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Examining factors affecting the acceptance of AI-powered creativity support tools among the industrial design community in China

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The emergence of artificial intelligence (AI)-powered creativity support tools (CSTs) is recently transforming the creative design industry. Yet within the specific industrial design field, such tools are neither widespread nor well-tailored to unique needs of the community. This gap makes the industrial design community's acceptance of AI-CSTs uncertain. To address the issue, this study explored key factors influencing the acceptance of AI-CSTs by extending the unified theory of acceptance and use of technology (UTAUT) model. The authors used a structural equation modeling approach to carried out an empirical study. Data were collected through a questionnaire survey with 515 industrial design stakeholders in China. The results indicated that technology optimism and personal innovativeness positively affected performance expectancy. Interactivity and facilitating conditions were positive determinants of effort expectancy. The variable "perceived risk" was constructed by three first-order components, namely ethical risk, privacy risk and output risk. Finally, intention to use was significantly affected by performance expectancy, effort expectancy, price value, and perceived risk. Based on the theoretical findings, we presented general AI-CST promotion strategies and specific AI-CST optimization strategies for the industrial design community. This study contributed to a deeper understanding of designers' behavioral intentions toward AI-CSTs and provides actionable insights for stakeholders to improve system usability, risk control, and technology fit in creative domains.

Keywords Artificial intelligence, Creativity support tools, Technology acceptance, Interactive design, Structural equation modelling

AI-CSTs refer to software systems and platforms that assist designers in generating, refining, and evaluating creative ideas by leveraging machine learning algorithms, natural language processing, and computer vision technologies[1,2]. These tools are designed to augment human creativity by automating repetitive tasks, offering novel design suggestions, and enabling real-time feedback, thereby enhancing the efficiency and quality of creative outputs[3]. Globally, AI-CSTs have been increasingly adopted in various creative sectors such as product design, graphic design, fashion design and architecture design[1,4–6]. For instance, Midjourney, an AI-driven image generator, transforms textual prompts into hyper-realistic visuals, empowering artists to prototype concepts rapidly without advanced technical skills. Similarly, DALL-E 2 interprets abstract textual descriptions to produce contextually coherent illustrations, bridging the gap between imagination and execution. In China, Alibaba's "Luban" platform stands as a leading example, employing GANs to generate massive volumes of highly customized e-commerce visual assets, including banners and product displays, dramatically accelerating marketing campaign production for online retailers. As AI-CSTs continue to evolve, they are expected to redefine creative processes by fostering closer collaboration between human ingenuity and algorithmic intelligence.

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Currently, AI-CST bridges efficiency, scalability, and creativity, redefining the future of design across individual, organizational, and sectoral dimensions. For front-line designers, AI-CSTs enable them to streamline repetitive tasks, generate diverse design concepts, and focus on refining creative ideas rather than manual execution[3]. For design enterprises, AI-CSTs facilitate rapid prototyping, cost-effective brand upgrades, and data-driven decision-making, empowering businesses to adapt swiftly to market demands and maintain competitive advantage[7]. Across the broader design industry, AI-CSTs foster transformative shifts by democratizing advanced creative capabilities, raising the baseline for innovation, and catalyzing new methodologies and collaborative workflows[8]. Collectively, these advancements are propelling the design industry towards a paradigm characterised by heightened efficiency, intelligent automation, and personalised solutions, establishing new frontiers for design innovation[9].

Despite demonstrating high performance and potential within design workflows, AI-CSTs still face hesitancy regarding designers' proactive adoption behavior. The main cause is from AI technology itself. Currently, users' concerns about the uncertainty, algorithmic bias, malicious use and insufficient explainability of AI technology dampen their adoption willingness[10–13]. For the industrial design community, they may worry that overreliance on AI will diminish their creativity or cause cultural and emotional design details to be overlooked. In addition, privacy and trust issues are critical. Furthermore, industrial design stakeholders may be unsure of how AI systems handle and protect their creative data, especially when data security and privacy measures are unclear. Therefore, they may concentrate on the potential negative impacts including privacy loss, copyright and originality disputes, over-reliance, and ethical issues[14,15]. Interaction factors also present challenges. The industrial design community may find that the complex operating interface of AI tools hinders their work efficiency and are skeptical about the reliability and accuracy of AI-generated results. The lack of understanding of the mechanisms of these technologies also further triggers distrust, who may feel that although AI technology provides convenience, it cannot yet fully understand or replace the fine artistic perception and value judgment in human design[16]. Moreover, industrial designers may exhibit caution towards AI's involvement in the design process due to their high valuation of "creative autonomy" and "individual expression." Consequently, gaining a deeper understanding of key factors influencing designers' adoption of AI-CSTs holds significant theoretical and practical value for industrial design stakeholders.

The UTAUT model is an integrative theoretical framework proposed by Venkatesh in 2003[17]. It consolidates several well-known prior technology acceptance theories, including the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), Theory of Reasoned Action (TRA), and Theory of Planned Behavior (TPB), to comprehensively understand users' acceptance and use behaviors regarding new technologies. At its core, the model is built around four key direct determinants of user behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. These core variables are posited to directly influence a user's behavioral intention to adopt a technology and, ultimately, their actual usage behavior[18]. Specifically, performance expectancy relates to the degree to which using a particular technology enhances users' work performance; effort expectancy reflects the perceived difficulty when using the technology; social influence emphasizes the impact of friends, family, and colleagues on users' behavior regarding technology usage; and facilitating conditions involve the availability of necessary resources and support during the technology usage process. Furthermore, UTAUT explores how individual characteristics such as gender, age, and experience act as moderating variables that affect the relationships between these core constructs and actual usage behavior, thereby providing more detailed insights for research[17]. In this article, the UTAUT model was selected as the theoretical basis for model construction.

This paper aimed to investigate industrial design stakeholders' intention to adopt AI-CSTs in China, and it had the following knowledge contributions. From a theoretical view, first, this study contributed to existing technology adoption studies by validating the UTAUT model under a novel context. Second, this paper considered users' technology adoption intention from a comprehensive viewpoint, integrating system design factors, individual characteristic factors, and perceived risk factors into the original UTAUT model. Overall, this study is an extension and modification of the traditional UTAUT model. Moreover, this paper examined the multidimensional nature of the variable "perceived risk" and model it as a formative structure comprised by three first-order components. From a practical view, this study provides a theoretical foundation and empirical support for the development and promotion of AI-CSTs. Specifically, the study developed general strategies for AI-CST promotion and AI-CST optimization strategies targeting the industry design community. Two research questions (RQs) were proposed: RQ1: What are the key factors impacting the acceptance of AI-CSTs among the industrial design community in China? RQ2: How can a theoretical model be constructed to uncover the mechanism of acceptance of AI-CSTs among the industrial design community?

Literature review

AI-CST and its application

CSTs denote technologies designed to enhance creative efficiency and stimulate inspiration among creators[19]. Within the design domain, CSTs primarily encompass software or platforms that facilitate the conception, creation, and quality optimisation of design outputs throughout the design process[20]. These include, but are not limited to, image design applications, 3D modelling software, and video processing systems[21–23]. The advent of artificial intelligence (AI) has ushered in a new era for creative assistance, forming AI-CSTs. Also known as Generative AI, AI-CSTs constitute a significant branch of AI, leveraging advanced technologies such as deep learning and natural language processing to provide creators with insights, creative stimulation, and resources. These tools leverage prompts and image inputs to autonomously generate artwork and assist designers with image editing, color harmonization, and stylistic modifications[24].

AI-CSTs fulfil a critical function within various creative industries. Within the music industry, AI algorithms analyze music theory and compositional patterns to generate novel melodies and harmonies, thereby furnishing composers and musicians with innovative tools[25]. YouTube and Google DeepMind's development of Lyria, an AI music generation model, enables artists to create diverse soundscapes through textual cues. In the design field, various AI-CSTs, such as Adobe Sensei, Canva, Midjourney, Stable Diffusion, Adobe Firefly, were developed to support practical workflows. More specifically, in the industrial design field, practitioners are integrating generative design methodologies to implement AI technology within product development workflows. For instance, a landmark industry collaboration between Autodesk Research and Philippe Starck yielded an AI-generated chair design for Kartell Furniture Company. Similarly, creative technologist Nathan Shipley and ArtDrunk founder Gary Yeh synthesised extensive historical art datasets to generate novel surface design concepts for the BMW 8 Series Gran Coupe. This BMW Art Car exemplifies the innovative convergence of artistic expression, automotive aesthetics, and technological integration, reflecting broader cultural and historical developments in interdisciplinary design. Also, Nike invited thirteen athletes to collaborate with their innovation team and utilize generative artificial intelligence tools in the co-creation of their ideal footwear. For instance, Kylian Mbappé envisioned shoes embodying "infinite speed," whereas Sha'Carri Richardson sought designs exemplifying "relentless power." From hundreds of AI-generated concepts, the team selected three leading contenders. Through the integration of hand-drawn sketches, immersive three-dimensional renderings, and computational design methods, these concepts were transformed into tangible footwear prototypes.

Usability of AI-CST

In the design field, many scholars are focusing on how to use AI-CSTs to create better interactive experiences and explore the application potential of AI-CSTs in artistic creation, creative design, and other fields[26–28]. Some research raises issues related to user experience and usability, emphasizing the need for users to understand how to write prompts rather than simply instructing the tool on how to achieve the desired results[29]. Some researchers are attempting to develop a set of usability and UX assessment scales to evaluate the fundamental characteristics of platforms like AI tools in depth[30]. For instance, Rossouw and Smuts try to recognizing the design requirements of AI tools and delve deeper into the interface design principles for AI tools[31]. Shen, Chen analyzed the usability of Midjourney through the Technology Acceptance Model. The results indicate a very positive evaluation of perceived ease of use, perceived usefulness, attitude, and behavioral intention, demonstrating Midjourney's positive impact on creativity[32]. Casteleiro-Pitrez compared the usability, user experience, and user satisfaction characteristics of Midjourney, Dream Studio Beta, and Adobe Firefly tools. The author surveyed 60 users about their experiences with AI-generated image tools[33]. The findings show that although GenAI image tools received high praise for usability, users' evaluations of the user experience, practicality, and ability to engage their positive emotions were not as favorable. These challenges could affect users' acceptance and adoption rates of AI technologies.

AI-CST adoption

The present review systematically analyzes empirical work directly related to AI adoption in creative industries, which contributes to form the research gap. The review was conducted by searching prominent academic databases, including ScienceDirect, Web of Science, Google Scholar, and Scopus. The search used keywords from three categories: AI tools (e.g., "AI-CST," "AIGC", "AI drawing/painting tools"), user acceptance (e.g., "adoption," "usage intention", "continuance intention," "usage intention," or "willingness,"), and target users (e.g., "designers," "users"). This yielded a final corpus of 10 relevant articles for in-depth analysis. The publication timeframe was deliberately set from 2021 to 2025 to capture the most recent empirical investigations of AI-CST, such as Stable Diffusion, DALL-E and Midjourney, which began to gain significant traction around 2022. Table 1 summarizes the key characteristics of the empirical-quantitative literature on AI-CST adoption examined in this paper, including authors and year, main research questions, participants, theoretical models and findings.

Regarding the theoretical foundations of the identified quantitative studies, the vast majority are grounded in established technology acceptance frameworks. The most frequently employed are the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Expectation Confirmation Model (ECM). TAM posits that perceived ease-of-use and perceived usefulness are core predictors of behavioral intention. UTAUT highlights that behavioral intention is influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions. ECM emphasizes the roles of perceived usefulness, expectation confirmation, and satisfaction in shaping usage intentions. Other studies rely on different theoretical frameworks to explain the influencing factors of intention to use AI-CSTs, such as the Push-Pull-Mooring model (PPM), the Theory of Planned Behavior (TPB), and Technology Readiness (TR) theory. Among these, TPB reveals the concurrent impact of attitude, subjective norms, and perceived behavioral control on behavioral intentions, while TR theory outlines the role of individual characteristics, including optimism, innovativeness, discomfort, and insecurity. The PPM model explains a person's decision by combining factors that push them away from their current situation, pull them toward a new one, and personal or circumstantial moorings that can either hinder or facilitate the change. For instance, in Liu and Ji's research, dissatisfaction with traditional painting tools, switching costs, and the attractiveness of AI tools were considered the push, mooring, and pull effects, respectively[34].

While classic technology acceptance models provide robust theoretical foundations, researchers often adapt them to their studies' specific contexts by adding relevant factors. These additional factors can be divided into the following levels: perceptual, individual, technical, and contextual. At the perceptual level, the risks associated with AI are often a popular topic and has been mentioned in three papers. Li and Fan and Jiang found that AI anxiety and AI risk exert negative impacts on behavioral intentions to use AIGC, and Wang and Chen classified AI risk into functional and emotional and derived that they could reduce users' trust in AIGC[29,35,36]. Liu, Zou's research indicated that privacy concerns and ethical concerns could impede intention to use[37]. Moreover, trust is another critical predictor of intention to use, and it was found to be predicted by perceived intelligence[38].

Author	Year	Main question	Theoretical model	Participants	Findings
Li	2024	What factors affect designers' intention to use AIGC?	UTUAT	404 designers	Performance expectancy, effort expectancy, social influence, and facilitating conditions affect intention to use AIGC, and perceived anxiety and perceived risk show negative impacts.
Wang and Chen	2024	How perceived characteristics, risks, and trust influence designers' behavioral intentions to use AIGC?	TAM and TPB	184 designers	Behavioral intentions are shaped by trust. Functional risk is a more significant positive predictor of trust than emotional risk. perceived ease of use, perceived usefulness and subjective norms can contribute to functional risk and emotional risk.
Yu et al.	2024	What affect users' continuance intention towards an AI painting application?	ECM, TAM, and UTAUT	443 users	Confirmation positively influences satisfaction and social impact. Personal innovativeness has a significant impact on confirmation. Satisfaction, flow experience, and social influence directly affect intention. Habit moderates the relationship between social influence and intention to use.
Wang and Chen	2024	What are the driving factors of designers' adoption toward AIGC?	TAM and TPB	226 designers	Facilitating conditions significantly affect self-efficacy, which in turn predicts designers' intention to use AIGC.
Xu et al.	2024	How is the acceptance of continuance intentions toward AI painting tools among Chinese users?	ECM and TAM	532 users	Emotional experience exerts the most significant direct influence on users' continuance intention, underscoring the value they place on emotional engagement. This is followed by the direct effects of satisfaction, attitude, perceived usefulness, and perceived trust. In contrast, perceived intelligence and perceived novelty exert only indirect effects, mediated by perceived trust and satisfaction.
Fan and Jiang	2024	What are the determinants of designers' continuance intention to use AI drawing tools?	ECM and ISC	398 designers	Continuance intention was determined by perceived switching cost, subjective norms and satisfaction. Perceived usefulness, expectation confirmation and perceived playfulness can contribute to satisfaction.
Liu and Ji	2025	What impacts designers' switching intention to AI painting tools?	Push-pull-mooring model	320 designers	Attractiveness is the primary driver of designers' switching intentions, with switching costs and dissatisfaction with traditional tools also exerting significant influence. Furthermore, perceived pleasantness was found to enhance attractiveness, while individual habits served to amplify switching costs.
Liu et al.	2025	How is the acceptance of AI-CSTs in Chinese creative industries?	UTAUT	435 users	The acceptance of AI-CSTs was affectedby performance expectancy, effort expectancy, and social influence, ethical concern and privacy concern, and regulatory environment. Interactivity and personalization had direct influences on effort expectancy.
Zhu and He	2025	What impacts users' intention to adopt VR for Wuhu iron painting?	UTAUT	688 users	Users' intention to adopt VR for Wuhu iron painting is driven by performance expectancy and social influence. Effort expectancy and facilitating conditions failed to exhibit a significant impact. Moreover, gender, age, VR and iron experience act as moderators.
Yao et al.	2025	What are the key factors influencing Chinese designers' of AIGC?	TAM and TR theory	462 designers	The adoption of AIGC is driven by its technical features and interactivity, which enhance perceived ease of use and usefulness, thereby fostering adoption intention. This process is further facilitated by designers' optimism and innovation, while being inhibited by insecurity.

Table 1. Empirical studies on AI-CST adoption in creative industries.

This factor can also serve as a mediator between behavioral intentions and its prerequisites[36]. In some cases, behavioral intentions can be triggered by individuals' flow experience, self-efficacy and emotional experience[36,38]. At the individual level, optimism and creative spirit were found to be facilitators while insecurity was found to be an inhibitor of intention to use[39]. Personal innovativeness can sometimes have a significant impact on confirmation[40]. Habit and individual non-innovation could significantly contribute to switching costs[34]. Besides, the role of demographic variables also cannot be neglected. Gender, age, and usage experience could act as moderators between intention to use and its drivers[41]. On the other hand, they were sometimes considered as control variables for users' behavior intentions. At the technical level, the interactive characteristics and technical features can be prerequisites of perceived ease of use and usefulness[39]. This finding was also supported by another study[37]. Consumption of time can lead to dissatisfaction with traditional AI tools[34]. At the contextual level, governmental regulations had associations with intention to use AI-CSTs[37].

Based a systematic analysis on prior literature, we found that there are research gaps that need to be filled. First, existing AI adoption literature often regards AI risk or AI anxiety as a unidimensional construct, rare attempt to investigate the multiple risk dimensions during AI adoption. Second, Venkatesh pointed out that individual feature variables could be potential preconditions of the UTAUT model in the AI adoption research agenda, but this statement has seldom examined in the existing research, especially in the context of AI-CST[18]. Third, the research objects in nearly all literature are described as AI painting/drawing tools, AIGC, or AI-CSTs, which is limited to 2D graphic design tools. Generally, the industrial design community requires 3D designed tools. However, few studies target industrial design fields and try to develop optimization strategies of AI-CST for the specific community. The distinction between 3D product design and 2D graphic design necessitates a new research direction for improving existing AI-CSTs. Based on above illustration, it is imperative to propose a systematic model to enhance the acceptance of AI-CSTs among the industrial design community and develop corresponding strategies for AI-CST optimization.

The construction of theoretical model

In this study, we followed Venkatesh's research agenda grounded in UTAUT to construct the theoretical model, as the UTAUT model has shown robust explanatory power and has been applied in various contexts related to AI adoption, including new product development, AI-painting tools, and chatbots among scholars[18,29,37,40–43]. Venkatesh pointed out the potential research directions for the extension of UTAUT during the AI adoption process. According to his statement, individual features, technology characteristics, environmental contexts and interventions can be considered as UTAUT-related predictors in AI adoption studies[18]. Therefore, two individual feature variables, "technology optimism" and "personal innovativeness" from Technology Readiness theory, were selected as the predictors of UTAUT variables in the outer layer of the proposed model. In the context of AI-CST, the industrial design community with optimism possesses a positive outlook on technological progress, viewing AI as a beneficial partner. This inherent trust lowers their perceived barriers to adoption, such as fear or skepticism, making them more willing to integrate AI tools into their workflows. Similarly, users with high personal innovativeness often regard novel AI-CSTs as opportunities rather than obstacles. This inherent trait drives them to actively seek out and master novel AI tools. Similar to Venkatesh's statement, Parasuraman also argued that innovativeness and technology optimism are positive contributors during technology adoption[44]. In academic fields, prior literature has emphasized the impact of these two individual feature variables on users' technology adoption willingness[45–47]. Additionally, interactivity served as a variable that demonstrates the technology characteristics of AI-CSTs. In the prior technology adoption study, when users interact well with a system, they are more likely to perceive its ease of use[48]. We therefore consider the variable as a potential precondition for UTAUT variables.

In the middle layer, four UTAUT variables, performance expectancy, effort expectancy, facilitating conditions and price value, were retained. The former three were core variables in the original UTAUT. We did not consider the variable "social influence" in this specific context of AI-CST adoption. The main reason is that the creative design process traditionally values unique individual skill and inspiration, potentially leading practitioners to prioritize personal judgment over peer trends. The variable "price value" reflects users' cost-benefit assessment during AI-CST usage[49]. At present, users often need to pay subscription fees and for virtual private network services when using AI-CSTs like Mid-journey or Stable Diffusion. Moreover, the learning cost, including time and money, cannot be neglected. We therefore introduce the variable "price value" to demonstrate the psychological mechanism of how users balance the perceived benefit and cost during AI-CST usage. Finally, given that the potential risk of AI adoption has been mentioned in many studies, we argue that it is necessary to consider the impact of perceived risk and include this variable in the proposed model[29,50]. Prior studies often neglected the complex and multi-dimensional nature of perceived risk and generalized individuals' risk perceptions into one variable during AI adoption[29,35]. Nevertheless, Lin et al. and Nguyen-Phuoc et al. argued that collapsing multidimensional risk items into a single construct oversimplifies perceived risk, so they modeled it as a formative second-order structure of its first-order dimension[51,52]. Hence, we conceptualized the perceived risk as a formative construct and included three risk dimensions in the final model.

Hypotheses development

Based on the literature review results, the researchers built a systematic framework to understand the acceptance of AI-powered CSTs among industrial design stakeholders, see Fig. 1. This framework aims to explain how individual characteristics (technology optimism, personal innovativeness), technology characteristics (interactivity), and risk perceptions (ethical risk, privacy risk and output risk) influence intention to use AI-CSTs. It is theoretically grounded in several established technology acceptance models, including the UTAUT and Technology Readiness Model.

Technology optimism

Technology optimism is a positive driver that encourages individuals to use new technologies. This factor is derived from Parasuraman's research[53]. In the TR theory, technology optimism is defined as a positive belief that technology offers people increased control, flexibility, and efficiency in their lives[54]. When users believe that a technology can bring positive outcomes, they will be more likely to embrace it. In the context of this study, technology optimism reflects one's readiness to employ AI-CSTs. These days, AI-CSTs are an emerging technology and not widely accepted by the industrial design community in China, and designers who hardly use them still hold a neutral or skeptical perception. If users are not confident in AI-CSTs, they will not realize the

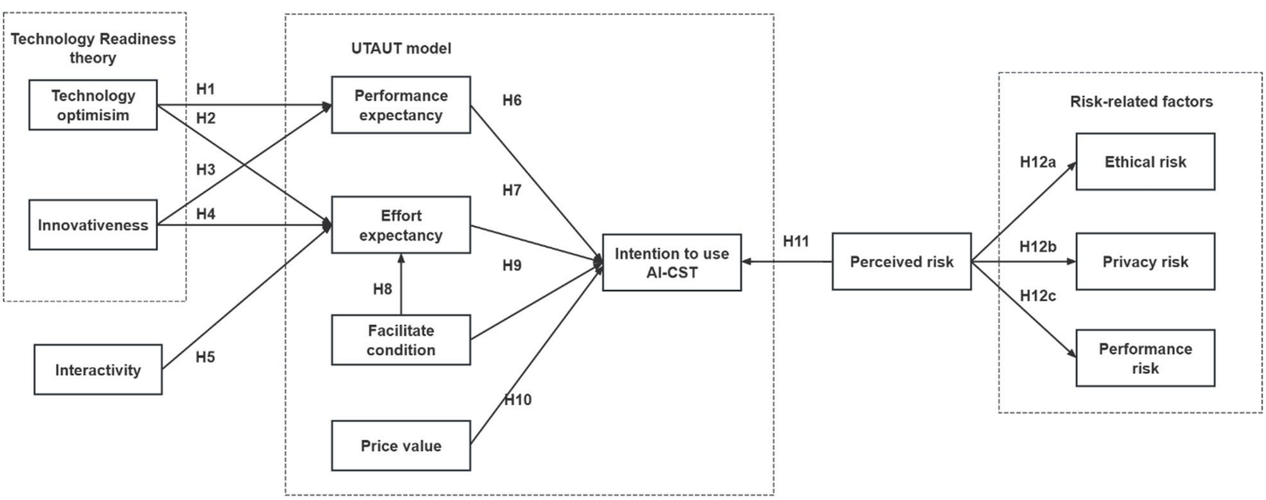

Fig. 1. Theoretical framework.

usefulness and ease of use of these smart tools. Finally, their perceptions will be negative and redundant to adopt AI-CSTs. Prior literature has validated the causal relationship between technology optimism and performance expectancy and effort expectancy. For example, Liu, Wang found that technology optimism could contribute to individuals' performance expectancy and effort expectancy toward AI companion robots[45]. Similarly, the study conducted by Álvarez-Marín, Velázquez-Iturbide demonstrated that technology optimism significantly influences users' favorable attitudes toward adopting augmented reality techniques[54]. Thereby, we argued that technology optimism could be a prerequisite of performance expectancy and effort expectancy, and developed the following hypothesis:

H1 Technology optimism has a positive impact on performance expectancy.

H2 Technology optimism has a positive impact on effort expectancy

Personal innovativeness

Along with technology optimism, personal innovativeness is another key variable that motivates individuals to accept new technologies. Derived from TR theory, personal innovativeness was proposed as a personality trait reflecting one's curiosity to try new technologies early[53]. This factor is different from the term "creativity". Generally, people characterized by high personal innovativeness are more likely to explore cutting-edge tools and act as technology pioneers among peers. In this study, the construct denotes an individual's curiosity and openness to explore the potential benefits of AI-CSTs and willingness to act as an early adopter of these AI tools. Generally, technology pioneers have more opportunities to experiment with the latest AI-CSTs, so they are more likely to perceive the usability and ease of use of AI-CSTs. Extensive academic research substantiates this proposition. For example, Liu, Wang found that personal innovativeness was a key predictor of performance expectancy and effort expectancy[45]. Similarly, Almaiah, Alfaisal demonstrated that personal innovativeness significantly affected both perceived usefulness and perceived ease of use[46]. Based on the above illustration, we proposed the hypotheses:

H3 Personal innovativeness has a positive impact on performance expectancy.

H4 Personal innovativeness has a positive impact on effort expectancy.

Interactivity

Interactivity is a user's subjective assessment of the degree to which they can engage in real-time, bidirectional communication, exert control over content, and experience responsive feedback within a digital environment or interface. It encompasses multiple dimensions, including the simplicity of operation, clarity of the interface, intelligent accessibility, degree of user autonomy, system error tolerance, as well as learning costs and guidance mechanisms[55]. Liu, Wan pointed out that interactivity involved immediate feedback, communication quality, and perceived control[56]. In the context of AI-CSTs in our study, interactivity refers to the bidirectional, real-time exchange between a designer and an AI agent that enables dynamic co-creation, iterative refinement of ideas, and adaptive responses to creative input. When users can interact with AI-CSTs in a more user-friendly and smoother manner, they will be more likely to perceive AI-CSTs' ease of use. The association between interactivity and effort expectancy has been verified in prior technology adoption studies[37,57]. Thus, we deduced that:

H5 Interactivity has a positive impact on effort expectancy.

Performance expectancy

Performance expectancy can be defined as users' perceptions of how a technology can assist them in enhancing their task performance[17,58]. In this study, performance expectancy specifically reflects designers' beliefs about whether the system can effectively assist them in completing tasks, such as generating creative concept images, creating renderings, or proposing product color schemes. If users perceive the technology as valuable in improving efficiency and effectiveness, their intention to adopt it will correspondingly increase. Prior studies have demonstrated the correlation between performance expectancy and intention to use[59,60]. Hence, we deduced that if creative workers view AI-CST as a tool that can deliver significant benefits, they are more likely to accept and utilize the technology positively, and the hypothesis was proposed:

H6 Performance expectancy has a positive impact on intention to use.

Effort expectancy

Effort expectancy refers to users' evaluation of the difficulty associated with using technology[17], reflecting the level of effort required when employing new technology[61]. In this study, the ease or difficulty of executing tasks directly determines users' effort expectancy. Previous research has shown that users' perceptions of effort expectancy with new technologies significantly impact their behaviors[62–64]. When the system interface is complex and users need to invest more time in learning how to use it, it will lead to negative emotions among users[65]. Complex interaction designs and difficult-to-understand operational methods often frustrate users, negatively affecting their overall experience with the product. Therefore, when faced with low effort expectancy, users may develop dissatisfaction with technology. On the other hand, if users can easily grasp how to use AI-CSTs without expending excessive effort, their technology adoption intention will increase[42,59,60]. Thereby, we can further deduce that the level of effort expectancy not only influences users' behavior intention during the use of AI-CSTs, and poses the following hypothesis:

H8 Effort expectancy has a positive impact on intention to use.

Facilitating conditions
The variable facilitating conditions was derived from the UTAUT model. It refers to the degree to which an individual perceives that organizational and technical infrastructure exists to support the use of a technology system. In the UTAUT model, facilitating conditions can directly lead to users' behavioral intention to adopt a technology[61]. In this study, facilitating conditions refer to the infrastructure that users can obtain while utilizing AI-CSTs, including resources, support, skill training, and creative materials[37]. When users can access necessary training or support, they are more likely to adopt AI-CSTs in a smoother way, thereby enhancing their perceived ease of use. In other words, if external facilitating conditions are more favorable, they will perceive that learning to use new technology requires less effort. Prior literature indicates that users can gauge the effectiveness and convenience of facilitating conditions through their evaluations[29,66,67]. Thus, we developed the hypothesis:

H8 Facilitating conditions have a positive impact on effort expectancy.

H9 Facilitating conditions have a positive impact on intention to use.

Price value
Price value refers to the rational trade-off that users make between the perceived benefits and the actual costs associated with adopting a particular technology[61]. It serves as a critical cognitive process through which individuals assess whether the value derived from a technology justifies its financial, temporal, or psychological investment. According to Nastjuk, Herrenkind the price of a product or service must be considered alongside its perceived quality and functionality to determine users' overall value perception[49]. In AI-CSTs adoption, industrial design stakeholders are more likely to accept the tools when perceived benefits outweigh actual costs; otherwise, high perceived costs can lead to resistance. As highlighted by Yin, Han price value emerges as one of the core determinants of generative AI usage intention, particularly in applied technology contexts where monetary or investment is substantial[60]. Therefore, we argued that understanding how designers rationalize costs relative to expected outcomes is essential for predicting AI-CST adoption intention, and price value could be included in the proposed model. The following hypothesis was forwarded:

H10 Price value has a positive impact on intention to use.

Perceived risk
The variable "perceived risk" was derived from the Health Belief Model (HBM). The HBM is a theoretical framework that seeks to explain and predict health-related behaviors through an individual's perceptions and beliefs[68]. Perceived risk refers to users' concerns about potential negative consequences when making decisions[69]. This perception typically stems from personal experience, knowledge, emotions, and social influences, and includes economic, psychological, social, and functional risks[14,70]. In the field of creative design, many creative professionals approach artificial intelligence technologies with caution, citing risk as a major concern. Currently, AI-CSTs remain underdeveloped, and their application in the creative industry is still limited, which may lead to a lack of user trust and raise ethical issues[71,72]. Additionally, since AI-generated content is based on extensive training data, users often find it challenging to determine whether elements of plagiarism are involved[73,74]. AI-CSTs have also been criticized for insufficient data protection and errors during task execution[75–77]. When using AI tools, users' behavioral data and preference information can be collected and shared, further heightening their awareness of the risks associated with AI. Prior studies also highlight the correlation between perceived risk and intention to use[29,78]. Thereby, we put perceived risk as one of the determinants of users' behavior intentions, and the following hypothesis was developed:

H11 Perceived risk has a negative impact on intention to use.

Conceptualisation and operationalisation of perceived risk
Prior studies have revealed that there are various dimensions of perceived risks according to the research objects and situations when examining users' behavioral intentions[78,79]. For example, Kim, Jung categorized perceived risk into financial risk, functional risk, aesthetic risk, and sanitary risk when investigating consumption behavior[80]. Tymoshchuk, Lou identified three types of perceived risks, which were functional risk, aesthetic risk, and sanitary risk[81]. Wang, Gu argued that users might experience privacy, performance, security, and conflict risks when employing ride-sharing services[78]. In the context of generative AI, existing research has also revealed several risks that might be caused by AI technology. For instance, Liu, Zou found that users might show privacy, ethics, and dependence concerns during adoption[37]. Beltran, Ruiz Mondragon conducted a comparative analysis and identified significant risks associated with generative AI adoption in the public sector, including information leakage, data privacy and security vulnerabilities, and public trust concerns[82]. Wach et al. grouped the identified ChatGPT threats into seven key clusters: (i) Unregulated AI market with urgent regulatory needs; (ii) Poor quality, weak oversight, deepfakes, and algorithmic bias; (iii) Job losses from automation; (iv) Personal data breaches, surveillance, and privacy violations; (v) Social manipulation eroding ethics and goodwill; (vi) Widening socioeconomic inequalities; (vii) AI-related technostress[83]. Based on previous studies, we confirmed three dimensions of AI-CST risk perception (ethical risk, privacy risk, and output risk) to highlight the multidimensional nature of the concept.

Ethical risk is related to unintended or harmful consequences arising from AI-CST adoption, involving issues like bias, copyright infringement, duplication, lack of transparency, and misuse, so ethical risk can be included in the present study. Moreover, the adoption of AI-CSTs introduces significant privacy risks, including inadvertent collection, retention of sensitive user inputs (e.g., personal conversations, creative works), and potential data breaches through insecure storage practices. Hence, we added privacy risk that also involves security risk in our study. Output risk, also called performance risk, refers to the potential that the AI tools fail to deliver reliable, high-quality, or contextually appropriate creative outputs consistently, hindering the user's creative process due to technical limitations, inaccuracies, or inconsistent results. The current AI-CSTs are still updating, and their functions are incomplete, so they may not perform as well as users expect. Thus, output risk containing functional risk was considered in our model. Notably, other risks, such as aesthetic risk, sanitary risk, and fairness risk, are often considered during consumption behavior research, which has few associations with AI-CST adoption. Thus, they were not included in the present study. Overall, our framework concerns three dimensions of perceived risks: ethical risk, privacy risk and output risk, which were used to clearly demonstrate the multidimensional character of perceived risk.

Privacy risk refers to the potential harm or misuse of personal data that individuals may face due to unauthorized access, exposure[11]. This concept encompasses not only the likelihood of data breaches but also the consequences of sensitive information being used without consent, such as identity theft or reputational damage. In the context of AI-CSTs, privacy risk specifically involves concerns about how user-generated content, behavioral patterns, and intellectual property are collected, stored, and processed by AI systems[37]. Users may fear that their confidential ideas, unfinished work, or personal creative expressions could be leaked, stolen, or used without their consent, leading to loss of competitive advantage or personal embarrassment. Consequently, concerns about how their creative data is stored, used, or potentially monetized by tool providers can generate significant apprehension and distrust. Actually, the European Union's AI Act establishes a risk-based regulatory framework for AI technologies addressing fundamental rights, safety, and privacy[11]. In academic fields, prior studies on technology adoption consistently show that heightened perceptions of privacy risk negatively influence users' intention to use[16].

Ethical risk is described as the potential harm or negative consequences arising from actions or decisions that violate moral, legal, or societal norms[10]. Guan, Dong pointed out that ethical risks associated with AI decision-making encompass moral and societal issues arising from biases in data or algorithms[84]. In this study, ethical risk specifically involves concerns such as plagiarism of artistic styles, bias in generated outputs, lack of transparency in AI contributions, copyright infringement, and the potential devaluation of human creativity[10,37,85]. Users, particularly creative workers, may perceive high ethical risks as undermining the authenticity and originality of their work, leading to distrust in the AI tool and apprehension about potential reputational damage or accusations of unoriginality. Furthermore, concerns about unintended bias in outputs or the potential for AI-CSTs to generate harmful, misleading, or copyrighted content can create significant apprehension about legal liabilities, ethical responsibilities, and the overall integrity of the creative process, deterring positive adoption intentions. In addition, prior research indicates that perceived ethical risks are negatively associated with users' intention towards adopting AI systems[37].

Output risk, also called performance risk, was proposed as the third risk dimension in this study. H.-H. Lee & Moon defined performance risk as the possibility that a product is disappointing when it does not cater to user needs[86]. Based on H.-H. Lee & Moon's depiction, we defined this factor as people's concerns about whether AI-CSTs could cater to their expectations and support them. People's doubtful perceptions toward AI-based CSTs may result from several causes. First, AI-driven CSTs are still an emerging technology and not widely applied in China's creative industry. Due to the limited user feedback, AI-CSTs may not be constantly updated and optimised to cater to users' needs. Second, the performance of AI tools may vary due to the distinction in their algorithm, databases, and interface design. Individuals unfamiliar with the AI creativity industry may not choose an appropriate AI tool. Third, users may worry about the complicated operations of AI-based CSTs. Taking AI painting as an example, users need to input appropriate keywords and base maps, set parameters, and adjust the power of the brush. Some artworks even need multiple adjustments and operations. In this case, poorly designed AI-CSTs will lead to a sense of puzzling and helplessness. Going through previous literature, Liang and Tao indicated the relationship between performance risk and attitudes[87]. Moreover, Wang, Gu's research pointed out that performance risk was a driver of perceived risk. If designers are concerned that an AI tool will not perform as expected, users' risk perceptions will probably increase[78].

Although perceived risk has been considered as a unidimensional construct in prior research, Lin, Sher believed that the methodological practice of integrating multidimensional items into a general value construct fails to capture the complete complexity of perceived risks[51]. In this case, they modeled perceived risk as a formative second-order structure that is comprised by its first-order risk dimensions. In addition, Carlson, O'Cass pointed out that it is more suitable to employ a formative structure when the constituent components of a variable are conceptually discrete and non-interchangeable[88]. The formative structure of perceived risk has been employed by scholars in various fields. For instance, Park and Tussyadiah developed a hierarchical second-order model of perceived risk that includes multiple dimensions[89]. Similarly, in Wang, Gu's research perceived risk was configured as formative construct and constituted by four dimensions: privacy risk, performance risk, security risk, and conflict risk[78]. Nguyen-Phuoc, Oviedo-Trespalacios conceptualized booking APP-related risk as multiple dimensions including performance risk, privacy risk, conflict risk and cyber risk[52]. Therefore, perceived risk was conceptualized as a formative second-order construct formed by three first-order dimensions: ethical risk, privacy risk and output risk. This construction can provide a comprehensive understanding of perceived risk in the context of AI-CST adoption. The following hypotheses were proposed:

H12a Ethical risk is a formative first-order component of perceived risk.

H12b Privacy risk is a formative first-order component of perceived risk.

H12c Output risk is a formative first-order component of perceived risk.

Materials and methods
Sampling and data collection
This study used a cross-sectional survey approach to explore key factors affecting users' acceptance of AI-CSTs in China. Compared to a longitudinal study or a controlled experiment, a cross-sectional design allows researchers to efficiently capture perceptions and intentions across a diverse population at a single point in time, thus enhancing the breadth and external validity of the study's findings. In technology acceptance research, cross-sectional surveys have been frequently employed to investigate users' perceptions and behavioral intentions toward novel systems or innovations. Therefore, applying this approach in our study can effectively validate the acceptance factors for AI-CSTs and provide generalizable insights into user readiness across different demographics and contexts. Data were collected via an online questionnaire survey between October 2024 and December 2024. We used a popular online platform called "Wenjuanxing" for questionnaire design. A stratified sampling was adopted to ensure sample representativeness and data collection efficiency. In this study, we carried out a power analysis approach to determine the lowers bounds on sample size in a SEM analysis. Power analysis can determine the minimum sample size by considering the model with the most predictors, requires the specification of statistical power, effect size, and significance level to calculate this requirement[90,91]. The G-power 3.1.9.7 version software was employed to calculate the required minimum sample size (85). Moreover, considering structural equation modeling conventions requiring a 10:1 response-to-item ratio and Covariance-Based SEM (CB-SEM) requires a middle and large sample size, the final sample size was determined to 450. We collected about 560 responses (10% buffer), securing approximately 500 valid answers to meet SEM's distributional assumptions. The target study population was users or potential users of AI-CSTs in China. Based on AI-CST usage scenarios and user characteristics, we selected occupation stratification dimensions to allocate sample sizes across subgroups. The sample allocation of each subgroup is divided as follows: industrial designers (45%), industrial design students (30%), enterprise design team managers (5%), design educators and researchers (20%).

A multi-channel dissemination strategy was implemented for each subgroup to optimize outreach effectiveness and appropriate sampling proportions. Industrial designers were primarily targeted through established online design communities and professional networks, including Huaban, Behance, Puxiang, ZCOOL, and 3D66, as well as social platforms such as WeChat, Xiaohongshu, and Douban design-focused groups. Industrial design students were reached primarily via academic channels, including course-specific WeChat groups, student forums (like the Industrial Design section on Baidu Tieba). For enterprise design team managers, recruitment was conducted through online social platforms. Moreover, based on the researchers' social networks, we sent direct personalized messages were to introduce the study and invite them for participation. Finally, we used a snow sampling approach to invite appropriate industrial design educators or researchers, as one of the authors also belonged to this user group. Dissemination also occurred via design education-oriented WeChat groups, scholarly public accounts, and academic websites like CNKI. To ensure accurate classification and proportionate representation, the questionnaire was designed with an initial screening question to identify the respondent's professional role. Furthermore, all collected data were screened for completeness, consistency, and validity, and responses that were incomplete, inconsistent, or did not align with the stated respondent category were excluded from the final analytical dataset. Finally, we collected a total of 515 valid responses for further analysis.

Survey instrument
In this study, data were collected through a structured questionnaire consisting of two sections: an introductory overview, demographic details, and the main survey items assessing key variables. The questionnaire was first developed in English and then translated into Chinese for distribution. To ensure clarity and ethical compliance, the introductory section provided respondents with the research background and objectives, definitions of key terms, and essential notices, including informed consent and ethical declarations. The second section gathered demographic information, such as gender, age, educational attainment, occupation and the usage experience of AI-CSTs. The third section measured 11 latent variables through adapted questions from existing studies, see the supplementary material. To be more specific, the items developed by Álvarez-Marín, Velázquez-Iturbide were used to measure technology optimism (TO) and innovativeness (INN)[54], and the measurement items of price value (PV) were developed from Nastjuk, Herrenkind's study[49]. The facilitating conditions (FC) scale was adapted from Tian, Ge[92]. The items of interactivity (INT) were based on Birkmeyer, Wirtz[48], and the items of ethical risk (ER) and privacy risk (PRR)were based on Liu, Zou and Esmaeilzadeh[14,37]. The scales of output risk (OUR) were taken from Esmaeilzadeh[14]. We employed the items from Ma and Huo to measure the variable performance expectancy (PE), and items from Li to measure the variable effort expectancy (EE)[29,93]. Intention to use (ITU) was measured by the items from Chi, Chi[94]. In total, there are 11 questions measuring latent variables and 37 sub-questions measuring observed variables. Responses were recorded on a five-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree").

Data analysis
The proposed model was tested based on an SEM analysis, which contains three stages. First, we conducted a descriptive analysis to demonstrate the gender, age, educational level, and usage experiences of respondents. Second, we conducted a confirmatory factor analysis (CFA) to check the reliability, convergent validity, discriminant validity, and goodness-of-fit of the conceptual model. Finally, the hypothesized structural relationships were examined through path analysis. Descriptive analysis and internal reliability testing were conducted using SPSS 25.0, whereas Mplus 8.3 was used for CFA and structural model testing. Notably, Covariance-Based SEM (CB-SEM) was selected in this study because the research aim focuses on testing

hypothetical constructs rather than theory establishment[95]. Moreover, compared to Partial Least Squares-based SEM (PLS-SEM), CB-SEM yields less bias and greater accuracy when testing theoretical models[65].

Results

Demographic information of participants

Table 2 summarizes the demographic characteristics of the 515 survey respondents. The sample comprised 251 males (48.7%) and 264 females (51.3%). Age distribution was categorized into five groups: under 20 years ($n = 76$, 14.8%), 20–30 years ($n = 184$, 35.7%), 30–40 years ($n = 144$, 28.0%), 40–50 years ($n = 68$, 13.2%), and over 50 years ($n = 43$, 8.3%). Educational attainment varied among participants: 41 (8.0%) held a high school diploma or technical secondary school, 132 (25.6%) had a vocational diploma, 234 (45.4%) possessed a bachelor's degree, and 108 (21.0%) had obtained a master's degree or higher. Moreover, 132 (25.6%) respondents had less than one year usage experience, 202 (39.2%) respondents had a 1–2 years usage experience, 127 (24.7%) respondents had a 2–3 years usage experience, and 54 (10.5%) respondents had more than 3 years of usage experience.

First-order measurement model

Before analyzing the measurement and structural models, the data's normality was evaluated. As shown in Table 2, the kurtosis (range: − 0.524 to − 1.344) and skewness (range: − 0.019 to − 0.727) for all observed variables were within the recommended limits of |3| and |10|, respectively[29], indicating acceptable univariate normality. Moreover, the visual inspection of normality via Q-Q plots showed the data points roughly followed the straight diagonal line, and boxplots demonstrated symmetry, with the median centered and whiskers of similar length. Although the Shapiro-Wilk and Kolmogorov-Smirnov tests returned p-values < 0.05, this is likely due to the high sensitivity of these tests to even minor deviations given the large sample size. Considering the strong evidence from the descriptive statistics (skewness and kurtosis) and graphical analyses, which are less sensitive to sample size, we conclude that any deviation from normality is not substantial enough to pose a practical problem for the subsequent analysis[96]. To check for multicollinearity within our model, the variance inflation factor (VIF) was computed using SPSS 25.0 software. The obtained VIF values of each latent variables (range: 1.230 to 1.501) were all below the conventional threshold of 5, confirming the absence of multicollinearity concerns in the model[52]. Moreover, we conducted the Harman's single-factor analysis to test the common method variance of data set using SPSS 25.0 software. The results shows that variance explained by the first factor (21.0%) does not exceed half of the total variance (70.3%) explained. This indicates that there is no single factor that can explain the majority of the variance in the data, and the common method bias is acceptable[97].

Table 4 presents the key metrics used to assess the reliability and validity of the measurement model. The analysis included Cronbach's alpha, standardized factor loadings, average variance extracted (AVE), and composite reliability (CR). Similarly, all composite reliability values surpassed 0.7, further confirming the scales' reliability[98]. Regarding convergent validity, both the standardized factor loadings (all > 0.7) and AVE values (all > 0.5) met established criteria, indicating adequate convergent validity. For discriminant validity, we compared the square roots of the AVE values with the correlation coefficients between constructs (Table 3)[98]. The results confirmed that each construct shared more variance with its indicators than with other constructs, thereby establishing satisfactory discriminant validity[98]. Collectively, these results demonstrate that the measurement model meets all necessary psychometric standards for reliability and validity (Table 4).

The indices of the model's goodness of fit are demonstrated in Table 5, including chi-square, degree of freedom (df), chi-square/df, the root mean square residual (SRMR), the root mean square error of approximation (RMSEA), normed-fit Tucker–Lewis Index (TLI), and comparative fit index (CFI). The results suggested both the measurement model (chi-square/df = 1.043, SRMR = 0.028, RMSEA = 0.009, TLI = 0.995, and CFI = 0.996)

Attributes ($N = 515$)	Indicators	Frequency	Percentage (%)
Gender	Male	251	48.7
	Female	264	51.3
Age	Below 20	76	14.8
	21–30	184	35.7
	31–40	144	28.0
	41–50	68	13.2
	Above 50	43	8.3
Educational level	High school or technical secondary school	41	8.0
	Diploma	132	25.6
	Bachelor	234	45.4
	Master and above	108	21.0
The usage experience of AI-CSTs	One year or below	132	25.6
	One year to two years	202	39.2
	Two Years to three years	127	24.7
	Three years or above	54	10.5

Table 2. Sample statistics.

Constructs	Items	VIF	Kurtosis	Skewness	Standardised factor loading	AVE	CR
Facilitating conditions (FC)	FC1	1.235	− 0.776	− 0.611	0.964	0.640	0.875
	FC2		− 0.770	− 0.561	0.758		
	FC3		− 0.925	− 0.503	0.758		
	FC4		− 1.029	− 0.471	0.693		
Price value (PV)	PV1	1.428	− 0.804	− 0.636	0.658	0.547	0.783
	PV2		− 0.776	− 0.645	0.778		
	PV3		− 0.722	− 0.639	0.777		
Interactivity (INT)	INT1	1.514	− 0.745	− 0.595	0.759	0.525	0.815
	INT2		− 0.881	− 0.558	0.753		
	INT3		− 0.979	− 0.450	0.671		
	INT4		− 0.865	− 0.525	0.711		
Technology optimism (TO)	TO1	1.425	− 1.042	− 0.360	0.767	0.578	0.804
	TO2		− 0.985	− 0.405	0.776		
	TO3		− 0.958	− 0.449	0.737		
Personal innovativeness (PI)	PI1	1.230	− 1.169	− 0.291	0.762	0.544	0.781
	PI2		− 1.171	− 0.367	0.759		
	PI3		− 1.209	− 0.302	0.689		
Performance expectancy (PE)	PE1	1.441	− 0.997	− 0.480	0.719	0.579	0.805
	PE2		− 1.014	− 0.517	0.773		
	PE3		− 1.036	− 0.485	0.789		
Effort expectancy (EE)	EE1	1.294	− 0.809	− 0.580	0.795	0.517	0.810
	EE2		− 0.969	− 0.504	0.704		
	EE3		− 0.788	− 0.592	0.697		
	EE4		− 0.693	− 0.639	0.675		
Ethical risk (ER)	ER1	1.369	− 1.246	− 0.161	0.779	0.586	0.809
	ER2		− 1.255	− 0.171	0.819		
	ER3		− 1.214	− 0.081	0.693		
Privacy risk (PRR)	PRR1	1.360	− 1.184	− 0.252	0.771	0.591	0.852
	PRR2		− 1.321	− 0.066	0.771		
	PRR3		− 1.238	− 0.167	0.793		
	PRR4		− 1.165	− 0.283	0.739		
Outcome risk (OUR)	OUR 1	1.293	− 1.344	− 0.019	0.850	0.651	0.848
	OUR 2		− 1.252	− 0.112	0.803		
	OUR 3		− 1.185	− 0.223	0.765		
Intention to use (ITU)	ITU1	1.501	− 0.524	− 0.727	0.708	0.504	0.752
	ITU2		− 0.691	− 0.668	0.748		
	ITU3		− 0.762	− 0.540	0.671		

Table 3. First-order measurement model evaluation.

Construct	AVE	FC	PV	INT	TO	PI	PE	EE	ER	PRR	OUR	ITU
FC	0.640	0.800										
PV	0.547	0.356***	0.740									
INT	0.525	0.350***	0.538***	0.725								
TO	0.578	0.336***	0.447***	0.470***	0.760							
PI	0.544	0.312***	0.372***	0.303***	0.339***	0.738						
PE	0.579	0.302***	0.417***	0.413***	0.508***	0.414***	0.761					
EE	0.517	0.314***	0.359***	0.477***	0.298***	0.270***	0.362***	0.719				
ER	0.586	0.074	0.147**	0.160**	0.176**	0.058	0.129*	0.064	0.766			
PRR	0.591	0.113*	0.136*	0.122*	0.149**	0.133*	0.162**	0.120*	0.537***	0.769		
OUR	0.651	0.073	0.022	0.087	0.143*	0.046	0.166**	0.090	0.471***	0.440***	0.807	
ITU	0.504	0.301***	0.499***	0.501***	0.480***	0.383***	0.504***	0.424***	0.008	− 0.039	− 0.096	0.710

Table 4. Correlation matrix and squared root of the AVE. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; the square root of AVE is on diagonal.

Research Model	Chi-square	df	Chi-square/df	TLI	CFI	RMSEA	SRMR
Benchmark value	–	–	1–5	> 0.9	> 0.9	< 0.08	< 0.08
Measurement model	598.527	574	1.043	0.995	0.996	0.009	0.028
Structural model	655.369	600	1.092	0.991	0.992	0.013	0.036

Table 5. Goodness of fit of the models.

Hypothesis	Relationship	Factor loadings	T value	*P* value	Result
H12a	PR→ER	0.742***	15.150	0.000	Supported
H12b	PR→PRR	0.720***	14.445	0.000	Supported
H12c	PR→OUR	0.630***	11.858	0.000	Supported

Table 6. Factor loadings of second-order constructs. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Hypotheses	Relationships	Standardised coefficient	T statistics	*P*-value	Result
H1	TO→PE	0.448	8.520	0.000	Supported
H2	TO→EE	0.060	0.869	0.385	Not supported
H3	PI→PE	0.286	4.804	0.000	Supported
H4	PI→EE	0.109	1.765	0.078	Not Supported
H5	INT→EE	0.380	5.785	0.000	Supported
H6	PE→ITU	0.346	5.487	0.000	Supported
H7	EE→ITU	0.225	3.924	0.000	Supported
H8	FC→EE	0.126	2.178	0.029	Supported
H9	FC→ITU	0.042	0.792	0.428	Not supported
H10	PV→ITU	0.332	5.090	0.000	Supported
H11	PER→ITU	− 0.197	− 3.302	0.001	Supported

Table 7. Hypothesis testing. *$p<0.05$; **$p<0.01$; ***$p<0.001$; the square root of AVE is on diagonal.

and structural model (chi-square/df = 1.092, SRMR = 0.036, RMSEA = 0.013, TLI = 0.991, and CFI = 0.992) had good model fits.

Second-order model evaluation

In this paper, the variable "perceived risk" was modeled as a second-order construct, and we employed several indexes to assess this formative structure. First, a second-order factor represents a common underlying dimension shared by its first-order components, which necessitates the presence of moderate to high correlations among the latter. The discriminant validity test (Table 4) revealed that the correlation coefficients among the three first-order dimensions of perceived risk were 0.537, 0.471, and 0.440, all of which exceeded 0.4. This indicates that the first-order constructs exhibit moderate intercorrelations, thereby satisfying the necessary condition for establishing a second-order factor structure. The VIFs for the second-order constructs (ethical risk, privacy risk, and output risk) demonstrated no evidence of multicollinearity, with all values well below the 5.0 threshold (see Table 2)[52]. This result provides empirical support for the formative measurement model specified for the second-order construct in this study. Lastly, the factor loadings of three second-order components were statistically significant and all exceeded 0.6, which could also prove the validity of the formative structure, see Table 6.

Structural model

We carried out path analysis to gain the result of the structural model, and the results are shown in Table 7; Fig. 2. The path analysis results indicated that nine hypotheses were accepted, except H2, H4 and H9. Among the supported hypotheses, six of them show high statistical significance ($p<0.001$), and two show slight statistical significance ($p<0.05$). Performance expectancy was positively influenced by technology optimism ($p<0.001$, t = 8.520) and personal innovativeness ($p<0.001$, t = 4.804), so H1 and H3 were supported. However, we found that technology optimism ($p>0.05$, t = 0.896) and personal innovativeness ($p>0.05$, t = 1.765) did not contribute to effort expectancy, so H2 and H4 were not supported. Effort expectancy was affected facilitating conditions ($p<0.05$, t = 2.178) and interactivity ($p<0.001$, t = 5.785), thereby H5 and H8 were supported. Moreover, we observed that intention to use were simultaneously determined by four variables: performance expectancy ($p<0.001$, t = 5.487), effort expectancy ($p<0.001$, t = 3.924), perceived risk ($p<0.01$, t = − 3.302) and price value ($p<0.001$, t = 5.090). Thus, H6, H7, H10 and H11 were supported. Facilitating conditions was not a predictor of intention to use, thereby H9 was not supported.

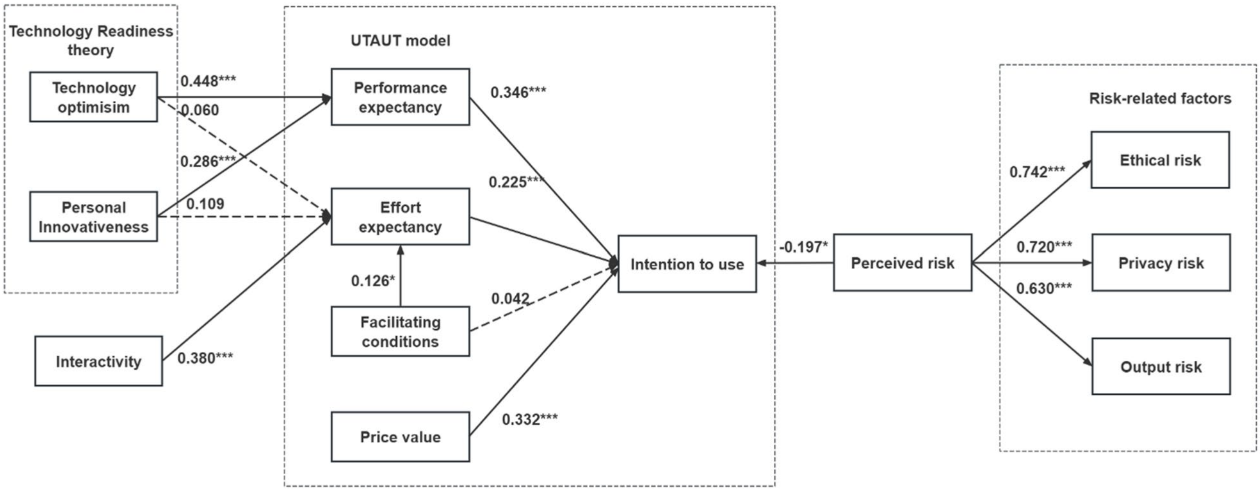

Fig. 2. The results of path analysis.

Discussion

According to the literature review and hypothesis testing results, the research model was constructed and refined. The framework explores key determinants of people's acceptance of AI-CSTs and reveals causal relationships among these variables. The variables in the model were derived from several well-known models, including Technology Readiness theory and UTAUT. Two individual feature variables were found to be critical determinants of performance expectancy and effort expectancy. Performance expectancy, effort expectancy, perceived value, and perceived risk were found to be key drivers of intention to use. Moreover, perceived risk was comprised by three first-order risk dimensions. Finally, we presented the discussion of these theoretical findings and propose general AI-CST promotion strategies and AI-CST optimization strategies for the industrial design community, see Fig. 3.

Findings and general AI-CST promotion strategies

Technology optimism was found to serve as a trigger of performance expectancy and effort expectancy, which was in accordance with Liu, Zou, and Álvarez-Marín, Velázquez-Iturbide[37,54]. This indicated that optimistic users are predisposed to believe these tools will be both highly useful (performance expectancy) and intuitive to use (effort expectancy), lowering adoption barriers. Conversely, users with low technology optimism may undervalue AI-CSTs regardless of actual capabilities, creating a "trust gap" that stakeholders must address. For AI-CST Developers, they can integrate explainable AI features that show how suggestions are generated to demystify AI processes and build user trust. For design company managers, they can launch pilot programs tracking technology optimism using validated metrics like optimism indices before and after AI-CST trials to identify adoption barriers. For policymakers, they can fund public digital literacy campaigns that showcase AI as a collaborative partner, such as workshops where artists co-create with AI-CSTs, to combat technophobia.

Personal innovativeness, a variable reflecting individuals' openness to experimenting with new technologies, directly fueled performance expectancy. This aligned with Almaiah, Alfaisal and Álvarez-Marín, Velázquez-Iturbide, confirming that technology pioneers exhibit a greater propensity to encounter the potential advantages and usability of AI-CSTs, which may be due to their inherent curiosity and risk tolerance[46,54]. For AI-CST developers, offering early access benefits can attract and engage innovative users before the official launch of AI-CST tools. Designers should create introductory guides that showcase unique features to generate interest among early adopters. It is also critical for developers to identify highly creative users early in the process. Before releasing the tool publicly, teams can use methods like closed beta testing or incentives tied to user experience to encourage these individuals to test the AI tools and share feedback. This approach helps refine the tool's ease of use and ensures it meets user needs. When designing interfaces and features, developers should focus on the tool's ability to spark exploration and creativity. Examples include adding an "AI surprise" function or experimental options for creative tasks. These features can boost user curiosity and motivation to try new things. To support ongoing use, developers should provide clear step-by-step instructions, practical examples, and interactive systems for feedback to make learning the tool more accessible.

The individual feature variables "technology optimism" and "personal innovativeness" did not contribute to effort expectancy. In other words, users trust in technology's potential openness to experimenting with new tools did not influence their perceptions of how easy AI-CSTs would be to use. This reveals a critical distinction: while these views drive motivation to adopt, they don't reduce expected effort. Optimistic or innovative users may eagerly try AI-CSTs but still anticipate complexity if interfaces seem unintuitive, onboarding is lacking, or technical support is inadequate. Hence, stakeholders should improve the interactivity. For AI-CST developers or designers, they should prioritize good interactions to ensure easier adoption. For instance, they can embed intuitive onboarding, like interactive guides that activate during complex tasks.

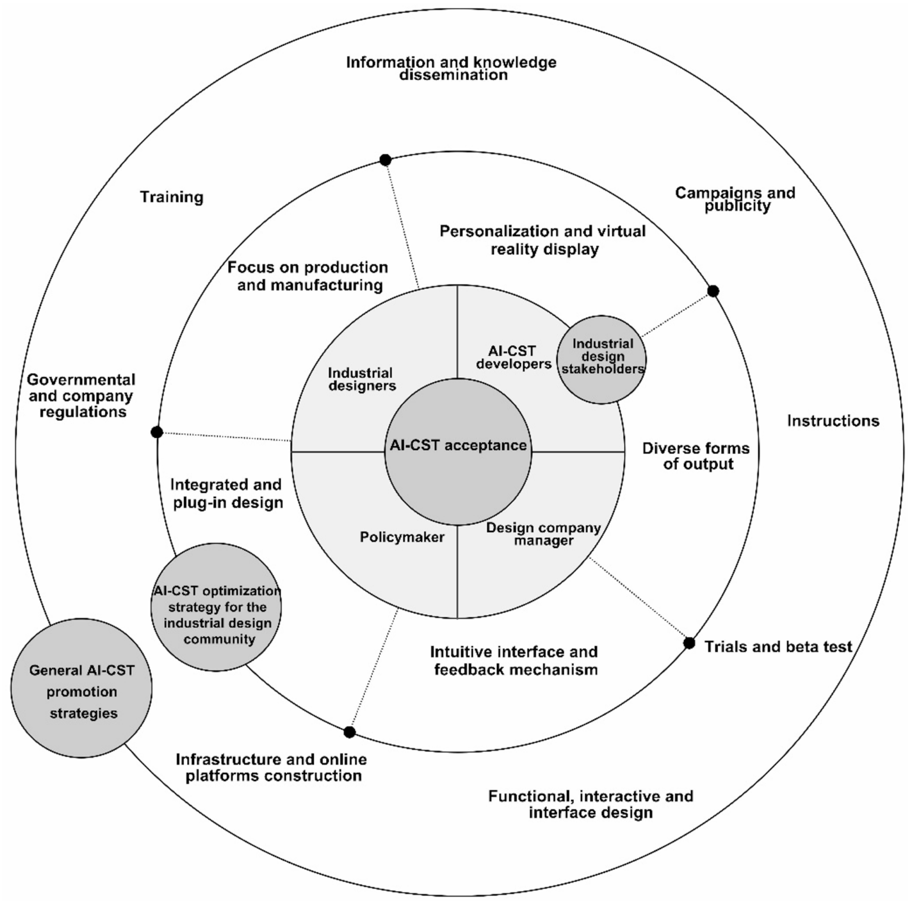

Fig. 3. AI-CST promotion and optimization strategies.

We observed that facilitating conditions played a noteworthy role in affecting effort expectancy, which aligns with Li's and Sukendro, Habibi's studies[29,99]. When users have access to dependable tools, training, and technical support, they find AI creativity tools easier to use. According to technology adoption theory, even advanced AI-CSTs seem easier to use when there are strong infrastructure, quick help, and support from the organization. Without these supports, users face difficulties no matter how well the tool is designed. For policymakers, they should provide funding for public access points, such as library AI workstations with fast computers, to close resource gaps. Design company managers should offer organized onboarding processes, assign specific tech support staff, and prepare approved AI toolkits to ensure teams can smoothly integrate AI tools.

Interactivity was another key determinant of effort expectancy, which was in accordance with Gupta, Prashar and Liu, Zou[37,57]. Users find tools easier to use when interactions are smooth and straightforward, reducing mental effort and removing obstacles. This transforms abstract AI capabilities into tangible, controllable experiences. For AI-CST developers, they should let users choose how much control the AI has, like switching between fully automatic settings and suggestion-only modes, to match individual comfort levels and maintain a sense of control. They should also prioritize quick responses, such as immediate visual changes when users tweak settings, and include undo/redo options for AI actions so users can test ideas without fear of mistakes. For AI-CST designers, they can add helpful guides, for instance, short videos that appear during tricky tasks and tools to fix errors easily, which reduces stress for new users. They should also use simple, intuitive controls, such as drag-and-drop editing of AI results or sliders to adjust creativity levels, making the tool easier to learn. Design company managers should regularly test how users interact with the tool, using recorded sessions to spot confusing moments like delays during collaborative tasks and give teams dedicated time to improve these small details.

Performance expectancy, effort expectancy, and price value were positive determinants of intention to use, validating the UTAUT model in the AI-CST context. This finding can echo Venkatesh, Thong, Xia and Chen, and Li[29,61,100]. When users clearly see a tool's usefulness and find it easy to use, they naturally accept it. This means even high-quality AI-CSTs may not succeed if users cannot understand their benefits or use them smoothly. Therefore, AI-CST developers should implement specific strategies to show the tool's value during usage. For instance, they can include visual feedback systems that display progress as user complete tasks. This helps reinforce their understanding of the tool's usefulness and builds confidence in using it. Developers can also set goals to measure success and create simple tools like rating systems to help users assess the quality and effectiveness of AI-CST outputs. For AI-CST designers, making the tool easy to use is equally critical. One effective method is introducing advanced features only after users learn the basics. This prevents beginners from feeling overwhelmed. Designers can also add helpful shortcuts, such as a one-click function to generate design summaries, to reduce the steps needed for common tasks and save time. At the organizational level, design managers can conduct comparison studies to evaluate results from AI-CSTs versus traditional methods. These comparisons provide clear evidence of the tool's value, reduce doubts among team members, and support wider use of AI-CSTs in real design workflows.

Our research also contributed to existing literature by verifying how perceived risk affects users' intention to use. This factor is an extra factor that extends the traditional UTAUT model. Consistent with previous evidence, people who perceive AI-CSTs as risky will be less likely to adopt the technology[29,37,78]. Moreover, this study also confirmed that the variable "perceived risk" could be conceptualized as a formative structure and constituted by three second-order components, which could mirror, Park and Tussyadiah, Wang, Gu, and Nguyen-Phuoc, Oviedo-Trespalacios[52,78,89]. Stakeholders should pay attention to these aspects to enhance the acceptance of AI-CSTs.

Firstly, we argued that ethical risks, like plagiarism concerns, output duplication, or moral conflicts, can directly erode trust and adoption intention. Users may hesitate to use AI-CST because of worries about unintended harm, such as accidental copyright issues, undervaluing human creativity, or unclear data use. These concerns often outweigh the tool's practical advantages, making even powerful AI-CSTs feel ethically risky. For AI-CST developers, they should build in safety measures to address these issues. Examples include real-time tools to detect copied content, watermarks for AI-generated work, and default settings that ask for user permission before using data. They should also develop systems to prevent AI from copying specific artists' styles by using official lists of creators who choose not to be included. Designers should prioritize transparency in how the tool works. Interfaces should clearly show which parts are created by AI, explain how results are generated, and share source details when possible. Policymakers should establish clear ethical guidelines, require reports on transparency, and mandate labels for AI-generated outputs to help users understand and trust the technology. This approach promotes fairness and encourages responsible use of AI-CSTs in professional design settings.

Secondly, we argued that AI-CST-related privacy risks, involving unauthorized data collection, misuse of creative inputs, or sharing user information without consent, directly undermine users' trust and adoption. Users worry that their private ideas, sketches, or sensitive client data might be used for AI training or leaked. To address this, AI-CST developers must make privacy a central part of development. This includes collecting only essential data, offering clear options for user consent, using local or offline processing when possible, and training AI with anonymized data that is ethically sourced. AI-CST designers should create interfaces that clearly explain how user input is handled, stored, and used. They should also give users control over their data, such as allowing them to delete specific inputs, opt out of training processes, or adjust access permissions. Policymakers should develop rules to protect creative content and personal information. This could include requiring companies to explain how data is used, setting standard data protection practices, and imposing penalties for unauthorized data use to increase accountability and trust. At the company level, design company managers should set clear policies for managing sensitive data safely. They should train employees on data ethics and privacy practices and choose AI-CST tools that meet industry privacy standards. These steps help create a secure and trustworthy environment for creative work.

Thirdly, we argued that AI-CSTs might concern output risks, such as unpredictable results, low-quality suggestions, or outright malfunctions, and this type of risk could negatively affect users' intentions. When AI-CSTs produce irrelevant, faulty, or unclear results, such as a logo design tool creating blurry images or crashing during a task, users see the tools as unreliable. These issues waste time, reduce trust, and make users doubt AI's ability to handle real tasks. To address this, AI-CST developers should focus on making the system more stable and the results better. This includes improving the AI models, making the system handle errors better, and adding features like auto-save to protect work if the tool crashes. It is also important to create a way for users to report problems, which helps improve the tool over time. AI-CST designers should ensure the outputs are useful and relevant. They can build systems that adjust suggestions based on what the user is trying to do, making the results easier to understand and more aligned with the user's goals. At the organizational level, design firm managers should encourage using set processes where AI helps. For example, having people and AI work together on tasks can maintain quality while using AI's speed. Setting clear quality rules and creating systems to check how well the AI performs regularly ensures the tools remain reliable and controllable in real design work. These strategies can help build user trust and encourage broader adoption of AI tools in design practice.

We observed an association between price value and intention to use, which is in line with Nastjuk, Herrenkind's research[49]. When users see the cost of an AI-CST as fair compared to its clear benefits, such as time saved, better quality, or increased revenue, they develop more adoption willingness. This balance between cost and value transforms pricing from a barrier into a reason to invest. Users accept higher costs when they can directly connect expenses to measurable results. However, unclear benefits create doubt even at low prices. To address this, AI-CST developers should clearly explain the main advantages of their tools, such as faster workflows, stronger creative support, or improved output quality. They should use real examples, test results, and other evidence to show how costs relate to benefits. Offering flexible pricing options like free trials, tiered subscriptions, or pay-per-use plans can also reduce initial cost barriers. AI-CST designers should consider how different users might use the tool and what they can afford. Inclusive design should aim to improve cost-effectiveness for various contexts. For example, simplified versions of the tool could be made available for large firms, startups, or freelancers to increase access and acceptance. Policymakers should create incentives to support fair and widespread use of AI-CSTs. This could include government funding or subsidies for small and medium-sized design firms to reduce financial barriers. They should also develop standard certification systems for AI tools to help users trust that higher prices reflect better quality. At the organizational level, design company managers should analyze how AI-CSTs impact real projects. By comparing time spent, output quality, and client satisfaction in AI-assisted versus traditional workflows, companies can make informed decisions about adopting these tools. This approach ensures transparency about investments and supports structured integration of AI-CSTs into design practices.

AI-CST optimization strategies for the industrial design community

Focus on production and manufacturing

During the creative stimulation phase, current AI-CSTs primarily provide visual renderings based on textual or image prompts. However, the industrial design community often requires consideration beyond aesthetics, including structural rationality, assembly feasibility, material compatibility, and manufacturing process constraints. Existing AI-CST typically overlook these critical multidimensional factors, leading to issues during subsequent production and implementation. Therefore, future AI-CSTs should be capable of generating multi-dimensional information. For example, when a designer inputs the command "organic-shaped portable baby stroller," the AI tool should not only offer aesthetic design suggestions but also concurrently produce detailed structural assembly diagrams and instructions to clarifying component relationships. It should additionally recommend suitable materials, such as lightweight aluminum alloys, steels, or carbon steels, complete with material properties. Guidance on manufacturing techniques, such as surface treatments, coating, anodizing, or powder coating, should also be provided. Furthermore, considerations for functionality and ergonomics, such as folding storage mechanisms, grip comfort, and ergonomic assessments for infant seating, should be integrated. For the industrial design community, such advancements would not only enhance the balance between aesthetic appeal and engineering practicality but also reduce iterative revisions caused by neglecting structural and process factors, thereby accelerating the overall product development timeline.

Diverse forms of output

Currently, the output of AI-CSTs predominantly remains confined to two-dimensional images, which limits their ability to meet the industrial design process's requirements for three-dimensional representation and process validation. For industrial designers, three-dimensional models support multi-angle visualization and serve diverse functions at various design stages. For instance, during the conceptual design phase, designers rely on rendered images and 3D models to quickly evaluate the feasibility of form proposals; during engineering validation, exploded assembly diagrams and technical drawings are essential for verifying structural rationality and manufacturing feasibility. Therefore, future AI-CST should transcend the limitations of 2D visualization by offering diversified outputs, including 3D product models, exploded assembly diagrams, and technical drawings, which can be integrated with engineering software for parameter adjustments and modifications. Such enhancements would facilitate more efficient collaboration between designers and various departments, thereby significantly improving tool practicality and adaptability.

Integrated and plug-in design

At present, most AI-CSTs remain standalone applications and have yet to achieve effective integration with mainstream industrial design software. This disconnection forces designers to frequently switch between multiple applications, resulting not only in increased time expenditure but also in potential file format compatibility issues and data loss. If AI-CSTs could be embedded as plugins into common industrial design software such as Rhino, SolidWorks, CATIA, and Keyshot, achieving seamless integration comparable to that between EndNote and Microsoft Word, they could be effectively incorporated into existing design workflows. This would reduce operational disruptions and enhance overall work efficiency. Through extended plugin functionality, designers would be able to directly utilize AI tools within their familiar software environments to accomplish tasks including concept generation, model modification, parameter optimization, and rendering presentation. Such integration not only improves the practicality and user acceptance of AI-CSTs but also transforms them from auxiliary tools into genuinely embedded collaborative partners within the design process. Several existing implementations exemplify this integration trend. For instance, KeyShot Studio 2025.2 has introduced three types of AI plugin functionalities: the Restyle mode allows users to replace materials, surfaces, and colors through text prompts while preserving geometric structures and lighting configurations; the Background mode automatically generates realistic backgrounds, eliminating the need for repetitive modeling and lighting adjustments; and the Imagine mode enables the generation of high-quality conceptual sketches prior to modeling, providing inspirational support during the early design stages. It is particularly noteworthy that all AI processing is performed locally, significantly reducing the risk of data leakage and effectively safeguarding corporate R&D privacy and intellectual property.

Intuitive interface and feedback mechanism

The interface and interaction design of AI-CSTs play a crucial role in enhancing their usability. Interface design should adhere to principles of intuitiveness and clarity, with core functional modules—such as model generation, material editing, and rendering settings—arranged in a logically compartmentalized layout. This approach minimizes multi-level menu nesting, thereby reducing the learning curve and improving operational efficiency. Current successful implementations in material rendering and scene switching, such as Adobe Substance 3D's modular panel design, demonstrate how dedicated functional zones for materials, textures, and lighting adjustments enable users to complete tasks without frequent interface switching. Furthermore, the interface should support synchronized multi-view display, allowing designers to simultaneously observe multiple perspectives and structural hierarchies of a model within a unified workspace, with seamless switching between appearance visualization and structural analysis. The system must also provide real-time visual feedback during operations, including instant previews of material updates, model modifications, and rendering effects. This enables designers to immediately assess adjustment outcomes and minimizes repetitive operations. To further enhance operational efficiency, AI-CSTs should incorporate visual parameter control mechanisms. Through interactive elements such as sliders, knobs, and color pickers, designers can directly adjust dimensions, angles, material properties, and lighting parameters without memorizing complex numerical values, thereby achieving precise control. For instance, in designing a stroller handle, real-time adjustments of surface curvature, wall thickness, and glossiness via sliders facilitate intuitive and refined design execution. Such integrated text and graphical interface interactions significantly enhance both the flexibility of the tool and its capacity to support design innovation.

Personalization and virtual reality display

Smart recommendation and personal is another direction of AI-CST improvement. AI-CSTs can provide parametric suggestions in areas such as structural optimization, material matching, and color scheme selection based on user operation history, design specifications, and generated outcomes, thereby reducing repetitive tasks and enhancing the rationality of design outputs. Furthermore, modular and customizable interface design enables users to configure functional panels, shortcut operations, and interface layouts according to their specific workflows, improving the tool's adaptability for designers with varying levels of experience. For instance, Blender's customizable workspace allows users to create dedicated panel combinations tailored to different project types, significantly enhancing operational efficiency. While current AI-CSTs can generate high-quality static images, they still lack multi-angle, dynamic virtual presentation capabilities. Virtual presentation functionality can support comparative analysis of multiple solutions during the conceptual phase and assist in result validation during the engineering phase. Taking the design of a smart walking stick for elderly users as an example, the system can simulate real-world usage scenarios through virtual environments, helping to identify design flaws and ergonomic compatibility issues while generating actionable improvement suggestions. This functionality elevates AI-CSTs from mere image generation tools to decision-support systems equipped with feedback mechanisms, thereby comprehensively enhancing the quality and reliability of design outcomes.

Conclusion

AI-CSTs offer transformative potential for enhancing innovation and efficiency within China's industrial design sector. Despite this potential, notable resistance or hesitancy exists among the industrial design community towards adopting these AI-driven tools, hindering their effective integration into the design process. To address the gap, this study attempted to build a systematic model to examine factors affecting the acceptance of AI-CSTs among the industrial design community. Overall, this article is interdisciplinary research that combines the knowledge from design science, information science, and behavior sciences, which has the following theoretical and practical implications.

Theoretical implications

This article presents substantial knowledge contributions to the literature: (1) This study developed a model that integrating the well-known UTAUT model, Technology Readiness model, and HBM and applied it in a context of AI-CST adoption. (2) This study conceptualized perceived risk as a formative second-order structure and confirmed three dimensions of risk perceptions during AI-CST usage, including ethical risk, privacy risk, and output risk.

First, this paper contributed to the development of technology acceptance studies. Existing research lacks a dedicated framework explaining the specific behavioral mechanisms driving AI-CST acceptance of the industrial design community. To address this gap, this study developed a model elucidating industrial stakeholders' intention to use AI-CSTs. Hence, we extended the UTAUT model and validate its explaining power under a context of AI-CST adoption. Furthermore, we address Venkatesh's AI adoption research agenda by integrating variables for individual characteristics and technology characteristics into the original model. The derivation of two key individual characteristic variables from the TR theory serves to validate the theory's relevance and delineate its application within the AI adoption domain[18]. In addition, this paper introduced the variable "interactivity" as a foundational antecedent to the UTAUT model. By formally defining this construct as a dynamic, bidirectional process and positioning it within the established UTAUT framework, our findings establish a theoretical link between design research and technology acceptance.

Second, unlike other AI adoption studies used a unidimensional construct of perceive risk, this article modeled perceived risk as multiple dimensions to understand the complete complexity of risk perceptions during AI-CST usage[29,50]. The constituent dimensions of perceive risk included ethical risk, privacy risk and output risk. This formative construct of perceive risk can mirror Wang, Gu and Nguyen-Phuoc, Oviedo-Trespalacios[52,78]. By deriving the "perceived risk" variable from the HBM, this study also validates the model's effectiveness and delineates its applicable context within AI-CST. Moreover, the proposed hierarchical model offered a parsimonious and practical framework for reconceptualizing risk in technology acceptance models applied to AI-CST. The measurement model results revealed that ethical risk, privacy risk and output risk could significantly contribute to forming perceived risk. Ultimately, the relationships between the first-order and second-order constructs provide actionable guidance for mitigating risks associated with AI-CSTs.

Practical implications

The practical contribution of this study main contains two facets. First, we present a series of general strategies for AI-CST promotion in the discussion section. These strategies involve information dissemination, campaigns and publicity, instructions, function design and interface design for general AI-CSTs, public investment and incentives, governmental and company regulations, trials and beta test, training, infrastructure and online platforms construction. Moreover, we also offer optimization strategy for AI-CSTs targeting the industrial design community. These strategies include five aspects: focus on production and manufacturing, diverse forms of output, integrated and plug-in design, intuitive interface and feedback mechanism, personalization and virtual reality displays. In practical contexts, our study can provide valuable insights for various stakeholders, including AI-CST developers and designers, creative works, policymakers and design company managers.

Limitations

However, this study has several limitations. First, the research focused solely on China, which limits how broadly these findings apply to other regions. Differences in technological infrastructure, regulatory frameworks, and socioeconomic factors across countries could significantly affect acceptance factors like resource availability or cost considerations. Second, cultural dimensions were not thoroughly analyzed, even though they may directly affect or serve as a mediator for users' AI adoption intentions. For example, collectivist tendencies in China, individualistic values in Western societies, or region-specific creative practices could deeply shape perceptions of risk, particularly ethical and privacy concerns, or optimism about technology. Third, the use of a purposive sampling strategy, while necessary to recruit information-rich cases relevant to the research question, means that the participant group may not be representative of the wider population. Hence, the transferability of the findings is bounded by the specific context and characteristics of the selected participants. Other researchers should exercise caution when applying these results to different settings. Fourth, the study grouped creative industries together without considering their unique characteristics. Fields such as graphical design, digital media production, and advertising may respond differently to factors like resource availability, perceived interactivity, or personal openness to innovation. For instance, architectural firms might prioritize reducing output-related risks more than marketing teams. Finally, because AI technology is advancing rapidly, our findings reflect current capabilities and user perceptions of AI-CSTs. Emerging innovations, such as generative video systems, real-time collaborative AI agents, or next-generation idea-generation platforms, could quickly change how users evaluate interactivity, cost sensitivity, or other acceptance factors.

Future studies

To address these limitations, future research should focus on four key areas. First, cross-cultural studies are needed to test whether factors influencing the acceptance of AI creativity support tools apply beyond China. Research in Western, Southeast Asian, and African settings can clarify how differences in infrastructure and cultural norms shape perceptions of risk or optimism about technology. Second, a thorough examination of cultural dimensions should be included to measure how they influence concerns about ethics and privacy. Third, research should examine differences across creative industries, such as graphic design, architectural visualization, and advertising. Empirical comparisons could reveal how factors like resource availability or cost perceptions vary in different workflows. Fourth, future studies could address the limitation of purposive sampling methods by employing stratified or random sampling methods to enhance generalizability and allow for broader statistical inferences. Finally, long-term studies tracking the adoption of AI-CSTs are crucial to understand how user expectations evolve as technology advances. Ongoing evaluations of emerging tools, such as generative video systems and collaborative AI agents, will ensure models adapt to new patterns of interaction and risk. Together, these efforts will develop culturally sensitive and industry-specific theories to guide the acceptance of AI-CSTs.

Data availability

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
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Informed consent
Informed consent was obtained from all subjects involved in the study.

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