Exploring Co-design with an AI Partner: The GAI-A Interface in Architectural Education

Leman Figen Gül[1](✉), Burak Delikanlı[1,2], Oğulcan Üneşi[2], and Ertuğrul Ömer Gül[3]

[1] Department of Architecture, Istanbul Technical University, Sarıyer, Turkey
{fgul,burak.delikanli}@itu.edu.tr
[2] Graduate School, Istanbul Technical University, Sarıyer, Turkey
unesi23@itu.edu.tr
[3] School of Computer Science and Engineering, University of New South Wales, Sydney, Australia
egul@unsw.edu.au

Abstract. The integration of advanced information and communication technologies has revolutionized collaborative working processes, especially in creative design, allowing stakeholders to interact across locations and time zones. Originally designed to facilitate human collaboration, these systems have evolved to include collaborative interactions between humans and Artificial Intelligence (AI) models, reaching new heights with the integration of Generative Artificial Intelligence (GenAI) models. In this study, we introduce a co-design interface, *Generative Artificial Intelligence for Architecture* (referred to as GAI-A), for the initial design phase to stimulate creative design. GAI-A provides a collaborative space for designers to work with an AI partner that suggests visuals based on the images provided. Over the span of four consecutive academic semesters, we have rigorously implemented and evaluated this innovative environment in the architectural design studio at Istanbul Technical University, aiming to elucidate its multifaceted applications and implications within the academic discourse of architecture. The interface of GAI-A is evaluated through Creativity Support Index and surveys and semi-structured interviews. The research explores critical aspects, including co-design possibilities with GenAI models, and optimal utilization techniques, providing valuable insights into design pedagogy.

Keywords: Co-design · AI Partner · Generative AI · Design Creativity

1 Introduction

The recent developments in the field of Artificial Intelligence (AI) are reshaping existing practices and discourses, particularly in domains reliant on creativity. The evolving relationship between human creativity and algorithmic intelligence, along with the emergence of image generators, has opened up new possibilities in architectural design, constituting a growing research area [1]. Undoubtedly, the application of AI models in domains necessitating design and creativity, distinct from their typical uses such as

Y. Luo (Ed.): CDVE 2024, LNCS 15158, pp. 1–12, 2024.
https://doi.org/10.1007/978-3-031-71315-6_1

advanced analytics, data processing, autonomous and intelligent systems, and Natural Language Processing (NLP). As stated by Leach [2], technological advancements have started numerous paradigm shifts over the past three decades, and it is reasonable to say that the integration of Generative Artificial Intelligence (GenAI) in design will be one of them. This new design paradigm blurs the boundaries between human and synthetic imagination, allowing for a radical departure from traditional conventions [3]. The term *Generative Artificial Intelligence* refers to deep-learning models capable of processing raw data (such as a collection of visuals used as training data) and acquiring the ability to generate statistically probable outputs upon request [4]. This term serves as a comprehensive descriptor for any form of AI capable of generating novel text, images, video, or audio clips. These models encode a simplified representation of their training data and utilize it to create new works that stand similarity to, but are not identical replicas of, the original data. We used the term GenAI, similar to Manovich [3], in narrower sense to refer to deep network methods to make media and design artifacts.

As AI technology moves from being limited to personal computers to becoming ubiquitous in everyday devices such as mobile phones, tablets etc., it needs to be seamlessly integrated into social and collaborative intelligence. However, it is evident that AI still lacks significant experience in collaborating with humans [5]. Rezwana and Maher [6] studied *Co-creative Systems* and three different interaction models emerged from their analysis: *Generative Pleasing AI Agents* that follow along with the user, *Improvisational AI Agents* that work spontaneously with users on a shared product, and *Advisory AI Agents* that both generate and evaluate the creative product. The concept of Human-AI Collaboration has appeared in recent studies examining user engagement with AI systems [7, 8]. This signifies a transition from viewing AI solely as automated to recognizing its potential as a collaborative partner in certain domains, indicating advancements in AI capabilities [6], design and architecture are those creative endeavors.

In this paper we will share preliminary findings from a large body of research that is still in progress. Our main goal in this work has been to develop a GenAI partner, *Generative Artificial Intelligence for Architecture* (referred to as GAI-A), which will ultimately support creativity that feeds on the visual and textual input of the designer user, and learns the user's design style over a period of time. Although such an approach is similar to the use of *Improvisational AI Agents* discussed by Rezwana and Maher [6], it has a unique value in that it generates alternatives by processing a visual data set consisting of different images as input and, if desired, also positive and negative prompt commands, especially as inspired by traditional collage making. GAI-A, as it was developed, has been experimented with students in the design studio for the past three semesters and improvements have been continued according to the feedback from the students.

2 Background

Creativity is commonly described as the ability to transcend traditional ideas, rules, relationships, and create meaningful novel ideas, methods, interpretations. Besides, creativity, which traditionally considered as a unique and mystical talent, is currently acknowledged as a skill that can be learned and enhanced [9]. Creative systems refer to computational or technological frameworks designed to support and enhance human creativity [10]. Davis et al. [11] discussed creative systems into three main categories according to the level of collaboration and its objectives. *Creativity Support Tools (CST)* refer to software and user interfaces designed to enhance creativity by empowering users and collaborative teams to be more productive and innovative [12, 13]. These tools aim to facilitate the creative process by providing features such as improved searching of intellectual resources, rapid discovery processes, generation of alternatives, and visualization for deeper insights. *Generative Computational Creativity* [11] represent a category aimed at autonomously producing creative outputs. Rooted in AI research, this approach deconstructs human creativity into observable behaviors such as narrative construction, poetry composition, ideation, analogy formation, and more. Researchers in this field develop computational models tailored to these specific creativity modules, with the aspiration and ongoing effort to integrate them with other embodied aspects of creativity in the future. *Co-creative Systems* are frameworks or setups that involve computer programs collaborating with human users on creative tasks [6, 14]. These systems emphasize a partnership between humans and AI in the creative process, where both entities work together to produce innovative and valuable outcomes. Co-creative systems focus on the interaction dynamics between humans and AI, such as turn-taking, contribution types, and communication, as essential components for effective collaboration. The goal of co-creative systems is to enhance creativity by leveraging the strengths of both human creativity and AI capabilities, leading to more meaningful and impactful creative endeavors. Our GAI-A approach proposes a system that is similar to a co-creative systems and works on both sides, supporting the human designer in their creative work and learning from the human user at the same time.

AI has emerged as a promising tool in augmenting human creativity across various domains [15]. The notion of AI supporting creativity stems from its ability to process vast amounts of data, recognize patterns, and generate novel outputs. Researchers have explored AI's potential to inspire creative thinking, facilitate idea generation, and enhance problem-solving abilities. For instance, *Generative Adversarial Networks* (GANs) [16] have been utilized in art generation, where AI systems autonomously produce artworks that blur the line between machine and human generated content [17]. Moreover, AI-driven recommendation systems in various domains have demonstrated their capacity to assist artists by suggesting novel ideas or refining existing ones [18].

Effective human-AI interaction interfaces play a pivotal role in leveraging AI's creative potential while maintaining user control and agency. These interfaces are designed to support co-creation, coordination, and communication between users and AI agents, fostering collaborative efforts in creative tasks, problem-solving, decision-making, and more. Designing interfaces for AI and human collaboration involves creating intuitive, transparent, and engaging platforms that support effective communication, coordination, and co-creation between users and AI agents across various tasks and domains. Various approaches have been proposed and evaluated in this domain. For instance, collaborative interfaces that allow real-time interaction between users and AI algorithms enable seamless integration of human expertise and AI capabilities [19]. Therefore, our research focuses not only on GenAI partner development but also on the requirements for an effective co-design platform. The design of a functional interface will not only improve the efficiency of the feedback AI receives from humans, but also foster immersion for this emerging medium.

3 Designing Co-design Interface: GAI-A

In this study, we introduce a co-design interface named GAI-A for the initial design phase to foster creativity. GAI-A provides a collaborative space for designers to work with an AI partner that suggests visuals (based on the images provided) and descriptions.

From the development point of view, GAI-A is a wrapper for the state-of-the-art GenAI tools and related methods. It is a website that contains a group of simple, objective-oriented web applications that can be used without prior knowledge in the field. This approach was adopted to provide a user-friendly and accessible interface to designers, while reducing the complexity, and eliminating the technical steps regarding the installation and operation of such tools. During our research, we have found that the learning curve of setting up and using generative AI models could become overwhelming for designers, and that they would rather use such tools through simple interactions such as web applications.

Our objective was to identify the needs of the students/designers and develop solutions that answer directly to their needs. In this regard, we started with identifying the possibilities within the current developments in GenAI models. In the scope of our research, our aim was not to develop AI models, but to rather provide an interface for the existing models while creating specific, streamlined methods for the identified needs. In order to be able to customize the users' experience and develop ready-to-use methods, the utilized models and methods had to be accessible and customizable up to a certain degree. As of the beginning of the research, OpenAI's Dall-E [20] and ChatGPT [21], and Midjourney [22] were quite new and popular. However, OpenAI's models were not open-source, and their API's were quite limited for what we were trying to achieve, and the same applied for Midjourney, which was even lacking of an official API. All of these models also had limited features regarding conditioning and fine-tuning. Thus, we chose to go forward with Stable Diffusion [23], exploring its possibilities and community-made tools, methods and approaches surrounding it, while also utilizing the previously mentioned models in some workflows and prototypes.

Our development process follows three, but not very distinctive, parallel loops. In one loop, we follow the developments around the AI tools, learn and experiment with them, and then develop new methods or update the existing ones with these new developments. Next, we observe the users' new or unanswered needs and try to match their needs with the new methods that we have been experimenting with. Finally, we follow a conventional feedback loop, improving our implemented features based on user feedback.

GAI-A is comprised of three steps in development. The first step is the GenAI workflows created, which respond to specific approaches and needs. These workflows have specific inputs and outputs depending on the identified needs and vary from text-to-image to image-to-image methods. The second step is the deployment of these workflows to external servers that undertake the computing loads. The last step the development of the website and the contained web applications, which also add additional functionality such as interactive canvases, model and workflow communication, and act as the User Interface (UI) to operate these workflows.

Through these layers, GAI-A is formed, and the users only interact with the provided web applications to produce their generations according to their needs. The complexity is hidden within the underlying layers, and the users can interact with the generative tools without the technical challenges. In the GAI-A interface, the users are given basic input fields and parameters as default, although advanced modes exist for more experienced users in each workflow, that cover almost all of the internal parameters.

The first prototype featured only a collage tool, based on a conventional way of developing a design concept. With this tool, the users were able to place images on a canvas to create a concept diagram, which in turn was used to create a prompt from the collage to generate an image that reflected the individual elements in a single design concept. The collage tool relies heavily on a canvas app that was implemented on the frontend (Fig. 1). Images can be uploaded on to the canvas, which can be then rotated, resized and ordered to create a composition on the center of the screen. Then, positive and negative text prompts can optionally be typed to further condition the generation. By default, this much input is enough to generate an output, although for fine-tuning the parameters an optional *Advanced Options* menu is included in the UI, which toggles a window that exposes the internal parameters of the sampler. Finally, the users can click the *Generate* button that sends these inputs to the model, which in turn returns the generated image onto the canvas. Users can hide the output and continue generating visuals, and return to their previous generations any time by toggling the *Outputs* menu, which keeps a generation history for the current session.

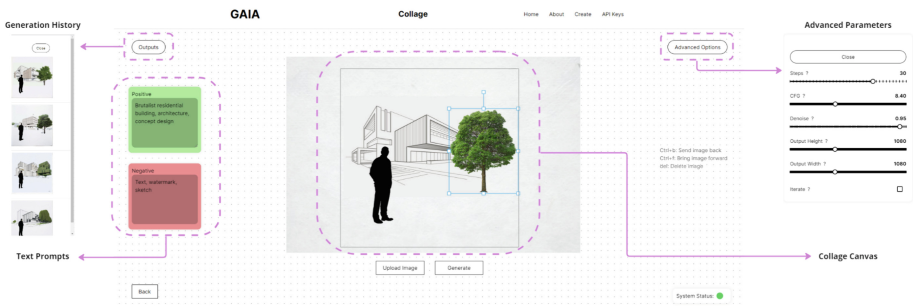

Fig. 1. GAI-A Collage Tool Interface

Through our observations and semi-structured interviews during this first iteration, we have found that the students had also expected to convert these collages, their simple drawings, and rough 3D models into stylized renderings (Fig. 2). As we have been experimenting with conditioning, we deployed another tool for the purpose of generating images based on the original images' physical features, through edge and depth detection. We have also improved the collage tool based on feedback, adding requested features such as layer ordering, same-seed generation and generation logging. Another improvement made on the collage tool was a complete rewrite of the workflow to accommodate a new parameter which enables the users to use the input collage between a literal composition and an abstract one, through an adjustable degree.

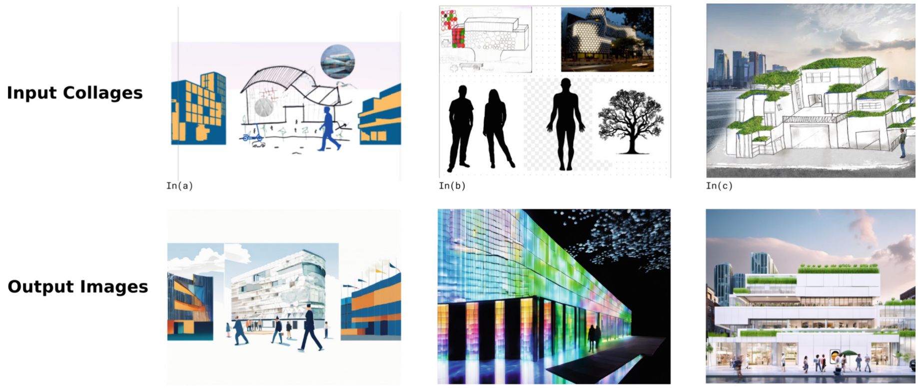

Fig. 2. Examples of Collage Tool Inputs and Outputs

During the development of GAI-A, many workflows were developed but not deployed until found necessary. Some of the approaches were first developed outside of GAI-A, e.g. producing an architectural program or a concept through conversing with a LLM (ChatGPT) and producing inspiring visuals through carrying the outcome to a separate latent diffusion model (Midjourney). Through the conducted workshops, interviews and surveys related to the research, we have identified and received requests for several workflows which are currently in development. Our future development plans also include a rating system implementation for the generated content to filter the results that can be used in fine-tuning models (i.e. LoRA training) [24].

4 Evaluating Co-design Interface

To comprehend collaborative creativity between designers and AI, we conducted surveys and semi-structured interviews within a design studio setting where the GAI-A platform serves as a creative partner. This innovative environment was rigorously implemented and evaluated across three academic semesters in the architectural design studio at Istanbul Technical University. Our goal was to illuminate its multifaceted applications and implications within the academic discourse of architecture (Fig. 3).

First, the interface of GAI-A is evaluated through *Creativity Support Index* (CSI) [25] and survey and semi-structured interviews with the study participants. This research utilized the CSI and a 5-point Likert scale survey. The CSI is a psychometric questionnaire designed to assess the creativity support and cognitive impact of digital tools. Its purpose is to evaluate a digital creativity support tool's effectiveness in aiding users' creative processes. The CSI measures various dimensions of creativity support, offering researchers a standardized metric for evaluating and enhancing the creativity support tools of applications. In addition, a questionnaire and semi-structured interviews were conducted with the students in the design studio to assess the use of the GAI-A interface in the early stages of design, especially in inspiration, creative imagery and concept definition. Here we only report the results of the questionnaire.

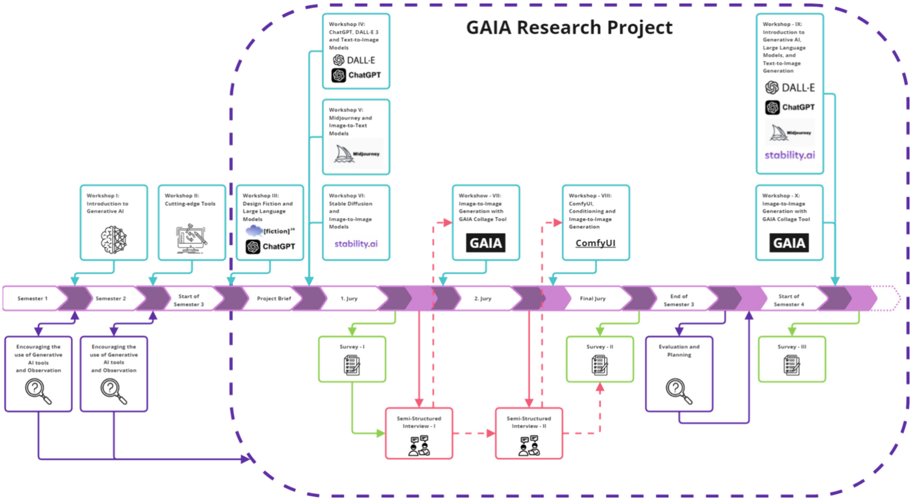

Fig. 3. Research Process Diagram

4.1 Results of the Creativity Support Index Survey

CSI (Table 1) scores offer insights into the effectiveness of a creativity support application in facilitating various dimensions of creativity and aid in identifying areas for interface enhancement. Our students (N = 18) generated an average CSI score of 75.75 (SD = 20.15) for the GAI-A interface in design studio workshops (Table 2). This is considered good creativity support but not excellent. The six individual factor scores detailed below provide indications of which aspects of the application require improvement. These factors include exploration, collaboration, enjoyment, results worth effort, immersion, and expressiveness.

Table 1. 12 Agreement Statements on the CSI: Each agreement statement is answered on a scale of "Highly Disagree" (1) to "Highly Agree" (10) [25]

Collaboration 1. The system or tool allowed other people to work with me easily 2. It was really easy to share ideas and designs with other people inside this system or tool
Enjoyment 1. It was easy for me to explore many different ideas, options, designs, or outcomes, using this system or tool 2. The system or tool was helpful in allowing me to track different ideas, outcomes, or possibilities
Exploration 1. I would be happy to use this system or tool on a regular basis 2. I enjoyed using the system or tool

(*continued*)

Table 1. (*continued*)

Expressiveness	
1.	I was able to be very creative while doing the activity inside this system or tool
2.	The system or tool allowed me to be very expressive
Immersion	
1.	My attention was fully tuned to the activity, and I forgot about the system or tool I was using
2.	I became so absorbed in the activity that I forgot about the system or tool that I was using
Results of Effort	
1.	I was satisfied with what I got out of the system or tool
2.	What I was also able to produce was worth the effort I had to exert to produce it

Table 2 presents the average factor counts, average factor scores, and average weighted factor scores for each of the six factors on the CSI. The average counts denote the frequency with which participants selected a specific factor as important to the task, irrespective of how well the tool supported those factors. It's worth noting that the average factor counts also shed light on which factors hold the most significance for this particular creative activity. Specifically, immersion (1.78) and collaboration (1.89) appear to be less relevant or important to users engaged in design tasks, whereas expressiveness (3.56) holds great importance, and exploration (2.78) and enjoyment (2.44) are also deemed relevant. The factor score represents the sum of agreement statement responses for a factor, each rated on a scale from 0 to 10, with a higher number indicating better support for that factor. Therefore, the maximum factor score is 20.

Table 2. The maximum count for any specific factor is 5, signifying that participants regarded it as more significant than any other factor.

Scale	Avg. Factor Counts SD (Max:5)	Avg. Factor Score (SD), out of 20	Avg. Weighted Factor Score (SD)
Exploration	2,78 (1.11)	15,33 (4.19)	42,77 (6.55)
Collaboration	1,89 (1.23)	15,00 (4.83)	31,68 (5.12)
Enjoyment	2,44 (1.50)	17,11 (4.01)	47,98 (3.48)
Results Worth Effort	2,39 (1.61)	16,22 (3.02)	44,81 (3.83)
Immersion	1,78 (1.63)	13,39 (3.79)	39,36 (6.49)
Expressiveness	3,56 (1.42)	14,94 (4.15)	51,22 (8.77)

In Table 2, all factors received relatively high ratings, with Enjoyment and Results Worth Effort being rated the highest, and Immersion the lowest. Collaboration and Exploration also received relatively high scores. While the collaboration score here focuses on the system's suitability for human-human collaboration, we generally focus on the GenAI system's suitability for human-AI partnership. A below-average count of Results Worth Effort (2.39) suggests it holds moderate importance for users engaged in the application, while its high score (16.22) indicates potential interactions that may be tedious or involve too many steps. Our observations and discussions with the students confirm this finding. The high factor score for enjoyment suggests that students are likely to use the system for their design tasks. Conversely, the lowest immersion scores indicate that notifications and interruptions may disrupt the workflow.

4.2 Assessing Design Processes with GAI-A as Collaborator

To assess the collaborative creative process between designers and AI, and understand students' perspectives on the GAI-A platform as a creative partner, we conducted a survey study. The results showed that 87% of all students (N:18) viewed the influence of GAI-A on their creativity during the design process positively, as depicted in the figure. Survey findings suggest that the GAIA interface can effectively aid in collaborative design compared to traditional methods. It received high praise as a beneficial partner, particularly in fostering a variety of design ideas and facilitating alternative creation, with an 89% approval rating. Another key aspect highlighted by students was the impact of the GAI-A interface on their visual imagery and thought processes. They noted that the generated images improved their ability to conceptualize design ideas and expanded their creative horizons (%84), as shown in Fig. 4.

Fig. 4. Students' self-perception concerning the effectiveness of evaluating the GenAI partner in supporting their creativity in the Architectural Design Studio.

Based on the findings from questionnaires and interviews, numerous students acknowledged GAI-A's potential to effectively discern intricate details during early design phases and contribute to conceptual design stages. During the idea generation phase, which marks the initial stage of design, they highlighted its departure from conventional methods, citing its ability to inspire, aid visualization, and provide diverse perspectives. Many students underscored the tool's positive influence on their creative thought processes, citing its capacity to streamline tasks, generate diverse ideas, present variations of these ideas, and expedite project development (%87). They also assessed its favorable impact on overall design skills, particularly in fostering broader and more detailed thinking at the ideation stage, as well as its positive effects on motivation and creativity. Overall consensus suggested that the GAI-A's utility tends to grow with prolonged use, positioning it as an increasingly vital tool for fostering creativity throughout the design process.

5 Conclusion and Discussions

Our findings provide support for the argument that GenAI models possess the potential to serve as collaborative partners in domains that require creativity, a viewpoint also echoed by Davis [26]. This assertion implies a forthcoming paradigm shift in the design process, wherein humans and computers can engage in co-creative endeavors as partners. Bown [27] emphasized the necessity for further investigation into the efficacy of creative systems operating in collaborative roles, underlining the pivotal role of interaction within co-creative processes. Our research contributes significantly to this discourse by investigating into the dynamics of this interaction, elucidating the expectations of students regarding the avenues of human-computer co-creativity, a concept as articulated by Davis [26]. In such system, humans and computers can work together as colleagues considered as one system through which creativity emerges.

Students who designed using the easy-to-use GAI-A interface evaluated their creative process and application. A notable observation from our study is that design students tend to create designs within the confines affordability offered by the tools at their disposal, including the ability to generate complex forms with curves. This observation resonates with the assertion made by Robertson and Redcliffe [28], who highlighted the logical progression of the design process in tandem with the mastery of utilized tools. Our study substantiated that students typically design within the limits of what they are able to visualize and conceive, and tools like the GAI-A can serve to extend the boundaries of these capabilities. Consequently, proficiency with design tools plays a pivotal role in the evolution of design concepts and ideas. That is similar to *Improvisational AI Agents* as suggested by Rezwana and Maher [6] where GAI-A works alongside users on a shared visuals spontaneously by generating visuals based on the user's comments.

In our studio, we emphasize teaching diverse methods and incorporating GenAI models as design aids, acknowledging the ongoing challenge of nurturing students to produce optimal creative ideas. By integrating advanced design tools like GenAI models and promoting an understanding of their significance in the design exploration process, we aim to cultivate working practices that not only facilitate the exploration of design alternatives and concepts but also underscore the importance of collaboration with GenAI in enhancing creative outputs.

Acknowledgments. We thank the participants of the study for their valuable contributions. This research was supported by Istanbul Technical University, Scientific Research Projects Unit (MGA-2023–44787). The Ethics Committee approval number: (PN-2023/11/13–418).

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Del Campo, M.: Diffusions in Architecture: Artificial Intelligence and Image Generators. Wiley, Hoboken (2024)
2. Leach, N.: Architecture in the age of artificial intelligence: an introduction to AI for architects. Bloomsbury Visual Arts (2022)
3. Manovich, L.: Preface. In: Del Campo, M. (ed.) Diffusions in Architecture: Artificial Intelligence and Image Generators. Wiley (2024)
4. Martineau, K.: What is generative AI?, https://research.ibm.com/blog/what-is-generative-AI, (2024)
5. Dafoe, A., Bachrach, Y., Hadfield, G.K., Horvitz, E., Larson, K., Graepel, T.: Cooperative AI: machines must learn to find common ground. Nature **593**, 33–36 (2021). https://doi.org/10.1038/d41586-021-01170-0
6. Rezwana, J., Maher, M.L.: Designing creative AI partners with COFI: a framework for modeling interaction in human-AI co-creative systems. ACM Trans. Comput. Hum. Interact. **30**, 1–28 (2023). https://doi.org/10.1145/3519026
7. Arous, I., Yang, J., Khayati, M., Cudré-Mauroux, P.: OpenCrowd: a Human-AI collaborative approach for finding social influencers via open-ended answers aggregation. In: WWW 2020: Proceedings of the Web Conference 2020. (2020). https://doi.org/10.1145/3366423.3380254
8. Oh, C., Song, J., Choi, J., Kim, S., Lee, S., Suh, B.: I lead, you help but only with enough details. In: CHI 2018: Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (2018). https://doi.org/10.1145/3173574.3174223
9. De Bono, E.: The Mechanism of Mind: Understand How Your Mind Works to Maximise Memory and Creative Potential. National Geographic Books (2015)
10. Wiggins, G.A.: A preliminary framework for description, analysis and comparison of creative systems. Knowl.-Based Syst. **19**, 449–458 (2006). https://doi.org/10.1016/j.knosys.2006.04.009
11. Davis, N., Hsiao, C.-P., Popova, Y., Magerko, B.: An enactive model of creativity for computational collaboration and co-creation. In: Zagalo, N., Branco, P. (eds.) Creativity in the Digital Age, pp. 109–133. Springer, London (2015). https://doi.org/10.1007/978-1-4471-6681-8_7
12. Shneiderman, B.: Creativity support tools: a grand challenge for HCI researchers. In: Redondo, M., Bravo, C., Ortega, M. (eds.) Engineering the User Interface, pp. 1–9. Springer, London (2008). https://doi.org/10.1007/978-1-84800-136-7_1
13. Shneiderman, B.: Creativity support tools: accelerating discovery and innovation. Commun. ACM **50**, 20–32 (2007). https://doi.org/10.1145/1323688.1323689
14. Karimi, P., Grace, K., Maher, M.L., Davis, N.D.: Evaluating creativity in computational Co-Creative Systems. arXiv (Cornell University). (2018). https://doi.org/10.48550/arxiv.1807.09886
15. Wu, Z., Ji, D., Yu, K., Zeng, X., Wu, D., Shidujaman, M.: AI creativity and the Human-AI co-creation model. In: Kurosu, M. (ed.) HCII 2021. LNCS, vol. 12762, pp. 171–190. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-78462-1_13

16. Goodfellow, I.J., et al.: Generative adversarial networks. arXiv (Cornell University). (2014). https://doi.org/10.48550/arxiv.1406.2661
17. Elgammal, A., Liu, B., Elhoseiny, M., Mazzone, M.: CAN: creative adversarial networks, generating “art” by learning about styles and deviating from style norms. arXiv (Cornell University). (2017). https://doi.org/10.48550/arxiv.1706.07068
18. Jordanous, A., Keller, B.: What makes a musical improvisation creative. J. Interdiscip. Music Stud. **6**, 151–175 (2011). https://doi.org/10.4407/jims.2014.02.003
19. Wienrich, C., Latoschik, M.E.: EXtended artificial intelligence: new prospects of human-AI interaction research. Front. Virtual Reality **2**, 686783 (2021). https://doi.org/10.3389/frvir.2021.686783
20. OpenAI: DALL·E: Creating images from text. https://openai.com/research/dall-e
21. OpenAI: Introducing ChatGPT. https://openai.com/blog/chatgpt
22. Midjourney: Midjourney. https://www.midjourney.com
23. StabilityAI: Stability AI Image Models — Stability AI. https://stability.ai/stable-image
24. Hu, E.J., et al.: LORA: low-rank adaptation of large language models. arXiv (Cornell University) (2021)
25. Cherry, E.C., Latulipe, C.: Quantifying the creativity support of digital tools through the creativity support index. ACM Trans. Comput. Hum. Interact. **21**, 1–25 (2014). https://doi.org/10.1145/2617588
26. Davis, N.: Human-computer co-creativity: blending human and computational creativity. In: Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment, vol. 9, pp. 9–12 (2021).https://doi.org/10.1609/aiide.v9i6.12603
27. Bown, O.: Player Responses to a Live Algorithm: Conceptualising computational creativity without recourse to human comparisons? In: ICCC, pp. 126–133 (2015)
28. Robertson, B., Radcliffe, D.: Impact of CAD tools on creative problem solving in engineering design. Comput. Aided Des.. Aided Des. **41**, 136–146 (2009). https://doi.org/10.1016/j.cad.2008.06.007