Proceedings of the Design Society, Volume 5: ICED25
https://doi.org/10.1017/pds.2025.10055

AI as an element to overcome creative fixation in design teams

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ABSTRACT: The aim of this research is to analyze the potential of Generative Artificial Intelligence (GenAI) to support the design process and overcome creative fixation in teams during the initial problem framing, ideation and concept exploration stage. Fixation is a common problem in design, and can be exacerbated during collaborative work due to diverse issues such as team dynamics or perceived hierarchy. Current research is exploring whether AI can help teams overcome this problem or on the contrary, might actually contribute to it. Through a creative ideation workshop with design students, we investigate how AI influences team dynamics as well as the creative results. We propose a conceptual model to work with AI in a team setting.

KEYWORDS: artificial intelligence, creativity, early design phases, teamwork, fixation

1. Introduction

The use of Generative AI is widespread in the design community. Creative teams use it for different activities throughout a design project, including research, analysis, brainstorming, concept generation and concept refinement. Current literature examines the potential of AI as a creative partner, within the concept of co-creativity (Rezwana & Maher, 2023). In this collaborative approach, each agent contributes to the creative product. In most AI models, the interaction occurs in a turn-based manner, where the designer gives instructions and the AI provides a result. However, ongoing research is being conducted on MI-CCs (Mixed Initiative Co-Creative Systems) (Yannakakis et al., 2014; Margarido et al., 2024) where the AI makes suggestions without the designer necessarily initiating an instruction. Additionally, much of the research is focused on how to clarify or elicit the intent of the designer when generating content in an AI model (Kreminsky & Chung, 2024).

Even if AI cannot follow the creative processes of humans, the results it generates could be perceived as creative. Some studies argue that AI can improve novelty, variation and quantity of ideas (Kim & Maher, 2023), enhance divergent thinking (Shaer et al., 2024) and promote abductive reasoning in designers (Guo et al., 2024). However, there is also an ongoing concern about the potential risks of using AI within the creative process, such as homogenization of results (Anderson et al., 2024) and design fixation (Wadinambiarachchi et al., 2024). There is also research on how the use of AI could affect creative team dynamics (Figoli et al., 2022). In this article we explore the potential for AI models, such as Large Language Models (LLMs) and Text to Image Models (TTIs) within design teams during the initial creative phases, in particular during problem-solution framing (Dorst, 2015) and initial concept creation and visualization.

The main research questions for this study were: how do teams collaborate when using AI tools? Does AI help overcome design fixation within teamwork or on the contrary, is it creating fixation? And what behaviour could future AI models adopt to enhance creative performance within a team?

2. Creativity in teams, design fixation and AI

There is a debate regarding whether individuals or groups can have a higher potential for creativity. Some researchers suggest that the knowledge, skills and abilities of a group should be greater than that of one individual, especially if the group is diverse (Paulus & Nijstad, 2003). However, this potential can be hindered by several factors, one of which is design fixation.

Design fixation is a phenomenon originally described by Jansson and Smith (1991), defined as *"a blind adherence to a set of ideas or concepts limiting the output of conceptual design"* (p.3). When given images of a particular design before the start of a creative design task, participants were prone to create similar solutions, even if told not to do so, and even if the inspiration image was not a good solution. Fixation can have different causes. Youmans and Arciszewski (2014) proposed three classifications of fixation: unconscious adherence to the influence of prior designs, conscious blocks to change, and intentional resistance to new ideas. They also distinguish between concept-based design fixation, fixation to a specific class of known design concepts, and knowledge-based design fixation (fixation to a problem-specific knowledge base). Crilly (2015) identified five sub-themes to fixation: exposure to precedents; commitment to initial ideas; project constraints; a blame culture; and the role of the briefing in inducing fixation. Crilly and Cardoso (2017) propose the following definition:

> *"Design fixation is a state in which someone engaged in a design task undertakes a restricted exploration of the design space due to an unconscious bias resulting from prior experiences, knowledge or assumptions" (p.6).*

For the authors "*. . . this could be seen as a cognitive 'error' because areas of the design space are inadvertently left unexplored"* (p.6). According to Crilly (2021):

> *". . . if fixation is more broadly considered as prior experience leading to implicit assumptions that restrict imagination, then fixation can be seen inhibiting the creative work that designers might do with both solutions and problems." (p.324).*

There is ongoing research regarding the effects of the use of AI during the initial concept phase and some studies regarding fixation in teams or groups. Han et al. (2024) analysed group dynamics in teams during a creative task. One aspect that they highlighted was the co-prompting process, in which group members create a prompt for the AI together:

> *". . . the co prompting process could be a double-edged sword, as it may facilitate creative ideation on the one hand to support team collaboration, but also add mental demands of strategic prompting, which could reduce team performance" (p.2).*

They also mention that collaborating with GenAI tools can induce participants to pay more attention to the AI itself rather than to the content being created.

Guo et al. (2023) explored a co-creation with Text to Image Models within four different designer groups. The first group used traditional brainstorming methods and then incorporated AI tools, while the other groups used AI from the beginning. The first group had more design agency, while the other groups had a less ideal collaboration: *". . . the design team's space for proactive engagement may be occupied by the proactivity of the machine"* (p.12).

Lee et al. (2024) explored the potential benefits of conversational agents (CA) based on Large Language Models as a critical element to avoid fixation in group projects. They argue that within teams, fixation can occur due to different hierarchies, opinions and uncomfortable silences, so designers might be more prone to use AI generated information. Therefore, AI can be a fixation element in group settings. The CA could act as a dissenter, questioning group decisions and promoting critical thinking.

There is also concern about reducing effort and creativity by relying too much on AI recommendations, an issue that has been named as algorithmic loafing, based on the term social loafing which refers to minimal effort by an individual within a group (Inuwa-Dutse et al., 2023). *"Akin to social loafing in human interaction, algorithmic loafing may occur when humans mindlessly adhere to machine recommendations due to reluctance to engage analytically with AI recommendations and explanations"* (p.1). In order to observe team collaboration and creativity using AI models, we carried out an exploratory study, which is presented in the following section.

3. Exploratory study

3.1. Participants

We conducted an exploratory study in a workshop format. Participants were recruited through an open invitation to students from all semesters at the Architecture Faculty. The workshop lasted two hours and was led by three facilitators: one teacher and professional designer, and two design students in their final bachelor semester. The facilitators roles included organizing groups, managing time, providing general tips on writing prompts, and assisting with technical issues such as setting up AI platform user accounts. The participants were students from architecture (bachelor's) and industrial design (master's) programs, ranging from the 1st to the 10th (final) semester. We aimed to explore the use of AI in two different disciplines: design and architecture. A total of 19 students (11 male and 8 female) participated, with ages ranging from 19 to 38.

3.2. Previous AI knowledge

Participants previous knowledge in respect to AI use for design was measured with a Likert Scale from 1-5 (1= little and 5=high), with the following results: 1=4, 2=8, 3=3, 4=4 and 5=0 participants respectively. The results show a tendency towards medium-low previous GenAI knowledge. In relation to the use of GenAI for their academic design projects, participants reported never using it (3), sometimes using it (13) and always using it (3). We also asked participants for which design phase they usually apply GenAI: 10 students reported using it in the first phase for research, 6 during the whole project, 2 for brainstorming and concept development and 1 for concept development.

3.3. Design task

The design task started with an open question: how would you minimize garbage production in a domestic environment? We defined this topic as an open, ill-defined or wicked problem (Rittel & Webber, 1973), which could give us more information on how the team would frame the problem-solution space.

Students were organized into 8 teams (5 teams of 2 members and 3 teams of 3 members). The project was carried out in four phases: 1. research, 2. concept creation, 3. concept development, each with a duration of 20 minutes, and 4. a short final presentation describing the design process and workflow of each team, with an allocated time of 5 minutes per team. The groups were instructed to use only an assigned LLM model in the first phase. These models were selected because they can provide feedback, assist in brainstorming and provide ideas on a particular topic. For the second phase, both an assigned LLM and TTI were used. For phase three the groups were encouraged to concentrate on creating a detailed visual of their concept with a TTI. These models were introduced because they can create realistic images to visualize concepts quickly with high quality. The workshop structure based on the four phases was aimed to ensure teams moved on to the next step and were mindful of time. The teams were not given any particular directions on how to organize, work together as a group, or how to give instructions to the AI models, except for some basic prompt strategies. Figure 1 summarizes the workshop structure and usage of AI models within the workshop.

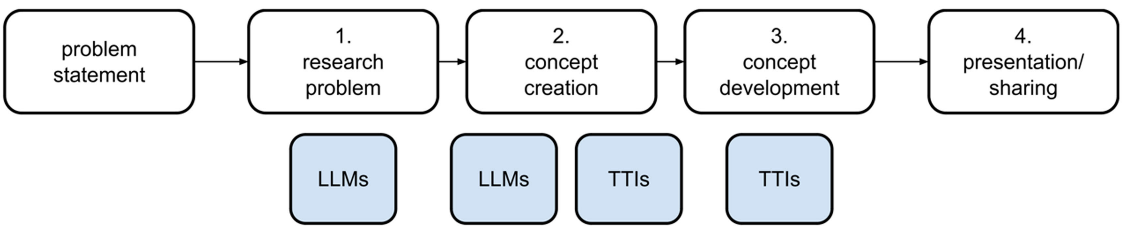

Figure 1. Workshop structure and usage of AI models

During phase 1 the groups used the specific LLMs ChatGPT, Claude.AI, and Gemini. In phases 2 and 3, students continued to use the LLMs and introduced the specific TTI Models Krea.AI, Vizcom, Meta, Leonardo.AI, Dall-E3, and Adobe Firefly. Each group was assigned a particular AI in each phase in a random manner, regardless of the discipline (designers and architects). The models were selected based on the following criteria: accessibility (free trial versions), ease of use and impact of results. Using different models allowed a wide range of possibilities, as well as comparing outputs within groups. The exploration process and results were documented via a Miro board, where teams shared the initial prompts and results, as well as the images generated.

Table 1. AI tools used by each team showing a balanced distribution

	Team 1	Team 2	Team 3	Team 4	Team 5	Team 6	Team 7	Team 8
LLM	Claude	Gemini	Gemini	ChatGPT	ChatGPT	ChatGPT	Claude	ChatGPT
TTI	Dall-e	Vizcom	Firefly	Firefly	KREA.AI	Meta	Leonardo	Leonardo

The workflow of students was observed, and notes were taken during the exercise by the leading researcher. The interaction between students within the group and with AI models was documented. For example, who within the group was instructing the AI, or if students were employing AI models simultaneously, as well as the devices they used such as smartphones, tablets, and laptops. Two teams of two members used laptops each, working in parallel. Three teams of two members used one laptop and a cell phone, while all three teams of three members used one laptop for undertaking the main tasks on this device while also working on their cell phones in parallel. Only one tablet was used.

4. Results

Each team presented a final concept based on images, ranging from highly technological home appliances to architectural solutions and digital services. In the first category, products such as a machine to recycle PET bottles into utensils like plates or cups, a home drinking water filter to reduce bottle consumption, and home organic composting units integrating plants were proposed. As architectural solutions, some teams introduced a sustainability park to raise citizen waste reduction awareness, shared recycling neighbourhood storage spaces and a recycled construction brick made from demolished building material. Only one team presented an app, a service to promote recycling across all actors within the city waste management ecosystem. Finally, one group presented a composting kit for children to teach them how to make their own compost at home and school.

The results were evaluated for overall creativity by two design experts using the Consensual Assessment Technique CAT (Amabile, 1982), based on criteria such as problem framing, similarity to previous existing ideas and context specificity. We found that the design solutions were obvious and generic, thus the solutions not necessarily focused on the specific problems of a context such as Mexico City. The design task in all projects seemed to be approached from a recycling perspective. This could be because the ideas were mainly driven by AI recommendations from phase 1. For example, a common process followed by students was to ask general questions to the AI in the first phase, obtaining general ideas and concepts and then choosing a direction. In the second and third phases, teams used LLMs to generate prompts with descriptions of the images and then copied and pasted the results into the TTI model, a common practice among the design community. Some of the resulting images are shown in Fig. 2. The quality and output of the images varied across the different AI tools, producing different results. This also depended on the prompting strategy and the previous AI knowledge of the groups.

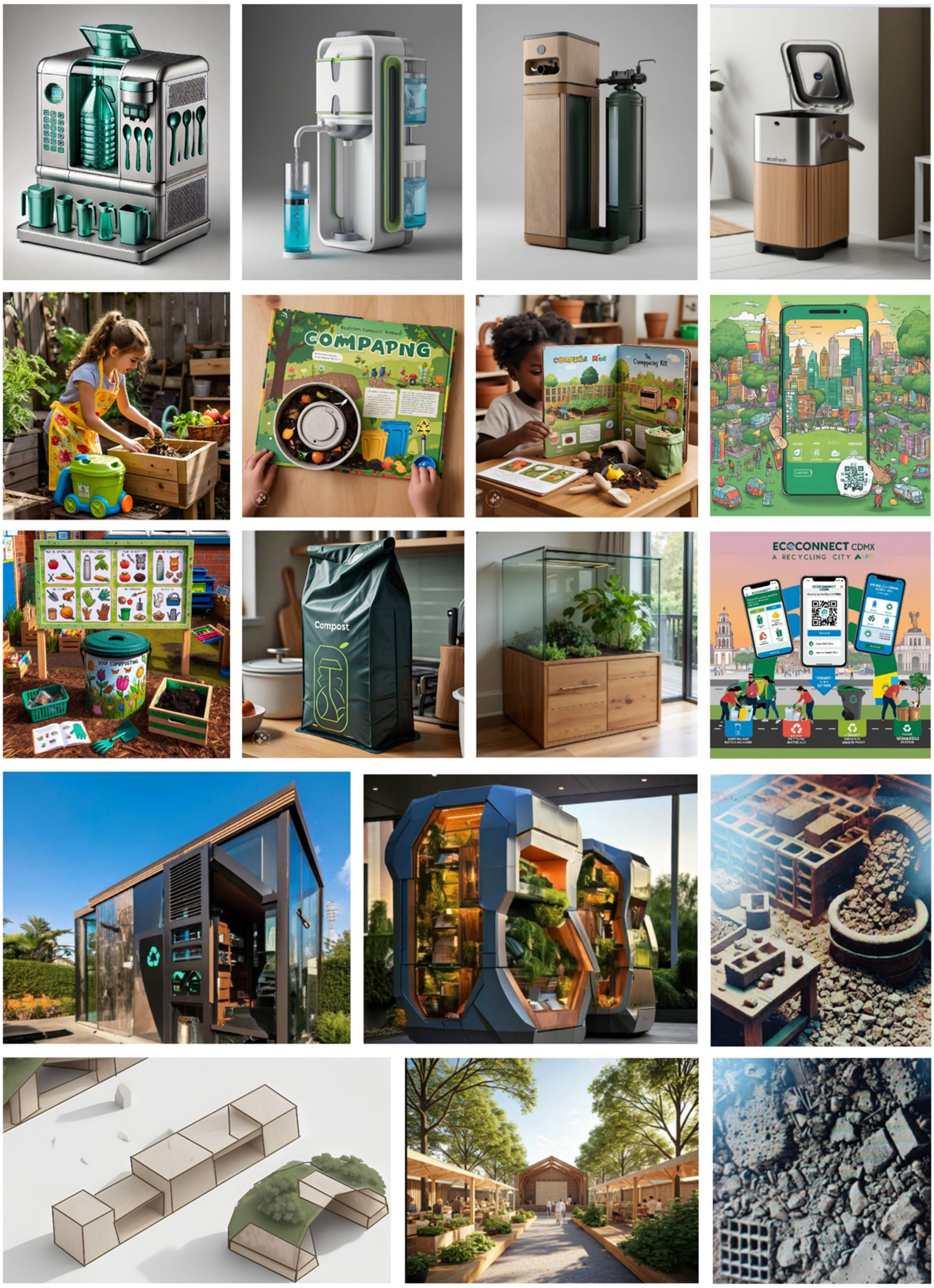

Figure 2. Visualizations of proposals created with different AI tools

Some of the findings were:

Students used AI right away, spending very little time discussing within the team the focus of the problem framing and solution. They first asked general questions to the AI such as "what are the main problems regarding garbage production?", "what are the causes of excessive garbage production of an inhabitant of Mexico City?", or "which strategies would you implement?” We mainly observed that the AI gave answers, and the students chose one of the suggestions without questioning or narrowing down the problem. This can be connected to the overreliance on AI or algorithmic loafing discussed previously (Inuwa-Dutse et al., 2023).

Only one team focused on a very local problem, which was initiated by asking the AI which borough of Mexico City generated more garbage and why. In this project the LLM steered the group to an area of exacerbated organic garbage production, the Central de Abastos, Mexico City’s biggest market where all products are centralized before being sent to minority vendors. The group then created concepts based on this problem. However, when switching to the image creation with TTI models, the group obtained general visuals that were not particularly focused on a local context. This may have occurred due to a lack of training data for the LLM in relation to that particular borough. The issue of insufficient training data can cause bias and generalization of results and is a common problem of LLMs and TTIs.

The diversity of the ideas within the groups was limited. Only one of the groups explored a broader range of possible ideas with concepts and images. The aesthetics or visual style of the first proposals generated by the TTI model steered the outcomes, with iterative variations differing very little.

Teams that used sketch-based AI tools like Vizcom found it challenging to create a clear visual representation of their concept. However, they were able to have more control over the final output. This is because the designer sets the initial sketch, with the AI tool serving mainly to enhance the impact and quality of the image.

Teams lost time with some of the TTI models not delivering the result they wanted, then changing the prompt or resorting to a different AI model, which generated frustration within participants. This corresponds to previously mentioned literature, where the focus shifts from the project to the AI tool itself (Han et al., 2024) and has to do with the problem of establishing or eliciting the intent of the designer (Kreminsky & Chung, 2024). This issue becomes particularly important in a team setting where each member might have a different design intention.

Figure 3. Teams collaborating during the workshop

We also observed different team dynamics, which we classify as follows:

4.1. Parallel prompting

Some teams worked in parallel, with each student exploring different prompts on multiple devices they usually work with, such as laptops, smartphones, or tablets. One group mentioned: *"... we were looking for information simultaneously on 5 different devices"*. Fig. 4 represents the parallel prompting approach, where D1 and D2 correspond to Designer 1 and 2, and AI 1, 2 etc. represent the different AI models used (LLMs and TTIs). The purple arrow represents the communication between designers, while the dotted arrows represent the prompting instructions from each designer to the AI.

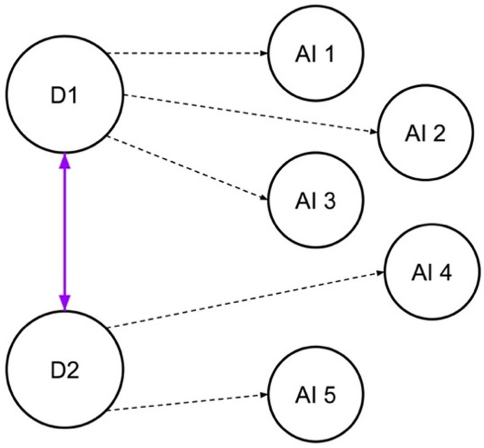

Figure 4. Team members working in parallel with multiple AI models

4.2. Co-prompting

Some teams started co-prompting from the beginning, with one team member typing the instructions for the AI while the other team members suggested options. *"We were searching on one computer and together we wrote the questions or what we were looking to obtain... we organized in a good way, obtained necessary information and managed to get to a proposal that we all agreed with"*.
Fig. 5 depicts the co-prompting approach where designers discuss the main idea for the prompt. Once they agree on the prompt, one of them types the instructions. The remark in the group about all agreeing with the proposal could correlate to fixation due to the AI itself, where the team resorts to AI suggestions to avoid debates or discussions.

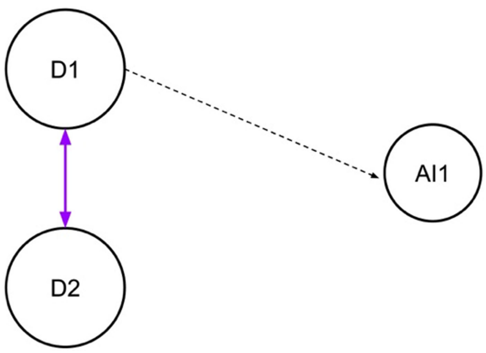

Figure 5. Team members working together by strategies such as co-prompting

The two forms of working also alternated within the same team at different phases. For example, some teams started with parallel prompting and finished with co-prompting to deliver the final images.
To conclude, participants answered a questionnaire about their experience with AI and how it influenced teamwork in the workshop. One of the questions was: how were the dynamics within your team while using AI? One group expressed that the conversation within their group mainly focused on giving

instructions to the AI, which correlates with the issue discussed previously, where the focus shifts from the project content to co-prompting strategies. Another question asked about dynamics during moments when AI was not being used. One group expressed that the conversation without AI was *"…more difficult because there was tension within the group in the idea generation process"*, suggesting that AI acts as a sort of mediator. However, this could also be linked to fixation on AI due to a reluctance to dissent within the team, as studied by Lee et al. (2024). Other answers reported that AI helped enhance the participation of team members and verbalize/visualize ideas quickly and easily: *"thanks to the AI, I could see that my team was more participative when intervening in something that is already generated either through image or text."*

One issue detected was that most teams were not aware that the AI might have led them to common concepts: *"it was an accelerated process, more fluid, with many ideas easily integrated, avoiding creative blocking to a great extent", "the collaboration was very good, we had many brainstorming ideas, could understand each other well with the AI, and came to concrete points".*

5. Discussion

The findings suggest that there are different variables regarding the use of AI in creative design teams that can lead to fixation or, conversely, prevent fixation. Some of the variables influencing outcomes are related to the team itself, such as design discipline, number of participants, level of AI knowledge, skills or age. Other aspects pertain to how AI tools are used and the typical causes of team fixation or algorithmic loafing, such as a reluctance to dissent. While conclusive results on whether co-prompting or parallel prompting produce better outcomes are lacking, we have identified various dynamics that can evolve within a team when working with GenAI tools over time.

We propose a conceptual model for co-creating with AI in teams to mitigate team fixation (Fig. 6). The colored arrow from the designers to AI and back represents the interaction with a Mixed Initiative Co-Creative System (main AI), where the AI can also initiate actions or elicit designer's intentions. In this model, we suggest that simultaneous AIs could be used by different team members and shared through a common AI platform.

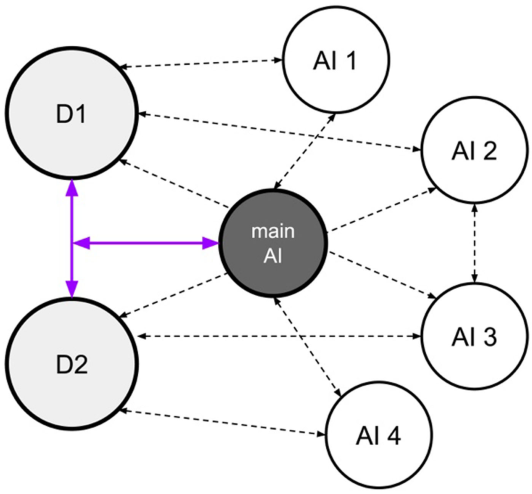

Figure 6. Proposed collaboration model

While the first set of AIs might be tools for search, concept exploration and image generation, the main AIs objective would be to enhance team creativity and collaboration. Based on the proposal of Lee et al. (2024) this main AI could act as the dissenter in the group, balancing ideas and nudging the team to explore the problem solution space in depth. The main AIs purpose should be to enhance the communication and exchange of ideas between team members (colored arrow). This AI could also act as a tool to promote critical thinking and abductive reasoning within team members. For example, instead of providing answers to questions, it could first ask open ended questions and help the team to elicit the design intent. In this sense the AI could act as another teammate. The main goal of this could be to encourage designers to explore the problem-solution design space, define the design task, and promote reflective practice (Schön, 1983).

A practical implementation of this model could work via a shared platform, where users connect when working on a design project. The platform could also connect to other AI tools. The main AI could be tweaked on the level of engagement, from asking questions to open the design space, to suggesting possible creative activities for the team such as brainstorming. Furthermore, it could capture team interactions and the overall exploration of the design space to visualize the progress.

While this study presented findings, there is a need for further research involving larger and more diverse participant groups to validate them. The proposed model would require an experimental phase, with a control group of students from the same cohort following the process without AI, in order to validate whether the team can achieve better creative performance with the appropriate use of AI. The studies would need to allocate more time for teams to develop the design task in order to deepen and develop the resulting concepts. While this study followed a similar format as previous studies investigating the effects of AI use on creativity (Wadinambiarachchi et al., 2024; Guo et al., 2023), one aspect that still needs to be investigated is if creative fixation could also be due to the different variables in the workshop format and dynamics, such as duration, team participant number, and the given design task. Attention should be given to this for future studies.

Some recommendations for education in design to mitigate challenges such as algorithmic loafing and overreliance on AI would be to emphasize the need to question the answers AI provides, as well as designing new interactions where AI does not give concrete answers but instead formulates relevant questions. Instructors, as well as students, should be aware of algorithmic loafing. This is fundamental in order to detect it and point out its emergence in design teamwork. Furthermore, it is essential to have an understanding of how AI works (see AI Literacy, Long & Magerko, 2020) and to be aware of the high probability of obtaining standard or generic answers. Instructors should promote critical thinking concerning the use of AI by pointing out its limitations. Finally, clarifying that AI can be a tool for dialogue can be interesting to promote reflective practice (Schön, 1983).

6. Conclusion

During the workshop, we observed different team collaboration modes with AI, namely co-prompting, parallel prompting and a combination of both. We propose a model where a central AI can act as a platform for critical thinking and abductive reasoning for a design team to explore a wider problem-solution space. This AI could be a MI-CC (Mixed Initiative Co-Creative System), asking questions with the main goal to explore the problem-solution design space and elicit the creative intention of the team. The aim of this paper is to contribute to ongoing research about co-creation with AI within creative design teams.

Acknowledgements

The authors thank Adriana Munguia and Vanessa Manzano, students of the Industrial Design Research Center (CIDI), Architecture Faculty, UNAM, for participating in the organization and moderation of the workshop.

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