

Research Article

Cite this article: Ge W and Hou G (2025). The effects of generative AI model type and visual stimuli type on design creativity. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, **39**, e17, 1–13 <https://doi.org/10.1017/S0890060425100061>

Received: 29 December 2024

Revised: 11 June 2025

Accepted: 18 June 2025

Keywords:

generative AI; visual stimuli; creativity; cooperation model; design education

Corresponding author:

Weichu Ge;

Email: echogeweichu@outlook.com

© The Author(s), 2025. Published by Cambridge University Press. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.



The effects of generative AI model type and visual stimuli type on design creativity

Weichu Ge¹  and Guanhua Hou²

¹Faculty of Innovation and Design, City University of Macau, Macau, China and ²School of Art, Southeast University, Nanjing, China

Abstract

Artificial intelligence (AI) facilitates designers in generating creative ideas. How designers work with AI to effectively stimulate and enhance their creativity is an urgent topic in the context of design education and creation. This study conducted a controlled experiment in a design education context to explore the effects of generative AI tools and visual stimuli on the creativity of designers in the early design stages. The results show that the use of text-to-image (T2I) AI tools and the stimulation of abstract visuals enhance the design creativity in both divergent and convergent thinking processes. However, it is important to be aware of the design fixation during this process. This study sheds light on the role and value of different AI tools for designers in the design process, offers a more effective solution of using AI for designers so as to improve creativity and design quality, and provides a theoretical basis for the application of AI-assisted design process.

Introduction

Creativity is seen as the key to design innovation. In the early stages of design, designers often use creativity tools that augment the generative outcomes (e.g., inspirational stimuli, analogy, boundary shifting, and multiple types of brainstorming) to facilitate the generation of creative ideas. Nowadays, artificial intelligence (AI) techniques have been applied to creativity tools to enhance the creativity of designers. AI improves the efficiency and satisfaction of designers by generating new visual stimuli and textual inspirations, which in turn effectively assist designers in the ideation process (Liao et al., 2020; Kwon et al., 2023; Lee and Chiu, 2023; Lewis, 2023; Jin et al., 2024). The stimulus of visual materials also plays an important role in enhancing the designer's creativity. For example, Goldschmidt and Smolkov (2006) argue that figurative and abstract images play different roles in different design phases: Abstract visual stimuli are more helpful in inspiring designers to think out of the box and be innovative, while figurative visual stimuli tend to be better at assisting designers with detailed optimization and practical application (Goldschmidt and Smolkov, 2006). However, these studies have not been carried out in conjunction with AI-based tools and have failed to fully explore the holistic effects of AI and visual stimuli on design creativity. It has not been fully addressed with regard to how to effectively inspire and improve the design creativity through AI under the stimulation of appropriate visual materials. In addition, previous studies mainly focus on the application of a particular type of AI-based tools and task mode, which are no longer applicable to the current needs due to the rapid development of AI. This article conducted a controlled experiment, with generative AI tools and visual stimuli as variables, to investigate the impacts of these variables on different dimensions of design creativity.

The Double Diamond Framework integrates fundamental principles to guide creativity, which involves both divergent and convergent thinking. Many distinctive ideas are generated during the divergent thinking process, while the evaluation and refinement of ideas take place in the convergent thinking process (Shi et al., 2017; Childs et al., 2022). This framework reflects the principles of divergence, that is, after the generation of ideas, convergence occurs through selecting and refining preferred ideas for further optimization and development. AI can help designers break through the design thinking stereotypes to provide new sources of inspiration, thus coming up with more innovative design solutions (Shi et al., 2017; Chen et al., 2019). AI image generation modalities are divided into two types based on input prompts: text-to-image AI models (T2I AI models: users generate corresponding images by inputting textual descriptions in the models, e.g., ChatGPT and DALL-E) and image-to-image AI models (I2I AI models: users generate variations or optimized images by inputting initial images in the models, e.g., Mid-Journey and Stable Diffusion). Existing research proposes that users expect AI to provide 'just enough instruction' during the creative process (Oh et al., 2018). T2I AI models assist designers in materializing abstract concepts, thereby enhancing creativity at the initial stage in design (Xu et al., 2018; Ku and Lee, 2023). Hanafy's (2023) study further discovered that T2I AI models are able to significantly enhance the diversity and novelty of designer creativity (Hanafy, 2023).



T2I AI models and I2I AI tools are both beneficial in the design process, and the combined stimuli of texts and images also promote creative thinking (Han et al., 2018). The benefits of I2I AI models in dealing with details and complexity have been preliminarily studied. However, there is a lack of systemic comparative studies regarding their specific role in assisting the design creativity process, as opposed to T2I AI models, as well as explorations on how prompts in generative AI models affect the design creativity enhancement (Joynt et al., 2023). Furthermore, although image generation AI has significantly facilitated designers in providing innovative visual solutions and details, problems still exist in terms of the difficult communications between designers and AI models in the process of co-creation, and of their reliance on specific details (Turchi et al., 2023).

The main advantage of T2I AI models is that specific visual references are not required, where designers can quickly generate various images by inputting natural language descriptions, thus providing great freedom in the early conceptualization phase in design and helping designers inspire and explore different directions, especially useful for interdisciplinary and conceptual design (Mansimov et al., 2015; Ramesh et al., 2021; Ko et al., 2023). However, T2I AI tools are highly reliant on the precision of textual descriptions during the output process, leading to unexpected outputs resulting from vague and polysemic languages when they are processing complex design details (Saharia et al., 2022). Although T2I AI models excel in generating diversified images, they tend to generate less accurately and consistently than I2I AI tools in detailed design scenarios (Nichol et al., 2021). I2I AI models perform excellently in high fidelity and design detail control, suitable for streamlining the design process by preserving the intricate details of input images and accurately adjusting the output images (Karras et al., 2019). They generate and optimize based on existing images and show significant advantages in visual details, style transformation, and image restoration (Isola et al., 2017). Nevertheless, I2I AI tools rely on the quality and richness of the initial input images, which directly determine the diversity and creativity of the generated outputs, limiting the creative freedom of designers to a certain extent (Lyu et al., 2023). T2I AI and I2I AI models have different advantages regarding the application scenarios and design process. Therefore, some studies suggest combining both types of AI-based tools as complements at different stages in design to cope with different creative needs (Lively et al., 2023; Akverdi and Baykal, 2024). However, there is still a lack of systematic comparisons and analyses in the current literature regarding the specific performance and application strategies of T2I AI and I2I AI models at different design stages. This article explores how these two types of generative AI tools enhance design creativity based on an empirical study, aiming to provide a theoretical basis and practical guidance for designers to make reasonable and effective use of generative AI tools. Although both T2I AI and I2I AI tools show the potential in improving design creativity, the existing literature lacks comparative research on the performance of these tools at different design stages and of their impacts on designers' creative activities. This study aims to delve into the specific impacts of generative AI tools on design creativity and to analyze their applicability and limitations in the early stages of design.

Visual stimuli can enhance designers' creative thinking by stimulating subconscious creativity (McKim, 1980). Appropriate visual stimuli can significantly improve idea generation (Gilhooly, 2007), and too much stimulation of visual materials might lead to information overload, which in turn inhibits creativity (Sternberg,

1999). Goldschmidt and Smolkov (2004, 2006) pointed out that different types of visual stimuli have varying impacts on designers: abstract stimuli were more effective in fostering divergent thinking, while concrete stimuli were more conducive to refining ideas and supporting goal-oriented design convergence (Goldschmidt and Smolkov, 2004; Goldschmidt and Smolkov, 2006). Although previous studies have explored the role of visual stimuli in design creativity, the specific mechanism by which visual stimuli function within the co-creative relationship between AI and designers remains underexplored. In recent years, the visual image generation capabilities of AI have been significantly improved, and AI-generated images are increasingly being used to support designers' inspiration and concept development. Tsidylo and Sendra (2023) found that design students interacting with AI tools, such as MidJourney, gained richer inspiration through AI-generated images, but they also needed the ability to translate visual intentions into verbal prompts to effectively guide AI outputs (Tsidylo and Sendra, 2023). Hou and Wang (2024) found that the emotional characteristics of AI-generated images may influence design creativity and provide empirical support for designers to select appropriate images based on the type of design task (Hou and Wang, 2024). Choi et al. (2023) proposed the CreativeConnect system, which uses AI to extract elements from reference images based on keywords and generate diverse sketches, thereby helping designers stimulate inspiration, expand their ideas, and significantly improve both the quantity of ideas and their self-rated creativity (Choi et al., 2023). This AI-driven visual interaction constitutes a novel human–AI co-creation scenario. However, current research overlooks the role of visual stimuli in the collaborative relationship between AI and designers. As a tool capable of generating visual content, AI plays a significant role in the expression and transformation of visual information, affecting designers' cognitive processing and creative decision-making. There is still a significant gap in the current literature on how figurative and abstract visual stimuli can specifically affect designers' creative processes with the assistance of different AI-based tools. Therefore, this study aims to explore the combined effects of concrete and abstract design stimuli on early stage design creativity, based on a comparison of different AI image generation modalities.

In summary, generative AI demonstrates great potential in supporting creativity in the design field. While AI can enhance design creativity, it may also inhibit it depending on how it is used. Moreover, how design stimuli influence the creative process during co-creation with AI still requires further investigation. Creativity is commonly defined as the ability to produce ideas or solutions that are both novel and appropriate (Amabile, 1983; Runco and Jaeger, 2012). It reflects not only the effectiveness of problem-solving but also an individual's cognitive flexibility in handling complex tasks, with an emphasis in this study on the quality of outcomes. The creative process focuses on the pathway through which these outcomes are generated during the progression of a design task. Having reviewed the literature on using generative AI models and visual stimuli in enhancing design creativity, we then present the methodology, a controlled experiment, to investigate the effects of figurative and abstract visual materials on design creativity in the early design stages with a comparison of a T2I AI model (ChatGPT-4o) and a I2I AI model (MidJourney) based on the Double Diamond Framework. It is followed by the discussions on the interaction of these variables by combining different types of generative AI tools and visual stimuli, with scores in different dimensions of creativity as

important indicators. The most effective combination that maximizes design creativity has also been figured out. The findings from this research provide a comprehensive theoretical basis and practical guidance to optimize the AI-assisted creative process.

Methods

Participants

A total of 84 university students took part in this study, with a male-to-female ratio of nearly 1:1 and an average age of 21 ± 0.92 years. All participants are students who majored in environmental design, with the number of sophomores and junior students being 42 each. Before the experiment, no participants had in-depth exposure to the generative AI-assisted design process. For the purpose of this experiment, all participants volunteered to undergo a 1-day training session on T2I AI and I2I AI tools in the week prior to the experiment. Participants were then divided equally into four groups, ensuring that the number of second- and third-year students within each group was within the range of 10–11. All participants confirmed that they had no prior knowledge of the topic and were suitable to participate in the experiment.

Experimental design

This study deploys a two (T2I AI vs. I2I AI) $\times$ two (figurative visual stimuli vs. abstract visual stimuli) between-groups experiment to examine the effects of AI-based tools and visual stimuli on design creativity. This experiment is based on the Double Diamond Framework (Design Council, 2005), which divides the design process into two stages: the divergent and convergent phases. The data were collected in a staged manner in correspondence with these phases.

In the divergent thinking phase, the task focuses on generating as many novel, diverse, and directionally varied initial ideas as possible, while ensuring the ideas are practically feasible and reflective of independent thinking. Therefore, we set five dependent variables – originality, fluency, flexibility, practicality, and repetition – to comprehensively reflect creativity performance at this stage. Originality measures the novelty of ideas and serves as a core indicator of creative quality; fluency reflects the number of ideas generated, indicating the fluency of thoughts; flexibility evaluates the diversity of idea categories or directions, representing the breadth and divergence of thinking; practicality assesses the feasibility and contextual appropriateness of ideas; and repetition is a reverse indicator used to identify whether AI intervention induces design fixation, leading to repetitive or dependent ideas. The combined assessment of these five dimensions enables a systematic evaluation of designers' divergent creativity in co-creation with AI.

The selection of these dimensions is grounded in established creativity evaluation frameworks. Specifically, originality, fluency, and flexibility are drawn from the core dimensions of the Torrance Tests of Creative Thinking (TTCT) (Torrance, 1966), which serve as foundational indicators of creative thinking in design. Given the nature of our experimental task, we further introduced practicality and repetition as supplementary dimensions to fully assess creative performance in an AI-assisted design context. The practicality dimension follows Amabile (1996) Consensual Assessment Technique (CAT), in which creativity is defined as the combination of novelty and appropriateness (Amabile, 1996). The

“appropriateness” criterion emphasizes the relevance of an idea to a given task, underscoring the importance of practicality. Mohanani et al. (2019) explicitly stated that practicality is one of the key attributes of creativity in evaluating innovative design tasks. Therefore, it is necessary to include practicality as a creativity indicator (Mohanani et al., 2019).

The repetition dimension is inspired by the concept of design fixation, proposed by Jansson and Smith (1991), referring to designers' repeated adoption of visual elements from prior examples, thereby limiting the emergence of novel ideas (Jansson and Smith, 1991). In our scoring process, judges compared participants' sketches with the AI-generated images they used to determine the degree of visual dependence. A higher repetition score indicates stronger reliance on AI-generated features, lower creative independence, and higher fixation tendencies. By incorporating these two additional dimensions, our evaluation system not only focuses on creativity's diversity and originality but also strengthens the assessment of practicality and independence, offering a more comprehensive reflection of AI-mediated creativity.

In the divergent phase, participants responded to an open-ended design challenge, using AI and visual stimuli to generate images and submit multiple initial creative frameworks. These ideas were expressed through keywords and sketches. Judges rated the submissions across five dimensions: originality (novelty), fluency (number of ideas generated), flexibility (diversity of perspectives), practicality (feasibility of the preliminary idea), and repetition (degree of reliance on AI exemplars).

In the convergent thinking phase, the task shifts to deepening, refining, and integrating previously generated ideas to form a final design proposal with clear expression, aesthetic appeal, and practical feasibility. Therefore, six dependent variables – originality, elaboration, flexibility, abstractness, aesthetic appeal, and contextual adaptability – were set to assess creativity at this stage. Originality evaluates the novelty and distinctiveness of the design concept; elaboration assesses the completeness of details and the precision of expression; flexibility reflects the adaptability and integration of the design in terms of function, form, and context; abstractness measures the depth of conceptual thinking and the ability to express abstract ideas; aesthetic appeal evaluates the visual attractiveness and emotional resonance of the design; and contextual adaptability examines how well the design fits the intended application scenario.

Through these six dimensions, the study systematically evaluates designers' deepened creativity performance during the convergent phase in AI-assisted design. The selection of these dimensions is informed by multiple classic creativity evaluation theories. Originality and flexibility, derived from the TTCT, are fundamental indicators of novelty and design diversity and are also widely used in Amabile (1983) CAT (Amabile, 1983; Amabile, 1996). Elaboration originates from TTCT's figural tasks and assesses the depth and detail of idea development. Abstractness draws from the Four C Model proposed by Kaufman and Beghetto, (2009), particularly the “Pro-C” level, emphasizing higher-order conceptual skills (Kaufman and Beghetto, 2009). Aesthetic appeal is based on the Creative Product Semantic Scale (CPSS) (O'Quin and Besemer, 1989), which evaluates visual attractiveness and aesthetic value (O'Quin and Besemer, 1989). Contextual adaptability, a concept proposed by Cheng and Atkinson (2020), emphasizes functional alignment and sustainability across dynamic settings (Cheng and Atkinson, 2020). It incorporates the definitions of “appropriateness” and the CPSS “resolution” dimension by Amabile (1983) and Runco and

Charles (1993), measuring the usefulness and task-fit of creativity in specific contexts (Amabile, 1983; Runco and Charles, 1993).

Among these, originality and flexibility are used in both stages because Guilford (1956) emphasized in his Structure of Intellect model that originality is a core component of creativity (Guilford, 1956). It reflects unique ideation during the generation phase and innovative breakthroughs in final outputs. Originality as an indicator of rarity and novelty is essential for distinguishing truly creative ideas (Torrance, 1966; Amabile, 1983). Flexibility reflects diversity in the divergent phase and the adaptability and integrative capability of solutions in the convergent phase (Guilford, 1956; Finke et al., 1992). Using these two dimensions with different emphases across both phases enables a more comprehensive evaluation of creative performance. Overall, the multidimensional framework

adopted in this study aims to systematically assess creativity outcomes in the AI-assisted design.

Materials

This study asked participants to work with AI models to creatively solve problems. The participants used two types of generative AI tools, a T2I AI model and an I2I AI model, with one group using the ChatGPT-4o, a T2I AI model, and the other group using Midjourney, an I2I AI model. The visual stimuli are divided into two categories: figurative visual stimuli (see Figure 1) and abstract visual stimuli (see Figure 2), with each group being given two reference images. Figurative visual materials are photos taken by the authors in the Terra-cotta Warriors Museum, and abstract visuals are



Figure 1. Figurative visual stimuli.

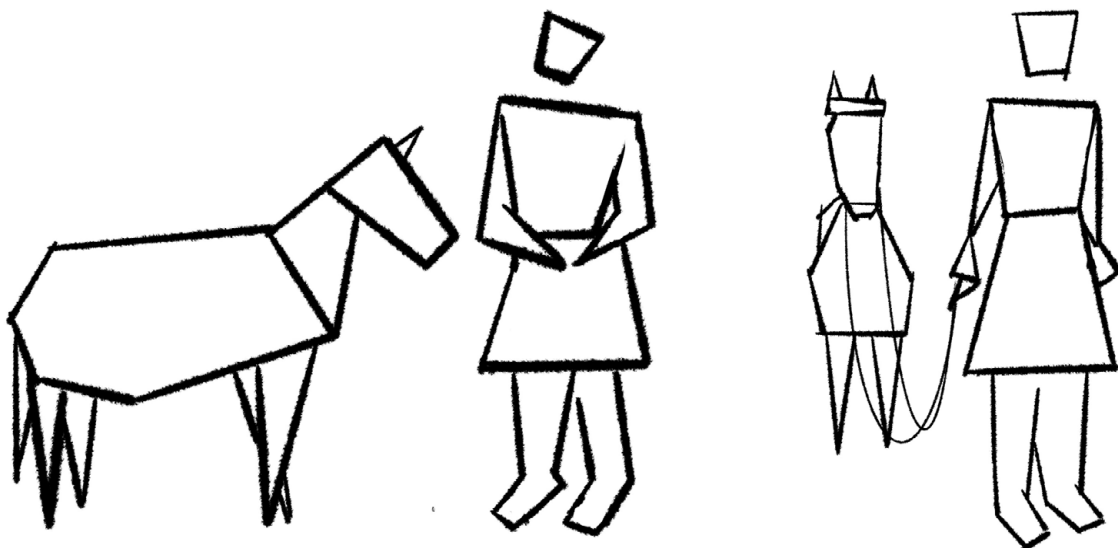


Figure 2. Abstract visual stimuli.

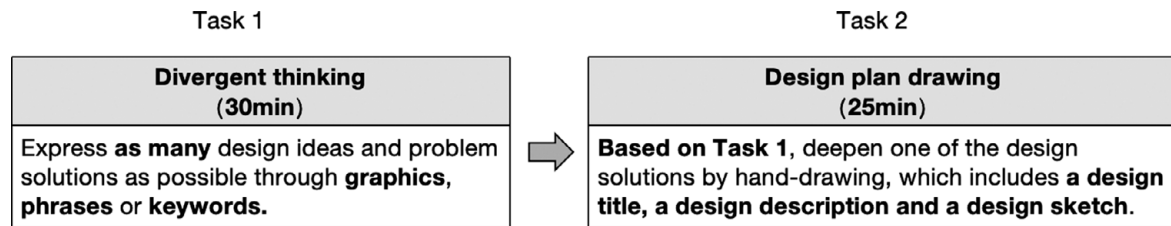


Figure 3. Task steps.

abstract paintings of geometrical blocks based on the figurative photos, which were painted by the authors. The visual materials have been confirmed by experts as suitable for visual stimuli.

Experimental procedure

Participants from different groups were arranged in different quiet classrooms or design studios and were given only the visual stimuli to work on, without other access to information. All participants were required to work independently and were not allowed to talk to each other or seek outside assistance. The experiment lasted 60 min (see Figure 3), and the procedure is outlined below.

- (i). A teacher explained the experimental procedures to the participants and gave them the tasks and visual materials, which took 5 min in total.
- (ii). Task 1: "If the Terracotta Warriors are to be exhibited abroad, how to show the feeling of a vast army with a single pair of warrior and horse statues?" Each group received two different reference images, and worked with different AI-based tools to generate images to provide as many design ideas and solutions as possible through graphics, phrases, or keywords. To complete the task, the following instructions should be followed:
 - a) Express the design ideas through clear keywords or phrases, and do not use confusing "internet slangs."
 - b) Graphics are only used to convey specific meaning, and it is not necessary to pursue the aesthetics.
 - c) Provide only one complete idea in each design frame.

This task lasted 30 min.

- (iii). Task 2: Based on Task 1, participants were asked to refine one of the design proposals by hand-drawing. They should provide a design theme, a design sketch, and a design description. This task lasted 25 min (see Figure 4).

Creativity assessment

Design creativity assessment contains two parts: design thinking and design solution refinement. To assess the creativity of design thinking, Torrance's (1966) TTCT was deployed, where the design thinking creativity is assessed in five dimensions: fluency, originality, flexibility, practicality, and repetition (Amabile, 1983). In addition, to measure the level of design fixation, according to the assessment criteria proposed by Jansson and Smith (1991), the dimension of repetition was added, which refers to the extent how design concepts repeat the features of images co-created with AI models. Fluency is measured on the basis of the total number of creative ideas generated, with higher scores indicating greater creativity. The judges counted the number of design concepts proposed by each participant within the given time. The participant

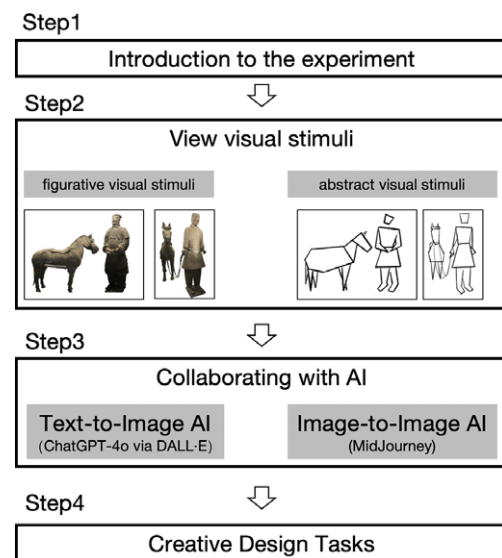


Figure 4. Procedure overview of the experiment.

with the largest number of ideas was assigned a score of 7, while the participant with the lowest number of ideas was assigned a score of 1. The remaining participants' scores were assigned accordingly. Originality refers to the degree of novelty of the design concepts, whether they are unique and witty in problem-solving, with higher scores indicating greater creativity in terms of uniqueness and novelty. Flexibility indicates the degree of diversity and variation of the design concepts during the thinking process, evaluating whether the participant is able to think from different perspectives. Higher scores in this dimension represent greater diversity. To score this dimension, the judges analyzed each participant's ideas, counted the number of categories those ideas might be divided into, and assigned the scores from lowest to highest. The scoring was conducted in the same way as for scoring fluency. Practicality refers to the practical application value and feasibility of the design concepts, assessing whether they can be implemented and accepted in real life. The assessment of refined design solutions integrates the CAT proposed by Amabile (1988) and the Four C-Model proposed by Kaufman and Beghetto (2009). The creativity of the refined design proposals is measured from six dimensions: originality, elaboration, flexibility, abstractness, aesthetic appeal, and contextual adaptability. The judging criteria of originality and flexibility remain the same. Elaboration indicates the amount of details and complexity of the solutions, and whether the participant can further elaborate and develop the preliminary ideas. A high score means that the idea is rich in detail and complete. Abstractness refers to the conceptual level and theoretical depth of the solutions, with higher scores indicating more profound ideological connotation or

theoretical foundation. Aesthetic appeal represents the value and attractiveness, and a higher score indicates a stronger appeal to the audience, as well as stronger visual and emotional impact. Contextual adaptability measures the degree to which the solutions may be adapted to the real context. A high score in this dimension indicates that the problem is solved and adapted perfectly to the context.

Graders were asked to approach each solution with an open mind and to rate the solutions provided by each participant on a scale of 1–7 for different dimensions. This study invited a total of eight experts with relevant professional backgrounds to serve as independent judges. They rated each design sample in multiple dimensions. The expert panel included two university design faculty members, two art museum directors, two senior curators, and two PhDs in design, all of whom had more than 5 years of professional or academic experience in design-related fields. Before the evaluation, all experts received standardized instructions and examples to ensure consistent understanding of the scoring criteria. The scoring part was conducted independently, with each expert scoring both the design thinking outcomes and the final exhibition proposals separately. To ensure reliability, the final score for each dimension was the average of the eight experts' scores. This scoring method follows the procedures proposed by Amabile (1982, 1996) and Kaufman et al. (2008), which have been widely validated in creativity research (Amabile, 1982; Amabile, 1996; Kaufman et al., 2008).

Results

The study aims to explore the effects of generative AI models and various types of visual stimuli on design creativity, which includes two stages of design thinking: the divergent and convergent thinking phases. The results of a two-way analysis of variance (ANOVA) (Table 1) demonstrate that in the divergence phase, the T2I AI model and abstract visual stimuli, respectively, show significant advantages in enhancing the originality, fluency, flexibility, and practicality of design thinking, but they tend to result in design fixation. In the convergence, the T2I AI model and abstract visual stimuli are beneficial to improve the originality, elaboration, flexibility, abstractness, aesthetic appeal, and contextual adaptability for refining solutions.

The impact of generative AI on design creativity

The results demonstrate that AI-based tools are able to enhance design creativity in both the divergent and convergent thinking phases. Compared to those using the I2I AI model, participants using the T2I AI model present better results in design creativity, but they are also more likely to experience design fixation. In the divergence phase, there are significant differences in the effects between participants using T2I AI and I2I AI models to facilitate design creativity in different dimensions. Furthermore, the main effects of different types of AI-based tools are significant in five different dimensions, including originality ($F = 14.837$, $p \leq 0.001$, $\eta^2p = 0.156$); fluency ($F = 20.032$, $p \leq 0.001$, $\eta^2p = 0.200$); flexibility ($F = 22.565$, $p \leq 0.001$, $\eta^2p = 0.220$); practicality ($F = 24.027$, $p \leq 0.001$, $\eta^2p = 0.231$); and repetition ($F = 15.456$, $p \leq 0.001$, $\eta^2p = 0.162$), which all show significance. This suggests that choosing suitable AI-based tools in the design divergence phase can help designers generate creative ideas, make the ideation process smoother, and increase the novelty, quantity, diversity, and feasibility of the ideas generated, especially in terms of practicality

($p < 0.001$) and flexibility ($p < 0.001$), both of which show greater significance. However, such choices have limitations in coping with design fixation.

There are also significant differences in the effects of the T2I AI model and the I2I AI model on various dimensions of design creativity in the convergence phase. Different types of AI-based tools show significant effects on the originality ($F = 12.278$, $p = 0.001$, $\eta^2p = 0.133$); elaboration ($F = 19.555$, $p < 0.001$, $\eta^2p = 0.196$); flexibility ($F = 17.373$, $p < 0.001$, $\eta^2p = 0.178$); abstractness ($F = 7.356$, $p = 0.008$, $\eta^2p = 0.084$); aesthetics appeal ($F = 19.040$, $p < 0.001$, $\eta^2p = 0.192$); and contextual adaptability ($F = 20.792$, $p < 0.001$, $\eta^2p = 0.206$) of creativity. These statistical results indicate that different types of AI models significantly affect the six dimensions of creativity in assisting designers during the convergence phase, especially in the dimensions of elaboration ($p < 0.001$), aesthetic appeal ($p = 0.024$), and contextual adaptability ($p < 0.001$). The results express that using appropriate AI-based tools at the convergent thinking stage can improve the novelty, refinement, diversity, depth of ideas and concepts, attractiveness, and adaptability to the context of the creative solutions.

Further post hoc comparisons of the data from the divergence phase reveal that the T2I AI model shows significant advantages over the I2I AI model in various dimensions, including originality (T2I AI vs. I2I AI: 3.685 ± 0.160 vs. 2.813 ± 0.160 , $p < 0.001$); fluency (T2I AI vs. I2I AI: 3.917 ± 0.186 vs. 2.738 ± 0.186 , $p < 0.001$); flexibility (T2I AI vs. I2I AI: 3.854 ± 0.171 vs. 2.702 ± 0.171 , $p < 0.001$); and practicality (T2I AI vs. I2I AI: 4.196 ± 0.173 vs. 2.997 ± 0.173 , $p < 0.001$). It indicates that the T2I AI model is more helpful in the design divergence phase to enhance the innovation, number of creative ideas, richness, and feasibility of design thinking. However, the higher score in the repetition dimension (T2I AI vs. I2I AI: 3.84 ± 0.148 vs. 3.003 ± 0.148 , $p < 0.001$) suggests that collaboration with the T2I AI model is more likely to result in a higher level of similarity between the generated ideas and the AI-generated outputs, leading to the design fixation more easily. To summarize, the T2I AI model not only inspires novel and diverse ideas in designers more smoothly, but also outperforms the I2I AI model regarding the feasibility of the generated design solutions.

The impact of visual stimuli on design creativity

The results suggest that visual stimuli are able to elevate design creativity in both the design divergence and convergence phases, and that participants who were stimulated with abstract visuals show better design creativity than those with figurative materials. In the divergent thinking phase, the use of different types of visual stimuli significantly affect designers' creative thinking in the dimensions of originality ($F = 9.872$, $p = 0.02$, $\eta^2p = 0.110$), fluency ($F = 4.612$, $p = 0.035$, $\eta^2p = 0.055$), flexibility ($F = 7.901$, $p = 0.006$, $\eta^2p = 0.090$), practicality ($F = 4.428$, $p = 0.038$, $\eta^2p = 0.052$), and repetition ($F = 8.778$, $p = 0.04$, $\eta^2p = 0.099$). It indicates that using appropriate visual stimuli in divergent thinking can help designers generate innovative ideas more effectively and smoothly in the meantime of increasing the novelty, number, variety, and feasibility of creative ideas. However, visual stimuli may also lead to the occurrence of design fixation, making it particularly important to select suitable visual materials to stimulate inspirations to avoid overreliance on references. In the convergence phase, visual stimuli show significant influences in all dimensions of design creativity, including originality ($F = 10.439$, $p = 0.002$, $\eta^2p = 0.115$), elaboration ($F = 5.517$, $p = 0.021$, $\eta^2p = 0.065$), flexibility ($F = 6.815$,

Table 1. Two-way ANOVA results of the types of generative AI models and visual stimuli on design creativity

Phase	Dependent variable	Independent variable	F	p
Divergent thinking	Repetition	Generative AI type (text-to-image AI and image-to-image AI)	15.456	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	8.778	0.004**
	Originality	Generative AI type (text-to-image AI and image-to-image AI)	14.837	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	9.872	0.002**
	Fluency	Generative AI type (text-to-image AI and image-to-image AI)	20.032	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	4.612	0.035*
	Flexibility	Generative AI type (text-to-image AI and image-to-image AI)	22.565	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	7.901	0.006**
	Practicality	Generative AI type (text-to-image AI and image-to-image AI)	24.027	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	4.428	0.038*
Convergent thinking	Originality	Generative AI type (text-to-image AI and image-to-image AI)	12.278	0.001**
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	10.439	0.002**
	Elaboration	Generative AI type (text-to-image AI and image-to-image AI)	19.555	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	5.517	0.021*
	Flexibility	Generative AI type (text-to-image AI and image-to-image AI)	17.373	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	6.815	0.011**
	Abstractness	Generative AI type (text-to-image AI and image-to-image AI)	19.04	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	6.226	0.015*
	Aesthetic appeal	Generative AI type (text-to-image AI and image-to-image AI)	5.274	0.024*
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	5.407	0.023*
	Contextual adaptability	Generative AI type (text-to-image AI and image-to-image AI)	20.792	0.000***
		Visual stimuli type (figurative visual stimuli and abstract visual stimuli)	4.329	0.041*

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

$p = 0.001$, $\eta^2 p = 0.078$), abstractness ($F = 6.226$, $p = 0.015$, $\eta^2 p = 0.072$), aesthetic appeal ($F = 5.407$, $p = 0.023$, $\eta^2 p = 0.063$), and contextual adaptability ($F = 4.329$, $p = 0.041$, $\eta^2 p = 0.051$). It reflects that, in the convergence phase of design, designers stimulated by appropriate visual materials perform better with regard to the novelty, completeness, diversity, depth of conceptualization, attractiveness, and conformity to the actual needs of the contexts.

Further post hoc comparisons show that in the design divergence phase, abstract visual stimuli reflect significant advantages in all dimensions, and present better performance in enhancing design creativity in the aspects of originality (abstract vs. figurative: 3.604 ± 0.160 vs. 2.893 ± 0.160 , $p = 0.002$); fluency (abstract vs. figurative: 3.610 ± 0.186 vs. 3.045 ± 0.186 , $p = 0.035$); flexibility (abstract vs. figurative: 3.619 ± 0.171 vs. 2.937 ± 0.171 , $p = 0.035$,

$p = 0.006$); and practicality (abstract vs. figurative: 3.845 ± 0.173 vs. 3.339 ± 0.173 , $p = 0.038$) than figurative materials. It suggests that abstract visual stimuli are advantageous in promoting innovation, the number of creative ideas, abundance, feasibility, and optimization in the design thinking. At the same time, abstract visual stimuli also significantly affect the repetition of creative thinking (abstract vs. figurative: 3.723 ± 0.148 vs. 3.104 ± 0.148 , $p = 0.004$), suggesting that using abstract stimuli will result in the high similarity between the designers' ideas and the AI-generated design samples, and is more likely to trigger design fixation. By contrast, using figurative visual stimuli can reduce the occurrence of design fixation.

In the convergent thinking phase, abstract visual stimuli also show significant advantages in multiple dimensions. They significantly affect the creative thinking of designers in terms of originality (abstract vs. figurative: 3.101 ± 0.139 vs. 3.735 ± 0.139 , $p = 0.002$), elaboration (abstract vs. figurative: 3.738 ± 0.160 vs. 3.205 ± 0.160 , $p = 0.021$), flexibility (abstract vs. figurative: 3.560 ± 0.146 vs. 3.021 ± 0.146 , $p = 0.011$), abstractness (abstract vs. figurative: 3.670 ± 0.097 vs. 3.327 ± 0.097 , $p = 0.015$), aesthetic appeal (abstract vs. figurative: 3.839 ± 0.147 vs. 3.357 ± 0.147 , $p = 0.023$), and contextual adaptability (abstract vs. figurative: 3.982 ± 0.143 vs. 3.562 ± 0.143 , $p = 0.041$). It demonstrates that the stimulation of abstract visual materials improves designers' innovativeness, detailing, diversity of ideas, conceptualization, attractiveness, and conformity to practical needs in the design solution refinement. These results further suggest that abstract visual stimuli are effective in enhancing design creativity in both divergence and convergence.

The effects of AI models and visual stimuli on design creativity

This section investigates the interactive effects of generative AI model type and visual stimuli type on design creativity, and analyzes the simple effects of these variables. The results show that different combinations of generative AI tools and visual stimuli significantly enhance multiple dimensions of design creativity in the convergence phase, but their effects are limited in the divergent thinking phase. In the divergence phase, none of the interaction effects of generative AI models and visual stimuli reach the significant level ($p > 0.05$). For example, none of repetition ($F = 0.683$, $p = 0.411$), originality ($F = 1.079$, $p = 0.302$), fluency ($F = 0.062$, $p = 0.804$), flexibility ($F = 0.333$, $p = 0.566$), and practicality ($F = 0.788$, $p = 0.377$) show significant interaction effects. This suggests that, during divergent thinking, different types of generative AI models and visual stimuli have limited effects in all different dimensions of design creativity. However, in the convergence phase, there are significant interaction effects between AI-based tools and visual stimuli in different design creativity dimensions, including: originality ($F = 5.964$, $p = 0.017$, $\eta^2 p = 0.069$), elaboration ($F = 4.688$, $p = 0.033$, $\eta^2 p = 0.055$), flexibility ($F = 5.127$, $p = 0.026$, $\eta^2 p = 0.078$), abstractness ($F = 6.66$, $p = 0.012$, $\eta^2 p = 0.077$), aesthetic appeal ($F = 5.274$, $p = 0.024$, $\eta^2 p = 0.062$), and contextual adaptability ($F = 4.087$, $p = 0.047$, $\eta^2 p = 0.049$). These results mean that the combination of different AI-based tools and stimulus visual materials in the design convergence phase contributes to boosting the innovation, detailing, diversity of thinking, conceptualization, attractiveness, and the ability to meet the contextual needs when designers refine the design solutions.

Further analyses of the simple effects disclose that (Table 2), in the convergence, the combination of figurative visual stimuli and the T2I AI model significantly enhances design creativity in design

Table 2. Descriptive comparisons of AI image generation modalities under concrete stimuli in the convergent thinking phase

Dependent variable	T2I		I2I		<i>p</i>
	M	SD	M	SD	
Originality	3.685	0.196	2.518	0.196	<.001 ***
Elaboration	3.952	0.227	2.458	0.227	0.002 **
Flexibility	3.658	0.206	2.357	0.206	0.001 **
Abstractness	3.690	0.137	2.964	0.137	0.001 **
Aesthetic appeal	4.048	0.207	2.667	0.207	0.002 **
Contextual adaptability	4.226	0.202	3.899	0.202	0.005 **

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

solution refinement, whereas abstract visual stimuli are less effective in improving creativity with less reliance on the type of AI-based tools. In the convergence phase, under the combination of figurative visual stimuli and the T2I AI model, the ability of design solution refinement is advanced in the aspects of originality (T2I AI vs. I2I AI: 3.685 ± 0.196 vs. 2.518 ± 0.196 , $p < 0.001$), elaboration (T2I AI vs. I2I AI: 3.952 ± 0.227 vs. 2.458 ± 0.227 , $p = 0.002$), flexibility (T2I AI vs. I2I AI: 3.658 ± 0.206 vs. 2.357 ± 0.206 , $p = 0.001$), abstractness (T2I AI vs. I2I AI: 3.690 ± 0.137 vs. 2.964 ± 0.137 , $p = 0.001$), aesthetic appeal (T2I AI vs. I2I AI: 4.048 ± 0.207 vs. 2.667 ± 0.207 , $p = 0.002$), and contextual adaptability (T2I AI vs. I2I AI: 4.226 ± 0.202 vs. 3.899 ± 0.202 , $p = 0.005$). It implies that when designers are stimulated by figurative visual materials, the T2I AI model is more useful in improving the design refinement ability of the designers, in terms of innovation, detailing, diversity of thinking, conceptualization, attractiveness, and contextual application during the phase of convergent thinking. Under the stimulation of abstract visual stimuli, designers' choice of AI-based tools does not show significance in solution refinement impacts in dimensions of originality ($p = 0.455$), elaboration ($p = 0.114$), flexibility ($p = 0.182$), abstractness ($p = 0.927$), aesthetic appeal ($p = 0.148$), and contextual adaptability ($p = 0.076$). In the stimulation of abstract visual materials, the effects of different types of generative AI models are not significant in all dimensions ($p > 0.05$), indicating that the combination of figurative visual stimuli and the T2I AI model more significantly increases designer creativity in refining solutions, whereas the abstract visual stimuli show less significant effects in this phase with less reliance on the choice of generative AI model type.

Discussion

This study investigates the effects of different types of generative AI-based models and visual stimuli on design creativity through an experiment. Based on the Double Diamond Framework of Creativity, we divided the design process into two stages – divergent and convergent stages – and examined how different combinations of AI tools and design stimuli performed in each phase (Design Council, 2005; Runco and Jaeger, 2012). The results revealed that, in both the divergent and convergent design stages, designers using the T2I AI model and stimulated by abstract visual materials scored significantly higher across multiple dimensions of design creativity than those using the I2I AI model with the same stimuli.

AI promotes design creativity in the meantime of risking design concept repetitions

Compared to the I2I AI tool, T2I AI models show significant benefits in both design divergence and convergence. T2I AI models present more flexibility in their collaboration with designers during the design process. T2I AI models deploy the form of dialogues and allow inputs of natural language, providing more flexibility and creative space. Designers can describe various possible design elements through verbal texts. I2I AI models mainly rely on existing images to generate new visuals, which restricts the creativity. The outputs provided by I2I AI models might be more affected by existing visual inputs, making it more difficult to generate brand-new design ideas.

The experiment results indicate that participants who used the T2I AI model in the design divergence phase scored significantly higher in the originality, fluency, flexibility, and practicality dimensions of design creativity than those who used the I2I AI model. This finding highlights the potential of the T2I AI models in stimulating designers' creative thinking. However, this advantage comes with a potential risk of design fixation, meaning that designers may become too reliant on AI-generated solutions, and that their ability to explore a wider range of ideas might consequently be limited. It is in line with previous research on the impact of different types of AI-based tools on creativity. Wadinambiarachchi et al. (2024) further suggest that the effectiveness of co-conceptualization with AI is not monolithic, but rather is influenced by the AI-prompted creative approaches chosen by the participant and the strategy of how they generate ideas based on the AI's suggestions (Wadinambiarachchi et al., 2024). They point out that, in the case of co-conceptualization with the T2I AI models, design fixation occurs when creating prompts for AI models and responding to AI-generated output images, demonstrating that this leads to fixation displacement, where the focus of attention shifts from the input sample images to the output images. It implies the importance of the way designers interact with AI models to stimulate creativity. Meanwhile, it reminds us of the risks of design fixation when using these tools.

According to the results, participants who used the T2I AI model during the design convergence phase scored significantly higher on originality, elaboration, flexibility, abstractness, aesthetic appeal, and contextual adaptability of design creativity than those

who used the I2I AI model. Researchers have noted that, in the AI-assisted design ideation, T2I AI models are particularly useful in generating detailed and unexpected combinations that can shift the designers' attention from technical tasks to visual appeal, cognitive engagement, and emotional resonance (Brisco et al., 2023; Joynt et al., 2023). I2I AI models' limitation of being dependent on the input images in the generation makes it outstanding in the field of image style transformation and image restoration, yet it potentially restricts its flexibility and innovation in creative design outputs, leading to limited creative applications in the process of collaborating with designers (Isola et al., 2017). By transforming existing images, new inspirations can be gained based on existing designs. Thus, this type of model helps designers optimize existing designs. In addition, these tools are able to provide designers with more creative possibilities and solutions through image outpainting and inpainting functions (Turchi et al., 2023).

T2I AI and I2I AI models, respectively, represent the processes of generating ideas from the ground up and from existing materials. T2I AI models promote creativity through communication with designers, allowing them to obtain visual inspirations from textual descriptions, stimulating new creative directions, breaking through the limitations of traditional thinking patterns, and fostering divergent thinking. In cooperation with T2I AI models, designers transform the visual stimuli they receive into natural language descriptions as prompts, and then gain output images through dialogues. This creativity-stimulating mechanism allows designers to express abstract concepts and ideas in a clearer way, where they are able to express their needs and generate creative ideas. For instance, in order to solve the problem of presenting the momentum of a vast army with statues of a person and a horse, one participant proposed to use lighting effects, mirror reflection, background or scene design, visual dislocation, sound effect atmosphere rendering and other ways to present the gallery design ideas, as illustrated in Figure 5. T2I AI models generate figurative images through natural language descriptions, directly translating designers' intentions into concrete visual elements, and making it easy for designers to change textual prompts for new designs (Chen et al., 2023). Lim et al. (2023) suggest that improved communication and empathy between humans and AI may further facilitate designers' rapid exploration in conceptual knowledge space, thus achieving enhanced creativity (Lim et al., 2023). Bresciani (2019) states that

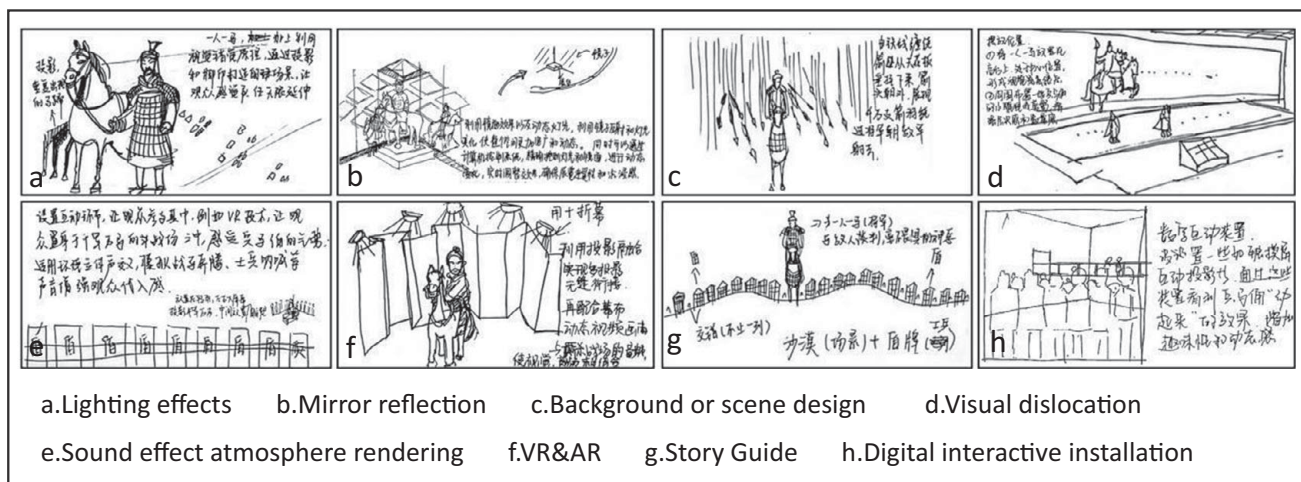


Figure 5. Example of T2I AI for design creative expression.

specific visual feedback can help designers better understand and adjust design details, improve design quality, and enhance creativity in detailing, conceptualization, and practical application (Bresciani, 2019). Lin et al. (2024) state that in the AIGC (Artificial Intelligence Generated Content) design paradigm, the dynamic interaction between designers and AI tools involves the dynamism of image generation, emphasizing the dynamic and generative nature of AI-based tools in the image generation process (Lin et al., 2024). Visual stimuli can be regenerated infinitely until the user is satisfied with the outputs. These generated images stimulate inspiration on an unlimited basis and offer insights for design creativity. When looking for inspiration or tackling design challenges, designers can use T2I AI models to stimulate inspiration, evoking a higher level of design creativity. In particular, when AI-based tools are used to generate inspirational images, making a dialogue with AI facilitates the generation of new ideas and visual elements that stimulate creativity and break stereotypes. However, designers need to be cautious of being overinfluenced by AI-generated images in the process.

The advantages of abstract visual stimuli in enhancing creativity and their limitations on design concept repetition and solution generation

Participants who were stimulated by abstract visual materials during the divergent thinking phase scored significantly higher on the originality, fluency, flexibility, and practicality dimensions of design creativity than those who were given figurative visual stimuli. This finding supports the argument proposed in Howard et al. (2010) and Jang et al. (2019) that ambiguous or less-detailed stimuli can be more effective in promoting idea generation and creative thinking by providing a wider range of interpretations (Howard et al., 2010; Jang et al., 2019). Although abstract visual stimuli work effectively in encouraging creativity, they are not significantly helpful in the number of solutions generated in a short period of time and in the avoidance of design fixation. It may be because abstract visual stimuli require designers to think more and make associations, thus prolonging the design time. It is consistent with the findings in previous studies that abstract stimuli can enhance creativity in design, but may also lead to increased design time (Goldschmidt & Smolkov, 2006). Design stimuli can indeed enhance the quality of creative outputs. However, in time-constrained tasks, the stimulus type significantly affects design efficiency. Compared to abstract stimuli, concrete stimuli are more effective in helping designers quickly focus on the problem, thereby improving task completion efficiency and feasibility (Kang et al., 2019).

Participants stimulated by abstract visual materials in the design convergence phase scored significantly higher on originality, elaboration, flexibility, abstractness, and contextual adaptability of design creativity than those inspired by figurative visual materials. Heimer (2023) shows that abstract visual materials are useful to stimulate creative thinking (Heimer, 2023). Smith (1995) emphasizes that using a variety of stimuli can break stereotypes and promote association and innovation. However, it may also impose a certain cognitive load (Smith, 1995). Abstract images provide unspecific visual elements from which designers can obtain inspiration and create freely.

To help design-based learners unleash greater creativity when searching for inspiration or tackling design challenges, designers can look for abstract referential images to generate inspiration and to stimulate higher design creativity. In particular, when using

AI-based tools to generate inspirational images, learners are encouraged to use abstract visual prompts to guide AI in generating images with uncertainty, thus stimulating more inspiration. They, however, need to be wary of being overinfluenced by AI-generated images in the process.

Advantages and disadvantages of different combinations of AI models and visual stimuli in the divergence and convergence phases

Further analyses suggest that, in the divergence phase, abstract visual stimuli perform better in improving the design creativity when designers use the I2I AI model. However, abstract visuals show insignificant enhancement in the number of generated solutions and a reduction in design fixation over a short time. Comparatively speaking, when the T2I AI model is used in divergent thinking, figurative visuals are more effective in stimulating creativity. The combination of the I2I AI model and abstract visual stimuli breaks the traditional thinking patterns and inspires creative ideas. The group of T2I AI model and figurative stimuli can transfer designers' intention to specific visual outcomes and enhance creativity. This finding corresponds with former studies with regard to the impact of abstract visual stimuli on creativity. When using I2I AI models, designers can choose abstract visual stimuli to better think outside the box and generate more innovative ideas. The abstract visual prompts for I2I AI models enable designers to think more and make more associations through uncertain visual elements, thereby improving their creativity. Figurative visual stimuli, used in combination with the T2I AI model, provide specific design references for designers to flesh out details and complete practical application more efficiently. Isola et al. (2017) suggest that I2I AI models can provide diversified visual stimuli and promote the generation of creative ideas (Isola et al., 2017). In Zhu et al. (2017), the CycleGAN model demonstrates the potential of abstract visual stimuli and its limitations in inspiring creativity (Zhu et al., 2017). Based on the analysis of experimental results, designers who used T2I AI and were exposed to abstract visual materials scored significantly higher on the repetition dimension compared to those who used I2I AI and concrete stimuli. This suggests that using both T2I AI and abstract materials may lead to higher design repetition, indicating a greater risk of design fixation. Therefore, to mitigate design fixation, we recommend prioritizing the use of I2I AI tools in combination with concrete design stimulus materials during the divergent thinking phase, which would help reduce designers' reliance on AI-generated examples.

Additional analyses show that, in the convergent thinking phase, the impact of different visual stimuli on design creativity varied significantly depending on whether designers used I2I or T2I AI tools. To be specific, the effect of AI tools and visual stimuli on creativity was not simply additive but exhibited clear combinatorial effects. Among these combinations, T2I AI paired with figurative design stimulus materials produced the most prominent results, particularly excelling in originality, elaboration, and flexibility. It reveals the distinct advantages of this combination in enhancing the specificity, detailed articulation, and practical feasibility of design solutions. In this study, it appears to be the most effective combination and is recommended as a preferred choice.

By contrast, if users have access only to I2I AI tools, we suggest using them with abstract visual stimuli. While this combination does not outperform the best choice, T2I with figurative stimuli, it still supports creativity well, especially in promoting conceptual novelty, detail refinement, cognitive diversity, conceptual

expression, visual appeal, and contextual alignment. This suggests a complementary interaction between abstract visual materials and the I2I modality. Although main effects analyses indicate that both T2I AI and abstract visual stimuli individually enhance creativity, interaction analyses further highlight that it is the combination of variables that plays a critical role in the convergent phase of the design process. In particular, the combination of T2I AI with figurative materials demonstrates significantly stronger synergistic effects across multiple dimensions. This finding underscores the importance of combinations of AI modalities and stimulus materials in supporting creativity during the design refinement stage.

In the divergent phase, although AI-generated images, generated based on abstract or concrete visual stimuli, serve as the initial visual inspiration for designers, the primary goal of this stage is to generate as many ideas as possible, emphasizing quantity and divergence. Designers are more inclined to think independently through personal associations, with AI tool type and image type stimulating creativity in relatively separate ways. As a result, no significant interaction effects were observed. However, the significant main effects of both AI tool type and image type suggest that each factor independently influences the quantity and diversity of creative ideas. In contrast, the convergent phase requires participants to select and refine one concept developed in the first task. This phase demands greater focus and completeness, with designers expected to achieve coherence in expression, logic, and detail. Therefore, the compatibility between AI tools and stimulus materials becomes more critical. Whether the combinations of tools and stimuli exhibit synergistic effects becomes a key factor influencing creative performance, which is reflected in the significant interaction effects observed during this phase. This distinction aligns with the theoretical logic of cognitive strategy shifts between the divergent and convergent stages, as emphasized in the Double Diamond framework of creativity (Guilford, 1950; Design Council, 2005).

Through the comparison of the performance of T2I AI and I2I AI models in design tasks, this study reveals the effects of different visual stimuli types on design creativity. It provides a theoretical basis and practical guidance for designers to choose appropriate types of AI-based tools and visual stimuli in their practices.

Conclusion and limitations

In conclusion, this research systematically compares the effects of generative AI (T2I AI vs. I2I AI) and visual stimuli (figurative vs. abstract) on design creativity, revealing their different mechanisms in the design divergence and convergence phases. It is concluded that designers should choose appropriate types of AI-based tools and visual stimuli based on the design phases (divergence or convergence) and targets (innovativeness, the number of ideas generated, etc.) in order to maximize the potential of AI in the design process. In addition, it emphasizes the importance of how designers interact with AI models in enhancing creativity. Meanwhile, it points out the risks of design fixation, where designers should avoid the overreliance on AI-generated content and keep initiative in the design process and flexibility in creativity. In the divergent thinking phase, the combination of the T2I AI model and abstract visual stimuli is preferred as an effective method to enhance design creativity. The dialogues with AI provide more flexibility and a larger number of inspirational stimuli. In this phase, if designers use I2I AI models, abstract visuals are better

choices in inspiring creativity. However, subject to the input of images, I2I AI models are unable to generate a large number of design ideas in a short time. In the design convergence phase, the collaboration of the T2I AI model and abstract visual stimuli makes the design process more flexible, thus promoting design creativity. Using the I2I AI model together with figurative visual stimuli can efficiently realize specific design goals.

This study provides theoretical references and practical guidance for designers in their choices of generative AI models and visual stimuli. However, it has certain limitations. First, it focuses only on the influence of AI on creativity during the early stages of the design process and compares a limited number of AI platforms. Second, while the experiments were conducted in a controlled educational context – helpful for reducing interference and ensuring data consistency – this setting differs from real-world design practices that involve multisource stimuli and collaborative dynamics. Third, although the visual stimuli served only as reference materials and were not closely related to the final design outcomes, their consistent presentation before AI use may have introduced a priming effect, potentially influencing creativity or eye-tracking behavior. This should be noted in future research. In addition, although generative AI has demonstrated positive potential in enhancing creativity, this study primarily explores its positive effects and does not investigate its possible negative impacts in depth, such as users' overreliance on AI-generated suggestions or uncritical acceptance of bias. Future research should further develop T2I AI technologies, exploring their application across different design domains and examining their long-term impact on creativity. A more comprehensive evaluation is needed to assess both the advantages and disadvantages of AI in the design process. Finally, this study highlights the potential of T2I AI models in design innovation and calls for more research to validate their effects.

Acknowledgments. The authors would like to thank their participants for their cooperation and insights, as this study would not have been possible without them.

Competing interests. The authors declare none.

Ethics statement. The research does not require further research ethics approval, as it does not involve animal or human clinical trials and is not unethical. In accordance with the ethical principles outlined in the *Declaration of Helsinki*, all participants have provided informed consent before participating in the study. The anonymity and confidentiality of the participants are guaranteed, and their participation is completely voluntary.

Disclosure statement. No potential conflict of interest was reported by the author(s).

References

- Akverdi C and Baykal GE (2024) Generative AI tools in design fields: Opportunities and challenges in the ideation process. In *Adjunct Proceedings of the 2024 Nordic Conference on Human-Computer Interaction* (pp. 1–5).
- Amabile TM (1982) Social psychology of creativity: A consensual assessment technique. *Journal of Personality and Social Psychology* 43(5), 997–1013. <https://doi.org/10.1037/0022-3514.43.5.997>.
- Amabile TM (1983) The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology* 45(2), 357–376. <https://doi.org/10.1037/0022-3514.45.2.357>.
- Amabile TM (1988) A model of creativity and innovation in organizations. *Research in Organizational Behavior* 10, 123–167.
- Amabile TM (1996) *Creativity and Innovation in Organizations*. Boston, MA: Harvard Business School Publishing. 396–239.

- Bresciani S (2019) Visual design thinking: A collaborative dimensions framework to profile visualisations. *Design Studies* 63, 92–124.
- Brisco R, Hay L and Dhami S (2023) Exploring the role of text-to-image AI in concept generation. *Proceedings of the Design Society 3*, 1835–1844.
- Chen L, Wang P, Dong H, Shi F, Han J, Guo Y and Wu C (2019) An artificial intelligence based data-driven approach for design ideation. *Journal of Visual Communication and Image Representation* 61, 10–22.
- Chen J, Wang D, Shao Z, Zhang X, Ruan M, Li H and Li J (2023) Using artificial intelligence to generate master-quality architectural designs from text descriptions. *Buildings* 13(9), 2285.
- Cheng PC and Atkinson SR (2020) The role of contextual adaptability in sustainable design. *Journal of Cleaner Production* 254, 120039. <https://doi.org/10.1016/j.jclepro.2020.120039>.
- Childs P, Han J, Chen L, Jiang P, Wang P, Park D, Yin Y, Dieckmann E and Vilanova I (2022) The creativity diamond—A framework to aid creativity. *Journal of Intelligence* 10(4), 73.
- Choi D, Hong S, Park J, Chung JYY and Kim J (2023) CreativeConnect: Supporting reference recombination for graphic design ideation with generative AI. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems (CHI '24)*. New York: Association for Computing Machinery, 11–16 May 2024, pp. 1–25. <https://doi.org/10.1145/3613904.3642794>
- Design Council (2005) *The Double Diamond Design Process Model*. London, UK: Design Council
- Finke RA, Ward TB and Smith SM (1992) *Creative Cognition: Theory, Research, and Applications*. Cambridge, MA: MIT Press.
- Gilhooly KJ (2007) Divergent thinking: Strategies and executive involvement in generating novel uses for familiar objects. *British Journal of Psychology* 98(4), 611–625.
- Goldschmidt G and Smolkov M (2004) Design problems are not of a kind: Differences in the effectiveness of visual stimuli in design problem solving. In *3rd International Conference on Visual and Spatial Reasoning in Design Massachusetts Institute of Technology*, Cambridge, USA 22–23 July 2004.
- Goldschmidt G and Smolkov M (2006) Variances in the impact of visual stimuli on design problem solving performance. *Design Studies* 27(5), 549–569.
- Guilford JP (1950) Creativity. *American Psychologist* 5(9), 444–454. <https://doi.org/10.1037/h0063487>.
- Guilford JP (1956) The structure of intellect. *Psychological Bulletin* 53(4), 267–293. <https://doi.org/10.1037/h0040755>.
- Han J, Shi F, Chen L and Childs PR (2018) The Combinator—a computer-based tool for creative idea generation based on a simulation approach. *Design Science* 4, e11.
- Hanafy NO (2023) Artificial intelligence's effects on design process creativity: A study on used AI text-to-image in architecture. *Journal of Building Engineering* 80, 107999.
- Heimer A (2023) The role of aesthetics in design education: Leverage of creativity through concrete and abstract form exploration. *Techné serien-Forskning i slöjdpedagogik och slöjdetenskap* 30(1), 31–45.
- Hou G and Wang X (2024) Emotional valence and arousal: The impact of AI-generated image stimuli on design creativity. *International Journal of Technology and Design Education*, 35, 1103–1122.
- Howard TJ, Dekoninck EA and Culley SJ (2010) The use of creative stimuli at early stages of industrial product innovation. *Research in Engineering Design* 21, 263–274.
- Isola P, Zhu JY, Zhou T and Efros AA (2017) Image-to-image translation with conditional adversarial networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 1125–1134).
- Jang SH, Oh B, Hong S and Kim J (2019) The effect of ambiguous visual stimuli on creativity in design idea generation. *International Journal of Design Creativity and Innovation* 7(1–2), 70–98.
- Jansson DG and Smith SM (1991) Design fixation. *Design Studies* 12(1), 3–11.
- Jin XE, Dong H, Evans M and Yao A (2024) Inspirational stimuli to support creative ideation for the design of AI-powered products. *Journal of Mechanical Design*, 146(12), 1–20.
- Joynt V, Cooper J, Bhargava N, Vu K, Kwon OH, Allen TR ... Radaideh MI (2023) A Comparative Analysis of Text-to-Image Generative AI Models in Scientific Contexts: A Case Study on Nuclear Power. arxiv preprint, [arxiv:2312.01180](https://arxiv.org/abs/2312.01180). <https://doi.org/10.48550/arXiv.2312.01180>
- Kang JKS, Meurzec RW, Chia PZ, Wood KL, Koronis G and Silva A (2019) Assessing the impact of abstract representations and reframing of design brief information on creative ideation. *Proceedings of the Design Society: International Conference on Engineering Design* 1(1), 279–288. [10.1017/dsi.2019.31](https://doi.org/10.1017/dsi.2019.31).
- Karras T, Laine S and Aila T (2019) A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. pp. 4401–4410.
- Kaufman JC and Beghetto RA (2009) Beyond big and little: The four c model of creativity. *Review of General Psychology* 13(1), 1–12.
- Kaufman JC, Plucker JA and Baer J (2008) *Essentials of Creativity Assessment*. Hoboken, NJ: John Wiley & Sons.
- Ko HK, Park G, Jeon H, Jo J, Kim J and Seo J (2023) Large-scale text-to-image generation models for visual artists' creative works. In *Proceedings of the 28th International Conference on Intelligent User Interfaces*. pp. 919–933.
- Ku H and Lee M (2023) TextControlGAN: Text-to-image synthesis with controllable generative adversarial networks. *Applied Sciences* 13(8), 5098.
- Kwon E, Rao V and Goucher-Lambert K (2023) Understanding inspiration: Insights into how designers discover inspirational stimuli using an AI-enabled platform. *Design Studies* 88, 101202.
- Lee Y and Chiu C (2023) The impact of AI text-to-image generator on product styling design. In *International Conference on Human-Computer Interaction*. Cham: Springer Nature Switzerland. 502–515.
- Lewis M (2023) AIXArtist: A First-Person Tale of Interacting with Artificial Intelligence to Escape Creative Block. *Proceedings of the 15th ACM Conference on Creativity and Cognition (C&C '23)*, June 19–21, 2023, Online. ACM, New York, NY, USA. <https://doi.org/10.1145/3591196.3593202>
- Liao J, Hansen P and Chai C (2020) A framework of artificial intelligence augmented design support. *Human-Computer Interaction* 35(5–6), 511–544.
- Lim J, Leinonen T, Lipponen L, Lee H, DeVita J and Murray D (2023) Artificial intelligence as relational artifacts in creative learning. *Digital Creativity* 34(3), 192–210.
- Lin H, Jiang X, Deng X, Bian Z, Fang C and Zhu Y (2024) Comparing AIGC and traditional idea generation methods: Evaluating their impact on creativity in the product design ideation phase. *Thinking Skills and Creativity* 54, 101649.
- Lively J, Hutson J and Melick E (2023) Integrating AI-generative tools in web design education: Enhancing student aesthetic and creative copy capabilities using image and text-based AI generators. *Journal of Artificial Intelligence and Robotics* 1(1), 23–33.
- Lyu Y, Shi M, Zhang Y and Lin R (2023) From image to imagination: Exploring the impact of generative AI on cultural translation in Jewelry design. *Sustainability* 16(1), 65.
- Mansimov E, Parisotto E, Ba JL and Salakhutdinov R (2015) Generating images from captions with attention. arxiv preprint, [arxiv:1511.02793](https://arxiv.org/abs/1511.02793). <https://doi.org/10.48550/arXiv.1511.02793>
- McKim RH (1980) *Experiences in Visual Thinking*. Monterey, CA: Brooks/Cole
- Mohanani R, Turhan B and Ralph P (2019) Requirements framing affects design creativity. *IEEE Transactions on Software Engineering* 46(12), 1318–1339. <https://doi.org/10.1109/TSE.2019.2909033>.
- Nichol A, Dhariwal P, Ramesh A, Shyam P, Mishkin P, McGrew B, ... Chen M (2021) Glide: Towards photorealistic image generation and editing with text-guided diffusion models. arxiv preprint, [arxiv:2112.10741](https://arxiv.org/abs/2112.10741). <https://doi.org/10.48550/arXiv.2112.10741>.
- O'Quin K and Besemer SP (1989) The development, reliability, and validity of the revised creative product semantic scale. *Creativity Research Journal* 2(4), 267–278. <https://doi.org/10.1080/10400418909534321>.
- Oh C, Song J, Choi J, Kim S, Lee S and Suh B (2018) I lead, you help but only with enough details: Understanding user experience of co-creation with artificial intelligence. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. pp. 1–13.
- Ramesh A, Pavlov M, Goh G, Gray S, Voss C, Radford A, ... Sutskever I (2021) Zero-shot text-to-image generation. arXiv preprint, [arXiv:2102.12092](https://arxiv.org/abs/2102.12092).
- Runco MA and Charles RE (1993) Judgments of originality and appropriateness as predictors of creativity. *Personality and Individual Differences* 15(5), 537–546. [https://doi.org/10.1016/0191-8869\(93\)90337-3](https://doi.org/10.1016/0191-8869(93)90337-3).
- Runco MA and Jaeger GJ (2012) The standard definition of creativity. *Creativity Research Journal* 24(1), 92–96. <https://doi.org/10.1080/10400419.2012.650092>.
- Saharia C, Chan W, Saxena S, Li L, Whang J, Denton EL, Ghasemipour SKS, Ayan BK, Mahdavi SS, Lopes RG, Salimans T, Ho J, Fleet DJ, Norouzi M

- (2022) Photorealistic text-to-image diffusion models with deep language understanding. *Advances in Neural Information Processing Systems* 35, 36479–36494.
- Shi F, Chen L, Han J and Childs P** (2017) A data-driven text mining and semantic network analysis for design information retrieval. *Journal of Mechanical Design* 139(11), 111402.
- Smith SM** (1995) Fixation, incubation, and insight in memory and creative thinking. *Creativity Research Journal*, 8(4), 345–353. https://doi.org/10.1207/s15326934crj0804_1
- Sternberg RJ** (1999) *Handbook of Creativity*. Cambridge, UK: Cambridge University Press
- Torrance EP** (1966) *Torrance tests of creative thinking: Norms-Technical Manual*. Princeton, NJ: Personnel Press.
- Tsidylo IM and Sendra CE** (2023) Artificial intelligence as a methodological innovation in the training of future designers: Midjourney tools. *Information Technologies and Learning Tools* 97(5), 203.
- Turchi T, Carta S, Ambrosini L and Malizia A** (2023) Human-AI co-creation: Evaluating the impact of large-scale text-to-image generative models on the creative process. In *International Symposium on End User Development*. Cham: Springer Nature Switzerland, pp. 35–51.
- Wadinambiarachchi S, Kelly RM, Pareek S, Zhou Q and Velloso E** (2024) The effects of generative AI on design fixation and divergent thinking. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. pp. 1–18.
- Xu T, Zhang P, Huang Q, Zhang H, Gan Z, Huang X and He X** (2018) Attngan: Fine-grained text to image generation with attentional generative adversarial networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. pp. 1316–1324.
- Zhu JY, Park T, Isola P and Efros AA** (2017) Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE International Conference on Computer Vision*. pp. 2223–2232.