A Study on Designers' Intention to Use Generative AI for Human-Machine Collaborative Design — Based on the Integrated Model of TAM and TTF

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Abstract. The application of generative artificial intelligence in human-machine collaborative design is gradually deepening, but designers' usage intention and its influence mechanism remain to be explored. Relevant hypotheses are proposed on the basis of integrating the TAM and TTF models, followed by an empirical analysis through questionnaire surveys. The results show that perceived ease of use has a significant positive impact on perceived usefulness and satisfaction, and perceived usefulness further improves satisfaction; both task characteristics and technology characteristics positively affect task-technology fit; both satisfaction and task-technology fit exert a significant positive impact on usage intention.

Keywords: Technology Acceptance Model, Task-Technology Fit Model, Generative Artificial Intelligence, Human-Machine Collaboration

1. Introduction

The breakthrough development of generative artificial intelligence (Artificial Intelligence Generated Content, AIGC, hereinafter referred to as generative AI) in recent years is restructuring the design industry with unprecedented breadth and depth. Therefore, generative AI tools represented by Diffusion Models and Large Language Models (LLM) have shown great potential as a "co-creator" in human-machine collaboration, that is, they have the abilities of independent understanding, perception, planning, memory and tool use. This naturally leads to a new relationship of human-machine collaboration, and also brings revolutionary opportunities for efficiency improvement and possibility expansion in design innovation. Therefore, the collaboration mode between human designers and AI tools has become a frontier topic in design research.

However, there is a clear and well-documented "intention gap" between revolutionary new technologies and the practical application of professional designers. The Technology Acceptance Model (TAM) has long well explained that users' perceived usefulness and perceived ease of use of technology are the two basic driving forces for their usage intention. Nevertheless, it is needless to say that in creative design activities with high contextuality, vague initial requirements and pursuit of unique value, it is inevitably insufficient to analyze users' usage intention merely from the perspective of general technology perception. Therefore, the Task-Technology Fit (TTF) model provides a very natural and powerful supplement: the actual improvement of performance by technology ultimately depends on the matching degree between its functions and users' specific task requirements. Therefore, how the capabilities of generative AI fit the unique needs of design tasks such as creative divergence, prototype generation and design evaluation is another fundamental dimension affecting designers' usage intention.

In view of this, this study intends to integrate the TAM and TTF models into a theoretical analysis framework suitable for the generative AI collaborative design scenario. Starting from designers' perception of the technical and task characteristics of generative AI, combined with perceptual experiences such as task-technology fit, perceived usefulness and perceived ease of use, this study explores designers' intention to use generative AI for human-machine collaborative design, and provides theoretical guidance for the development and promotion of generative AI tools in design practice accordingly.

2. Related research

2.1. TAM and TTF models

The TAM model is a classic theoretical framework proposed by Davis in 1989 to explain users' adoption of information technology behaviors [1]. It clearly points out that users' perceived usefulness and perceived ease of use of technology are the two core factors affecting their attitude towards use and behavioral intention. Specifically, perceived usefulness refers to the degree to which users believe that using a certain technology helps improve work performance, while perceived ease of use refers to the degree of effort that users believe is required to use the technology. More importantly, a large number of existing studies consistently support that perceived ease of use not only directly affects whether users use a certain technology, but also indirectly affects users' views on the usefulness of the technology, thus having a dual effect on the final adoption behavior [1]. Since the TAM model does not fully and systematically examine the differences in technology use when dealing with different task contexts, Goodhue and Thompson proposed the TTF model [2]. This model has three clear and interrelated variables: task characteristics, technology characteristics and task-technology fit. Its basic viewpoint is very clear: whether information technology can improve user performance fundamentally depends on the matching degree between technology characteristics and task requirements. If the functions of technology are conducive to users completing tasks, users will be satisfied with the technology and are more likely to form a clear intention to continue using the technology. Several scholars have made systematic attempts to integrate the TAM and TTF models to simultaneously explain users' subjective judgments and the matching relationship between tasks and technologies. Dishaw and Strong further supplemented this research: task-technology fit not only affects system use performance, but also affects users' views on the usefulness and ease of use of technology, thereby affecting their behavioral intention [3]. Therefore, the integrated TAM and TTF model has been widely used in many fields such as e-commerce, online learning and social media, and sufficient evidence has shown that the model has reliable explanatory power for users' technology adoption behaviors [3].

2.2. Generative AI and human-machine collaborative design

Generative AI is fundamentally different from traditional computer-aided design tools. It can not only execute instructions, but also naturally and reasonably generate content in various forms such as text, images and codes through deep learning models, so it has real collaborative creation capabilities. Therefore, the way human designers participate in creation together with artificial intelligence can be regarded as a new paradigm of human-machine collaborative design, which will inevitably change the previous design process dominated by a single subject.

From the current relevant literature, the academic community has an almost unified discussion on the role of generative AI in the design process. In the early stage of design, generative AI can be used to quickly generate creative concepts and design schemes, which is conducive to expanding the creative space; in the design and development stage, it can be used as a tool for prototype generation, visual representation and design iteration; in the design evaluation stage, it is suitable for data analysis and user feedback analysis to support design decisions.

In addition, the effect of human-machine collaborative design in practical application is inevitably affected by several factors. First, designers need to have a positive judgment on the functions and value of AI tools, that is, they believe that it helps improve creative efficiency and optimize the design process. Second, whether the functions of AI tools themselves truly meet the needs of design tasks are both directly related to designers' experience in use. If the results generated by generative AI cannot meet design needs, or the interaction process is too complex, it will increase the use burden and thus inhibit the intention of continuous use.

2.3. Research deficiencies of generative AI in the design field

At present, research on generative AI in the design field mainly focuses on technical capabilities and application scenarios. However, research examining designers' usage intention and behavioral mechanism from the designers' perspective is still very scarce. More importantly, for design activities, whether technology can truly support creative generation, scheme exploration and design iteration is the most direct and core criterion for judging its application value. Therefore, there are obvious limitations in explaining designers' behaviors merely from the perspective of technology perception. Therefore, integrating the TAM and TTF models to analyze designers' usage intention of generative AI from the dual perspectives of technology perception and task matching has strong theoretical value.

3. Research hypotheses and research model

3.1. Research hypotheses

3.1.1. The relationship between perceived usefulness, perceived ease of use and satisfaction

As mentioned in the above theories, users' perceived usefulness and perceived ease of use of technology are the two fundamental factors affecting their attitude towards use and behavioral intention. Therefore, in the specific context of generative AI applied in the design field, if designers believe that generative AI tools have practical and clear help in creative generation, scheme exploration, design expression and other aspects, they will think that the technology has extremely high practical value and have a more positive experience in use. In perfect complement to this, if generative AI tools have good interaction design and extremely low learning difficulty, designers can easily master their use methods, thereby effectively reducing the cognitive load in use and more easily obtaining satisfaction.

In addition, the TAM model points out that perceived ease of use not only directly affects user experience, but also enhances users' cognition of technology value by improving the understandability and operability of technology. Therefore, most information technology application studies treat perceived ease of use as a positive factor affecting perceived usefulness [4].

Based on the above analysis, the following research hypotheses are proposed:

H1: Perceived ease of use positively affects perceived usefulness.

H2: Perceived ease of use positively affects satisfaction.

H3: Perceived usefulness positively affects satisfaction.

3.1.2. The relationship between task characteristics, technology characteristics and task-technology fit

The TTF model emphasizes that the improvement of user performance by information technology does not only depend on the technology itself, but on whether the technical functions can effectively support users to complete specific task requirements.

Design activities often show strong openness and creativity in the actual development process. When completing tasks, designers need diverse information support and rely on more flexible expression methods to promote schemes. If generative AI can provide high-quality text generation, image generation or concept expansion capabilities, and can respond to designers' needs quickly, then technology characteristics are more likely to form a matching relationship with design tasks and improve task-technology fit. On the contrary, if generative AI cannot meet design task requirements in terms of output quality, interaction mode or functional support, it may reduce designers' evaluation of technology fit. Therefore, the characteristics of the task itself and the characteristics of the technology are regarded as important factors affecting task-technology fit.

Based on the above analysis, the following research hypotheses are proposed:

H4: Task characteristics positively affect task-technology fit.

H5: Technology characteristics positively affect task-technology fit.

3.1.3. The relationship between satisfaction, task-technology fit and usage intention

In information system and technology adoption research, user satisfaction is usually regarded as an important factor affecting continuous usage intention. Positive experience when users use technology will improve their overall evaluation of the technology, and such evaluation changes are conducive to promoting subsequent behaviors such as continuing to use the technology or recommending it to others [5].

On the other hand, task-technology fit also affects usage intention. In design activities, if generative AI can help designers quickly generate creative schemes, optimize design expression and improve design efficiency, designers will think that the technology is very suitable for completing current tasks, thus increasing usage intention.

Based on the above analysis, the following research hypotheses are proposed:

H6: Satisfaction positively affects designers' usage intention.

H7: Task-technology fit positively affects designers' usage intention.

3.2. Research model

Based on the above theoretical basis, this study constructs a research model integrating the TAM and TTF models. The model explains the behavioral mechanism of designers using generative AI from two dimensions: the technology perception path and the task adaptation path. The research model is shown in Figure 1.

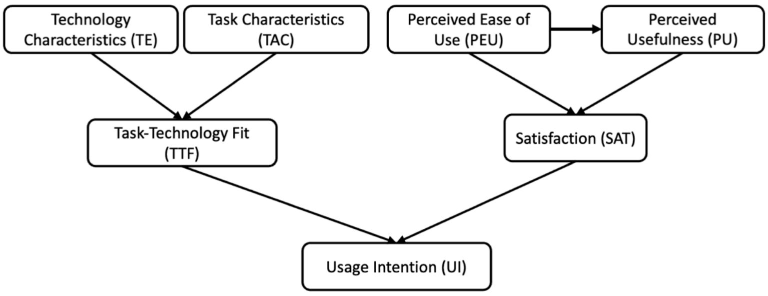

Figure 1. Influence mechanism model of designers' usage intention of Generative AI based on the integrated TAM and TTF model

4. Research design

4.1. Scale construction

To ensure the scientificity and reliability of research measurement, in the process of questionnaire design, this study first referred to relevant general scales at home and abroad, and then reasonably adjusted some items combined with the practical application scenario of generative AI in human-machine collaborative design. Finally, all items were measured by the Likert 5-point scale, that is, the scoring range of each item is 1 to 5, 1 means strongly disagree and 5 means strongly agree. Respondents answered according to their true feelings.

The latent variables involved in this study include seven latent variables: task characteristics, technology characteristics, task-technology fit, perceived ease of use, perceived usefulness, satisfaction and usage intention. The measurement items of these variables are mostly derived from scales repeatedly verified in existing studies, and revised on this basis combined with specific scenarios.

Before the formal distribution of the questionnaire, a small-scale pre-test was conducted in the research process, and relevant professionals were invited to provide feedback to test whether the item expressions were clear and easy to understand. Some contents were optimized and adjusted according to these feedbacks, making the overall understanding of the questionnaire clearer and improving the accuracy of measurement to a more appropriate level.

4.2. Sample characteristics

The research collected data through questionnaire surveys. The survey subjects mainly included design practitioners and design-related professionals with experience in using generative AI, specifically covering employees of design companies, Internet product designers, design majors in universities and other groups. The questionnaire was distributed through online platforms and spread via social media and design industry communities, which expanded the coverage of the sample to a certain extent.

A total of 235 questionnaires were collected in this survey. After excluding incomplete questionnaires, questionnaires with obvious regular answers and questionnaires without experience in using generative AI, 220 valid questionnaires were finally obtained, with an effective rate of 93.6%.

From the basic characteristics of respondents, in terms of gender distribution, the proportion of male and female samples is basically balanced. In terms of age distribution, most people are in the

20-35 age group, which is the most important and active user group of generative AI at present. In terms of occupation distribution, product designers, visual designers, interaction designers, postgraduate and undergraduate students majoring in design are the main groups. All these groups have a high acceptance of digital technology and generally use generative AI tools directly in study and work.

In terms of the use of generative AI, most respondents have used text generation, image generation or design-assisted AI tools, such as ChatGPT, Midjourney, Doubao, etc., and mainly use them to solve problems such as creative conception, conceptual design, design reference collection and copywriting. Therefore, it can be considered that the samples have practical experience in human-machine collaborative design.

5. Research analysis

5.1. Reliability and validity test

To test the measurement quality of the questionnaire scale, this study conducted reliability and validity analysis on each latent variable. The reliability was mainly judged by Cronbach's α coefficient, and the validity was evaluated by confirmatory factor analysis. The results are shown in Table 1.

Table 1. Reliability and validity test of each latent variable in the study on designers' intention to use Generative Artificial Intelligence for human-machine collaborative design

Variable	Measurement Item	Factor Loading	Cronbach's α	AVE	CR
Task Characteristics	I need to obtain relevant information at any time during the design process	0.763	0.871	0.693	0.91
	I need to conduct frequent information queries during the design process	0.736			
	I need to generate text or creative content during the design process	0.842			
	I need to use tools to expand design ideas during the design process	0.839			
Technology Characteristics	Generative AI can respond to my needs in a timely manner	0.759	0.895	0.668	0.893
	Generative AI has relevant functions to support design tasks	0.801			
	Generative AI can provide relatively comprehensive services	0.853			
	Generative AI can provide personalized output results	0.857			
Task-Technology Fit	Generative AI can meet my needs in information acquisition	0.625	0.871	0.657	0.88
	Generative AI can meet my needs in content generation	0.869			
	Generative AI can effectively assist me in completing design tasks	0.848			
	Generative AI can provide me with new design perspectives	0.874			

Table 1. (continued)

Perceived Ease of Use	Generative AI is easy to use	0.873	0.926	0.759	0.929
	I can master the use method of generative AI relatively easily	0.891			
	Generative AI can better understand my input intention	0.856			
	It takes a short time to learn to use generative AI	0.865			
Perceived Usefulness	Generative AI can improve my design efficiency	0.875	0.894	0.654	0.883
	Generative AI can improve my creative expression ability	0.793			
	Generative AI can provide effective support for design	0.872			
	Generative AI is helpful to my study or work	0.682			
Satisfaction	I am satisfied with the overall use experience of generative AI	0.878	0.875	0.692	0.9
	The output results of generative AI meet my expectations	0.763			
	I am happy to use generative AI for design collaboration	0.748			
Usage Intention Variable	I am willing to continue using generative AI for design in the future	0.788	0.898	0.693	0.91
	I am willing to recommend generative AI to others	0.854			
	I am willing to use generative AI in more design tasks	0.848			
	Compared with traditional methods, I prefer to use generative AI	0.837			

In terms of reliability test, the Cronbach's α coefficient of each latent variable is higher than 0.8, indicating that the scale has good internal consistency, and the measurement items have high correlation with each other, which can stably reflect the connotation of the corresponding latent variables.

In terms of validity test, the standardized factor loadings of each measurement item on the corresponding latent variable are higher than 0.6, indicating that the scale has good convergent validity. At the same time, the CR of each latent variable is higher than 0.8 and the AVE is higher than 0.6, indicating that the latent variables can better explain the variance of their measurement items. In terms of discriminant validity, as shown in Table 2, the square root of AVE of each latent variable is greater than the correlation coefficient between it and other latent variables, indicating that each variable has good discriminant validity.

Table 2. Discriminant validity of each latent variable in the study on designers' intention to use Generative Artificial Intelligence for human-machine collaborative design

	Task Characteristics	Technology Characteristics	Task-Technology Fit	Perceived Ease of Use	Perceived Usefulness	Satisfaction	Usage Intention
Task Characteristics	—	—	—	—	—	—	—
Technology Characteristics	0.693^{***}	—	—	—	—	—	—
Task-Technology Fit	0.675^{***}	0.683^{***}	—	—	—	—	—
Perceived Ease of Use	0.612^{***}	0.607^{***}	0.615^{***}	—	—	—	—

Table 2. (continued)

Perceived Usefulness	0.695***	0.650***	0.633***	0.683***	—	—	—
Satisfaction	0.624***	0.626***	0.628***	0.614***	0.647***	—	—
Usage Intention	0.636***	0.617***	0.629***	0.578***	0.611***	0.596***	—
Square root of AVE	0.832	0.817	0.811	0.871	0.803	0.832	0.832

Note: ***P<0.001.

5.2. Overall fit test

This study used AMOS software to estimate the model and evaluated the overall fit of the model through multiple indicators. The analysis results show that all fitting indicators of the research model meet the recommended standards. Among them, χ^2/df is 1.881<3, GFI is 0.903, IFI is 0.975, and RMSEA is 0.05, indicating that the overall fit of the model is good, and the constructed research model can better explain the relationship between variables.

5.3. Path analysis

The path analysis results are shown in Table 3. Perceived ease of use has a positive impact on perceived usefulness (β=0.468, $P<0.001$), and H1 is supported; perceived ease of use has a positive impact on satisfaction (β=0.923, $P<0.001$), and H2 is supported; perceived usefulness has a positive impact on satisfaction (β=0.628, $P<0.001$), and H3 is supported; task characteristics have a positive impact on task-technology fit (β=0.293, $P<0.001$), and H4 is supported; technology characteristics have a positive impact on task-technology fit (β=0.412, $P<0.001$), and H5 is supported; satisfaction has a positive impact on usage intention (β=0.327, $P<0.05$), and H6 is supported; task-technology fit has a positive impact on usage intention (β=0.211, $P<0.05$), and H7 is supported.

Table 3. Path analysis of the study on designers' intention to use Generative Artificial Intelligence for human-machine collaborative design

Hypothesis	Estimate	S.E.	C.R.	P-value	Test Result
H1 Perceived Ease of Use → Perceived Usefulness	0.468	0.06	7.912	***	Supported
H2 Perceived Ease of Use → Satisfaction	0.923	0.083	10.78	***	Supported
H3 Perceived Usefulness → Satisfaction	0.628	0.143	4.97	***	Supported
H4 Task Characteristics → Task-Technology Fit	0.293	0.144	2.377	***	Supported
H5 Technology Characteristics → Task-Technology Fit	0.412	0.151	3.071	***	Supported
H6 Satisfaction → Usage Intention	0.327	0.136	2.759	0.005	Supported
H7 Task-Technology Fit → Usage Intention	0.211	0.089	2.432	0.014	Supported

Note: ***P<0.001.

6. Conclusions and implications

6.1. Conclusions

Based on the TAM and TTF models, this study constructs an influence mechanism model of designers using generative AI for human-machine collaborative design, and then empirically tests the influencing factors of designers' usage intention through questionnaire surveys.

From the existing results, at the level of technology acceptance, perceived ease of use has a clear positive impact on perceived usefulness: if designers think tools are easy to use and have low operation costs, they are more likely to objectively and fully perceive the value of technology in the design process. Consistently, both perceived usefulness and perceived ease of use have a direct positive impact on satisfaction, and the characteristics of tools such as improving efficiency and reducing use difficulty will naturally improve the overall experience.

At the level of task-technology fit, both task characteristics and technology characteristics have a direct impact on fit. The better the matching between the needs of design tasks and the capabilities of selected technologies, the easier it is for the technology to show its effect in actual tasks. More importantly, both satisfaction and task-technology fit have a clear positive effect on usage intention: if designers have a good experience in the use process and think that technology is truly conducive to completing tasks, their willingness to use continuously will be greatly enhanced. Therefore, combining the two models can more fully and accurately explain designers' technology adoption behaviors in the collaborative design scenario, and also provide solid empirical support for relevant use decisions.

6.2. Implications

The research results have certain reference value for the development of generative AI tools and design practice. First, tool development must pay attention to the design of interface and interaction process, so it is necessary to take the initiative to minimize the learning cost, improve the operation efficiency as much as possible, and make it more acceptable to designers. Second, the functions of tools should have a better matching relationship with specific design tasks, and provide direct and strong support in creative generation, information integration, design expression and other aspects, so as to improve task-technology fit. Furthermore, when introducing generative AI tools, relevant organizations should organize training in a planned and systematic way, so that designers can gradually get familiar with the technology, integrate the use method with the work process naturally and smoothly, and form a stable and reliable human-machine collaborative design mode after full accumulation, and finally truly improve the overall efficiency and innovation ability to a new level.

6.3. Limitations

There are also some limitations in the development of this study. In terms of sample acquisition, the samples were collected from online questionnaires, so the sample structure is significantly affected by the collection channels, and the representativeness of the samples can be improved. In terms of research methods, the current analysis is based on questionnaire data, and there is no direct observation of designers' collaborative behaviors in the real design process, so the relevant process information is not sufficient. Follow-up research can introduce case analysis or experimental methods to conduct a more detailed and solid investigation on the actual process of human-machine collaborative design.

Acknowledgements

Humanities and Social Sciences Planning Fund of the Ministry of Education (23YJAZH090)

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