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Comparing AIGC and traditional idea generation methods: Evaluating their impact on creativity in the product design ideation phase

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A R T I C L E I N F O

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A B S T R A C T

In the early stages of product design, generating creative ideas is crucial for designers as it lays the groundwork for innovative products. This study explores how different idea generation methods, including modern artificial intelligence-generated content (AIGC) and traditional approaches, affect designers' creativity. Using a mixed-methods approach, we conducted a detailed experiment with 38 s-year university students majoring in product design, comparing four methods: traditional brainstorming (with and without images) and AIGC (using DCGANs and PGGANs). Our findings indicate that while AIGC offers benefits, it does not consistently surpass traditional techniques in fostering creativity. The quality of AIGC-generated images significantly impacts creativity, with higher-quality images proving more inspirational. Additionally, gender differences were observed: male designers preferred traditional methods, while female designers favored AIGC for creative enhancement. Male designers generated more creative ideas when working with low-quality images, whereas female designers were more productive with high-quality stimuli. This study suggests that to optimize creativity in product design, it is essential to balance the benefits of both AIGC and traditional methods, choosing the approach that best fits the project's unique needs rather than focusing solely on the latest or most advanced methods. Moreover, maintaining a good balance between AIGC and traditional idea generation methods throughout the process should be considered.

1. Introduction

Creative ideas play a crucial role in the product design ideation phase, serving as the foundation for original concepts and driving product innovation (Howard, Dekoninck & Culley, 2010). Various idea generation methods have been developed to foster the generation of promising creative ideas essential for innovation. These methods assist designers in producing alternative designs (Shah, Smith & Vargas-Hernandez, 2003), finding solutions, and exploring new opportunities. Thus, identifying an effective method to inspire designers is of paramount importance.

With the advancement of technology, idea generation methods have evolved significantly. These methods can be classified into traditional and AIGC based on the degree of technological integration and the use of artificial intelligence.

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Traditional idea generation methods rely on human creativity and interaction, serving as foundational tools in the product design ideation phase. These methods include a variety of techniques, such as brainstorming (Wilson, 2013), mind mapping (Crowe & Sheppard, 2012), storyboarding and role-playing (Brown, 2019). Brainstorming, one of the most widely recognized techniques for idea generation, has been extensively adopted across various industries to stimulate a wealth of ideas. As demonstrated by Osborn (2012), brainstorming advocates for an open, judgment-free environment where no idea is bad, criticism is set aside, ideas are built upon, and emphasis is placed on the quantity of ideas rather than their quality. This approach encourages participants to think freely and creatively without the fear of negative evaluation. During the product ideation phase, brainstorming is widely used to facilitate designers in generating diverse and multiple creative ideas. For instance, Ginting, Ishak and Syahda (2020) used brainstorming to generate innovative designs for a standard static bicycle for post-stroke patients. Sharples et al. (2012) implemented the brainstorming method in medical device design, using a user-device interaction model. Howard et al. (2010) analyzed idea production using the brainstorming method to identify how designers' creative performance is influenced by the provision of creative stimuli. In the automotive industry, design individuals or teams often use brainstorming sessions to conceptualize new vehicle features and aesthetics, leading to innovative designs that meet customer needs and market trends (Bacciotti, Borgianni & Rotini, 2016; Pacana & Czerwińska, 2020; Shandilya et al., 2016). Brainstorming is widely recognized for its effectiveness in stimulating creative thought and generating a large quantity of diverse ideas. Its simplicity allows participants to engage in the process with minimal preparation, making it an ideal choice for various settings, including educational, professional, and research environments (Murphy, Daly & Seifert, 2023). Given its proven track record in fostering creativity and innovation, especially in the early stages of product design, we plan to utilize brainstorming in our experimental study.

With advancements and breakthroughs in generative language models, AIGC (Artificial Intelligence Generated Content) methods have become a key focus worldwide. AIGC idea generation methods leverage AI to generate ideas, analyze data, and provide innovative solutions (Cao et al., 2023; Wu, Gan, Chen, Wan & Lin, 2023). They have shown great content generation ability and are revolutionizing how designers conceptualize and create visual content (Epstein et al., 2023; Liu & Chilton, 2022). By utilizing advanced algorithms and machine learning techniques, AIGC enhances the creative process by processing vast amounts of data quickly, identify patterns, and generating novel ideas not immediately apparent to human thinkers (Anantrasirichai & Bull, 2022). For example, AI-driven design tools can analyze market trends (Pradeep, Appel & Sthanunathan, 2018), customer preferences (Harris, Katta, Slater & Woodall, 2022), and suggest new product features or improvements, automating repetitive tasks and allowing designers to focus on creative and strategic aspects of product development (Gan et al., 2021; Liu, Gao & Wang, 2019).

In product design, AIGC has emerged as a novel paradigm and is regarded as "the next wave of intelligent design automation" (Dean & Loy, 2020; Soddu, 2002). Researchers have explored AIGC's potential to inspire designers during the ideation phase. For instance, Kato, Osone, Oomori, Ooi and Ochiai (2019) introduced DeepWear, a garment design model using AIGC methods to generate diverse creative design schemes automatically. Nasrin and Rasel (2020) applied AIGC methods to create a variety of henna art images, demonstrating its potential in creative art design. Liu et al. (2019) and Schmitt (2018) utilized AIGC methods for chair design, generating diverse chair images to inspire designers. Moreover, Lyu, Shi, Zhang and Lin ((2023)) demonstrated that AI image generators in jewelry design redirect the designer's attention from technical tasks to strategic decisions concerning visual appeal, cognitive engagement, and emotional resonance. Additionally, Hwang (2022) revealed that AIGC tools primarily facilitate the generation and execution of ideas, being less involved in the early stages of co-creation. Adopting AIGC idea generation methods marks a significant trend in the product design industry, showcasing the beneficial effects of AI tools on design creativity (Ali Elfa & Dawood, 2023; Kim & Maher, 2023; Yin, Zhang & Liu, 2023). However, concerns persist regarding whether AIGC methods consistently enhance designers' creativity during product design. Are there circumstances in which traditional idea generation methods offer advantages over AIGC methods? This study aims to investigate whether AIGC idea generation methods outperform traditional methods in facilitating designers' creativity during the product ideation phase and explores potential influencing factors.

2. Literature review

2.1. Visual stimuli and image quality

Creativity involves the creation of useful new products, services, ideas, procedures, or processes by individuals collaborating within a complex social system (Amabile, 1982; Wang, Zhang & Martocchio, 2011). It is central to design (Lawson, 2006) and crucial for product innovation (Sarkar & Chakrabarti, 2011). In product design, creativity is about solving problems and inventing solutions, with designers' outputs being inherently creative (Ho & Siu, 2009; Yilmaz & Seifert, 2011). Researchers have consistently examined the nature of creativity in the product design process and explored various idea generation methods to enhance designers' creativity (Kim & Maher, 2023; Yilmaz & Seifert, 2011).

Visual stimuli serve as a crucial external source of information for inspiration and are recognized as a fundamental approach to supporting idea generation and facilitating creativity (Du, Miller, MacDonald & Gormley, 2015). Numerous studies have demonstrated that visual stimuli enhance creativity in the ideation processes across various dimensions (Bacciotti et al., 2016; Goucher-Lambert & Cagan, 2019; Guo & McLeod, 2014; Saliminamin, Becattini & Cascini, 2019). These dimensions may encompass not only the breadth and depth of generated ideas but also their originality, novelty, and feasibility.

Image, as common and primary visual stimuli, play an essential role in inspiring designers during the ideation phase of the creative design process and have significant potential to spark creativity in design concepts (Borgianni, Maccioni, Fiorineschi & Rotini, 2020; Casakin, 2005; Goldschmidt & Smolkov, 2006; Gonçalves, Cardoso & Badke-Schaub, 2014). For instance, Zhao, Yang, Zhang and Siu (2019) suggested that image stimuli could lead to more creative ideas during the ideation phase. Casakin (2005) found that browsing through a wide variety of images could enhance the quality of a designer's solutions. Borgianni et al. (2020) indicated that exposure to pictorial stimuli could increase the uniqueness and non-obviousness of ideas. Malaga (2000) noted that image stimuli could encourage designers to generate more creative ideas in ice-cream flavor design. Goldschmidt and Smolkov (2006) observed that a design environment enriched with images provided more creative inspiration than one without. These studies demonstrate that image stimuli can effectively facilitate designers' creativity, suggesting they could be beneficial tools in both AIGC and traditional methods.

Low-quality images may indeed stimulate designers' creativity, as evidenced by several studies exploring ambiguity. Both low-quality images and ambiguity in images introduce uncertainty or lack of clarity into visual information. Ambiguity arises when an image can be interpreted in multiple ways or when its meaning is not immediately clear, while low image quality results in unclear, fuzzy, or pixelated visuals. Numerous studies have highlighted ambiguity as a catalyst for creative thinking among designers (Gaver, Beaver & Benford, 2003; Jang, Oh, Hong & Kim, 2019; Scrivener, Ball & Tseng, 2000; Tseng, 2017). Ambiguity, where a situation can be interpreted in more than one way (Frisch & Baron, 1988), significantly influences the quality of images. Research indicates that the ambiguity of visual stimuli can impact various dimensions of creative thinking, such as elaboration and abstraction (Jang et al., 2019). Ambiguous images may prompt individuals to explore multiple interpretations, fostering a deeper level of elaboration as they generate more detailed and nuanced ideas (Gaver et al., 2003). Similarly, resolving ambiguity encourages abstraction, as individuals distill complex and unclear images into more generalized concepts.

Several researchers have investigated the effects of ambiguity on designers' creativity. For example, Tseng (2017) explored how image ambiguity stimulates creativity in hand-drawn designs for both experts and novices, finding that ambiguous sketches with uncertain characteristics catalyze complex visual translation and reasoning processes among design experts. Goel (1995) demonstrated that an ambiguous symbol system plays a crucial role in inspiring creative cognition. Scrivener et al. (2000) demonstrated that the ambiguity of sketches can aid a designer in exploring new interpretations and novel features in a highly flexible manner. Jang et al. (2019) found that ambiguous visual stimuli played a mediating role in the design ideation process, assisting designers in developing detailed and rich ideas without necessarily sharing them. In cases where ideas were shared, ambiguous visual stimuli supported the in-depth expansion of ideas. These studies were mainly conducted within the traditional design paradigm, without the involvement of AIGC methods.

In the realm of AIGC design, disparities in datasets and algorithm performance can lead to the generation of images of varying quality. For example, in our previous studies (Lin, Deng & Zhang, 2023), we observed that PGGANs and DCGANs produced images of different qualities, suggesting potential variations in their influence on designers' creativity. In the study conducted by Gan et al. (2021), the social robot design image generated by the DCGAN model may not have been of high quality, yet it demonstrated an effective ability to support designers in innovatively and efficiently creating new products.

The varying levels of image quality produced by AIGC can impact its capacity to inspire creativity among designers. Additionally, the quality of images generated by AIGC may influence its comparative advantage over traditional methods in fostering creative design. Therefore, further investigation into the impact of image quality on stimulating designers' creativity within the AIGC design paradigm is warranted.

2.2. Gender differences

Gender has frequently been selected as a variable in design studies because it represents individual differences that can influence designers' performance (Demirbas & Demirkan, 2007). Exploring gender differences in creative design has attracted extensive research, highlighting the need for further investigation to comprehend the differences between male and female designers and their impact on product creation (Kemmelmeier & Walton, 2016; Souto, Faria & dos Santos, 2015).

For example, Dong and Zhu (2023) studied the impact of gender on the creativity scores of first-year design students, revealing that female students achieved higher scores in novelty, affective qualities, and elaboration characteristics. Pretorius, Razavian, Eling and Langerak (2020) explored the connection between gender, cognitive style, and performance outcomes related to software, revealing a positive correlation between gender and the inventiveness of software, highlighting the impact of gender on cognitive style decisions in software design. Souto et al. (2015) examined gender differences in cognitive style preferences in software feature design, finding that men prioritize usability and innovation, while women emphasize user requirements and project goals. Demirbas and Demirkan (2007) analyzed the academic performance of design students by gender and found that male students excelled in technology-oriented courses, while female students performed better in fundamental and artistic subjects, leading to higher overall academic achievement among female students. Lee and Wong (2017) observed gender-based disparities in system design performance, noting that female students excelled in development methodologies and system analysis, while male students exhibited strong skills in other areas.

This body of research suggests that gender can significantly affect creative performance when using different idea generation methods in the design process. When comparing traditional and AIGC idea generation methods, designers of different genders having distinct needs regarding these methods. In the AIGC design paradigm, there is still relatively little research on stimulating the creativity of male and female designers. Conducting related research can enhance our understanding of gender differences in the utilization of AIGC design methods. By leveraging insights into gender impact, we can better assist designers of different genders in selecting appropriate idea generation methods to maximize their creativity. Tailoring AI-driven design tools to meet the specific needs of designers of different genders can enhance customization and creativity maximization in design processes.

3. Research objectives and questions

This study aims to compare AIGC and traditional methods by evaluating their impact on creativity during the product design ideation phase. The primary objective is to conduct a preliminary investigation to determine whether AIGC idea generation methods consistently outperform traditional methods in the context of product design.

Based on the literature review, understanding the interplay between traditional and AIGC methods, image quality, and gender is crucial for comprehending contemporary creative generation methods. AIGC offers innovative tools and approaches that can significantly alter the creative process compared to traditional methods. However, its effectiveness and reception may be influenced by image quality and gender dynamics. Images play a pivotal role in creative outputs, serving as both a medium and a source of inspiration. Gender, on the other hand, can impact creative preferences, interpretations, and the reception of generated content. By examining these factors together, researchers can uncover nuanced insights into how AI-driven creativity operates within different contexts and demographics, leading to more inclusive and effective creative tools and strategies.

The current paper raises three research questions that warrant in-depth exploration, focusing on a preliminary comparison between AIGC and traditional idea generation methods, analyzing their effectiveness, efficiency, and impact on creativity in the product design process. These research questions are as follows:

RQ1. Are AIGC idea generation methods more effective than traditional methods in stimulating designers' inspiration during product design?

While AIGC is often demonstrated to be effective in fostering creativity (Ali Elfa & Dawood, 2023; Kim & Maher, 2023; Yin et al., 2023), this study will investigate whether there are circumstances where traditional methods outperform AIGC through empirical study.

RQ2. Are low-quality images more effective than high-quality images in stimulating designers' inspiration within the AIGC design paradigm?

Based on previous studies suggesting that the ambiguity of visual stimuli can foster better creativity (Gaver et al., 2003; Jang et al., 2019; Scrivener et al., 2000; Tseng, 2017), this research will explore whether low-quality images are more effective than high-quality images in the AIGC design paradigm.

RQ3. Do designers of different genders experience differential impacts from traditional and AIGC idea generation methods in terms of creative stimulation and design outcomes?

This question aims to understand how gender influences the effectiveness of different idea generation methods in stimulating creativity and design outcomes, examining the preferences and experiences of male and female designers.

4. Methods

We conducted an empirical study to better understand the impact of traditional and AIGC idea generation methods on the creative processes of designers. This comparative study aimed to explore how these methods stimulate creativity across genders during the product ideation phase.

4.1. Participants

Prior to gathering data, we conducted an a priori power analysis using G*Power (Faul, Erdfelder, Buchner & Lang, 2009), which showed that a minimum of 34 participants was required to achieve a statistical power of 0.80. This calculation was established on a medium effect size of $f = 0.25$ and an alpha probability value of $p = 0.05$.

In our study, we enrolled 38 participants consisting of 19 males and 19 females, with an average age of 20.5 years (SD = 2.26). All participants were second-year university students majoring in product design. Prior to commencing the study, informed consent was obtained from all participants, and the research protocol was approved by the Institutional Review Board of Quzhou University.

After completing the experiments, we invited two product design experts, each with more than ten years of experience in vehicle or product design, to evaluate the participants' creative design outputs.

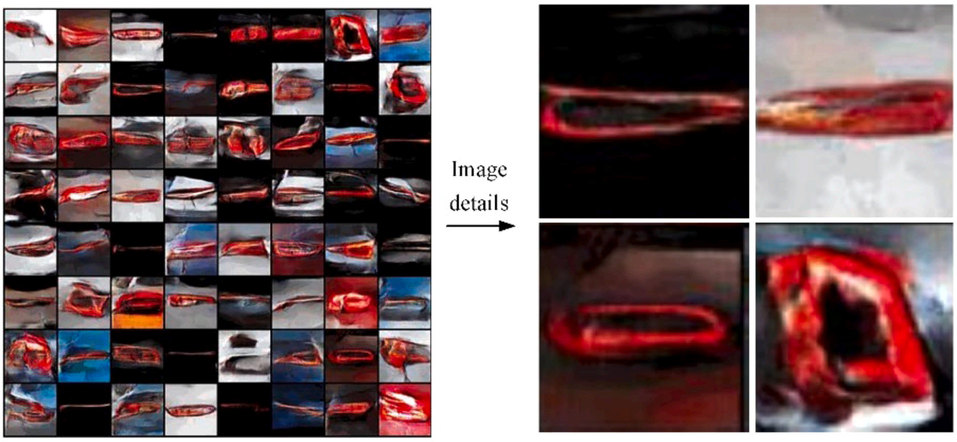
4.2. Material

The shape of taillights has been chosen as the design subject for this study, with a focus on the aesthetics of taillight shapes in our experimental design task. There are several reasons for this choice: First, in the highly competitive automotive industry, technological advancements are increasingly becoming indistinguishable among competing products, making visual aesthetics more crucial to a vehicle's market success. Taillights, as a key component of a car, play a pivotal role in shaping its visual identity and influencing consumer perceptions. The aesthetic design of taillights has been a leading factor in vehicle design innovation and creativity. Second, taillight shapes offer significant freedom in design and can incorporate intricate internal patterns, making them an ideal subject for exploring diverse creative design approaches. Third, aesthetic factors are a key component of design creativity (Cropley & Kaufman, 2018). They are closely linked to design creativity (Casakin et al., 2008; Cropley & Cropley, 2005; Cropley & Kaufman, 2018; Han, Forbes & Schaefer, 2021) and can guide creative problem-solving, particularly in enhancing a product's beauty (Hagtvedt & Patrick, 2014; Hoegg, Alba & Dahl, 2010; Zuo, 1998). The creative design of taillight shapes can be effectively reflected in its aesthetics. Therefore, studying the aesthetic design of taillight shapes provides insights into how various methods can stimulate and guide creativity in practical design contexts, offering valuable perspectives for the design field. Finally, taillight shape design stands at the forefront of automotive design innovation (Mügge & Hohmann, 2016), making it a valuable area for exploring idea generation methods and gaining new insights into future product design and creativity.

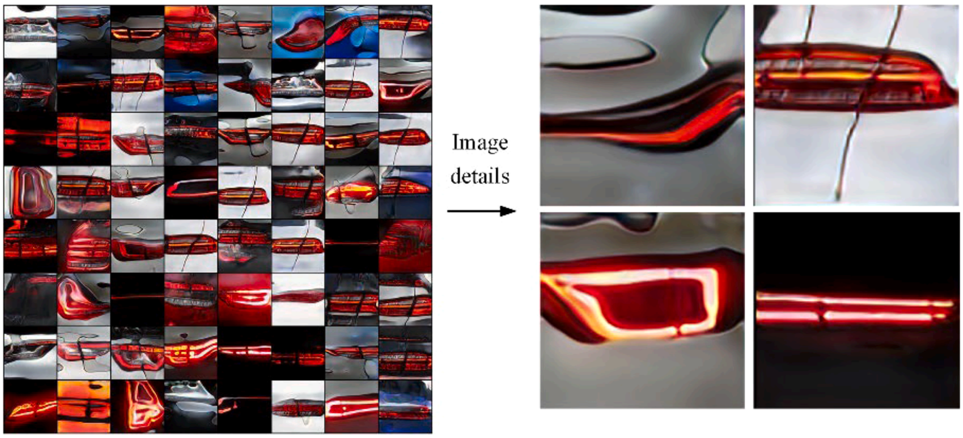
We explored four idea generation methods categorized into traditional and AIGC groups, which the participants employed during the experimental stage.

The first group encompassed traditional idea generation methods, consisting of two variations of the brainstorming technique: one with and one without reference to design resources (Internet images). We labeled the approach without design resources as traditional idea generation method 1 and the technique involving the observation of Internet images as traditional idea generation method 2. Traditional idea generation method 1 encouraged designers to think freely and generate ideas without external stimuli, while traditional idea generation method 2 involved referring to Internet images as external stimuli to inspire diverse proposals. In the traditional idea generation 2, participants were required to retrieve images using image databases such as the Baidu Image Search Engine, which is the most commonly used image retrieval website in China.

The second group comprised AIGC idea generation methods, featuring two distinct methods introduced in our previous research (Lin et al., 2023). These involved two generative models: one utilizing Deep Convolutional Generative Adversarial Networks (DCGANs) and the other employing Progressive Growing of GANs (PGGANs) for the creative design of taillight shapes. These models can generate sustainable, unique, novel, and inspiring design schemes for taillight shapes and have been shown to effectively aid designers during the ideation phase, as evidenced by a questionnaire study with designers. The primary distinction between these two AIGC methods lies in the quality of the generated images: Method 1 produces low-quality ambiguous images, whereas Method 2 generates high-quality clear images. Both methods and their generated images are depicted in Fig. 1. This study aimed to investigate whether the varying qualities of images generated by AIGC methods correlated with their effectiveness in simulating creativity for designers, and to compare their creative stimulation effects with those of traditional methods. Table 1 presents descriptions of the four



(a) AIGC idea generation method 1: Taillight Shape images generated based on DCGANs (Generative design module 1)



(b) AIGC idea generation method 2: Taillight Shape images generated based on PGGAN (Generative design module 2)

Fig. 1. The generated images of two AIGC idea generation methods.

idea generation methods explored in this study.

To empirically validate the creative stimulation effects of two AIGC models on participants, we developed a Browser/Server (B/S) architecture on Windows 10 and constructed a functional vehicle taillight shape creative generative design system. This system assists designers in the ideation phase using the two aforementioned AIGC models. AIGC idea generation method 1 was implemented within Generative Design Module 1, while AIGC idea generation method 2 was implemented within Generative Design Module 2.

In this taillight shape creative generative design system, users first register and log into their account. The initial interface features two modules, allowing users to access the generative design interface by selecting either Generative Design Module 1 or Generative Design Module 2. This interface showcases multiple, diverse, and novel taillight shapes for designers' reference. If users are unsatisfied with the current images displayed, they can click the 'regenerate' button to generate new images until they find the optimal ones to evoke design inspiration. The interfaces of Generative Design Module 1 and 2 are similar but differ in the images generated, as they are based on different AI algorithms (PGGANs or DCGANs). The procedure of utilizing the taillight shape creative generative design system is illustrated in Fig. 2.

4.3. Design

The within-subject independent variable was idea generation methods, and the between-subject independent variable was gender (female and male). A 4 × 2 repeated-measures experimental design was employed to compare the creative stimulation effects of the four creative idea generation methods (e.g., traditional method 1 vs. traditional method 2 vs. AIGC method 1 vs.AIGC method 2). If the two design levels of AIGC idea generation methods (e.g., AIGC method 1 vs AIGC method 2) were compared, a 2 × 2 repeated-measures ANOVA was performed. The dependent variables included metrics (detailed in Section 4.5) evaluating the creative stimulation effects of design works derived from the four creative idea generation methods.

4.4. Procedure

Each participant was personally greeted upon entering the laboratory and directed to a table equipped with a Dell Precision 5510 computer and several sheets of A4 white paper. Once the participants were ready, they were briefed on the design tasks, focusing on taillight shape creative design across four sequential tasks. To mitigate the learning effect across the design tasks, the sequence of the four tasks was balanced. Given that design sketches are an intuitive expression of design work (Goel, 1995; Taura et al., 2012) and are commonly seen as meaningful creative design outputs (Chen, Zhao, Zhang & Luo, 2018; Luo & Dong, 2017), the participants were instructed to freely draw sketches centered on taillight shape design.

Before each design task, the researcher provided instructions and initiated the task with a command phrase. Design Task 1 involved generating taillight shape designs through brainstorming on paper within a 10-minute timeframe (traditional idea generation method 1). This 10-minute duration was based on previous studies (Beaty & Silvia, 2012; Jang et al., 2019; Toh & Miller, 2016), which suggest that creative idea generation tends to plateau after approximately 9–10 min. In Design Task 2, the participants brainstormed design concepts by referring to Internet images within the same timeframe (traditional idea generation method 2). In Design Task 3, the participants were required to log into our team-developed AIGC creative design aid system—the taillight shape creative generative design system—and use Generative Module 1 (AIGC idea generation method 1) to generate their design concepts within 10 min. Design Task 4 replicated this process but with Generative Module 2 (AIGC idea generation method 2) to generate multiple design concepts. All tasks aimed to produce as many taillight shape creative designs as possible, with each design concept numbered, within a 10-minute timeframe. To prevent the learning bias across the design tasks, the order of the four tasks was carefully arranged for balance. The participants were encouraged to come up with new ideas for taillight shape design using the four different idea generation methods and to offer a written description for each idea, including their source of inspiration, design details, and any insights or concepts.

Upon completing all the design tasks, the participants were asked to complete an online survey to provide feedback on their experience with the four design tasks. Finally, they had a face-to-face in-depth interview, lasting approximately 5 min, with the experiment host to freely share their user experience and insights regarding all the idea generation methods during the product ideation phase.

4.5. Creativity assessment

To assess the creative stimulation effects, several metrics were employed to evaluate the creativity of design works (Li, Chu & Tang, 2024). Shah et al. (2003) introduced four creative metrics for idea generation in product design: quantity, quality, novelty, and variety of ideas. Dong and Zhu (2023) assessed the creativity of artifacts in an artifact production task measuring three metrics: novelty and

Table 1
Descriptions of four idea generation methods in this study.

Code		Design Method	Description of Design Method
T	T1	Traditional idea generation method 1	Design without referring to any design resources
	T2	Traditional idea generation method 2	Design with reference to Internet images
A	A1	AIGC idea generation method 1	Design based on a product (taillight shape) creative generative design model utilizing DCGANs
	A2	AIGC idea generation method 2	Design based on a product (taillight shape) creative generative design model utilizing PGGANs

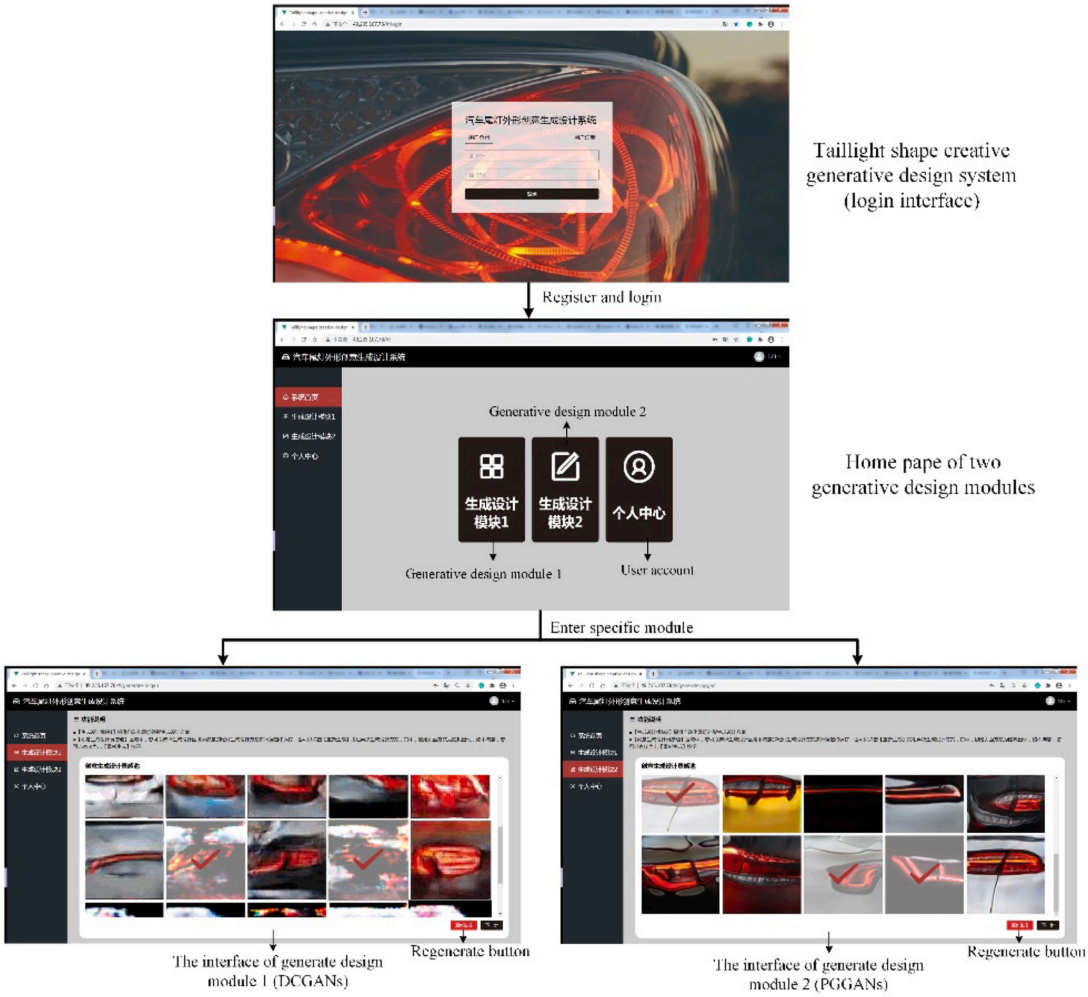


Fig. 2. The procedure of utilizing the taillight shape creative generative design system.

affective characteristics, design principles, and elaboration characteristics. Borgianni et al. (2020) proposed six creativity metrics for idea generation: originality, quality, non-obviousness, quantity, rarity, and variety. Demirbas and Demirkan (2007) suggested numerous keywords for evaluating creative impacts in interior design, including coherent, integrated, and novel. Goldschmidt and Smolkov (2006), on the other hand, measured creative stimulation by expert evaluation of three factors: practicality, originality, and general quality. Given the lack of unified indicators for evaluating creative effects (Laing & Masoodian, 2016), this study defined six metrics: assistance ability of creative design, fluency in usage, quality, quantity, originality, and elaboration of creative design concepts.

The assistance ability of creative design in this paper reflects perceived user experience with methods aiding product creative design, with higher scores indicating greater effectiveness (Bittner, Mirbabaie & Morana, 2021; Karkh & Samsonovich, 2018). Fluency in usage measures designers' capacity to generate multiple design concepts within a given timeframe, emphasizing speed and ease of use (Li et al., 2024; Torrance, 1977). Quality assesses the feasibility of a concept and its alignment with design specifications (Nelson, Wilson, Rosen & Yen, 2009). Quantity counts the total number of ideas produced by an individual or a group in a given period or throughout all stages of the design process, serving as an indicator of active thinking (Basadur & Thompson, 1983; Shah et al., 2003; Verhaegen, Vandevenne, Peeters & Duflou, 2013). Originality assesses the novelty and uniqueness of design concepts (Luo & Dong, 2017; Sternberg & Lubart, 1999; Zhao et al., 2019), but does not include inappropriate, unconventional ideas (Runco & Charles, 1993). It evaluates the extent to which the participants' proposals deviate from conventional or existing design solutions, emphasizing innovative thinking and creativity(Laing & Masoodian, 2016). Elaboration measure the thoroughness and intricacy of specific elements within the design proposals, often used to gauge the completeness and richness of design details (Jang et al., 2019; Mahmoud, Kamel & Hamza, 2023; Said-Metwaly, Fernández-Castilla, Kyndt & Van den Noortgate, 2018) and it is widely used to assess the richness of design concepts and details.

In this study, the participants were required to complete an online survey, providing feedback on their experience with the four design tasks. Two metrics were analyzed: perceived creative design assistance ability and fluency in usage. Furthermore, two design experts were invited to judge the participants' design outputs. One design expert had over ten years of vehicle design experience and worked for a new energy vehicle company in China. The other had over ten years of design education experience and was a co-founder of a product design company. These judges evaluated the sketches of each design task based on the four metrics mentioned above: quality, quantity, originality, and elaboration of creative ideas. Quantity ratings were based on the practical number of concepts proposed by participants, while ratings for remaining five metrics were all assigned using a 5-point Likert scale, where 1 corresponded to poor, 2 to poor-average, 3 to average, 4 to average-excellent, and 5 to excellent (Demirkan & Afacan, 2012; Dong & Zhu, 2023; Goldschmidt & Smolkov, 2006).

5. Results

In total, 38 datasets were collected and analyzed using SPSS 25. No extreme data were observed. Reliability analysis yielded a Cronbach's alpha coefficient value of 0.848, surpassing the threshold of 0.8 (Cortina, 1993). This result indicated that the analyzed data were reliable and suitable for further analysis. A repeated-measures ANOVA with a 2 × 2 or 4 × 2 design was conducted to analyze the variables. When comparing the traditional and AIGC idea generation methods (abbreviated as T vs. A), the arithmetic mean of the two idea generation methods within the same group was used as the group value. Table 2 shows the average values and standard deviations of the creativity scores for each method. Table 3 displays several design works rated by design expert in terms of low and high quality across three metrics: quality, originality and elaboration.

5.1. Traditional versus AIGC idea generation methods (T vs. A)

When comparing traditional (T) and AIGC (A) idea generation methods, a significant two-way interaction effect between method and gender was found on the metric of assistance ability for creative design [$F(1,36) = 5.295$, $p = 0.027$, $\eta^2 = 0.128$] (Fig. 3(a)). The findings indicated that male designers preferred traditional idea generation methods to aid their idea generation, whereas female designers favored novel AIGC methods over traditional ones. Significant main effects of design methods were observed in the following metrics: quality [$F(1,36) = 7.364$, $p = 0.010$, $\eta^2 = 0.170$], originality [$F(1,36) = 11.906$, $p = 0.001$, $\eta^2 = 0.249$], and elaboration [$F(1,36) = 7.061$, $p = 0.012$, $\eta^2 = 0.164$]. These results suggest that AIGC idea generation methods can enhance the quality, originality, and elaboration of creative ideas more effectively than traditional methods. However, no significant differences were observed in the metrics of fluency in usage and quantity.

5.2. Traditional idea generation method 1 versus 2 (T1 vs. T2)

Comparing traditional idea generation methods 1 and 2, significant main effects of design methods were observed across various metrics: assistance ability [$F(1,36) = 16.624$, $p < 0.001$, $\eta^2 = 0.316$], fluency of usage [$F(1,36) = 17.154$, $p < 0.001$, $\eta^2 = 0.323$], quality [$F(1,36) = 21.725$, $p < 0.001$, $\eta^2 = 0.376$], originality [$F(1,36) = 26.471$, $p < 0.001$, $\eta^2 = 0.424$], and elaboration [$F(1,36) = 26.452$, $p < 0.001$, $\eta^2 = 0.424$]. The findings indicate that brainstorming with the aid of Internet images can better assist in generating creative ideas, smoothing the ideation process, and enhancing the quality, originality, and elaboration of the generated ideas compared to brainstorming without Internet images. However, no significant differences were observed between the two methods in the quantity of ideas generated.

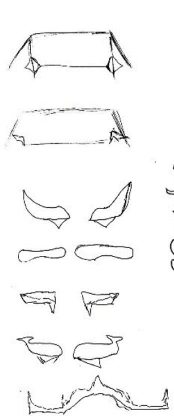
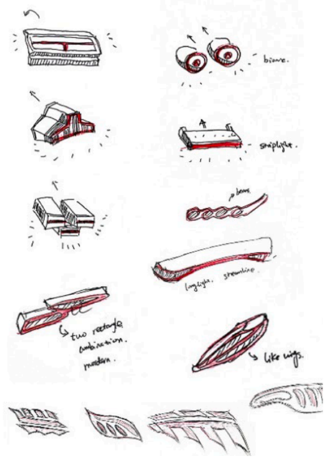
5.3. AIGC idea generation method 1 versus 2 (A1 vs. A2)

By comparing AIGC idea generation methods 1 and 2, significant main effects of design methods were observed across various metrics: fluency of usage [$F(1,36) = 4.587$, $p = 0.039$, $\eta^2 = 0.113$], quality [$F(1,36) = 13.135$, $p < 0.001$, $\eta^2 = 0.267$], originality [$F(1,36) = 8.129$, $p = 0.007$, $\eta^2 = 0.184$], and elaboration [$F(1,36) = 10.425$, $p = 0.003$, $\eta^2 = 0.225$]. The data suggested that AIGC idea generation method 2 (taillight shape creative generative design based on PGGANs) facilitated a smoother idea generation process, enhancing the quality, originality, and elaboration of the generated ideas compared with AIGC idea generation method 1 (taillight shape creative generative design based on DCGANs). Additionally, a significant two-way interaction effect between method and gender on the metric of quantity was found [$F(1,36) = 8.654$, $p = 0.006$, $\eta^2 = 0.194$] (Fig. 3(b)). The findings indicated that male designers using AIGC idea generation method 2 could generate more creative ideas, while female designers using AIGC idea generation method 1 produced more creative ideas. No significant differences were observed between the two methods in terms of their assistance

Table 2
Mean values (SDs) of the creativity scores for each idea generation method.

Methods	Creative design assistance ability	Fluency in usage	Quality	Quantity	Originality	Elaboration
T	3.97(0.09)	3.89(0.11)	3.04(0.08)	3.74(0.26)	3.13(0.09)	3.21(0.09)
A	4.01(0.12)	4.06(0.10)	3.24(0.08)	3.97(0.26)	3.47(0.12)	3.45(0.12)
T1	3.63(0.14)	3.51(0.16)	2.68(0.10)	3.47(0.25)	2.74(0.14)	2.87(0.14)
T2	4.32(0.11)	4.28(0.13)	3.39(0.12)	4.00(0.33)	3.53(0.11)	3.55(0.11)
A1	3.93(0.15)	3.93(0.14)	3.00(0.07)	4.08(0.26)	3.29(0.15)	3.24(0.15)
A2	4.09(0.11)	4.19(0.09)	3.47(0.12)	3.87(0.29)	3.66(0.11)	3.66(0.11)

Table 3
Several taillight shape design works.

	Low quality, originality and elaboration	High quality, originality and elaboration
Participants' design works		

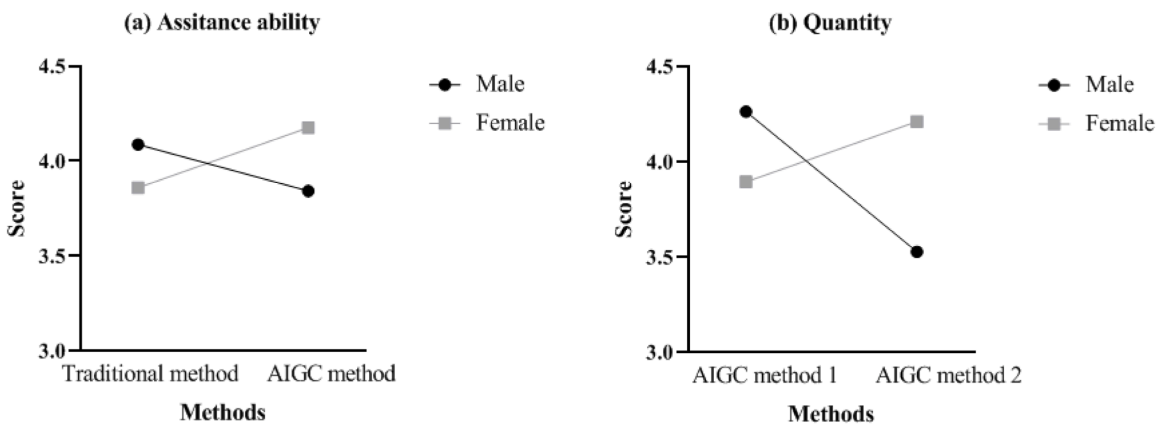


Fig. 3. The interaction effect between idea generation methods and gender on the dependent variables: (a) assistance ability and (b) quantity.

ability in generating creative ideas. The mean and standard error of creativity scores of different idea generation methods was shown in Fig. 4.

5.4. *Comparison of the four idea generation methods (T1 vs. T2 vs. A1 vs. A2)*

Comparing the four idea generation methods, significant main effects of design methods were observed across various metrics: assistance ability [$F(3,34) = 5.583, p = 0.003, \eta^2 = 0.330$], fluency of usage [$F(3,34) = 6.421, p = 0.001, \eta^2 = 0.362$], quality [$F(3,34) = 10.370, p < 0.001, \eta^2 = 0.478$], originality [$F(3,34) = 11.139, p < 0.001, \eta^2 = 0.496$], and elaboration [$F(3,34) = 11.385, p < 0.001, \eta^2 = 0.501$]. The data indicated that AIGC idea generation method 2 (taillight shape creative generative design based on PGGANs) and traditional idea generation method 2 (brainstorming with reference to Internet images) significantly enhanced assistance in generating creative ideas, smoothed the ideation process, and improved the quality, originality, and elaboration of the generated ideas compared with the other two methods. In terms of the quantity of ideas, AIGC idea generation method 1 (taillight shape creative generative design based on DCGANs) significantly stimulated the production of more creative ideas compared with traditional idea generation method 1 (brainstorming without referring to any design resources), while no significant differences were observed among the other methods. Fig. 5 displays the average creativity scores and standard errors for the four idea generation methods.

The analysis of participants' interviews on the traditional and AIGC methods revealed significant variation in preference, with a strong inclination towards customized design methods over generic ones. Designers also demonstrated a tendency to utilize multiple idea generation methods during the product design ideation phase, highlighting the importance of carefully considering both traditional and AIGC methods. When uncertain about which method to employ, designers should prioritize their preferences and select a

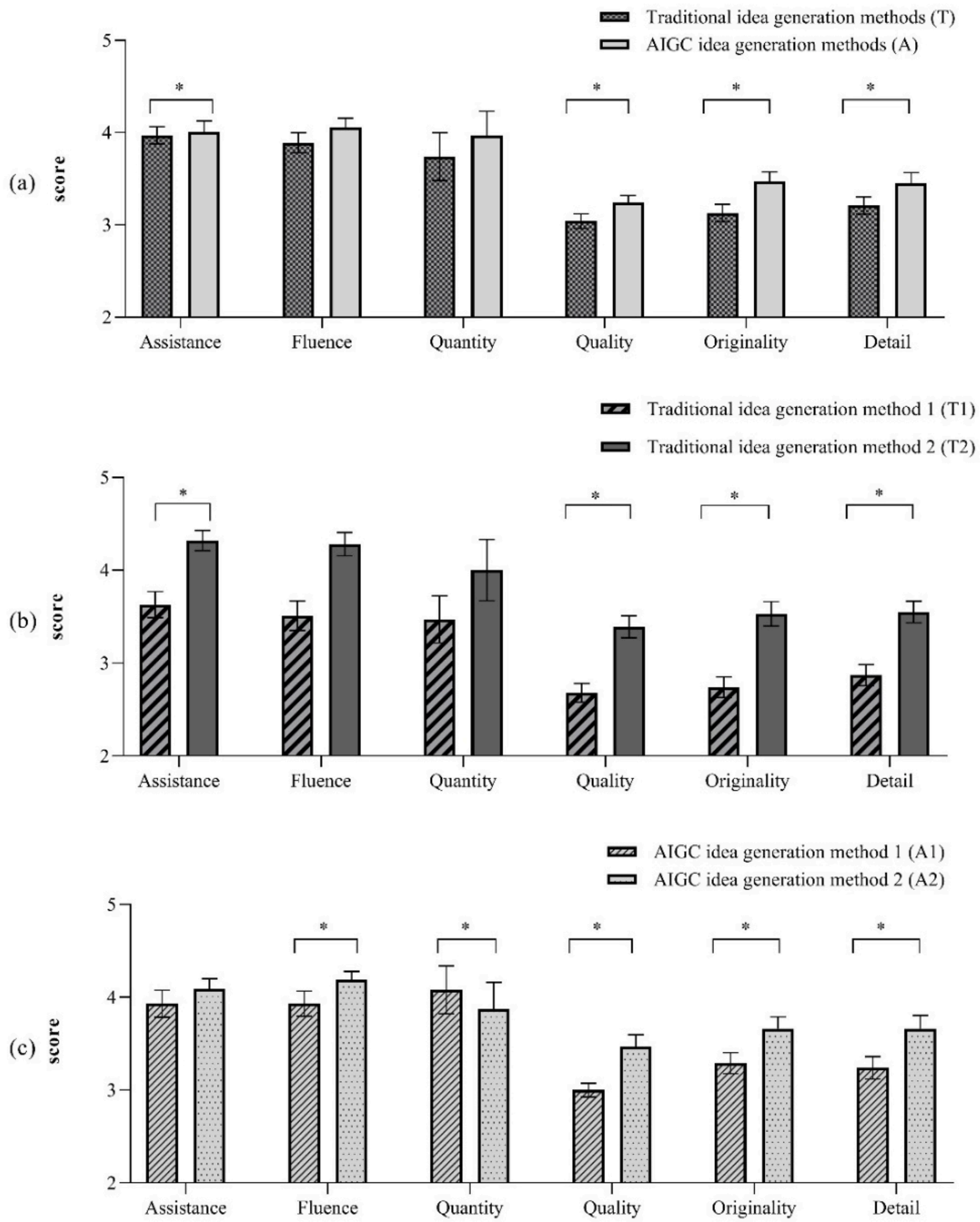


Fig. 4. The average creativity scores and standard errors for various idea generation methods (T vs. A (a); T1 vs. T2 (b); A1 vs. A2 (c)). * statistically significant at 0.05 level.

suitable combination based on their specific needs and objectives.

6. Discussion

This study investigated how AIGC and traditional idea generation methods stimulate creativity among designers during the product

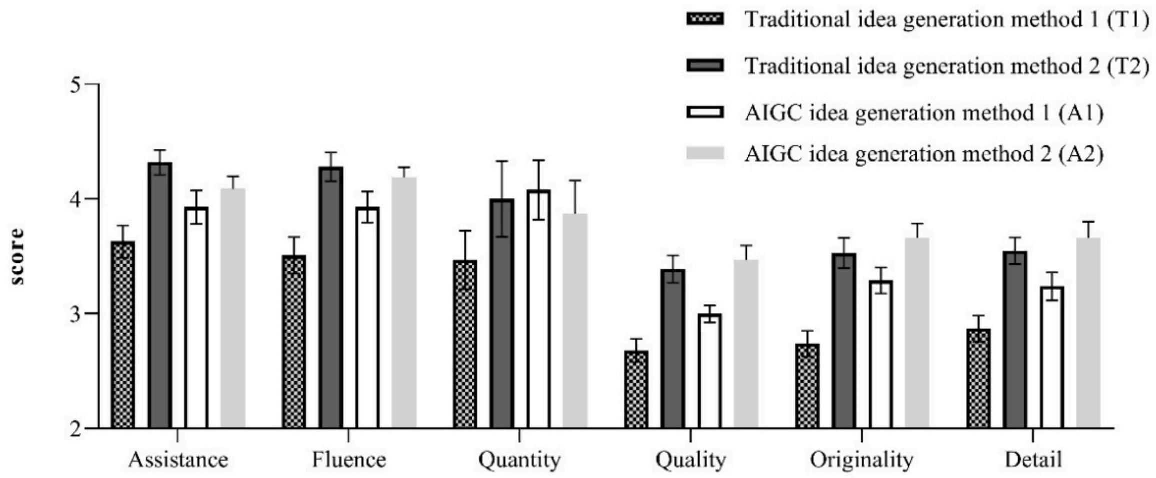


Fig. 5. The average creativity scores and standard errors for the four idea generation methods. * statistically significant at 0.05 level.

ideation phase. We conducted four distinct design tasks to evaluate the impact of these methods on creative stimulation. Based on our investigation, we raised three questions, and observed some intriguing insights into the creative process.

Regarding RQ1, we found that AIGC idea generation methods offer benefits, they do not consistently outperform traditional methods in inspiring creativity. Each method has unique strengths in sparking designers' inspiration. Our analysis highlighted that certain AIGC and traditional methods (specifically Method 2 of each) were more effective across various creative metrics, such as assistance ability, fluency, quality, originality, and elaboration, than their counterparts (Method 1 of each). This suggests that both AIGC and traditional methods can significantly enhance creativity depending on their inherent qualities. This observation aligns with Lee and Chiu (2023), who found that AI-generated visual stimuli positively impact product design. However, their research suggests that such stimuli are not inherently superior to visual stimuli obtained through online searches. Additionally, Tang, Mao, Naumann and Xing (2022) noted that technology products can sometimes hinder students' creativity due to increased cognitive load. Consequently, while AIGC methods offer potential benefits, they may not consistently outperform traditional methods in stimulating designers' creativity. This underscores the importance of tailoring idea generation methods to the specific context and goals of the design task, rather than solely relying on novel AIGC approaches. Furthermore, the distinct effects of different AIGC idea generation methods on creative stimulation indicate that image quality plays a crucial role in enhancing creativity.

We found no significant differences in the quantity of creative ideas generated by different methods. This suggests that while some methods may improve idea quality and innovation, they do not necessarily increase the quantity of ideas. This lack of differences in the quantity of ideas across different design tasks has been consistently observed in the literature (Laing & Masoodian, 2016; Luo, Bian & Hu, 2020), possibly due to the limited time available for idea generation. Our findings reinforce the value of providing any type of stimulus to designers during the idea generation phase. In line with the findings of Howard et al. (2010), we observed that exposing designers to any form of information or stimulus tended to be more beneficial for idea generation than providing no information at all. This underscores the role of stimuli, irrespective of their source, in facilitating the creative design process.

These findings imply that designers should not focus exclusively on the newest or most innovative idea generation methods. Rather, they should select methods that best suit the needs of their projects, balancing the advantages of both traditional and AIGC approaches to maximize creativity. This supports the notion that "AIGC is effective for inspiring product design creativity, but it is not all-powerful."

Regarding RQ2, our findings indicate that high-quality generated images were more effective than low-quality ones in inspiring designers within the AIGC design paradigm. This finding contradicts the expectation that low-quality or ambiguous visual stimuli might better stimulate creative thinking. High-quality images led to superior results across various creativity metrics, such as creative design assistance ability, fluency, quality, originality, and elaboration. This outcome challenges the traditional belief supported by Howard et al. (2010) and Jang et al. (2019) that vague or less detailed stimuli could more effectively prompt idea generation and creative thought by providing a broader scope for interpretation. The discrepancy between our study and these prior findings may indicate that the effectiveness of visual quality in stimulating creativity is highly context-specific and may depend on the dynamic nature of generative stimuli, as opposed to the static images previously researched. Unlike traditional idea generation methods, the interaction between designers and AI-driven design tools in the AIGC design paradigm is dynamic. This dynamism can be understood in two aspects. Firstly, it involves the dynamics of human – computer interaction, where designers interact with and respond to the content that generated by AI-driven design tools. Secondly, it encompasses the dynamism of image generation, wherein image stimuli can be regenerated an unlimited number of times until users are satisfied with the results. These generated images stimulate unlimited inspiration and provide insights for creativity.

In our study, the dynamic and generative nature of the stimuli provided designers with a variety of design solutions, suggesting a preference for clear and detailed information to support their creative processes. This deviation implies that, in the context of AIGC idea generation, designers might favor precision and clarity over ambiguity for creative inspiration. The differences observed could also be attributed to the unique characteristics of the stimuli used in our study versus those in prior research, as well as individual variances among designers, such as personal preferences and cognitive styles, which could influence how they respond to different qualities of stimuli.

Further investigation is essential to uncover the factors and conditions that determine how image quality influences creative stimulation within the context of AIGC idea generation. A thorough understanding of these dynamics can enhance both theoretical perspectives and practical applications in design and creativity.

Regarding RQ3, male and female designers were found to respond differently to various idea generation methods in terms of creativity stimulation. We found distinct gender-based preferences in the effectiveness of design approaches in enhancing creativity. Male designers preferred traditional idea generation methods and valued them for their support in creative tasks. In contrast, female designers were more inclined toward AIGC idea generation methods for creative enhancement. Interestingly, gender-specific trends were observed between the AIGC idea generation methods. Male designers were more likely to produce a greater number of creative ideas when working with low-quality images, whereas female designers were more productive with high-quality stimuli. This reflects broader research indicating that gender differences in creative expression may vary by domain and task (Taylor & Barbot, 2021), highlighting the necessity of considering gender when evaluating responses to design stimuli and methodologies.

The analysis of participants' interviews on the traditional and AIGC methods revealed significant variation in preference. When employing AIGC for design creativity, designers should carefully select appropriate methods, taking into account their preferences. For example, female designers may favor for AIGC method 2, while male designers may prefer AIGC method 1. Future AIGC idea generation tool interfaces could provide customization options tailored for male or female designers. For example, users could input their gender, and upon logging in, the interface would adapt accordingly. For male designers, stimuli could include low-quality or ambiguity images, while female designers could be presented with high-quality or clear images. This customization aims to enhance creativity by aligning stimuli with designers' tendencies.

These insights into gender-specific preferences for design methods shed light on how AI-driven design tools can be optimized to stimulate creativity among male and female designers. Acknowledging the varied impacts of design methods on creativity across genders (Dong & Zhu, 2023) underlines the importance of integrating gender considerations into the development and deployment of AI in design. However, interpreting empirical evidence regarding gender differences in creativity remains challenging. Research in this area has yielded mixed outcomes, with some studies suggesting higher creativity among females and others indicating the opposite (Baer & Kaufman, 2008). Given the complexity of gender and creativity, caution must be exercised when drawing definitive conclusions from such findings. A deeper and more nuanced exploration of how gender influences responses to design stimuli and methodologies will provide a solid basis for further research and application in the design and creativity fields.

Designers frequently employ one or more of creative idea generation methods to achieve the desired level of creativity during new product development (Botega & da Silva, 2020). Therefore, the integration and balance of AIGC and traditional methods present a significant opportunity to enhance creative generation in designers (Huang, Liu, Dong & Lu, 2024). By combining the strengths of both approaches, we can create a more robust and effective design process. AIGC methods offer the advantage of rapid idea generation and the potential for novel and unexpected concepts (Wu et al., 2024). On the other hand, traditional methods such as brainstorming allow for more human intuition and creativity (Murphy et al., 2023). To optimize creative generation, it is essential to leverage the benefits of both AIGC and traditional methods. By doing so, we can create a synergistic approach that capitalizes on the strengths of each method while mitigating their respective limitations. This combinational approach can be particularly beneficial for designers. For example, during the product design ideation phase, AIGC methods can be used to quickly generate a wide range of initial concepts, while traditional methods can be employed to refine and further develop these ideas based on human intuition and expertise. Moreover, integrating AIGC and traditional methods fosters collaboration and exchange of ideas between designers and AI systems (Huang et al., 2024). This collaborative approach encourages interdisciplinary thinking and facilitates the exploration of diverse perspectives, ultimately leading to more innovative and impactful design solutions.

This study has several limitations that suggest avenues for future research. Our primary focus on the early conceptual divergence stage of product design, overlooking the entire product design process. Further exploration into the impact of AIGC and traditional methods on the entire design process is warranted. Another notable limitation was that our participants were student designers with relatively limited design experience. Given that design experience significantly impacts a designer's creative stimulation (Blom & Bogaers, 2018; Linsey, Wood & Markman, 2008; Wang, 2020), this aspect could influence the outcomes of our study. Future studies should involve more experienced designers to ensure broader diversity of perspectives and experiences.

This investigation serves as an initial exploration into comparing traditional and AIGC methods for stimulating designers' creativity. Preliminary examination was conducted on the gender and image quality aspects of AIGC tools. Moving forward, our aim is to employ more nuanced and comprehensive methodologies to delve into these two factors individually, with a greater emphasis on detail and specificity. Additionally, incorporating a wider range of design tasks and stimuli (beyond taillight shape design) could provide a more comprehensive comparison between AIGC and traditional idea generation methods in supporting creative design. Another important consideration is the cultural context of our research. The findings may predominantly reflect the Chinese cultural setting. Therefore, future research should include participants of both genders from various cultural backgrounds to facilitate a more global understanding of how different idea generation methods affect creative stimulation across cultures. This approach helps clarify the universal and culture-specific aspects of creative design processes.

7. Conclusion

This study investigated how various idea generation methods, including AIGC and traditional idea generation methods, affected designers' creativity in the early phases of product design. We found that although AIGC can be advantageous, it does not always outshine traditional methods in terms of fostering creativity. This suggests that designers should not always focus solely on the latest or the most advanced methods but choose the approach that best fits their project's unique needs. Finding a balance between the benefits of traditional methods and AIGC can maximize creativity to the fullest extent possible.

An intriguing finding was that the quality of AI-generated images significantly influenced creativity within the AIGC context. High-quality images tended to inspire more creativity than lower-quality images. Additionally, our research indicated that male and female designers may respond differently to various idea generation methods, showing unique preferences in how these methods encourage creativity. Therefore, future AIGC generation tools could be customized based on gender, in order to maximize creativity for designers of different genders by generating images of varying quality.

The findings of this study are particularly valuable in the evolving field of design ideation. They highlight the importance of a customized approach when selecting idea generation methods. The key insight is that innovation involves more than simply adopting the latest technologies; it concerns how these tools can be effectively integrated into the creative process. Moreover, this study sheds light on the role of creativity in design from the designer's perspective, laying the groundwork for future research aimed at enhancing creativity.

CRediT authorship contribution statement

Huan Lin: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Xiaoliang Jiang:** Writing – review & editing, Supervision, Methodology. **Xiaolei Deng:** Writing – review & editing, Validation. **Ze Bian:** Methodology. **Cong Fang:** Validation, Data curation. **Yuan Zhu:** Data curation, Validation.

Declaration of competing interest

The authors declare that there is no conflict of interest. We do not have any possible conflicts of interest.

Data availability

Data will be made available on request.

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