International Association of Societies
of Design Research Congress 2023
LIFE-CHANGING DESIGN

Politecnico di Milano
9-13 October 2023

Rethinking designer agency: A case study of co-creation between designers and AI

Guo, Xinyu[a]; Xiao, Yi*[a]; Wang, Jiaqi[a]; Ji, Tie[a]

[a] School of Design, Hunan University, Changsha, China
* yixiao_csee@hnu.edu.cn

doi.org/10.21606/iasdr.2023.478

The creativity exhibited by generative artificial intelligence (AI) has caused anxiety among some designers. This generative ability has a tremendous influence on the creative activities of designer. Therefore, this study aims to explore the process of co-creation between designers and generative AI, investigate the impact of generative AI on designers' creative activities and its underlying mechanisms, and explore how designers utilize agency to respond to this new challenge. Based on the theory of creative segment, a human-AI co-creative segment model is proposed to elucidate the mechanism of AI-augmented design. An observational study was conducted on a workshop where designers and generative AI collaborated in creating a design. Through analysing designers' cognitive behaviour during this process, their agency was identified, and three interactive modes of human-AI co-creation were proposed. Based on the above analysis, this study reflects on the current state of designer design and AI-augmented design tools, proposing that AI and designers should evolve collaboratively, and designers should exert their agency when facing new technologies like AI. Relevant tools and research should also aim to facilitate this process.

Keywords: agency; human-AI collaboration; generative AI; AI-augmented design

1 Introduction

Artificial Intelligence (AI) is experiencing the fourth tide, as machines attempt to create meaningful and beautiful things, creating a new category known as " Generative AI" (Sonya et al., 2022). As a technology that showcases computer creativity and has the potential to become a practical tool, generative AI has gained widespread attention from designers. When midjouney demonstrated its powerful creativity in image generation, illustrators and designers began to experience AI anxiety (Li & Huang, 2020). However, despite some designers' concerns that AI will replace their work, others have seamlessly integrated AI tools into their design processes (Kocaballi, 2020). What factors contribute to different designers' effectiveness in Generative AI design?

Previous research has shown that AI can serve as an image generator (Figoli et al., 2022) in the designer's conceptualization phase, providing rapid visual feedback that catalyzes the evolution of the designer's idea into a design concept (Karimi et al., 2020; Sun et al., 2013). The specific role of visual feedback is to drive the iteration of internal ideas through external representations. Building upon the creative segment theory of Sun et al. (2013), we propose a co-creative segment model for the ideation stage, aimed to better understand the interaction between designers and AI, demonstrating AI's enhancing role in design.

However, what causes different designers to have different effects when using AI for design? It is necessary to explore the factors that influence human-machine relationships. Sun et al. (2020) proposed the concept of degree of agency between human and machine to build a good human-machine relationship. Agency is a concept in philosophy that refers to the ability of actors to act in a given environment (Wilson & Shpall, 2016). In this article, we discuss the concept of designer agency, which refers to the designer's ability to perform design cognition behaviours in the given design task context. Is the specific process of interaction between designers and generative AI consistent with our proposed model, and how does it demonstrate different designer agency? A series of questions prompted us to conduct an open workshop.

Our paper intends to make the following contributions to the existing design literature:

- Proposing a human-AI co-creative segment model for the ideation process
- Validating the model through an observational experiment, observing three types of interaction patterns between humans and AI
- Summarizing the expression of designers' agency in human-AI co-creation and proposing reflections.

2 Related work

2.1 AI as visual stimuli in the ideation process

Ideation is one of the core stages in the design process, which is a creative process for designers to generate, develop, and communicate new ideas (Kim & Maher, 2023). Designers generate design ideas through ideation, and then generate different concepts to produce innovative design solutions (Akin, 1990; Atman et al., 1999; Brophy, 2001; Cross, 2001; Liu et al., 2003). Ideation is the process from design ideas to design concepts, which includes different modes of expression. In this process, designers externalize their ideas through sketching and other means, and receive visual stimuli feedback to continuously deepen their ideas until a design concept is generated. AI can serve as a powerful medium to augment human creativity, especially when it plays the role of visual stimuli (Karimi et al., 2020; Sun et al., 2013). Whether intentional or random, designers can draw inspiration from AI. In summary, AI can provide visual stimuli feedback to designers to assist them in the ideation stage.

2.2 Human-machine relationship and designers' agency

To explore how to build a good human-machine relationship, relevant research has been conducted from different perspectives. (Figoli et al., 2022) summarized the relationship between AI and designers in the collaborative process from the different roles played by AI and designers. Due to AI's participation in the design process, it can complete more and more operational tasks, and designers take the lead in the process and become the designer arbiter responsible for evaluating and making choices (Figoli et al., 2022). Crouser & Chang (2012) explored the affordances provided by AI and humans in the collaborative interaction process from the perspective of interaction theory, demonstrating the interaction possibilities in the human-machine collaborative process and the extent to which they can be utilized. In the early field of human-machine engineering research, scholars used function allocation to quantitatively specify the functional tasks of humans and machines in the human-machine collaborative process (Dekker & Woods, 2002; Jordan, 1963; Price 1958). However, current generative AI is not only used for analysing problems but also for generating images to assist in creative activities, which has a profound impact on the creative process of designers. We need to re-examine the impact of AI on designers in the collaborative process of generative AI and designers, as well as designers' response to it. This article represents the abilities of humans and machines in the collaborative creation process using agency.

Sun et al. (2020) proposed that the distribution of human-machine agency is a key issue in human-machine intelligent cooperation, which refers to how the agency of humans and machines is allocated in the collaboration between them. By clarifying the agency range of intelligent systems, including the boundary of their behavioural and decision-making abilities, and fully considering human agency, the agency of humans and machines can form a good match in collaboration. In philosophy, agency refers to the ability of an actor to act in a given environment. Chakraborti & Kambhampati (2018) discussed the relevant issues of human mental modeling to promote effective human-machine collaboration, including the representation of psychological states, to understand the abilities and cognitive characteristics of humans in the loop. This article attempts to analyse the agency of designers in the workshop process, which promotes effective human-machine collaboration, based on the design cognitive behaviours they perform in the context of a given design task.
From a cognitive perspective, design can be divided into two parts: information processing and decision-making activities, which include specific behaviors. Information processing activities describe how to access, use, and generate information. These activities include accessing information about design requirements, monitoring progress, clarifying and checking key design objectives, and verifying how the solution meets design requirements, etc. Specific activities such as monitoring, organizing, accessing, clarifying, checking, and evaluating can be used to represent categories of encoded information processing behaviors. Decision-making activities mainly focus on what types of changes have been made to the design state. These include redefining design constraints, modifying solutions to improve performance, and planning and revising design tasks. Encoded categories include changes to design plans, problem representations, or solution representations (Adams & Atman, 1999).

3 The model of human-AI design process

To guide us in better understanding the interaction between designers and AI, while also demonstrating the specific manifestations of AI-augmented design and its underlying mechanisms, this study proposes a model human-AI co-creative segment in ideation stage (as figure 1) based on the concept of creative segments in the sketching process (Sun et al., 2013). The ideation process is the process by which a designer goes from a design idea to a design concept. This process is often facilitated through the utilization of prototype tools such as sketches, physical models, and digital models, contributing to the construction of cognitive objects. These prototype tools not only facilitate the transition from abstraction to concretization, but also support the establishment of consensus with other stakeholders, such as team collaborators (Beltagui et al., 2023). Designers typically externalize their internal ideas using conventional means, including traditional sketches, to acquire visual feedback and progressively refine their concepts until a design concept takes shape. When AI participates in this process, its capability for rapid image generation enables it to potentially serve as a low-fidelity design prototyping tool that could replace traditional sketches in providing visual feedback. Specifically, we divide the process into two stages: from idea to concept formation, and from concept formation to complete visual presentation. The former is mainly the process by which a designer forms a concept from a design idea in their mind, during which AI mainly stimulates the designer's internal ideas to continually deepen through visualizing the ideas expressed by the designer. The latter is mainly the process by which a designer presents a fully-formed design concept, with the designer controlling the AI input to present the visual effects formed in their mind.

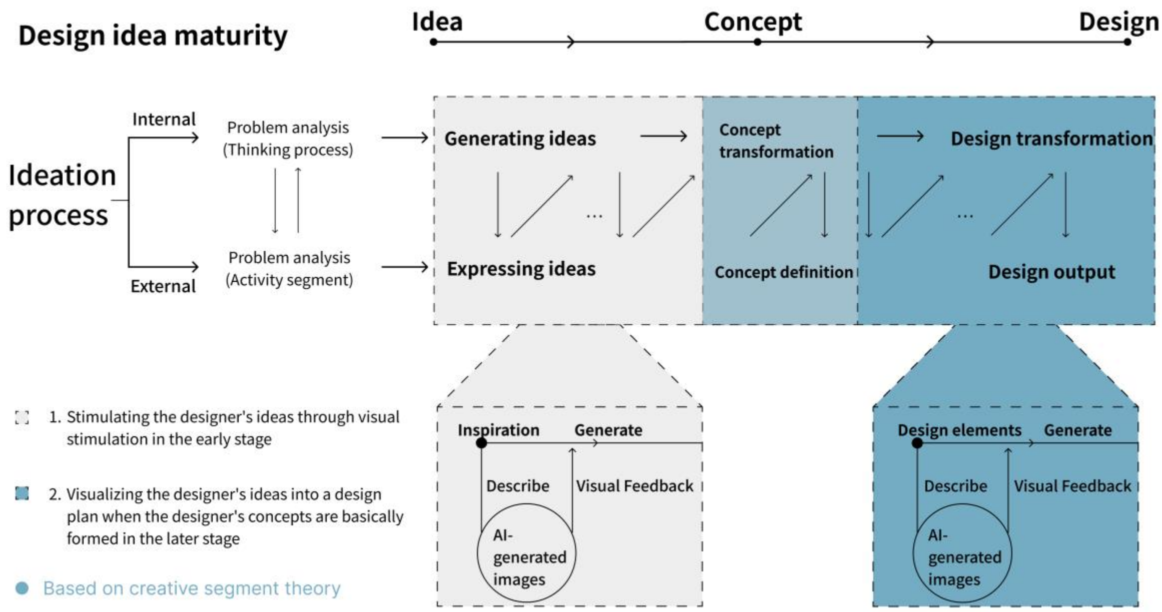


Figure 1. The model of human-AI co-creative segment in ideation stage.

4 Method

Based on the guidance of the human-AI co-creative segment in ideation design stage model proposed in the previous section, which explores the role of AI-augmented design and the forms of human-AI interaction, we conducted an open workshop to examine the specific process of human-AI co-creation and test the validity of our model. Through observation and analysis, we also explored the performance of designers' agency in the process of human-AI co-creation. In order to explore the research question more openly, we did not set too many restrictive conditions, aiming to provide a space for designers to fully exert their agency and explore the core of the problem. We set the theme of "designing future VR glasses" which is conceptual and personalized styling in conceptual design. We recruited 20 participants (7 males/ 13 female, aged 19 to 38 with backgrounds in Industrial design, Computer Science (Table 1). During the grouping process, we tried to balance the composition of each group by including one student with a computer background to assist other students in using AI generation tools quickly and efficiently. At the same time, we ensured that all members of each group had prior experience collaborating with one another. To ensure that there is a good history of teamwork among members within each group and to maintain one member with a computer science background and four members with design backgrounds in each group, we made appropriate personnel arrangements. In the workshop, each group was invited to follow the rapid creative modeling concept design, focusing on the theme and co-creation, and each group output two conceptual design proposals. We provided three points of consideration: user groups, usage scenarios, and styling intentions, and suggested possible uses for AI: mainly to quickly visualize ideas, secondly to communicate quickly with team members to reach consensus, and other application scenarios. Before the formal AI generation workshop, our research team conducted effectiveness trials of existing AI tools and selected tools suitable for conceptual design, while also creating instructional documents to allow participants to try and familiarize themselves beforehand. We selected AI generation tools suitable for different design scenarios, including Midjouney for generating scene graphs, Huggingface for making local adjustments, and WenXinYiYan for generating sentences. We observed and recorded all materials used or created by all participants, and finally, all participants were invited to participate in semi-structured interviews. During these interviews, we explored the following aspects:

1. The extent to which AI generation tools assisted participants in their design process, including their feelings and reflections on collaborating with AI, explanations of design actions captured in screen recordings, and interpretations of recorded verbal language.
2. We also investigated team collaboration issues, aiming to understand the impact of AI generation tools on collaborative teamwork.

The textual records of the interviews not only validated our analysis of participants' design behaviors in alignment with their actual design process but also facilitated the coding and analysis of participants' behaviors.

Table 1. The participants' information of the workshop

Group	ID	Background	Occupation	Indus. Exp. Tears	Familiarity with AI
1	1-1	Industrial Design	Student/ MA	4-7	Used
	1-2	Industrial Design	Student/ MA	4-7	Used
	1-3	Industrial Design	Student/ BS	0-4	Used
	1-4	Computer Science	Student/ PhD	0	In-depth research
	1-5	Industrial Design	Student/ MA	4-7	Used
2	2-1	Industrial Design	Student/ MA	4-7	Used
	2-2	Industrial Design	Student/ PhD	7-10	Used
	2-3	Computer Science	Student/ PhD	0	In-depth research
	2-4	Industrial Design	Student/ PhD	7-10	Used
	2-5	Industrial Design	Student/ MA	4-7	Used
3	3-2	Industrial Design	Student/ MA	4-7	Used
	3-3	Industrial Design	Student/ MA	4-7	Used
	3-4	Computer Science	Student/ PhD	7-10	In-depth research

	3-5	Industrial Design	Student/ BS	0-4	Used
4	4-1	Industrial Design	Student/ MA	4-7	Used
	4-2	Industrial Design	Student/ MA	4-7	Used
	4-3	Industrial Design	Student/ PhD	7-10	Used
	4-4	Industrial Design	Student/ MA	4-7	Used
	4-5	Computer Science	Student/ PhD	0	In-depth research

5 Result

This section will demonstrate the co-creation process between designers and AI. There were four groups participating in the workshop, with one group using traditional brainstorming methods to generate design ideas, and later incorporating AI in idea generation and representation. The other groups used AI to generate design ideas from the outset. The group using traditional brainstorming exhibited significant designer agency, demonstrating that designers maintained ample design thinking even after AI intervention, and ultimately exhibited good human-AI co-creation in the presentation. However, the other groups that directly used AI in design showed less than ideal collaboration with AI. Therefore, we compared and analysed the effectiveness of these two design strategies based on the four design stages of the double-diamond model.

5.1 Discover: idea generation-idea expression

In the discover stage, designers aimed to collect inspiration and find a design direction. This can usually be achieved through three methods: spontaneous inspiration, analysis and reasoning, and associative abstraction and contrast. These results illustrated in Table 2.

Table 2. The results of the first stage

	Traditional brainstorming group	**AI-involved group**
prompt	"VR glasses, line pipes, technology sense, cool, fashion props, signage - tips, shopping social"	"Doctor, glasses, surgery"
output		

The traditional brainstorming team demonstrated their agency in the following ways:

- Monitoring: Members realized that "the key words should be intention keywords, just saying functional vocabulary does not belong to brainstorming" in this design phase.
- Organization: They proposed to divide the divergent keywords they came up with into three categories: "concerts and education, what I wrote are all scenes", "this is function", "this is style".
- Planning: After a round of brainstorming, they proposed to "use the keywords of the three categories (scenes, style, function) to generate a chart" to test the effectiveness of the previous brainstorming work.
- Clarification: Members used association and analogy to discuss each other's ideas, "Harajuku style, pedestrian street, it's very Japanese, right?" "Is it Y2K?".
- Reflection: The image generated by the AI was not ideal, and they immediately reflected on the accuracy of the design description, "The keywords are not enough, we need more" and "We need to find more associative meanings for the keywords".

On the other hand, the AI-assisted design team demonstrated their agency in the following way:

- Intuition: "AI helped me think, it met my requirements at that time, and we reached a consensus on this picture." It was a state of choosing a certain solution without any reason.

Comparing the two, the traditional brainstorming team effectively leveraged the agency of the designers by stimulating their organizational ability and visualizing their ideas. The traditional team was able to reflect on the difference between the images and ideas generated by AI and their own concepts, while the AI-assisted team showed disappointment in the lack of conceptual inspiration brought by the AI-generated images.

Ultimately, the traditional brainstorming team once again demonstrated their agency by organizing and planning for the next step, while the AI-assisted team did not adjust their plan for the next step and continued to rely on AI to provide inspiration and topics for their designs.

5.2 Define: concept transformation-concept definition

In the definition stage, the designer's goal is to converge thinking and evaluate ideas. These results illustrated in Table 3.

Table 3. The results of the second stage

	Traditional brainstorming team	**AI-involved team**
prompt	"Bionic, fox mask, fashionable eye makeup, dance party"	"Future scene, doctor, glasses, surgical operation "
output		

Traditional brainstorming team's initiative reflected:

- Planning: After the first attempt of AI-generated images, they reflected on the issue of "the keywords are not sufficient, we need to describe the fashionable way in our minds" and planned to come up with new keywords.
- Improvement: They found that the description of keywords has a decisive effect on the quality of image generation. "Fashionable" is too broad, and they optimized and iterated their previous ideas by expanding and refining it, such as earrings and eye makeup.
- Feedback: The generated images were "cool" and inspired them to come up with new vocabulary. This stimulated team members to retrieve and invoke relevant information in their minds, leading to words such as "sexy" and "leather".

AI-involved team's initiative reflected:

- Intuition: "The image in the top left corner fits my feeling well."

Comparing the two, the traditional brainstorming team uses accurate keywords to describe their ideas, while the AI-involved team uses more generalized words to expect AI-generated images. The traditional brainstorming team reflects on and critiques the images, differentiating their own ideas from the new inspirations brought by AI images, and extracting unexpected visual elements from AI-generated images. On the other hand, the AI-involved team does not refine and summarize the images that bring new inspirations too much, and only starts the next stage of generation after finding a direction. In the end, the traditional brainstorming team has a clear plan for the next steps, which is to converge and deep-think the concepts to define their own design direction, while the AI-involved team's next plan is still vague.

5.3 Develop: concept definition-design transformation

In the third stage, designers expect AI to complete their vague design concepts in their minds. If AI does not achieve the desired effect, designers will supplement the design concepts through their own thinking. These results illustrated in Table 4.

Table 4. The results of the third stage

	Traditional brainstorming team	**AI-involved team**
prompt	"Bionic, fox mask, fashionable eye makeup, dance party"	"Personalization, exclusive, full coverage, lines, arcs, lamp strips, clear glass, minimalist style" "Mechanical, Computer Graphics, metal, head-mounted VR glasses, techwear mask, many details"
output		

Traditional Brainstorming Group - Designer Initiative Reflecting:

- Evaluation: The designers in the traditional brainstorming group use design themes to describe words such as materials, scenes, and atmosphere, and evaluate the compatibility of the AI-generated results with their conceptual ideas: "Through these images, we can determine the color schemes of some design themes and showcase the elements we want."
- Reflection: Evaluating the generated images as "more like decorations for VR glasses" and proposing the key to problem-solving: "We need to change the keywords."

AI Direct Involvement Group - Designer Initiative Reflecting:

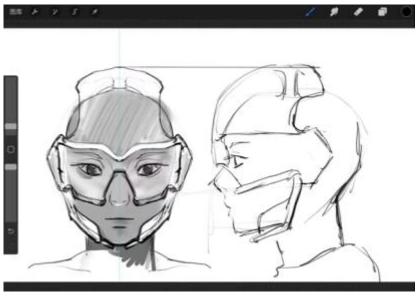
- Planning: Proposing the principle of selecting images based on "inputting curves, glass, and starting from the word that matches our requirements."
- Selection: In the limited time, designers in the AI direct involvement group choose the styling that is easier to create visual effects as the output: "So, should we go for minimalist or mechanical styling? We won't be able to finish drawing everything, minimalist is easier to draw."

Comparison reveals that the traditional brainstorming group emphasizes the accuracy of word usage when inputting keywords, aiming to generate styling that is most relevant to the concept. In contrast, the descriptions from the AI direct involvement group may be more random in the generated results.

5.4 Deliver: design transformation-design output

In the final stage, the designers in the traditional brainstorming group mainly focus on the visual representation of the styling design concepts, using visual means to quickly express their design concepts by utilizing the key elements determined through previous collection. These results illustrated in Table 5.

Table 5. The results of the fourth stage

	Traditional brainstorming team	AI-involved team
prompt	"Bionic, fox mask, fashionable eye makeup, dance party"	/
output		

Traditional Brainstorming Group's Designer Initiative Reflected:

- Evaluation: After multiple adjustments to input keywords, the traditional brainstorming group generated an image that "received appreciation from all members and matched our expectations," with "realistic images and even models trying on the designs. The style is fashionable and futuristic, in line with the design theme, and the rendering also has high quality." The quality of this proposal was evaluated.
- Selection: The traditional brainstorming group analyzed the multidimensional aspects of the image and decided to use this image as the design proposal. "I think this style looks great, and this is our final product."

AI's Direct Intervention in the Designer's Initiative Reflected:

- Planning: Even though AI directly intervened in the group's design process, it did not stop at the image generated by AI. The designer issued a task to the team: "Everyone can diverge their own ideas and draw a perspective view based on this image."
- Improvement: Using their drawing skills to complement the deficiencies of the AI-generated design, the designer defined their own design style based on the inspiration provided by AI.

Comparison reveals that the traditional brainstorming group successfully obtained a visual proposal that matches the design concept through continuous trial and modification of keywords. However, the AI directly intervened group faced difficulties in the generation process. Despite fine-tuning of keywords, the generated image still could not meet the designer's requirements. For example, the designer may be satisfied with the style of the headphones but unable to adjust the orientation of the wearer's face, and can only manually adjust it in software such as Photoshop. As designers find it difficult to directly convey the visual image in their mind to AI, AI cannot fulfill the role of an intelligent image editing assistant as envisioned by the designers, but this is the most urgent need of designers at this design stage.

6 Discussion and conclusion

6.1 Designer agency

Table 6. Comparison chart of two groups' agency.

Stage	Traditional brainstorming team	AI-involved team	Agency of Machines	Key Role of Agency	Differences in Agency
1	Monitoring, Organizing, Planning, Clarifying, Reflecting	Planning, Intuition	1.Challenging Human Blurriness with Clear Images 2.Manifesting Designer's Expressive Differences 3.Randomness Brings Additional Inspiration	1.Fully leverage design ideas 2.Think independently without interruptions 3.Criticism can help clarify ambiguous intentions within teams	In traditional teams, the emphasis is on team members' proactivity in monitoring, organizing, planning, clarifying, and reflecting. In contrast, in AI-involved teams, AI provides visual stimuli, and designers rely more on intuition. Image information provides designers with more direct insights.
2	Planning, Improvement, Access	Intuition	1.Extra Inspiration from Randomness	1.Clarify ideas 2.Express ideas using concrete vocabulary	In traditional teams, the focus is on team members' planning and arranging in defining problems, continuous improvement and optimization of solutions, as well as necessary information access and retrieval. In contrast, in AI-involved teams, intuition serves as a primary cognitive behavior, which may indicate that AI, as a tool or resource, has relatively lower proactivity and cannot actively participate in various cognitive

					behaviors like human members do, resulting in a slower design progress in AI-involved teams.
3	Evaluation，Reflection	Planning, Selection	1.Challenging Human Blurriness with Clear Images 2.Reflecting Designers' Expressive Differences	1.Evaluate images generated by AI 2.Provide feedback on keyword modifications	In the cognitive behavior of AI directly participating in the group, through the second round of brainstorming, designers may discover the advantages of AI's autonomy, manifested in the ability to re-plan and make choices.
4	Evaluation，Selection	Planning, Improvement	1.Generating Descriptive Images 2.Additional Effects from Randomness	1.Embrace criticism to achieve objectives 2.Iterate on keyword modifications continuously 3.Refine image details through modifications	In this stage, designers who are directly involved in the group with AI provide feedback on AI's proposals, indicating a lack of autonomy in evaluation, reflection, and other cognitive behaviors between early concept definition and design conversion. This inconsistency in design output with original ideas may be caused by the lack of autonomy in evaluating and reflecting on AI's proposals.

The most intuitive representation of the difference in team proactivity between the two design teams can be observed from the Table 6. The biggest difference lies in the divergent cognitive behavioral preferences in team proactivity. In the traditional brainstorming team, the emphasis is placed on the proactive participation of team members. In the AI direct involvement team, the AI-generated images are used as the focal point of discussion, and the design team's space for proactive engagement may be occupied by the proactivity of the machine. This indirectly leads to the phenomenon of design team proactivity being suppressed: as the design activity approaches its conclusion, designers in the AI direct involvement team may actually be dissatisfied with the results generated by the AI, and eventually choose to use their own proactivity to regain the lost initiative in the earlier stages. This is also related to the limited expression of design team proactivity in the early stages: designers may feel that the images generated by AI do not effectively convey their own ideas in the early stages, but still leave room for their own proactivity to be expressed through AI.

6.2 The interaction between designer and AI

The analysis above has validated the two scenarios in which AI provides visual feedback in our proposed human-machine co-creation approach. Additionally, we have identified three modes of interaction between designers and AI, including these two scenarios: interaction between designers and AI, including these two scenarios:

6.2.1 AI-inspired

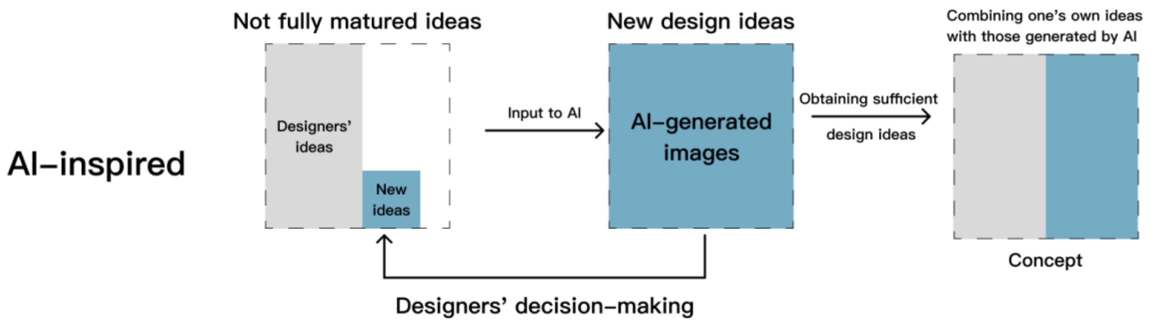


Figure 2. The interaction process of AI inspiring designer.

This interactive scenario (as figure 2) occurs when a designer has a nascent idea for a design problem and describes the idea to an AI, which generates images that contain new ideas. The designer uses the visual stimuli from the AI-generated images to gain new ideas. When the designer has enough ideas, they define the concept by combining their own ideas with the AI-generated ideas. During this process, the results generated by the AI are used for the designer to critique and supplement their own ideas. The new elements from the AI-generated images serve as inspiration for the designer to complement their own nascent ideas, aligning with the initial stages of the model mentioned earlier.

6.2.2 Visualization using AI

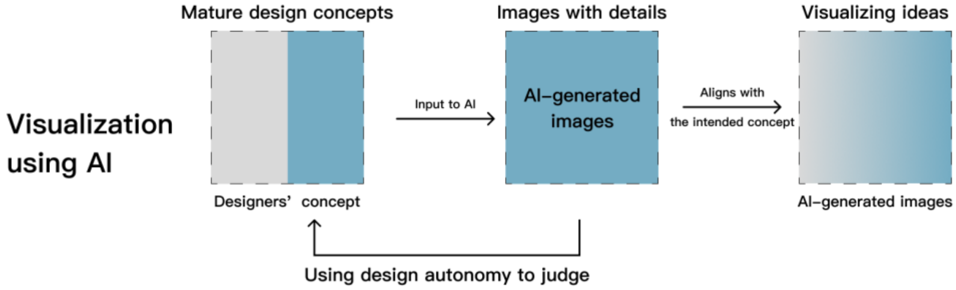


Figure 3. The interaction process of AI visualing designer's idea.

This interactive scenario (as figure 3) occurs when a designer's matured idea has been defined as a concept, and the AI assists the designer in visualizing the idea. The results generated by the AI are used to create a visual representation of the designer's idea, ideally with detailed images that may even surpass the designer's original vision, aligning with the later stages of our model's description.

6.2.3 AI without augmented design

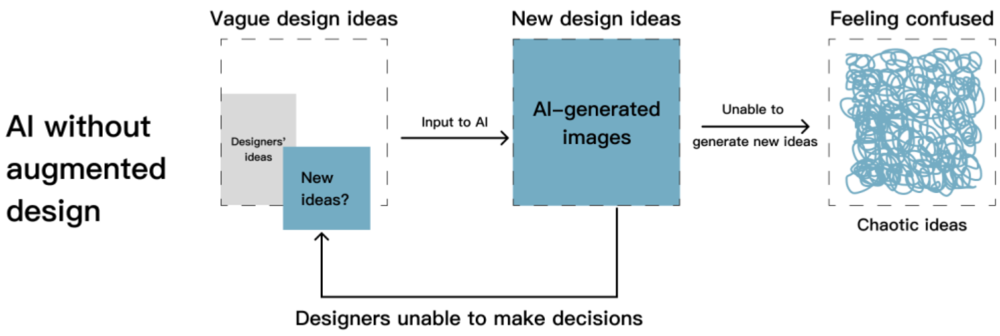


Figure 4. The interaction process of AI does not augment design ideas.

This interactive scenario (as figure 4) occurs when AI is involved in the design process from the beginning, before the designer has started exploring the conceptual space of the design topic. The AI generates a highly detailed image directly from a simple prompt, such as 'VR glasses', causing cognitive load on the designer, as the information-rich image generated by the AI overwhelms the designer's independent thinking process (Zhang et al., 2021). When the designer lacks any design ideas and lacks knowledge in a specific task, they are more likely to rely on machine-generated outputs (Figoli et al., 2022). However, mid-journey and other AI generation tools have not changed the mechanism by which designers trigger AI, and the quality of prompts input to the AI determines the quality of the generated images and whether they align with the designer's needs. When the designer does not thoroughly and critically reflect on their own design proposal and relies solely on AI, the AI cannot generate innovative solutions from keywords related to physical space, ultimately failing to advance deep conceptual space exploration. The designer becomes lost in the process, immersing themselves in obtaining complete design concepts through visual feedback from inputting ideas into AI, and focusing only on exploring object space while neglecting in-depth exploration of conceptual space (Jansson & Smith, 1991).

6.3 Reflection

6.3.1 Reflecting on the current state of designer's design education

The emergence of AI has prompted designers to reflect on their design agency, testing their professional design skills, firm design attitudes and positions, as well as clear and sharp design speculative thinking in the process of collaborating with AI in design (Rowe, 1991). From the disappointment of designers with the generated images from AI in the early stages of the workshop, it can be observed that they expect AI to complement their vague design concepts in their minds. However, when AI fails to fulfilling this expectation, designers need to leverage their design agency. However, the analysis of the results above shows that most groups did not demonstrate enough design agency for a significant portion of the time.

At the same time, we are also considering that the process of AI learning to generate visual images is similar to the process of designers browsing and integrating inspirational images to form design proposals. The difference is that AI far surpasses designers in terms of knowledge learning capability and speed (Sheynin et al., 2022).

6.3.2 Reflection on enhancing conceptual design research with ai and ai-assisted tool design.

Previous research has primarily focused on the application of AI in inspiring and assisting in generating design ideas in conceptual design (Lin et al., 2020; Kazi, et al., 2017; Zhou, et al., 2020). However, our workshop research results indicate that excessive use of AI in the ideation stage of design may result in adverse outcomes, weakening designers' in-depth design thinking and impacting the output of design concepts, especially when AI is involved in ideation too early. We advocate for AI to evolve in tandem with designers, maintaining a similar level of cognitive and understanding of the design task. For example, in the early stages of ideation, AI-generated images should align with the cognitive level of keyword descriptions when designers have vague design ideas. Co-evolving AI can guide designers to demonstrate their design agency during the design process, maximizing the utilization of their professional skills.

In this state, we call on designers to rethink their design agency and reflect on the current state of design (Yun et al., 2022). At the same time, relevant AI tools should stimulate designers' design agency and support design computation tools that are centred around designers' own abilities.

6.4 Conclusion and limitation

The aim of this study is to investigate the reasons behind the two different states of effects that designers may encounter when using AI tools, and propose an interaction model for human-AI co-creation process. The findings of the research indicate that AI can serve as a personalized tool for generating visual feedback and inspiration for designers, but its effective use depends on designers' ability to leverage their design agency. Based on these findings, we reflect on the current state of designers' interaction with AI-assisted design tools and call for efforts from various perspectives to stimulate designers' agency, enabling synergistic evolution between AI and designers. In this "co-evolutionary" partnership, designers and AI always maintain a similar level of cognitive and conceptual understanding of design tasks. They engaging in a continually evolving mutually beneficial collaboration, akin to the concept of " the artifacts are capable of learning and performing a social practice together with people," as described in co-performance (Stoimenova & Price 2020). At the same time, AI-powered generative tools can guide designers to enhance their creative abilities, enabling them to apply their design expertise more effectively.

However, it is important to acknowledge the limitations of our study, which may have restricted a complete simulation of all possible aspects of designer-AI collaboration:

3. Limited Variety of AI Generation Tools: The workshop did not extensively utilize a wide range of AI generation tools, including cutting-edge natural language interaction tools like ChatGPT. This limitation might introduce biases in the interaction patterns between designers and AI. Additionally, the available AI tools have not been specifically trained on datasets targeting the design domain, possibly resulting in suboptimal outputs. Future research could explore the impact of a broader array of AI tools, including those fine-tuned for design-related datasets, to better encompass the diverse facets of designer-AI cooperation.

4. Homogeneity of Workshop Participants: Despite our efforts to include participants from both industrial design and computer science backgrounds, it is important to note that all participants were students from Hunan University and not seasoned professional designers. This may introduce variations in their utilization of AI-generated tools.

These limitations signify that our research might not fully capture all potential scenarios of designer-AI collaboration in the real-world design context.

Additionally, this paper creatively introduces the philosophical concept of agency as an expression of human capability into human-AI co-creation, and through an open description and analysis of a human-AI co-creation workshop, attempts to uncover behavioural manifestations of designers' agency, but lacks a clear theoretical framework and research methodology for investigating designers' agency. Further in-depth research and exploration can be conducted in these areas.

In the future, we plan to explore and conduct more detailed research on human-AI co-creation by distinguishing the interactive dynamics and approaches in various scenarios through the categorization of AI competency levels and complexity levels (Stoimenova & Price 2020; Yang, 2020). This will allow us to delve deeper into the focus of this paper, human-AI co-creation, and provide a more thorough analysis and investigation.

References

Adams, R. S., & Atman, C. J. (1999). Cognitive processes in iterative design behavior. In FIE'99 Frontiers in Education. 29th Annual Frontiers in Education Conference. Designing the Future of Science and Engineering Education. Conference Proceedings (IEEE Cat. No. 99CH37011 (Vol. 1, pp. 11A6-13). IEEE. 10.1109/FIE.1999.839114

Akin, Ö. (1990). Necessary conditions for design expertise and creativity. Design Studies, 11(2), 107-113. https://doi.org/10.1016/0142-694X(90)90025-8

Atman, C. J., Chimka, J. R., Bursic, K. M., & Nachtmann, H. L. (1999). A comparison of freshman and senior engineering design processes. Design Studies, 20(2), 131–152. https://doi.org/10.1016/S0142-694X(98)00031-3

Beltagui, A., Bell, A., & Candi, M. (2023). A sociomaterial perspective on epistemic objects in design practice. Design Studies, 87, 101201. https://doi.org/10.1016/j.destud.2023.101201

Brophy, D. R. (2001). Comparing the attributes, activities, and performance of divergent, convergent, and combination thinkers. Creativity Research Journal, 13(3–4), 439–455. https://doi.org/10.1207/S15326934CRJ1334_20

Chakraborti, T., & Kambhampati, S. (2018). Algorithms for the greater good! on mental modeling and acceptable symbiosis in human-ai collaboration. arXiv preprint arXiv:1801.09854. https://doi.org/10.48550/arXiv.1801.09854

Crouser, R. J., & Chang, R. (2012). An affordance-based framework for human computation and human-computer collaboration. IEEE Transactions on Visualization and Computer Graphics, 18(12), 2859-2868. 10.1109/TVCG.2012.195

Cross, N. (2001). Design cognition: Results from protocol and other empirical studies of design activity. In Charles M. Eastman, W. Michael McCracken & Wendy C. Newstetter(Eds.), Design knowing and learning: Cognition in design education (pp. 79–103). Elsevier. https://doi.org/10.1016/B978-008043868-9/50005-X

Dekker, S. W., & Woods, D. D. (2002). MABA-MABA or abracadabra? Progress on human–automation co-ordination. Cognition, Technology & Work, 4, 240-244. https://doi.org/10.1007/s101110200022

Figoli, F. A., Rampino, L., & Mattioli, F. (2022). AI in design idea development: A workshop on creativity and human-AI collaboration. PROCEEDINGS OF DRS, 1-17. https://doi.org/10.21606/drs.2022.414

Jansson, D. G., & Smith, S. M. (1991). Design fixation. Design studies, 12(1), 3-11. https://doi.org/10.1016/0142-694X(91)90003-F

Jordan, N. (1963). Allocation of functions between man and machines in automated systems. Journal of applied psychology, 47(3), 161. https://doi.org/10.1037/h0043729

Karimi, P., Rezwana, J., Siddiqui, S., Maher, M. L., & Dehbozorgi, N. (2020, March). Creative sketching partner: an analysis of human-AI co-creativity. In Proceedings of the 25th International Conference on Intelligent User Interfaces (pp. 221-230). https://doi.org/10.1145/3377325.3377522

Kazi, R. H., Grossman, T., Cheong, H., Hashemi, A., & Fitzmaurice, G. W. (2017, October). DreamSketch: Early Stage 3D Design Explorations with Sketching and Generative Design. In UIST (Vol. 14, pp. 401-414). https://doi.org/10.1145/3126594.3126662

Kim, J., & Maher, M. L. (2023). The effect of AI-based inspiration on human design ideation. International Journal of Design Creativity and Innovation, 11(2), 81-98. https://doi.org/10.1080/21650349.2023.2167124

Kocaballi, A. B. (2023). Conversational ai-powered design: Chatgpt as designer, user, and product. arXiv preprint arXiv:2302.07406. https://doi.org/10.48550/arXiv.2302.07406

Li, J., & Huang, J. S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. Technology in Society, 63, 101410. https://doi.org/10.1016/j.techsoc.2020.101410

Lin, Y., Guo, J., Chen, Y., Yao, C., & Ying, F. (2020, April). It is your turn: Collaborative ideation with a co-creative robot through sketch. In Proceedings of the 2020 CHI conference on human factors in computing systems (pp. 1-14). https://doi.org/10.1145/3313831.3376258

Liu, Y. -C., Chakrabarti, A., & Bligh, T. (2003). Towards an ‘ideal’ approach for concept generation. Design Studies, 24(4), 341–355. https://doi.org/10.1016/S0142-694X(03)00003-6

Price, H. E. (1985). The allocation of functions in systems. Human factors, 27(1), 33-45. https://doi.org/10.1177/001872088502700104

Rowe, P. G. (1991). Design thinking. MIT press.

Sheynin, S., Ashual, O., Polyak, A., Singer, U., Gafni, O., Nachmani, E., & Taigman, Y. (2022). Knn-diffusion: Image generation via large-scale retrieval. arXiv preprint arXiv:2204.02849. https://doi.org/10.48550/arXiv.2204.02849

Sonya Huang， Pat Grady， GPT-3 (2022, September 28). Generative AI: A creative new world. Sequoia Capital. https://www.sequoiacap.cn/article/generative-ai-a-creative-new-world/

Stoimenova, N., & Price, R. (2020). Exploring the nuances of designing (with/for) artificial intelligence. Design Issues, 36(4), 45-55. 10.1162/desi_a_00613

Sun, L., Xiang, W., Chai, C., Wang, C., & Huang, Q. (2014). Creative segment: a descriptive theory applied to computer-aided sketching. Design Studies, 35(1), 54-79. https://doi.org/10.1016/j.destud.2013.10.003

Sun, X., Zhang, Y., & Qin, J. (2020). Review on human-intelligence system collaboration [J]. PACKAGING ENGINEERING, 41(18), 1-11.10.19554/j.cnki.1001-3563.2020.18.001

Wilson, G., & Shpall, S. (2016). The nature of action and agency. Stanford Encyclopedia of Philosophy.

Yang, Q. (2020). Profiling Artificial Intelligence as a Material for User Experience Design [Carnegie Mellon University]. http://reports-archive.adm.cs.cmu.edu/anon/hcii/abstracts/20-100.html

Yun, G., Cho, K., Jeong, Y., and Nam, T. (2022) Ideasquares: Utilizing generative text as a source of design inspiration, in Lockton, D., Lenzi, S., Hekkert, P., Oak, A., Sádaba, J., Lloyd, P. (eds.), DRS2022: Bilbao, 25 June - 3 July, Bilbao, Spain. https://doi.org/10.21606/drs.2022.484

Zhang, G., Raina, A., Cagan, J., & McComb, C. (2021). A cautionary tale about the impact of AI on human design teams. Design Studies, 72, 100990. https://doi.org/10.1016/j.destud.2021.100990

Zhou, C., Chai, C., Liao, J., Chen, Z., & Shi, J. (2020, December). Artificial intelligence augmented design iteration support. In 2020 13th International Symposium on Computational Intelligence and Design (ISCID) (pp. 354-358). IEEE. 10.1109/ISCID51228.2020.00086

About the Authors:

Xinyu Guo: Xinyu Guo is a master's graduate student at the School of Design in Hunan University, with research focus on intelligent design and collective intelligence.

Yi Xiao: Dr. Yi Xiao is a full professor of the School of Design in Hunan University and the Director of the Digital Culture Innovation Lab. His research interests

include computer graphics, computer vision, machine learning, human-computer interaction, and intelligent design.

Jiaqi Wang: Jiaqi Wang is an undergraduate student at the School of Design in Hunan University, with research focus on intelligent design and service design.

Tie Ji: Dr. Tie Ji is the dean of the School of Design in Hunan University, the secretary general of the Teaching Design Subcommittee of the Industrial Design Department of the Ministry of Education. His research interests include digital communication, immaterial design and sustainable strategy...etc.

Acknowledgement: This work is supported by the National Key R&D Projects (2021YFF0900600).