raise doubts about using this service. These findings highlight the importance of considering psychological aspects, financial literacy, and financial behavior in using Pay Later responsibly [9].

2.3. Factors that influence technology acceptance

2.3.1. Perceived Usefulness

Perceived Usefulness (PU) is defined as the degree to which a person believes that using a particular system will improve his/her job performance [4]. In research related to e-commerce, PU is considered to play an important role in influencing consumer purchasing intentions. PU can influence consumer attitudes and directly influence their behavior. This makes PU an important indicator in determining whether consumers will use e-commerce technology to make purchases [10].

2.3.2. Perceived Ease of Use

Perceived Ease of Use (PEOU) is a key concept often used in technology adoption studies to evaluate how easy a particular technology is for individuals to use [4]. In a study that discussed how Perceived Ease of Use (PEOU) affects the intention to use chatbots in eyewitness interviews. Perceived Ease of Use (PEOU) is considered to play an important role in influencing the intention to use chatbots in eyewitness interviews. PEOU affects individuals' attitudes and directly influences their intention to use chatbots in the interview process. This study found that the higher the level of PEOU, the more likely individuals are to accept and use the chatbot during investigative interviews. This makes PEOU an important indicator in determining whether users will adopt chatbot technology for eyewitness interviews. [11]

2.3.3. Trust in AI

In a study, it is said that trust in AI is defined as a combination of reliance and extra factors. Reliance refers to the scientific validity of AI output, while extra factors include responsibility, commitment, and goodwill. Thus, trust in AI involves not only reliance on technical reliability, but also moral and normative aspects that make AI trustworthy as a whole.[12]

2.3.4. Functional & Emotional Risk

Functional Risk refers to the risk that a product or service will not function as intended. In the context of e-service adoption, Functional Risk includes the possibility that the e-service may malfunction and fail to deliver the expected benefits. The failure of an e-service to operate according to its promised specifications may result in losses or inaccurate results for users.
Emotional Risk refers to the anxiety or emotional discomfort that users may experience when using a new technology or service. In the context of AI and e-services, Emotional Risk can include the fear of losing control, creativity, or even self-identity when interacting with automated, technology-based systems. The anxiety or stress caused by uncertainty in the use of technology is also included in Emotional Risk [13].

Trust in AI-based systems is not only shaped by technical performance, but also by perceptions of ethical risk and concerns about excessive reliance on automated systems [14].
The use of AI technology in learning or work activities, such as Microsoft Copilot, needs to be balanced with strengthening the user's critical thinking skills. Excessive reliance on AI can hinder personal development and reduce autonomy in the decision-making process, especially in creative and reflective contexts [15].

2.3.5. Subjective Norms

Subjective norms are normative beliefs that reflect an individual's view of what is considered acceptable or expected behavior by important people around them. According to Ajzen (1991), subjective norms are one of the main determinants of behavioral intention. This behavioral intention, in turn, is a direct predictor of actual behavior [5]. Research that SN has a significant influence on online purchasing intentions, with attitudes and beliefs as mediators [16]. In addition, SN has a significant effect on the intention to purchase environmentally friendly packaging [17]. These results indicate that SN plays an important role in influencing individual intentions and behaviors in various contexts, reflecting social pressures and expectations from the surrounding environment that can influence an individual's decision to adopt technology or perform a behavior.

3. Research methods

This study adopts a combination approach of Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) to understand technology acceptance and user behavior in using Copilot in design [3]. TAM is used to assess technology acceptance based on perceived usefulness and perceived ease of use [18], while TPB is used to understand user behavior through subjective norms, perceived risks, trust, and behavioral intention [19].

This research model includes the following variables :

1. Perceived Usefulness (PU) - Perceived usefulness of Copilot in improving efficiency and creativity.
2. Perceived Ease of Use (PEU) - Ease of using Copilot without requiring much training.
3. Subjective Norms (SN) - Social influence in the decision to use Copilot.
4. Functional Risk (FR) - Risk of inconsistency or inaccuracy of results from Copilot.
5. Emotional Risk (ER) - Anxiety and discomfort in using Copilot.
6. Trust (TRU) - Trust in Copilot in supporting design.
7. Behavioral Intention (BIU) - Intention to use Copilot continuously.

3.1. Research hypothesis

Relationship between Perception and Trust in AI:
TAM (Technology Acceptance Model) shows that when technology is perceived as useful (e.g., helping to complete tasks more efficiently or increasing productivity), users are more likely to believe that the technology is reliable and meets their needs. This trust is an important foundation for technology acceptance and continued use [4].
Hypothesis H1 states that Perceived Usefulness (PU) has a positive effect on Trust (TRU). In other words, the greater a user's perception that a technology or system (in this case, artificial intelligence in an academic environment) has significant benefits for their work, the greater their trust in the technology [18]. Meanwhile, Perceived Ease of Use (PEU) also has a positive effect on Trust (TRU). This means that if users feel that a system or technology is easy to use, they tend to have a higher level of trust in the technology [21].
Furthermore, H3 states that Subjective Norms (SN) has a positive effect on Trust (TRU). Subjective Norms refer to social pressure or influence from significant people around an individual, such as friends, colleagues, or lecturers, that can encourage an individual to accept or trust a particular technology [22].

- H1: Perceived Usefulness (PU) has a positive effect on Trust (TRU).
- H2: Perceived Ease of Use (PEU) has a positive effect on Trust (TRU).
- H3: Subjective Norms (SN) has a positive effect on Trust (TRU).

Relationship between Trust and Intention to Use:

Hypothesis H4 states that Trust (TRU) has a positive effect on Behavioral Intention to Use (BIU). Trust, which includes dimensions such as benevolence, integrity, and competence, plays an important role in building user confidence in a technology or system. When users feel confident in a technology, they are more likely to have a strong intention to use it.

In the context of this study, trust is a key factor that reduces the sense of doubt or vulnerability that users may feel, especially towards relatively new or unfamiliar technologies. This trust provides a sense of security, thus encouraging individuals to be more open to using the technology in their daily activities [23].

- H4: Trust (TRU) has a positive effect on Behavioral Intention to Use (BIU).

Relationship between Risk and Trust in AI:

Functional Risk (FR) has a negative effect on Trust (TRU). Functional Risk refers to the potential risk or failure associated with the functioning of a technology or system. When users perceive that a technology may not function as intended, is unreliable, or fails to meet their needs, trust in the technology tends to decrease [24]. Emotional Risk (ER) also has a negative effect on Trust (TRU). Emotional Risk refers to feelings of anxiety, fear, or emotional discomfort that users may experience when interacting with a technology. This risk often arises from concerns that the technology may lead to undesirable outcomes, such as misinformation, wrong decisions, or unhealthy dependency [25].

- H5a: Functional Risk (FR) has a negative effect on Trust (TRU).
- H5b: Emotional Risk (ER) has a negative effect on Trust (TRU).

Relationship between Perception and Perceived Risk:

Hypothesis H6a in this paper states that Perceived Usefulness (PU) has a negative effect on Functional Risk (FR). This means that the greater the user's perception that a technology or system is significantly useful in meeting their needs, the lower their level of concern or perception of the functional risk of the technology [24]. Hypothesis H6b in this study states that Perceived Usefulness (PU) has a negative effect on Emotional Risk (ER). This means that the higher the user's perception of the benefits of a technology or system, the lower the level of emotional risk they feel [27].

Hypothesis H7a states that Perceived Ease of Use (PEU) has a negative effect on Functional Risk (FR). This means that the easier a technology or system is to use, the lower the functional risk perceived by the user [26]. Based on the contents of this paper, hypothesis H7b states that Perceived Ease of Use (PEU) has a negative effect on Emotional Risk (ER). This means that the easier the technology or system is to use, the lower the emotional risk perceived by the user [29].

- H6a: Perceived Usefulness (PU) has a negative effect on Functional Risk (FR).
- H6b: Perceived Usefulness (PU) has a negative effect on Emotional Risk (ER).
- H7a: Perceived Ease of Use (PEU) has a negative effect on Functional Risk (FR).
- H7b: Perceived Ease of Use (PEU) has a negative effect on Emotional Risk (ER).

Relationship between Subjective Norms and Risk:

In addition to influencing trust, Subjective Norms can also have an impact on risk perception. Hypothesis H8a states that Subjective Norms (SN) have a negative influence on Functional Risk (FR). This means that the greater the social pressure from the environment that encourages the use of technology (such as Microsoft Copilot), the lower the risk of failure of the technology. This is due to trust in the social assessment of people around who support the use of technology [30].

- H8a: Subjective Norms (SN) have a negative effect on Functional Risk (FR)
- H8b: Subjective Norms (SN) have a negative effect on Emotional Risk (ER)

3.2. Research design

This study uses a quantitative approach with a survey method to collect data from respondents. The survey was conducted using a 5-point Likert scale-based questionnaire (1 = Strongly Disagree, 5 = Strongly Agree). This questionnaire was designed based on previous research instruments that have been validated.

3.4 Population and Sample

3.4.1. Population

The population in this study are active students in the creative field who use or have the potential to use Copilot in their work or activities. This population includes individuals who work in various design fields, such as graphic design, UI/UX, digital illustration, and other creative fields, both those who work professionally and design students who are studying the use of AI in design.

3.4.2. Samples and Sampling Techniques

Data collection was carried out by distributing online questionnaires via Google Form to respondents who met the inclusion criteria. The data collection process began on March 10, 2025, and ended on May 17, 2025. This study uses the Lemeshow method to determine the sample size with a margin of error of 10% to streamline costs and time in the data collection process. The sampling technique used is purposive sampling, which is selecting respondents based on certain criteria that are in accordance with the objectives of the study.

Respondent Criteria:
1. Respondents are professional designers or design students who are familiar with or use AI-based technology in design.
2. Respondents have experience or understanding of the use of Copilot or similar AI technology.
3. Respondents are willing to participate in the study by filling out the questionnaire completely.

To ensure the representativeness and relevance of the characteristics of the participants in this study, all respondents were individuals with a professional background in product design. They had undergone systematic formal education in design theory, had skills in manual drawing and the use of graphic design software, and were able to complete design projects independently, in accordance with the qualifications equivalent to beginner-level designers.

Of the total 100 respondents involved and whose data were declared valid, their demographic profiles can be detailed as follows:
1. Based on gender, 31% were male and 69% female;
2. Based on age, 5% were 18 years old, 20% were 19 years old, 32% were 20 years old, 23% were 21 years old, 14% were 22 years old, and 6% were 23 years old;
3. Based on experience using Artificial Intelligence-Generated Content (AIGC) technology, 86% of respondents have experience using Copilot and have mastered the workflow and methods, while 14% of respondents have not had direct experience but have shown interest in implementing this technology in future design projects, see Table 1.
4.

Table 1: Basic Information.

Profile	Items	Number	Percentage (%)
Gender	Male	31	31%
	Female	**69**	**69%**
Age	18	5	5%
	19	20	20%
	20	32	32%
	21	23	23%
	22	14	14%
	23	**6**	**6%**
Experience using Copilot	Yes	86	86%
	No	**14**	**14%**

3.5. Measurement Instruments

This study uses seven main constructs adapted from the TAM and TPB models, and is complemented by external constructs such as Trust, Functional Risk, and Emotional Risk. Each construct is measured through three indicators expressed in the form of closed-ended statements using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Although this scale is technically ordinal, in this study it is treated as an interval scale in order to be analyzed using a parametric statistical approach such as SEM-PLS.

The measurement instruments in this study were largely adapted from previous studies, including Davis (1989) for PU and PEU [4], Ajzen (1991) for SN [5], and Wang and Chen (2024) for TRU, FR, ER, and BIU [3]. Editorial adjustments were made to suit the context of AI users in the graphic design and digital creative fields, see Table 2.

Table 2: Instruments and Sources

Variable	Source	Question
Perceived Usefulness (PU)	[4]	PU1 Copilot helps improve my efficiency in completing design tasks. PU2 Copilot can provide useful creative ideas and solutions in the design process. PU3 Using Copilot allows me to focus more on the strategic aspects of design.
Perceived Ease of Use (PEU)	[4]	PEU1 Copilot is easy to use without the need for much customization or training PEU2 I feel comfortable using Copilot in my daily design tasks. PEU3 Copilot does not require much effort to understand and implement in my design workflow.
Subjective Norms (SN)	[5]	SN1 My coworkers or supervisor encourage the use of Copilot in the design process. SN2 I feel there is social pressure to use Copilot to remain competitive in the industry. SN3 The use of Copilot within the design community is increasingly common and accepted.
Functional Risk (FR)	[3]	FR1 I am concerned that Copilot provides inconsistent or inaccurate design results. FR2 Copilot sometimes provides suggestions that do not match my design needs. FR3 I feel the need to always verify the results provided by Copilot to match my standards.
Emotional Risk (ER)	[3]	ER1 I feel uncomfortable or anxious if I rely too much on Copilot in my designs. ER2 The use of Copilot makes me feel like I am losing my personal touch in my design work. ER3 I am worried that using Copilot will reduce my creativity and skills as a designer.

Trust (TRU)	[3]	TRU1 I believe that Copilot can be relied upon to support my design work. TRU2 Copilot is designed to assist, not replace the designer's creativity. TRU3 I believe that using Copilot will improve the overall quality of my design output.
Behavioral Intention to Use (BIU)	[3]	BIU1 I am interested in continuing to use Copilot in my design work. BIU2 I would recommend Copilot to my coworkers. BIU3 I would like to learn more about the features provided by Copilot.

3.6. Data Analysis Technique

The data obtained will be analyzed using statistical methods with the help of Jamovi software for Structural Equation Modeling (SEM). The analysis is carried out through the following stages:

- Validity and Reliability Test
- Using Average Variance Extracted (AVE) and Cronbach's Alpha to ensure the internal consistency of the instrument.
- Model Test and Relationship Between Variables
- Using SEM-PLS to analyze the relationship between PU, PEU, SN, FR, ER, TRU, and BIU variables.
- Hypothesis Test
- Using the t-statistic and p-value to determine whether the hypothesis is accepted or rejected.

With this method, the research is expected to provide deeper insights into technology acceptance and user behavior in the context of using Copilot in design.

4. Results and Discussion

4.1. Reliability and Validity Testing of the Measurement Model

To ensure that the data is feasible to analyze through factor analysis and can describe the research constructs well, an initial validity test was conducted using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity.
The test results show that the KMO value is 0.796, which means it is in the middling to skyrocketing high category (Kaiser, 1974). This value exceeds the minimum limit of 0.5, so it can be concluded that the number and quality of samples are sufficient for further factor analysis.
In addition, Bartlett's Test of Sphericity yielded a chi-square value of 1193.258 with degrees of freedom (df) of 210 and significance <0.001. This significance value is well below 0.05, which indicates that the correlation between items in the correlation matrix is statistically different from zero, thus supporting the assumption that the data can be extracted into statistically valid factors.
Thus, based on these two test results, it can be concluded that the data is suitable for further analysis using a factor analysis approach in order to validate the construct.
The next stage is to conduct an internal reliability test using Cronbach's Alpha to evaluate the consistency of indicators in each construct in the research model; the complete results are in Table 3.

Table 3 Confirmatory factor analysis.

Latent Variable	Indikator	Standard Factor Loading	Croanbach's Alpha	AVE
PU	PU1 PU2 PU3	0.815 0.824 0.946	0.821	0.747
PEU	PEU1 PEU2 PEU3	0.775 0.826 0.799	0.720	0.640
SN	SN1 SN2 SN3	0.795 0.743 0.799	0.678	0.608
ER	ER1 ER2 ER3	0.722 0.733 0.930	0.758	0.641
FR	FR1 FR2 FR3	0.915 0.737 0.828	0.798	0.689
TRU	TRU1 TRU2 TRU3	0.854 0.961 0.854	0.868	0.794
BIU	BIU1 BIU2 BIU3	0.850 0.830 0.706	0.715	0.637

4.2. SEM (Structural Equation Model)

Based on the results of hypothesis testing using the SEM-PLS method, it was found that of the ten relationships tested, four of them showed a statistically significant effect. Perceived Ease of Use (PEU) has a significant positive effect on Trust (TRU) with a coefficient value of $\beta = 0.263$, $t = 2.426$, and $p = 0.008$. Similarly, Perceived Usefulness (PU) also has a significant effect on Trust ($\beta = 0.288$; $t = 2.380$; $p = 0.009$). In addition, Subjective Norms (SN) showed a significant effect on Trust ($\beta = 0.217$; $t = 2.200$; $p = 0.014$), indicating that social influence has a role in shaping users' trust in Copilot. Most notably, Trust (TRU) has a very strong and significant influence on Behavioral Intention to Use (BIU) with a coefficient value of $\beta = 0.663$, $t = 11.508$, and $p = 0.000$. Meanwhile, other relationships such as Emotional Risk (ER) → Trust, Functional Risk (FR) → Trust, as well as the influence of PU, PEU, and SN on FR and ER did not show statistical significance ($p > 0.05$), see Table 4. so that these hypotheses cannot be accepted. These results indicate that user trust is a key factor bridging the perceived benefits, ease of use, and social norms to the intention to use generative AI technologies such as Microsoft Copilot.

Table 4: Hypothesis Test Results Using SEM-PLS

Code	Connection	Beta	T-Value	p-Value	Result
H1	PU→TRU	0.288	2.380	0.009	Supported
H2	PEU→TRU	0.263	2.426	0.008	Supported
H3	SN→TRU	0.217	2.200	0.014	Supported
H4	TRU→BIU	0.663	11.508	0.000	Supported
H5a	FR→TRU	-0.033	0.257	0.399	Unsupported
H5b	ER→TRU	0.003	0.024	0.490	Unsupported
H6a	PU→FR	0.163	0.837	0.201	Unsupported
H6b	PU→ER	0.133	0.610	0.271	Unsupported
H7a	PEU→ER	-0.101	0.597	0.275	Unsupported
H7b	PEU→FR	-0. 069	0.310	0.378	Unsupported
H8a	SN→FR	0.009	0.046	0.482	Unsupported
H8b	SN→ER	0.118	0.700	0.242	Unsupported

5. Conclusion

This study contributes novel insights to the field of technology adoption, particularly within the context of Artificial Intelligence-Generated Content (AIGC) tools such as Microsoft Copilot. By integrating core constructs from the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) with additional variables—Trust, Functional Risk, and Emotional Risk—this research presents a more comprehensive framework for understanding user intention. The key findings reveal that trust plays a central mediating role, significantly influenced by perceived usefulness, perceived ease of use, and subjective norms. In turn, trust has a strong positive impact on behavioral intention to use the technology.

Interestingly, functional and emotional risks do not exhibit significant direct effects on trust or behavioral intention in this study, suggesting that users may be more influenced by the utility and usability of the tool than by their concerns or discomfort. This underscores a practical implication: in the design and deployment of AI tools for creative professionals, enhancing trust through usability and peer influence may be more effective than mitigating perceived risks. These findings not only affirm the robustness of TAM and TPB in AI contexts but also extend their applicability to modern design workflows mediated by generative AI.

Future research could explore additional psychological or contextual factors that may influence trust and intention, or investigate these relationships in varied professional domains beyond design.

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References

[1] Mehta, M., Shah, H., & Dasgupta, R. (2024). ARTIFICIAL INTELLIGENCE (AI): PRACTICES AND PROBLEMS EXPERIENCED BY INTERIOR DESIGNERS. *ShodhKosh: Journal of Visual and Performing Arts*, *5*(2), 99–107. https://doi.org/10.29121/shodhkosh.v5.i2.2024.1424

[2] Narayanaswamy, A. (2024). Working with Microsoft Designer. In: Microsoft Copilot for Windows 11. Inside Copilot. Apress, Berkeley, CA. https://doi.org/10.1007/979-8-8688-0583-7_9

[3] Wang, S. F., & Chen, C. C. (2024). Exploring Designer Trust in Artificial Intelligence-Generated Content: TAM/TPB Model Study. *Applied Sciences (Switzerland)*, *14*(16). https://doi.org/10.3390/app14166902

[4] Davis, Fred D. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarterly*, vol. 13, no. 3, 1989, pp. 319–40. *JSTOR*, https://doi.org/10.2307/249008. Accessed 11 Mar. 2025.

[5] Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. In *Psychology and Health* (Vol. 26, Issue 9, pp. 1113–1127). https://doi.org/10.1080/08870446.2011.613995

[6] Cao, Y., Li, S., Liu, Y., Yan, Z., Dai, Y., Yu, P. S., & Sun, L. (2023). *A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT*. http://arxiv.org/abs/2303.04226

[7] Yao, Y., Wang, X., & Sun, K. (2025). Research on key factors influencing Chinese designers' use of AIGC: An extension based on TAM and TRI. *PLoS ONE*, *20*(2 February). https://doi.org/10.1371/journal.pone.0314306

[8] Softer, D., Bawala, J., & Tanaamah, A. R. (2024). Evaluation of Fintech Use Using Methods Technology Acceptance Model (TAM). *Jurnal Indonesia Sosial Teknologi*, *5*(8), 3088. http://jist.publikasiindonesia.id/

[9] Fatmawati, S., & Suwardi, E. (2024). Paylater as The Millennial Payment: Theory Planned Behavior. *Jurnal Akuntansi Dan Keuangan*, *26*(2), 91–102. https://doi.org/10.9744/jak.26.2.91-102

[10] Abidin, Z. (2024). The effect of perceived usefulness, perceived ease of use, and lifestyle on purchase intention. *Journal of Management and Business Insight*, *2*(1), 62–70. https://doi.org/10.12928/jombi.v2i1.935

[11] Tomas, F., & Immerzeel, J. (2025). Chatbots in eyewitness interviews: perceived usefulness and ease of use drive intent to use conversational agent. *Journal of Criminal Psychology*. https://doi.org/10.1108/JCP-11-2024-0110

[12] Durán, J. M., & Pozzi, G. (2025). Trust and Trustworthiness in AI. *Philosophy and Technology*, *38*(1). https://doi.org/10.1007/s13347-025-00843-2

[13] Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human Computer Studies*, *59*(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

[14] Binns, R., van Kleek, M., Veale, M., Lyngs, U., Zhao, J., & Shadbolt, N. (2018). "It's reducing a human being to a percentage"; perceptions of justice in algorithmic decisions. *Conference on Human Factors in Computing Systems - Proceedings, 2018-April*. https://doi.org/10.1145/3173574.3173951

[15] Pratita, A., Suryanto, T. L. M., Pratama, A., & Wibowo, A. (2025). ChatGPT in Education: Investigating Students Online Learning Behaviors. *International Journal of Information and Education Technology*, *15*(3), 510–524. https://doi.org/10.18178/ijiet.2025.15.3.2262

[16] Afifah, A. N., & Arafah, W. (n.d.). *PENGARUH SUBJECTIVE NORMS TERHADAP PURCHASE INTENTION DIMEDIASI OLEH ARTIFICIAL INTELLIGENCE PADA E-RETAIL.*

[17] Allahyari, M. S., Marzban, S., Berjan, S., El Bilali, H., & Ben Hassen, T. (2025). Assessing the Use of ChatGPT among Agri-Food Researchers: A Global Perspective. *Journal of Agriculture and Food Research*, 101616. https://doi.org/10.1016/j.jafr.2024.101616

[18] Lv, H., Ning, Y., Meng, L., Yang, C., Jiang, Y., Li, X., Tang, L., Li, X., & Li, X. (2025). Factors influencing medical students' acceptance of clinical virtual simulation experiments: A combined TAM and TPB approach. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3547901

[19] Wang, H., Hou, X., Liu, J., Zhou, X., Jiang, M., & Liao, J. (2024). Framework effect and achievement motivation on college students' online learning intention–based on technology acceptance model (TAM) and theory of planned behaviour (TPB) model. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-13254-1

[20] Osman, Z., Alwi, N. H., Mohamad Jodi, K. H., Ahmad Khan, B. N., Ismail, M. N., & Yusoff, Y. (2024). Optimizing Artificial Intelligence Usage among Academicians in Higher Education Institutions. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, *14*(2). https://doi.org/10.6007/ijarafms/v14-i2/20935

[21] Vazirani, M. (2024). Impact of artificial intelligence on consumer behavior in reference to online shopping. *International Journal of Advanced Scientific Research and Management*, *9*(1), 9–18. https://doi.org/10.36282/ijasrm/9.1.2024.1925

[22] Ayanwale, M. A., & Ndlovu, M. (2024). Investigating factors of students' behavioral intentions to adopt chatbot technologies in higher education: Perspective from expanded diffusion theory of innovation. *Computers in Human Behavior Reports*, *14*. https://doi.org/10.1016/j.chbr.2024.100396

[23] Wistedt, U. (2024). Consumer purchase intention toward POI-retailers in cross-border E-commerce: An integration of technology acceptance model and commitment-trust theory. *Journal of Retailing and Consumer Services*, *81*. https://doi.org/10.1016/j.jretconser.2024.104015

[24] Salman, H., Aljawder, M., Almohsen, E., & Buzaboon, A. (n.d.). *Artificial Neural Network Modeling of Users' Behavioral Intention to Adopt M-Government Services.*

[25] Singh, S., & Kumar, A. (2024). Investing in the future: an integrated model for analysing user attitudes towards Robo-advisory services with AI integration. *Vilakshan - XIMB Journal of Management*. https://doi.org/10.1108/XJM-03-2024-0046

[26] Ismatullaev, U. V. U., & Kim, S. H. (2024). Review of the Factors Affecting Acceptance of AI-Infused Systems. *Human Factors*, *66*(1), 126–144. https://doi.org/10.1177/00187208211064707

[27] Nguyen, O. T. (2020). Factors affecting the intention to use digital banking in Vietnam. *Journal of Asian Finance, Economics and Business*, *7*(3), 303–310. https://doi.org/10.13106/jafeb.2020.vol7.no3.30

[28] Dirsehan, T., & Can, C. (2020). Examination of trust and sustainability concerns in autonomous vehicle adoption. *Technology in Society*, *63*. https://doi.org/10.1016/j.techsoc.2020.101361

[29] Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*. https://doi.org/10.1016/j.tele.2022.101925

[30] Chong, A. Y. L. (2013). Predicting m-commerce adoption determinants: A neural network approach. *Expert Systems with Applications*, *40*(2), 523–530. https://doi.org/10.1016/j.eswa.2012.07.068