Journal of Theoretical and Applied Information Technology
30th April 2026. Vol.104. No.8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

WHAT AFFECTS THE ACCEPTANCE OF ARTIFICIAL INTELLIGENCE (AI)-POWERED CREATIVITY SUPPORT TOOLS AMONG THE INDUSTRIAL DESIGN COMMUNITY IN CHINA—A QUALITATIVE STUDY

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ABSTRACT

Artificial intelligence-based creative support tools (AI-CSTs) have currently been progressively adopted in the creative industry. These tools demonstrate significant potential for enhancing creative efficiency and optimizing workflow processes. Yet, the unique acceptance dynamics of AI-CSTs in the industrial design field, as opposed to tools in graphic design, constitute a significant and unexamined research gap. This paper aims to explore the key factors influencing the acceptance of AI-CSTs among the industrial design community. This study employed in-depth interviews, conducted via online platform and face-to-face communication, with 18 industrial design stakeholders possessing over three years of professional experience. All interview content was transcribed, coded, and analyzed using NVivo 12.0, with a thematic analysis approach adopted to identify the primary influencing factors. The findings reveal that users' acceptance of AI-CSTs is influenced by multiple factors, including the perception level (performance expectancy, effort expectancy, perceived risk), individual level (technology optimism, innovativeness), and technical level (facilitating conditions, price value, interactivity). Understanding users' attitudes and concerns regarding the use of AI-CSTs is critical for both technology developers and policymakers to optimize tool design and promotion strategies. This study contributed to enhancing the acceptance and practical effectiveness of AI-CSTs.

Keywords: *Artificial Intelligence; Creativity Support Tools; Technology Acceptance; Industrial Design; Qualitative Research*

1. INTRODUCTION

The design industry is currently confronting a critical challenge, which is to effectively promote and apply AI-CSTs across various design disciplines and usage scenarios to meet the escalating demands of creative production [1]. With the rapid advancement of AI technology, these tools have demonstrated significant advantages in areas such as conceptual generation, image creation, and style transfer [2-3]. In China, leading design firms and technology enterprises have actively championed the integration of AI into creative workflows, notably through the introduction of AI-CSTs into design practice. To enhance design efficiency and maintain a competitive edge, these companies provide their in-house design teams with essential technical resources and training support, encouraging designers to experiment with and adopt various AI-CSTs, including image generation tools, style transfer systems, and intelligent suggestion platforms. Several tech companies have developed AI platforms to assist designers in creative ideation, rapid prototyping, and brand visual expression, including such as Doubao, ERNIE-ViLG, Tongyi Wanxiang, and Tencent Zhiying. These tools are progressively being integrated into multiple stages of the design process, from initial conceptualization to final visualization [4].

Despite the widespread adoption of AI-CSTs by designers in China, their integration within the industrial design community remains limited, leading to suboptimal utility. A primary factor for this disparity is the distinct requirement profile of industrial designers, which diverges significantly from that of general designers. Industrial design tasks extend beyond aesthetic exploration to encompass precise control over three-dimensional geometry, digital modeling, material specifications, and manufacturing constraints, in addition to rigorous ergonomic evaluation [5]. For instance, in the design of a car seat, industrial designers must not only consider stylistic coherence and appearance but also generate precise 3D models to validate ergonomic fit. Concurrently, they are required to simulate the performance of various materials, such as leather, fabric, or composites, assessing attributes like strength, durability, and comfort, while also evaluating mass production feasibility. In contrast, prevailing AI-CSTs like Midjourney and Stable Diffusion are predominantly capable of generating two-dimensional renderings. Although these outputs can serve as a source of aesthetic inspiration, they lack the capacity to produce editable three-dimensional models, simulate material properties, analyze assembly methods, or model production processes. Consequently, designers must continue to rely on conventional modeling software and engineering simulation tools, as the outputs of current AI-CSTs cannot be seamlessly integrated into the end-to-end industrial design workflow. This functional misalignment has given rise to emerging demands within the industrial design community for AI-CSTs capable of product-specific form optimization, editable model generation, material configuration, process simulation, and feasibility assessment.

Generally, factors affecting people's AI adoption willingness are mixed and complex. Hence, this paper is grounded by Venkatesh (2022)'s AI adoption research agenda to obtain inspiration [6]. According to his findings, users' acceptance of AI can be influenced by various causes, including individual features, technical features, environmental features, and interventions. This statement can be echoed by the well-known Technology Readiness (TR) theory proposed by Parasuraman [7]. Within the TR framework, the main mental drivers that help people accept new tools are Optimism and Innovativeness. These two personal qualities tend to push individuals to try and take up new technologies with an open mind. On the other hand, the central factors that slow down or block the use of new tools are Discomfort and Insecurity. These mental hurdles can lower a person's trust in new systems, often showing up as doubts about whether the tool will work as promised or worries about how hard it is to use [8].A qualitative research approach is particularly suited to this investigation, as it can offer deep insights into the "lived experiences and situated practices of the designer," allowing the researcher to remain attuned to the complex realities of the industrial design workflow and understand the perceptual, individual, and technical factors that influence the adoption of AI-CSTs [9]. Furthermore, the understanding and expectations of AI-CSTs are not monolithic but vary significantly across the industrial design community when comparing traditional two-dimensional and emergent three-dimensional tools. Research on established two-dimensional AI-CSTs has often concentrated on automating discrete tasks within graphic or communication design. In contrast, the new generation of three-dimensional AI-CSTs, which can generate and manipulate complex forms, presents a paradigm shift with unique implications for the core competencies and creative processes of industrial designers. Therefore, by employing a qualitative methodology to engage directly with designers as collaborative partners in dialogue, this study aims to construct a more nuanced, contextualized, and authentic understanding of the critical factors that will determine the successful integration of three-dimensional AI-CSTs into professional industrial design practice. Given this context, our study seeks to answer the question of what factors affect the acceptance of AI-CSTs among the industrial design community in China. From the practical viewpoint, this paper can provide evidence-based strategies and recommendations for optimizing the integration of AI tools, enhancing designer creativity and efficiency, improving design outcomes, and contributing sustainably to the innovation and competitiveness of the industrial design industry.

2. LITERATURE REVIEW

2.1 The application of AI-CST in the industrial design field

AI-CSTs have evolved from traditional CSTs. In the field of design, CSTs primarily refer to software tools or platforms that assist designers in conceptualizing ideas, executing creative work, and enhancing the quality of outputs during the design process[10-11]. AI-CSTs, by contrast, leverage generative AI technologies such as deep learning and natural language processing to provide creators with insights, creative stimulation, and support. These AI tools can significantly improve both the efficiency and the output quality of creative professionals [2]. Within the design sector, AI-CSTs like Adobe Sensei, Canva, Midjourney, Stable Diffusion, and Adobe Firefly have been developed to assist in practical creative design workflows. Specifically, in industrial design, numerous creative practitioners have integrated AI generative design methodologies into product development processes. For instance, the domestically developed automotive styling design platform "MaiYi Artboard," created by Shenzhen Rayvision Technology Co., Ltd., achieves full-process intelligent workflow from conceptual design to 3D modeling and VR evaluation through the deep integration of generative AI with industrial design systems [12]. Practical application has demonstrated that M-Y Artboard reduces the time required for appearance design to under one hour, substantially shortens the overall vehicle styling development cycle, and increases modeling efficiency by a factor of 360. Furthermore, its intelligent review system supports multi-modal, multi-terminal collaborative assessments, comprehensively overcoming the efficiency and collaboration bottlenecks inherent in traditional design processes. Creative technology expert Nathan Shipley and Gary Yeh, founder of Art Drunk, developed a new surface decoration design scheme for the BMW 8 Series by integrating extensive historical art datasets [13]. This BMW Art Car successfully merges artistic expression, automotive aesthetics, and surface treatment technology. In August 2025, Tech Print Industries launched a web-based "Design Gallery" platform at the Silmo optical fair in Paris, enabling brands and designers to complete the entire creative process from parametric customization to virtual try-on[14]. This AI platform integrates real-time 3D adjustment, virtual fitting, and AI-powered rendering functionalities. By establishing an integrated digital process of "design-visualization-printing-wearing," it significantly shortens product development cycles and is reshaping the paradigms of customized production and design within the eyewear industry.

2.2 AI-CST adoption in the creative industry

Recent studies have examined the antecedents of AI adoption in creative industries, establishing or extending various acceptance models. Li incorporated AI anxiety and AI risk into the UTAUT model and investigated designers' adoption willingness in using AIGC tools [15]. Yu, Yang examined users' continuance intention toward AI painting applications by integrating the well-known Flow Theory and technology adoption models [16]. Xu, Ren constructed a model based on user experience by integrating the Expectation Confirmation Model (ECM) and Technology Acceptance Model (TAM) to explore Chinese users' continuance intention in using AI painting tools [17]. Liu and Ji introduce a Push-pull-mooring framework to reveal the push, pull, and moor effects of influential factors on users' intention to switch to AI-generated content (AIGC) tools [18]. Zhu and He created a virtual reality system to simulate the procedure of Wuhu iron painting and examined the key determinants of users' intention to adopt VR design tools[19]. Yao, Wang integrated technical and interactive features with the Technology Acceptance Model (TAM) to investigate designers' intention to use AIGC in China [20]. Fan and Jiang combined ECM with information systems continuance theory to examine people's continuance intention to employ AI drawing tools [21].

2.3 Research gaps

Going through previous literature, we found that there are research gaps that need to be filled. First, while existing research on AI-CSTs focuses on 2D graphic tools like AI painting or drawing and AIGC tools, the industrial design field requires 3D solutions [20-22]. This fundamental distinction between design domains has resulted in a lack of tailored investigation in industrial design fields, highlighting the need for new research dedicated to 3D product design. Second, most existing studies use a quantitative approach but lack a qualitative investigation. Through an exploration of the lived experiences and situated practices of the designers, qualitative inquiry elucidates the key factors shaping AI-CST adoption within the industrial design workflow. Therefore, it is necessary to examine key factors affecting users' acceptance of AI-CST among the industrial design community and develop corresponding strategies for AI-CST optimization.

3. RESEARCH METHODOLOGY

3.1 Study design

This study employed a qualitative research approach to investigate the key factors influencing the acceptance and the primary challenges hindering the adoption of AI-based Creativity Support Tools (AI-CSTs) within the industrial design community. To gather rich, contextual insights, semi-structured interviews were conducted with a purposive sample of industrial design stakeholders, including professional designers, researchers, and design company managers. The data collection period spanned from August 2024 to October 2024. The interview transcripts were subsequently analyzed using thematic analysis, following the iterative process outlined by Braun and Clarke [23]. This methodological approach was selected to facilitate an in-depth exploration of the complex, nuanced perceptions and lived experiences of the participants, allowing the central challenges and acceptance factors to emerge directly from the data.

3.2 Sample and Sampling

A combined purposive and snowball sampling strategy was employed to recruit participants [24]. This targeted approach was selected to access a knowledgeable pool of industrial design stakeholders while mitigating the limitations of either method in isolation, thereby strengthening the study's validity. Participants were required to meet three inclusion criteria: (1) possession of a bachelor's degree or higher in industrial design or a closely related field, ensuring a foundational professional knowledge; (2) verifiable hands-on experience with AI-CSTs, such as Midjourney, Stable Diffusion, or comparable tools, to provide informed perspectives; and (3) a stated willingness to contribute detailed insights on their experiences. In accordance with methodological guidance suggesting 12 to 30 participants for a heterogeneous sample, a target of 18 interviewees was set [25-26]. This number was determined to sufficiently capture a diversity of viewpoints while remaining practicable for in-depth qualitative analysis. Recruitment was conducted through professional networks and online industrial design communities.

3.3 Data collection

Following participant recruitment, a semi-structured interview protocol was developed and scheduled. All interviews were conducted between August and October 2024 via video conferencing platforms (primarily WeChat Video and Tencent Meeting), selected based on participant convenience, and were carried out in Mandarin by researchers with a design background trained in qualitative interviewing techniques. Each session lasted approximately 30 minutes. The process began with a researcher providing a brief introduction to the study's purpose, interview process, key terms, and ethical guidelines. Participants were then asked to complete a short demographic survey covering age, gender, occupation, and years of experience. The core of the interview involved guiding participants through the semi-structured protocol. With prior consent, all interviews were audio-visually recorded to ensure data accuracy. Following each session, participants were debriefed, thanked for their time, and provided with a token of appreciation. The recorded data were then transcribed verbatim in preparation for thematic analysis, which was conducted by the research team according to a pre-established coding strategy.

3.4 Data analysis

The study employed thematic analysis to analyze the interview data. The process followed the established six-phase framework: familiarize with the data, generate initial codes, search for themes, review themes, define themes, and produce the report (see Figure 1). The analysis was conducted manually, with NVivo 12.0 software utilized to facilitate data management. This procedure involved coding, identifying, extracting, and reviewing themes to systematically organize and present the qualitative data. To enhance the analytic rigor, the coding and theme identification were data-driven, thereby minimizing researcher subjectivity and strengthening the reliability and replicability of the findings.

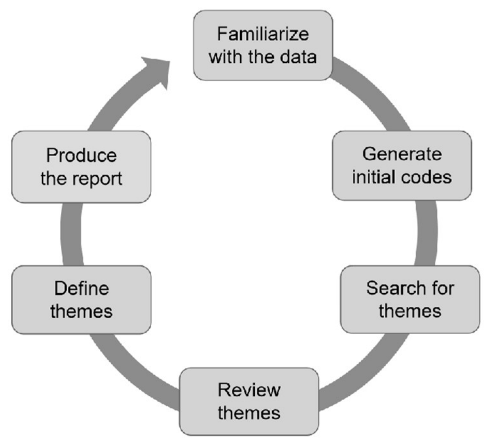

Figure 1: Thematic analysis process

4. RESULTS

4.1 Participants

The demographic profile of the 18 interview participants is presented in Table 1. The sample was purposively selected to include Chinese nationals working in various cities across China, all of whom possessed professional expertise in industrial design and practical experience with AI-CSTs. This selection criterion ensured that all respondents had systematic training in design theory, mastery of relevant drawing skills, and the capacity to execute design projects independently. The cohort comprised 10 males and 8 females, aged 26–46, with a range of educational attainment (6 bachelor's, 8 master's, and 4 doctoral degrees). Most held professional roles that involved practical application or decision-making regarding AI tools. Furthermore, three participants (Interviewees 2, 7, and 12) had lived abroad, enriching the data with insights into internationally prevalent software. Collectively, this demographic composition

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

provided a foundation for gathering diverse and expert perspectives pertinent to the study.

4.2 Main challenges during AI-CST usage

Based on the interview results, several main challenges that hinder AI-CST usage were identified, including potential risk, incomplete function, difficulty in adoption, absence of infrastructure, and high cost.

4.2.1 potential risk

Potential risk was the most mentioned obstacle. Informants argued that they might face various types of risk during AI-CST adoption. For instance, an industrial designer believed that AI-CST might infringe on the copyright of someone else's work and lead to ethical risks. As she mentioned,

"There are many AI design tools in the market currently, but the models and algorithms of these AI tools are similar-they are all trained based on a massive amount of data and other works. However, we are not sure whether they used unauthorized data or works, and this may cause infringement issues. As a professional designer, I am clear that the negative impact of infringement issues on my work. As you know, my design works are generally for business use. If they (my design works) involve infringement issues, it will be a disaster for my company and me."

A senior lecturer in design pointed out that works generated by AI may raise copyright issues since the existing regulations are not complete. As he mentioned,

"According to China's copyright laws, you can own the copyright of the design work you have contributed to. For a design work made by humans, it is easy to verify your contributions. However, for the AI-generated content (AIGC), it is hard to clarify the contribution of you or the AI tools for it. In this case, whether the copyright of the design content belongs to you is unclear. As far as I know, there are several controversies related to the copyright of AIGC, and most of them need to be justified in court. Although the copyright law is updating, the copyright of AIGC is still a headache, right?"

Another design researcher emphasized the potential privacy issues during AI-CST usage, as he mentioned:

"While AI tools offer convenience, they also raise privacy and security concerns. When users upload their design works or personal information to AI tools, their personal data or design works may be collected by AI without their authority. Moreover, AI automatically grasps a huge amount of data (including texts and figures) for training. These data may contain someone's personal works or data. In addition, when you register for an account in an AI design platform, your demographic information may be leaked during usage. Unfortunately, current regulatory frameworks can hardly play a role in protecting users' privacy during AI-CST adoption."

4.2.2 incomplete function

Informants believed that incomplete function would impede users from continuously adopting AI-CSTs, and this challenge may be improved with persistent updates.

A senior lecturer in design argued that homogenization was a main problem and would limit the promotion of AI-CSTs. As he noted:

"Currently, many AI-CSTs suffer from severe homogenization. Their functions are largely similar, lacking specialized, distinctly differentiated tools tailored for specific domains. For instance, while there are AI tools specifically designed for graphic design, interaction design, product design, landscape design, or architectural design, their functional distinctions within these concrete application areas remain unclear, making them fundamentally comparable."

Another design researcher argued that current AI-CSTs could not perform well in evaluating design work. As he mentioned:

"Furthermore, these AI creative assistance tools are predominantly used during the creative ideation phase. However, in the creative evaluation phase, especially when conducting professional critiques of generated visual renderings, AI often struggles to provide valuable, expert-level insights. Consequently, current AI creative assistance tools are still incapable of replacing professional design experts to deliver evaluations and feedback."

4.2.3 difficulty in adoption

Respondents also noted that if they found an AI-CST difficult to use, they would likely quit employing it, as there were many alternatives available at present. As an industrial designer stated:

"If an AI-CST is not easy to grasp, I may hardly try to use it. It is because it will take a long time to learn it. However, my design work often takes up a lot of my time, so I do not have enough time to learn it. As an AI-CST, Stable Diffusion (SD) has a robust function but is not welcomed by some designers. I

argued that the main reason is that it (SD) is not user-friendly for novel players."

She then shared her own experience regarding AI-CST usage. *"Once I had attempted to learn it, but I determined to give up learning it later. It is too complex for me. Similarly, comfyUI also faces this challenge, although it has been introduced by many companies. Overall, a well-designed AI-CST should be easy to use for users, especially these new users."*

In addition, language barrier should also be paid attention to, as these points can be an obstacle for non-native users. As a senior lecturer in design noted:

"Many international AI-CSTs are in English. For those who do not have a good command of English, learning international AI-CSTs is a disaster. Particularly, there are many jargons or terminologies in the user interface of these AI-CSTs. As you know, many designers, including me, used to be art student in high school, which means most of us are not proficient in English. "

4.2.4 Lack of support

Lack of support is a critical obstacle to AI-CST usage, and this issue involves several aspects, such as money support, training support, and infrastructure support.

An industry designer in a small enterprise mentioned this point several times:

"Some useful AI-CSTs require you to become a premium member or subscribe to them. Otherwise, you can only enjoy the basic functions, but these basic functions are often not enough to use."

She then complained that her company did not provide support for AI-CST adoption. *"I work in a small company, which only has three designers in total. In fact, designers' works are not attached importance here. I have requested the manager to subscribe Midjourney for several times, but there are no responses. As you know, I would never pay for it. In this case, although I want to use the AI tool in my work, no one want to pay for it."*

Another industrial designer noted that lack of training opportunities will improve the difficulty of AI-CST adoption, thereby hinder people's usage intention. As he noted:

"Today, almost everyone, even you are not a designer, can use AI-CST to generate a design scheme. It can be said that there is no bar of AI support design. However, there is a high bar to generate high-quality design works. As I know learning to master AI-CSTs is a systematic and complex process. You need to how to input text prompts, image prompts, upscaling, modification based on feedback. All of these skills are not easy to master, which need both self-efforts and external training."

Infrastructure support is also indispensable for AI-CST adoption, including hardware and software. For instance, several informants noted that virtual private network (VPN) tools are necessary when using some of AI-CSTs. As an industrial designer stated:

"When you use some abroad AI-CSTs, such as Midjourney, a stable VPN is necessary. Otherwise, you cannot access its official website. However, when it concerns for VPN, it means that it will take you an extra cost to adopt it. Moreover, some VPN tools are not stable."

4.3 Key factors affecting AI-CST adoption

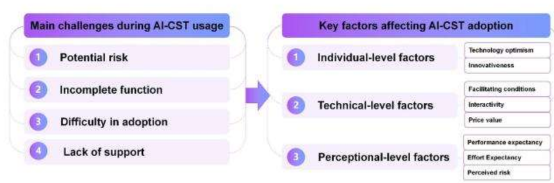

Figure 2: Key factors and main challenges influencing user's using AI-CSTs

Several key factors influencing AI-CST adoption willingness were further clarified through user interviews. These factors can be categorized into individual level, technical level and perceptional level. Individual-level themes include technology optimism and personal innovativeness, technical-level themes have facilitating conditions, interactivity and price evaluation, and perceptional-level theme contain performance expectancy, effort expectancy, and perceived risk, see figure 2.

4.3.1 individual-level factors

Technology optimism

Technology optimism is defined as the belief that technology can bring positive impacts and potential benefits. It reflects an individual's psychological readiness to accept and engage with new technologies [27]. In this study, technology optimism specifically refers to users' positive perceptions of the role AI-CSTs can play in supporting and improving their daily design tasks. Although AI-CSTs are not yet widely adopted in the industrial design field and are mainly applied in specific stages of the design process, individuals who demonstrate technology optimism are more inclined to focus on the practical advantages and value of these tools, such as increased efficiency and creative support, rather than on potential risks related to privacy or intellectual property. In the interview, most participants demonstrated a technology optimistic attitude and believed that AI-CSTs have broad application prospects and practical value in use. This optimistic perception directly contributes to the proactive adoption and continued use of AI-CSTs.

An industrial designer with nine years of experience noted that AI-CSTs have significantly improved the efficiency of generating renderings from sketches. He stated, *"From the beginning, I believed AI-CSTs would definitely become a trend in the future. They have already saved me a lot of time on sketching."* He further added that AI-CSTs can quickly transform sketches into visual renderings, greatly reducing the time spent on communication and revisions. He believes this is particularly beneficial for the field of product design.

A designer with seven years of experience mentioned that he has a high tolerance for AI technology. He stated, *"Even though there is a lot of negative discourse surrounding AI-CSTs now, I still choose to use them, and many of my peers continue to do so as well. The development of any new technology inevitably goes through phases of criticism and skepticism. This is a normal part of the evolution process."* This reflects his high-risk tolerance toward AI tools and his willingness to continue exploring their potential and value despite ongoing criticism.

Innovativeness

Innovativeness has been described as a personal quality that shows a person's interest in trying new technologies ahead of others [7]. This trait should not be confused with the separate idea of creativity. People who score high on personal innovativeness are usually more willing to explore advanced tools and often serve as early testers among their colleagues. This quality reflects an individual's natural curiosity and readiness to look into the possible benefits of AI-CSTs, as well as a willingness to be among the first to use these tools. Because early users have more chances to work with the newest AI-CSTs, they tend to find these tools more useful and easier to operate. Most of the people in this study showed a favorable view of technology, and this view often helped them keep using AI-CSTs over time. For these working designers, AI-CSTs serve not only as a means to get work done faster but also as a helpful resource for finding new ideas and trying out fresh creative directions.

A designer in a machinery equipment company said, *"As soon as I hear about a new design tool, I want to try it. When KeyShot released its AI-powered features, I downloaded the update the same day. I wanted to see how the restyle mode could change material finishes without me having to rebuild the scene,"* she described herself as someone who enjoys experimenting with emerging tools before they become mainstream, noting that this early exposure helps him evaluate both the usability and creative potential of AI-CSTs.

A senior industrial designer with ten years of experience said, *"I'm never afraid to try something new, even if my first few attempts turn out messy. With AI-CST, I can quickly explore different product shapes and textures before deciding on the final concept." She added that she likes to adopt new tools early, which helps her quickly see how features like background generation can boost efficiency. "The faster I come up with a concept, the more time I have to refine it. That is where AI really shines because it cuts out repetitive work and leaves more room for creative thinking."*

A product manager in the home appliance industry said that adopting AI-CST early was a strategic decision. *"I was driven by strong curiosity and the desire to stay ahead in a highly competitive market. Using these tools before they are fully developed allows me to gain valuable hands-on experience and discover their creative potential. By entering different keywords and design requirements, I can generate diverse visual outcomes that inspire new ideas and enable fusion, adaptation, and reconfiguration beyond traditional design frameworks".*

4.3.2 Technical-level factors

Facilitating conditions

Facilitating conditions are traditionally defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a technology [28]. This factor encompasses factors such as access to resources, technical support, training opportunities, and compatibility with existing workflows. In this study, facilitating conditions help explain how external support systems impact users' engagement with AI-CSTs. In the interviews, users frequently mentioned that factors such as company-sponsored subscriptions, abundant resources, organized training sessions, technical support, and the overall convenience of enabling conditions created a favorable environment for exploration and adoption.

A designer with seven years of experience mentioned:

"Actually, I think as long as you put in the effort, most of these tools are easy to use. As for paid versions, that's acceptable, though there are some things that are beyond individual control. For example, network issues. Our company is generally supportive, but the problem is that all our computers and documents are encrypted. If you want to use these tools, you still need a VPN, which is often unstable. Because of these infrastructure limitations, I can't access some foreign AI-CSTs. "

A designer with six years of experience said:

" I'm currently using Midjourney, and the company covers the subscription cost. They also provide the necessary VPN software. Some of my friends are using Stable Diffusion (SD); I've looked into it before. With SD you either deploy it locally or in the cloud. Local deployment actually demands very high computer specifications—our machines probably can't meet SD's requirements. If you deploy it in the cloud, you need to go through a third-party website that provides remote GPU resources. But that's a paid service, and there's also a greater risk of data leakage when you work in the cloud."

Interactivity

Interactivity is usually understood as the ease with which users can work with AI tools. This idea covers several areas, such as how simple the tool is to operate, how clear the screen layout and controls are, how easy it is to access smart features, how much freedom users have to guide the tool, how well the system handles mistakes, and how much effort and help are needed to learn the tool [29]. In this study, interactivity refers to the extent to which AI-CSTs can provide effective support in terms of interaction and functional design, whether designers can quickly master their usage methods, and whether the tool's performance meets designers' expectations collectively determines the level of user adoption. A smoother, more intuitive, and controllable interaction enhances users' perception of the system's capability, increasing their willingness to continue using it. In the interviews, many respondents mentioned the impact of interactivity on their use of AI-CSTs.

A designer with ten years of experience mentioned:

"The domestic AI-CSTs I'm currently using are relatively easy to operate, and some of the software offers good control. I use them regularly to generate creative ideas or to optimize parts of the creative process."

A designer with 9 years of experience said:

"The AI software I use varies in interface complexity. Some are simple and don't require much time or effort to learn, so as a beginner, I tend to use those more frequently. I haven't used Stable Diffusion (SD) much so far, mainly because I don't have enough time to explore it, and I find it relatively difficult to use… If I have time later, I will try to study it more, because once you're skilled with it, the image quality it produces is better than that of other software."

Price value

Price value concerns the practical balance users strike between the gains they expect from AI-CSTs and the money or effort they must spend to obtain it [30,31]. When users feel that the AI tool is too costly or does not deliver enough value for the price, they may be less likely to adopt or keep using it. Thus, how users weigh the cost against the benefit not only shapes their view of the tool's worth but also directly affects their plan to continue using it. In the interviews, participants voiced worries about the cost of AI tools and widely agreed that pricing plays a key role in their willingness to engage with them. Several designers noted that if an AI tool provides strong value by clearly improving the speed and quality of their work, they are open to paying for it. In contrast, other participants mentioned that steep prices or the absence of a free trial option discourage them from giving the tool a chance. Moreover, some designers stressed that when their workplace covers the cost, they tend to use AI-CSTs much more often.

A designer with ten years of experience said:

"I think tools like Midjourney are used quite often in our daily work. Right now, the cost is a bit over 2,000 RMB per year in China, which I find acceptable. But if it goes beyond 3,000 RMB, I might reconsider whether to continue using the software. If the software has a steep learning curve but helps me overcome that challenge, I think it's worth the money. There are also other AI-CSTs in China that require payment. On the other hand, tools like Doubao are free for now. I'm not sure if they'll charge in the future, but currently, they can

already replace many paid AI tools. I even think Doubao could replace ChatGPT in some cases."

Another designer with ten years of experience said:

"We may eventually stop using this AI software, primarily because it is a paid tool with a monthly fee of over 200 RMB. Whether we continue to use it in the future depends on how well its features are developed. ... At present, it does provide support in several aspects of our workflow, but that doesn't necessarily mean we'll rely on it long-term. Another influencing factor is the instability of VPN connections. Since the software requires access through a VPN, occasional connection failures or inaccessible pages can directly impact how frequently and heavily we use it."

4.3.3 Perceptional-level factors

Performance expectancy

Performance expectancy refers to the extent to which individuals believe that using a given technology will enhance their job performance [32]. In the creative design industry, performance expectancy reflects designers' belief that a tool can support them in completing specific creative tasks, such as generating concept sketches or suggesting color schemes[33-34]. When designers believe that AI-CSTs bring clear benefits, they are more likely to accept and actively use these tools.

An industrial designer said, *"My daily work requires me to quickly come up with several product concepts, and I often need to draw many sketches. Since I started using the MJ generation tool, I have found that it can quickly help me produce some creative design sketches. This allows me to spend more time on refining and improving them. Although the generated content is not always perfect, it is a good starting point for me."*

A senior lecturer in design said, *" In teaching and research, I often need to prepare innovative lesson plans and collect new creative product cases. If AI tools can help me quickly analyze market trends and extract design highlights, that will be very valuable for me. Today, students have already started to use various AI tools. If these tools can give them clear improvements in efficiency and quality during the idea generation and solution optimization stages, their value will increase greatly. Although AI tools are not yet mature in these areas, I am still willing to explore and try them, hoping to find the best way to integrate them into teaching and design practice."*

Effort Expectancy

Effort expectancy means how easy or difficult users think it is to use a technology. It shows how much effort is needed when using a new technology [28]. In this study, the design of the AI-CSTs interface and how easy or hard it is to complete tasks directly affect effort expectancy. Effort expectancy can strongly influence user behavior. If the system interface is complex and users need to spend more time learning to use it, effort expectancy will drop, which may cause negative feelings [35]. Complex designs and hard-to-understand operations can make users frustrated and harm their overall experience. When effort expectancy is low, users may feel dissatisfied with the technology.

An industrial designer stated, *"When I first started using it, I felt the interface was a bit complicated and not like the software interfaces we are used to. Some functions were hidden in multi-level menus, and it took me a few days to get familiar with them. But after I got used to it, it really helped me save a lot of time. If it could give more clear guidance at the beginning, I could learn it faster."*

A Design director commented, *"AI-CSTs will become the infrastructure of future design work. The key lies in who can master them best and use them flexibly as tools. Their value goes beyond saving time and improving efficiency; they also enhance the quality of product performance and design expression. Those who truly understand how to leverage AI-CSTs will gain a competitive advantage."*

Perceived risk

Perceived risk is commonly defined as users' concerns about potential negative consequences when making decisions [36]. It arises from factors such as personal experience, knowledge, emotions, and social influences, and encompasses multiple dimensions, including economic, psychological, social, and functional risks [37-38]. In the creative design field, perceived risk plays a particularly important role, as many professionals approach artificial intelligence technologies with caution, identifying risk as a major barrier to adoption. Designers commonly express concerns about privacy, copyright, and the protection of originality when using AI-CSTs, especially in contexts involving commercial projects or sensitive corporate information.

A designer with seven years of experience stated:

Journal of Theoretical and Applied Information Technology
30th April 2026. Vol.104. No.8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

"During the process, I worry about issues related to privacy, copyright, or originality when using AI-CSTs. Especially in commercial projects, although AI-CSTs can offer some creative direction, I still hesitate to use their generated content directly due to the risk of plagiarism. Additionally, when I upload finalized product images to an AI tool, I'm also concerned that my original work might be leaked. This makes me feel unsafe."

A designer with five years of experience noted:

"To protect originality, I'm very cautious when using AI-CSTs. If AI-CSTs can infer my original ideas just by approaching the question from a different angle, I feel that this capability infringes on my creative work. Situations like this make me rely less on AI, using it only for relatively unimportant tasks."

A designer with ten years of experience also mentioned:

"I do have some concerns about the originality of AI-generated content. For example, when using similar text descriptions to generate reference images, AI may produce similar outputs. Even though it's just a supporting tool, I still worry that the final ideas might resemble someone else's, which could lead to copyright or infringement risks."

A designer with over 10 years of experience further said:

"When using AI to generate product scenario images, I occasionally encounter content that doesn't align with Eastern cultural contexts. This may be due to the AI tool's limited understanding of cultural nuances, sometimes resulting in images that are ethically inappropriate. Additionally, I'm concerned about the security of uploading my work. Our company has strict confidentiality policies, but I worry that the AI platform might leak content or even recommend my work to other users."

The interview results show that users are worried about several kinds of risks, including the copying of original work, the leaking of private information, and dissatisfied with the quality of what the AI tool produces. These concerns have shaped how designers feel about using AI-CSTs. To encourage greater use of AI-CSTs within the creative field, better technical safeguards and clearer rules are needed in areas such as protecting user data, securing ownership rights over creative work, and ensuring that the tool's outputs meet acceptable standards.

5 DISCUSSION

5.1 The discussion of findings

Our study reveals that the adoption of AI-CSTs in industrial design is hampered by a complex interplay of four key challenges: potential risks, incomplete function, lack of support, and difficulty in adoption. These challenges can be understood as two interrelated clusters: the first concerning the inherent limitations of the technology itself (incomplete functions, difficult adoption), and the second concerning the external ecosystem in which it is deployed (potential risks, lack of support). The usability and functionality gaps are particularly problematic in a field reliant on precise, iterative manipulation of form and function, where tools must integrate seamlessly into a non-linear creative process [39-40]. Furthermore, the concerns over ethical risks, such as data privacy and the provenance of AI-generated concepts, and the lack of institutional support (training, policy, funding) create a "double barrier." This means that even if the tools were to mature technically, their adoption would likely remain stalled without concurrent development of organizational policies and trust-building measures. This finding underscores that the challenge of integrating AI into design practice is not merely a technical problem but a profound socio-technical one, requiring co-evolution of both the tools and the professional environments that use them.

Moreover, this paper also investigated the key factors influencing the adoption of AI-CSTs among the industrial design community. The findings indicated that users' decision-making processes were not determined by a single variable but were instead shaped by a combination of perceptual factors, individual traits, and technical factors. At the perceptional level, we found that performance expectancy and effort expectancy exerted a strong, positive influence on the behavioral intention of industrial designers, aligning robustly with the core tenets of the UTAUT and its predecessors [32]. This confirms that, like users of other information systems, designers are fundamentally pragmatic in their technology adoption decisions. They are more likely to intend to use an AI tool if they believe it will help them achieve gains in their job performance. In this case, Demos and tutorials should showcase how an AI-CST solves specific, painful problems in the design workflow, such as generating a high volume of concept sketches in minutes or automating CAD model preparation for 3D printing. Moreover, the finding also confirms that AI-CSTs with high effort expectancy, for

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

example, a complex interface, non-intuitive commands, or a steep learning curve, disrupt this flow. When users operate within complex tools like CAD and sketching software, they will be wary of tools that feel like 'yet another application' to learn. Therefore, effort expectancy is heavily influenced by how effortlessly the AI tool integrates into their established workflow. Plug-ins or tools that work within familiar environments like SolidWorks, Rhino, or Adobe Creative Suite will be perceived as having lower effort expectancy than standalone platforms that require disruptive data export/import processes.

Meanwhile, perceived risk, encompassing privacy, ethical, and output risks, also exerts a significant influence on users' acceptance of AI-CSTs. Privacy risk denotes the potential for harm resulting from the unauthorized access or processing of personal data. During AI adoption, the collection and possible sharing of behavioral data and user preferences may further increase users' perception of risk [15,37,41]. Ethical risk encompasses the negative consequences of actions that breach established moral, legal, or societal standards. It also includes potential issues regarding intellectual property, such as training data infringement, unclear attribution, or non-transparent secondary use. Because AI-generated content relies on large-scale training data, users often find it difficult to determine whether plagiarism is involved [42-43]. Studies in creative and design contexts further indicate that uncertainties surrounding copyright, training data compliance, attribution, and traceability directly constrain organizations' and individuals' willingness to integrate generative AI into design workflows [44-45]. Moreover, divergent legal interpretations regarding the copyright protection of AI-generated outputs across jurisdictions exacerbate practitioners' compliance and commercial risk expectations, reinforcing a cautious approach to adoption. Output risk refers to users' concerns about whether an AI-CST can perform well as they expected and cater to their needs or offer support. As emerging technology in China's creative industry, AI-driven CSTs receive limited user feedback, hindering their optimization. Furthermore, their performance varies significantly by algorithm, database, and design, making tool selection difficult for newcomers. In summary, risks related to privacy/data governance, ethics/compliance, and output controllability systematically reduce designers' acceptance and continuance intention toward AI-CSTs by amplifying uncertainty, undermining trust, and weakening performance expectations.

At the individual level, innovativeness and technological optimism were critical determinants of AI-CST adoption intentions. This finding can echo prior AI adoption studies, which indicate that technology pioneers exhibit a higher acceptance tendency, often perceiving AI-CSTs as having significant potential advantages and usability, which may stem from their inherent optimism and greater risk tolerance[46-48]. Personal innovativeness, reflecting an individual's willingness to try new technologies, directly enhances their perception of the potential value of AI-CSTs, thereby strengthening positive expectations regarding the technology's performance. In other words, designers with a higher degree of innovativeness are more likely to believe that AI-CSTs can offer advantages in creative generation, efficiency improvement, and task quality. Simultaneously, technological optimism predisposes designers to believe in the long-term benefits of AI technology, reducing concerns about associated risks and uncertainties. This positive psychological expectation not only fosters trust in the functionality of AI-CSTs but also promotes their adoption and usage behavior. Relevant studies

At the technical level, facilitating conditions, interactivity, and price evaluation were significantly associated with intention to use AI-CSTs. First, since AI-CSTs are still emerging technologies, users often rely on external structures such as training, technical guidance, and access to creative resources to reduce uncertainty and support adoption [49-50]. Generally, users with favorable facilitating conditions are more likely to perceive AI-CSTs as beneficial and easy to integrate into their workflow, leading to stronger acceptance intention [51-53]. When organizations put resources into AI-CSTs and offer clear support systems, they help lower the hurdles related to both cost and the time needed to learn the tools. This kind of support can reduce users' doubts and make them more willing to try and use the tools. Such backing from the organization not only makes the use of AI in daily work feel more accepted but also builds a setting where trying new ideas is encouraged. Second, interactivity was also decisive. The usability of the interface, the clarity of task execution, and the perceived balance between functionality and ease of use significantly impacted designers' acceptance. While powerful features were attractive, excessive complexity or steep learning curves often discouraged long-term use. Designers preferred tools that combined efficiency with simplicity, especially under tight project deadlines. Existing research also indicates that AI tool's ability to offer support in interaction, and functional design, as well as the designer's ability to rapidly learn how to use it, directly influences adoption rates [54-55]. Moreover, once users can learn to use AI-CSTs with only a little effort, they are more likely to have a good experience, which increases their acceptance and trust in the technology [56-57]. Third, when users perceive that the returns from using the technology outweigh the costs incurred, price evaluation will have a positive impact on their behavioral intention. Many AI-CSTs, such as Midjourney, ChatGPT Plus, and Stable Diffusion, are paid products, making price evaluation a critical factor. Nastjuk et al. (2020) also pointed out that price evaluation is especially indispensable in situations where users are required to bear actual costs [31].

Overall, this study highlights that the adoption of AI-CSTs cannot be explained by technological aspects alone. Instead, designers' acceptance is a dynamic process shaped by the interaction between individual readiness, social environment, and tool design. These findings provide important implications for both AI tool developers and designers with regard to improving the current AI-CSTs to make them more appropriate for the industrial design community. In addition, three AI-CST optimization strategies for the industrial design community were proposed as below, which are the fragmentation of AI-CSTs and the need for a unified framework, integrated design and manufacturing reasoning, and towards collaborative AI design partners.

5.2 AI-CST optimization strategies for the industrial design community

5.2.1 The fragmentation of AI-CSTs and the need for a unified framework

The current landscape of AI-CSTs is characterized by a significant technological split that limits their application in industrial design. Models like GPT excel in semantic knowledge but fail to ensure visual-structural consistency; diffusion models generate high-fidelity images but are incapable of incorporating engineering or manufacturability logic; and closed-source models like Midjourney prioritize aesthetics at the cost of transparency and control. This divide, creating a gap between semantic and visual-structural intelligence, means existing tools cannot support the holistic integration of materials, manufacturing processes, structural integrity, and functionality required by the discipline. To bridge this gap, a new paradigm is needed—a hybrid knowledge framework that synthesizes real-time retrieval, engineering knowledge graphs, and manufacturing constraints with advanced generative models. Such a system would elevate AI-CSTs from simple content generators to integrated platforms equipped for sophisticated design reasoning and decision-making.

5.2.2 Integrated design and manufacturing reasoning

Multimodal reasoning is poised to become the pivotal breakthrough for next-generation AI-CSTs. Current models are largely confined to 2D image generation, whereas industrial design practice demands the simultaneous comprehension and generation of 3D geometry, internal structures, modular logic, component assembly relationships, material properties, and manufacturing constraints. Future systems must establish a consistent cross-modal semantic mapping mechanism that bridges "language, vision, structure, and manufacturing." Such a system would not only provide aesthetic proposals but also generate editable 3D models, exploded-view diagrams, manufacturing path analyses, ergonomic parameters, and physical simulation predictions. Concurrently, an engineering consistency verification mechanism will become indispensable, enabling the system to automatically identify conflicts between form and structure, mismatches between materials and processes, and potential manufacturing difficulties or fatigue risks, thereby reducing late-stage rework. Achieving this capability relies on high-quality, professional data resources, such as structurally annotated drawings, assembly semantics, material mechanical parameters, and process flow data. However, existing open-source image training sets are insufficient for covering these specialized domains. Therefore, constructing a legitimately licensed, engineering-grade data ecosystem is a critical step for the evolution of AI-CSTs, one that will not only enhance the models' design reasoning but also mitigate copyright and security risks.

5.2.3 Towards collaborative AI design partners

The evolution of AI-CSTs in industrial design hinges on a critical paradigm shift: from being mere tools to becoming collaborative partners. To integrate AI into enterprise-level design workflows, systems must prioritize controllability, transparency, cross-software interoperability, and process auditability. Seamless integration with mainstream CAD, CAE, and rendering software via plugins is essential to minimize platform switching and enhance data continuity, allowing designers to perform AI-assisted modeling, parametric optimization, 3D modifications, and rendering within their familiar digital environment. Furthermore, future AI-CSTs should embody "proactive design assistance" through capabilities such as task decomposition, structural optimization suggestions, manufacturability feedback, and iteration logging, thereby achieving genuine human-machine collaboration. Concurrently, as AI is deployed at scale, ethical guidelines, model transparency, training data traceability, copyright compliance, and adherence to industrial standards will become indispensable. Establishing a comprehensive governance framework, incorporating provenance mechanisms, security validation, design process recording, and enterprise deployment protocols, is a prerequisite for the safe, effective, and sustainable application of AI in industrial design. Ultimately, this evolution from assistive tools to core intelligent partners will shift the industry paradigm from experience-based to knowledge-augmented design.

6. CONCLUSION

6.1 Theoretical implications

This study represents a significant contribution to the field of AI in design by revealing the complex dynamics of factors that influence the acceptance of AI-based creativity support tools, including the perception-level factor, individual-level factor, and technical-level factor. Our findings provide a framework of determinants that can be targeted to enhance adoption and lay the foundation for developing concrete AI-CST optimization strategies for the industrial design community. The theoretical implication is as follows:

First, this paper contributes to the literature on AI-CST adoption by pinpointing domain-specific acceptance factors. Existing technology acceptance models often lack the granularity to explain the unique challenges and drivers within the 3D industrial design workflow. To address this, our findings delineate a set of key factors that are critical for this professional community. Thereby, we extend the scope of AI-CST acceptance research beyond graphic and visual media into the realm of tangible product creation. Second, this research bridges qualitative findings with established theoretical frameworks. The identified factors serve to contextualize and validate constructs from the TR theory and the UTAUT model within the 3D design field. For instance, the factor technology optimism and personal innovativeness directly echoed the TR theory, while performance expectancy, effort expectancy, price value and facilitating conditions reflected the construct in UTAUT. This establishes a crucial theoretical link, demonstrating how these classic models manifest in a complex, AI-augmented creative professional environment. Third, the study demonstrates the value of a qualitative methodology in technology acceptance research. By prioritizing in-depth interviews over quantitative scales, this research uncovers the nuanced 'why' behind statistical relationships. This approach allowed for the emergence of rich, context-laden factors that might be overlooked in predefined survey instruments. Consequently, our findings offer a foundational qualitative understanding that can inform and refine future quantitative studies, providing a more complete picture of the adoption phenomenon.

6.2 Practical implications

In practical contexts, the findings on what drives user acceptance and the suggested ways to improve AI-CSTs provide useful guidance for all involved parties. For those who design and build AI-CSTs, the results point toward features that users care about most: improving facilitating conditions and effort expectancy, increasing the sense of two-way interaction through responsive design, and lowering perceived risks. Developers should also build on users' excitement about technology by creating smooth teamwork between human and machine, and address cost concerns by offering different levels of feature access. For users of AI-CSTs, tools designed with these ideas in mind can speed up creative work by drawing on a user's natural willingness to try new things, support affordable brainstorming through clear value, and lessen mental strain by providing steady and reliable support. For managers at design firms, this study highlights several practical steps: putting resources into training to improve team readiness, showing clear returns on investment to make the cost worthwhile, and building trust in new tools through small test programs. Such steps can lead to wider use that supports business growth, ongoing tool improvements, and solutions that meet changing creative needs in a responsible way. Moreover, these findings offer important direction for officials who set rules for AI creative tools. The results point to a need for clear guidelines to reduce risks tied to ethics, privacy, and reliability of results. Rules should also help people adopt these tools by improving infrastructure and offering financial support programs for creative fields. At the same time, public efforts should promote a positive view of technology through education campaigns and support personal creativity through national training programs.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

6.3 Limitations and future recommendations

This study is subject to two limitations that should be considered. First, the data gathered from interviews conducted via the Tencent Meeting platform may not be as comprehensive as data obtained from in-person interviews. The digital medium can occasionally hinder the establishment of a strong rapport and may obscure non-verbal cues that are often pivotal in a qualitative context. However, in-person interviews were deemed less practical due to the significant logistical challenges they posed for participant sampling. Therefore, it is more appropriate to collect interview data by face to face in future studies. Second, the qualitative and exploratory nature of this study, while effective for uncovering rich, contextual insights, inherently limits the generalizability of its findings. A subsequent quantitative and empirical study would be necessary to validate these qualitative findings and provide more robust, statistically significant evidence. Although proposing and validating a theoretical framework through empirical methods would be a logical next step, this was beyond the scope of the current investigation due to article length constraints. Therefore, future research is strongly recommended to develop a theoretical model based on these findings and validate it through large-scale empirical methods, such as surveys, to strengthen the evidence base.

Figure 1: Description Is Placed Right Below The Figure

REFERENCES:

[1] Grilli, L. and Pedota, M., 2024. Creativity and artificial intelligence: A multilevel perspective. *Creativity and innovation management*, 33(2), pp.234-247.

[2] Kim, M., Joo, M. and Han, K., 2025. Understanding the differences in an AI-based creativity support tool between creativity types in fashion design. *International Journal of Human – Computer Interaction*, 41(18), pp.11881-11894.

[3] Ivcevic, Z. and Grandinetti, M., 2024. Artificial intelligence as a tool for creativity. *Journal of Creativity*, 34(2), p.100079.

[4] Zhou, X., Lin, H., Xu, Z., Shen, Z., Zhang, R. and Chen, Y., 2025, May. AI-Driven Creativity: Redefining Cultural Product Design in Kaihua District. *In International Conference on Human-Computer Interaction* (pp. 238-246). Cham: Springer Nature Switzerland.

[5] Dovramadjiev, T., 2025. 3D Digital Design in Ergonomics and Human Factors. CRC Press.

[6] Venkatesh, V., 2022. Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of operations research*, 308(1), pp.641-652.

[7] Parasuraman, A., 2000. Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of service research*, 2(4), pp.307-320.

[8] Walker, R.H., Craig‐Lees, M., Hecker, R. and Francis, H., 2002. Technology‐enabled service deliveryAn investigation of reasons affecting customer adoption and rejection. *International Journal of service Industry management*, 13(1), pp.91-106.

[9] He, X., Mao, Y., Cao, H., Li, L., Wu, Y. and Yang, H., 2024. Factors influencing the development of nursing professionalism: a descriptive qualitative study. *BMC nursing*, 23(1), p.283.

[10] Frich, J., MacDonald Vermeulen, L., Remy, C., Biskjaer, M.M. and Dalsgaard, P., 2019, May. Mapping the landscape of creativity support tools in HCI. *In Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1-18).

[11] Ning, B., Liu, F. and Liu, Z., 2023, May. Creativity support in AI co-creative tools: Current research, challenges and opportunities. *In 2023 26th International Conference on Computer Supported Cooperative Work in Design (CSCWD)* (pp. 5-10). IEEE.

[12] Zhong Jingwen., 2025. How Rayvision's 'Mai Art Board' Uses AI to Restructure Industrial Processes. https://caijing.chinadaily.com.cn/a/202503/04/WS67c6ca91a310510f19ee9b70.html .

[13] BMW, 2024. INNOVATION CAR. 2024 https://www.bmw.com/en/innovation/creative-ai-bmw-8-gran-coupe-art-with-artificial-intelligence.html.

[14] Mohoujun., 2025. TPI to Unveil Novel 3D Printing Eyewear Design Software with AI-Powered Visualization at Paris Silmo Expo. https://www.mohou.com/articles/article-12710.html

[15] Li, W., 2025. A study on factors influencing designers' behavioral intention in using AI-generated content for assisted design: Perceived anxiety, perceived risk, and UTAUT. *International Journal of Human – Computer Interaction,* 41(2), pp.1064-1077.

[16] Yu, X., Yang, Y. and Li, S., 2024. Users' continuance intention towards an AI painting application: An extended expectation confirmation model. *PLoS One*, 19(5), p.e0301821.
[17] Xu, J., Ren, X., Huang, Y., Wu, R. and Pan, Y., 2024. Persist or abandon? Exploring Chinese users' continuance intentions toward AI painting tools. *IEEE Access*, 12, pp.135469-135488.
[18] Liu, Y. and Ji, P., 2025. Understanding designers' switching intention to AI painting tools using the PPM framework. *Scientific Reports*, 15(1), p.2246.
[19] Zhu, Y. and He, X., 2025. Factors influencing user acceptance of virtual reality in preserving Wuhu iron painting from the unified theory of acceptance and use of technology perspective. *Scientific Reports*, 15(1), p.22714.
[20] Yao, Y., Wang, X. and Sun, K., 2025. Research on key factors influencing Chinese designers' use of AIGC: an extension based on TAM and TRI. *PloS one*, 20(2), p.e0314306.
[21] Fan, P. and Jiang, Q., 2024. Exploring the factors influencing continuance intention to use AI drawing tools: Insights from designers. *Systems*, 12(3), p.68.
[22] Xu, J., Ren, X., Huang, Y., Wu, R. and Pan, Y., 2024. Persist or abandon? Exploring Chinese users' continuance intentions toward AI painting tools. *IEEE Access*, 12, pp.135469-135488.
[23] Braun, V. and Clarke, V., 2006. Using thematic analysis in psychology. *Qualitative research in psychology*, 3(2), pp.77-101.
[24] Parker, C., Scott, S. and Geddes, A., 2019. Snowball sampling. SAGE research methods foundations.
[25] Saunders, M., 2009. Research methods for business students. Person Education Limited.
[26] Baker, S.E. and Edwards, R., 2012. How many qualitative interviews is enough.
[27] Chung, N., Han, H. and Joun, Y., 2015. Tourists' intention to visit a destination: The role of augmented reality (AR) application for a heritage site. *Computers in human behavior*, 50, pp.588-599.
[28] Venkatesh, V., Thong, J.Y. and Xu, X., 2012. Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology1. *MIS quarterly*, 36(1), pp.157-178.
[29] Yang, Y., Luo, J. and Lan, T., 2022. An empirical assessment of a modified artificially intelligent device use acceptance model—From the task-oriented perspective. *Frontiers in psychology*, 13, p.975307.
[30] Yin, M., Han, B., Ryu, S. and Hua, M., 2023, July. Acceptance of generative AI in the creative industry: Examining the role of AI anxiety in the UTAUT2 model. *In International conference on human-computer interaction* (pp. 288-310). Cham: Springer Nature Switzerland.
[31] Nastjuk, I., Herrenkind, B., Marrone, M., Brendel, A.B. and Kolbe, L.M., 2020. What drives the acceptance of autonomous driving? An investigation of acceptance factors from an end-user's perspective. *Technological Forecasting and Social Change*, 161, p.120319.
[32] Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D., 2003. User acceptance of information technology: Toward a unified view1. *MIS quarterly*, 27(3), pp.425-478.
[33] Guo, S., Jin, Z., Sun, F., Li, J., Li, Z., Shi, Y. and Cao, N., 2021, May. Vinci: an intelligent graphic design system for generating advertising posters. *In Proceedings of the 2021 CHI conference on human factors in computing systems* (pp. 1-17).
[34] Lin, H., Chi, O.H. and Gursoy, D., 2020. Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. *Journal of Hospitality Marketing & Management*, 29(5), pp.530-549.
[35] Gursoy, D., Chi, O.H., Lu, L. and Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International journal of information management*, 49, pp.157-169.
[36] Chao, C.Y., Chang, T.C., Wu, H.C., Lin, Y.S. and Chen, P.C., 2016. The interrelationship between intelligent agents' characteristics and users' intention in a search engine by making beliefs and perceived risks mediators. *Computers in Human Behavior*, 64, pp.117-125.
[37] Esmaeilzadeh, P., 2020. Use of AI-based tools for healthcare purposes: a survey study from consumers' perspectives. *BMC medical informatics and decision making*, 20(1), p.170.
[38] Xie, J., Ye, L., Huang, W. and Ye, M., 2021. Understanding FinTech platform adoption: impacts of perceived value and perceived risk. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(5), pp.1893-1911.
[39] Eswaran, U. and Eswaran, V., 2025. AI-driven cross-platform design: Enhancing usability and user experience. *In Navigating usability and*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

user experience in a multi-platform world (pp. 19-48). IGI Global.

[40] Hall, E., Seyam, M. and Dunlap, D., 2023, June. Identifying usability challenges in AI-based essay grading tools. *In International Conference on Artificial Intelligence in Education* (pp. 675-680). Cham: Springer Nature Switzerland.

[41] Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A. and Galanos, V., 2021. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, 57, p.101994.

[42] George, J., 2024. Data to AI: Building a solid data foundation for your generative AI applications in the cloud. *International Journal of Science and Research Archive*, 11(01), pp.2601-2604.

[43] Liu, V., Vermeulen, J., Fitzmaurice, G. and Matejka, J., 2023, July. 3DALL-E: Integrating text-to-image AI in 3D design workflows. *In Proceedings of the 2023 ACM designing interactive systems conference* (pp. 1955-1977).

[44] Pasetti, M., Santos, J.W., Corrêa, N.K., de Oliveira, N. and Barbosa, C.P., 2025. Technical, legal, and ethical challenges of generative artificial intelligence: an analysis of the governance of training data and copyrights. *Discover Artificial Intelligence*, 5(1), p.193.

[45] Sag, M., 2023. Copyright safety for generative AI. *Hous. L. Rev*., 61, p.295.

[46] Almaiah, M.A., Alfaisal, R., Salloum, S.A., Al-Otaibi, S., Shishakly, R., Lutfi, A., Alrawad, M., Mulhem, A.A., Awad, A.B. and Al-Maroof, R.S., 2022. Integrating teachers' TPACK levels and students' learning motivation, technology innovativeness, and optimism in an IoT acceptance model. *Electronics*, 11(19), p.3197.

[47] Álvarez-Marín, A., Velázquez-Iturbide, J.Á. and Castillo-Vergara, M., 2023. The acceptance of augmented reality in engineering education: The role of technology optimism and technology innovativeness. *Interactive Learning Environments*, 31(6), pp.3409-3421.

[48] Liu, J., Wang, X. and Zhang, J., 2025. Investigating elderly individuals' acceptance of artificial intelligence (AI)-powered companion robots: the influence of individual characteristics. *Behavioral Sciences*, 15(5), p.697.

[49] Norzelan, N.A., Mohamed, I.S. and Mohamad, M., 2024. Technology acceptance of artificial intelligence (AI) among heads of finance and accounting units in the shared service industry. *Technological Forecasting and Social Change*, 198, p.123022.

[50] Chen, L., Wang, P., Dong, H., Shi, F., Han, J., Guo, Y., Childs, P.R., Xiao, J. and Wu, C., 2019. An artificial intelligence based data-driven approach for design ideation. *Journal of Visual Communication and Image Representation*, 61, pp.10-22.

[51] Chatterjee, S., Bhattacharya, M., Lee, S.S. and Chakraborty, C., 2023. Can artificial intelligence-strengthened ChatGPT or other large language models transform nucleic acid research?. *Molecular therapy Nucleic acids*, 33, pp.205-207.

[52] Huang, F., Schoop, E., Ha, D. and Canny, J., 2020, March. Scones: towards conversational authoring of sketches. *In Proceedings of the 25th International Conference on Intelligent User Interfaces* (pp. 313-323).

[53] Roh, T., Park, B.I. and Xiao, S.S., 2023. Adoption of AI-enabled Robo-advisors in Fintech: Simultaneous Employment of UTAUT and the Theory of Reasoned Action. *Journal of Electronic Commerce Research*, 24(1), pp.29-47.

[54] Liu, J., Wan, F., Zou, J. and Zhang, J., 2023. Exploring factors affecting people's willingness to use a voice-based in-car assistant in electric cars: An empirical study. *World Electric Vehicle Journal*, 14(3), p.73.

[55] Murdoch, B., 2021. Privacy and artificial intelligence: challenges for protecting health information in a new era. *BMC medical ethics*, 22(1), p.122.

[56] Chi, O.H., Gursoy, D. and Chi, C.G., 2022. Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking. *Journal of travel research,* 61(1), pp.170-185.

[57] Moriuchi, E., 2021. An empirical study on anthropomorphism and engagement with disembodied AIs and consumers' re‐use behavior. *Psychology & Marketing*, 38(1), pp.21-42.