From Ideation to Refinement: Understanding the Human-AI Co-Creation Across User Expertise

Ayon Mazumder[1], Jeba Rezwana[1]

[1]*Towson University, Maryland, USA*

Abstract

Human-AI co-creation is a process where humans and AI both share a platform for their creative work. The increasing usage of generative AI (GenAI) has accelerated the human-AI co-creation process and transformed this collaborative process in creative fields, especially in design. But current research on co-creation remains limited across user groups, interaction approaches, and creative phases. This paper explores how users with different design expertise interact with AI tools across different creative phases, particularly during ideation and refinement. A systematic literature review of relevant prior research identified 22 papers using defined search terms and inclusion/exclusion criteria. We analyzed the final corpus and found four themes: creative phase support, interaction strategies across creative phase, user control and alignment, and impact of user expertise. The findings indicate that AI is most effective in ideation by facilitating brainstorming, inspiration, and exploration, while its effectiveness in refinement depends on the control mechanisms, including editing and interaction tools. Interaction design plays a crucial role in human-AI collaboration, with misalignment between AI outputs and users' intent remaining a major problem. Differences between designers and non-designers need a more inclusive and user-centered design. Overall, these results indicate the necessity of developing phase-aware, interactive, and user-adaptive AI systems to enhance co-creative workflows.

Keywords

Human-AI Co-creation, Co-design, Creative Phases, User Expertise, Interaction

1. Introduction

With the rise of generative AI (GenAI), research on how humans and AI interact in creative work has grown quickly. In human-AI co-creativity, AI collaborates with humans as partners rather than mere tools [1]. Among the various forms of co-creation, co-design is a well-established paradigm in which users and AI systems iteratively collaborate to generate, explore, and refine design ideas [2]. Different user groups, like professional designers and those without formal design training, use co-creative AI for co-designing in different creative phases, like ideation and refinement. However, the existing human-AI co-creativity literature is still limited across different user groups and creative phases. The study aims to synthesize how individuals with varying expertise, particularly experts and non-experts in design, utilize AI tools during key creative phases. Recent studies in HCI and creativity research largely focus on the quality and efficiency of creative AI models; however, there is growing recognition that how people interact with such systems in different contexts warrants more substantial research attention [1].

Creativity is often characterized as phase-dependent. Various types of human–AI interaction are beneficial at distinct stages of the creative process, particularly on both the divergence (idea development) and the convergence (concept evaluation) phases [3]. Prior work also categorizes creativity into phases such as ideation, generation, and refinement [1]. Studies show that users use AI as a co-creator in early design rather than merely as a tool for final rendering [4]. However, AI support can also limit exploration, depending on how it is introduced [5]. Therefore, systems should be designed to support users across different creative phases. This is especially important when users have to switch between exploring possibilities and selectively narrowing them down [6].

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*Corresponding author.

amazumd2@students.towson.edu (A. Mazumder); jrezwana@towson.edu (J. Rezwana)

Different levels of user expertise entail distinct creative needs when working with a co-creative system. Research indicates that non-designers mostly rely on templates and structured guidance, while expertise influences how effectively users collaborate with AI [7]. According to the literature, designers used AI for early ideation to support sketching, concept generation, and as a co-creator rather than a tool [4]. Another research indicates that novice users mostly rely on system assistance rather than precise control [8].

The design discipline encompasses many subdomains, including graphic design, industrial design, architectural design, fashion design, and UI/UX design. Every design field employs different creative processes, different cognitive activities, and interacts with physical embodiment and materiality in different ways [4, 9]. In this paper, we focus on the context of digital and visual design, where the primary creative medium is screen-based visual output, including images, sketches, layouts, and concept rendering. In recent times, GenAI has been extensively used and experimented with in the digital and visual design domain. Even though this body of work is expanding rapidly, it frequently focuses on a single aspect at a time, such as interface principles, designer processes, non-designer demands, or ideation support, without synthesizing how these aspects intersect [10]. Therefore, the literature remains limited in how users with different levels of expertise interact with co-creative AI across creative phases.

To address this gap, the study aims to explore ***how users with different levels of design expertise interact with co-creative AI systems across different creative phases***. To investigate this, we conducted a systematic literature review, which resulted in 22 selected papers using defined search terms and inclusion/exclusion criteria. The analysis and synthesis of the literature review resulted in four key themes: creative phase support, interaction strategies across creative phase, user control and alignment, and impact of user expertise. We present these themes and discuss the implications of them for developing effective co-creative AI systems as our research contributions.

2. Background

Co-creativity refers to the collaborative involvement of multiple partners in the creative process [11]. Supporting this, existing literature defines human-AI co-creativity as a creative process in which humans and AI work collaboratively [12] and considers them as one system [13]. This collaborative outcome is often more creative than what any individual could achieve on their own, since it arises from interaction among collaborators [13]. However, the influence of AI on different creative phases is not entirely clear. Hwang claims that AI is most useful in the later stages of co-creation rather than the earlier stages [14]; however, there have been empirical studies such as Creative Sketching Partner [15] and Aideation [16] that provide evidence that AI is helpful in early ideation, which contradicts Hwang's arguments. The effectiveness of AI depends not only on the phase of co-creation entirely, but on both the user and the usage context [17]. So an important question that has not been sufficiently explored in existing work that AI effectiveness and phase are influenced by the user's expertise or not.

Creative work naturally goes through multiple stages, generally advancing from ideation to refinement [16]. However, the literature explains the creative process in multiple phases depending on the context, as Shaer et al. describe the divergence stage focused on idea development and the convergence stage focused on evaluation and selection of the idea [3]. On the other hand, Rezwana and Maher identified that AI can play three different roles in the creative process, such as generation, evaluation, and definition [1]. Across these phases, ideation and refinement reflect the two ends of the divergence and convergence spectrum, and these two phases have been widely discussed in the design and creative literature [18]. Studies show that AI can influence user creativity by offering suggestions, feedback, or alternative perspectives during ideation phases [15], while still allowing humans to guide outcome [9]. But, users frequently encounter difficulties during the refinement process due to accidental adjustments and a trial-and-error approach, making refinement a crucial phase for assessment [19].

User expertise also influences interaction with AI in creative contexts; inexperienced users frequently rely on rough and flexible inputs, but experienced users demand fine-grained control and may get

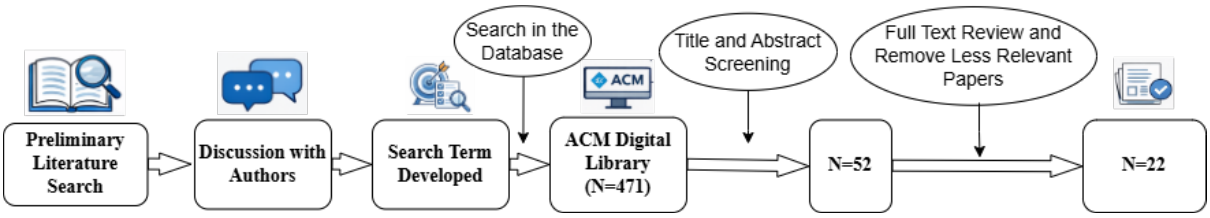

Figure 1: Literature Review Procedure

irritated when systems fail to precisely align intent [8]. In addition, less experienced designers struggle to identify and use design elements compared to professionals [20].

These findings highlight the need for research into how users with different design expertise interact with co-creative AI across creative phases, as they show that both expertise level and creative phase significantly affect how users convey purpose, make decisions, and refine outputs.

3. Methods

To address the gaps, we conducted a systematic literature review (SLR) (Figure 1) to explore how users with varying expertise interact with co-creative AI in different creative phases.

We began our SLR by developing our search term based on our preliminary research, the research team's expertise, and iterative discussion among the authors. We develop our search term to capture user expertise on AI tools in different creative phases. We used a trial-and-error approach and iterative discussions to refine our search term and identify relevant papers for our study. **Inclusion criteria** focus on peer-reviewed studies involving the application of co-creative AI or generative AI in creative visual design with differing user expertise in design and focused on creative phases such as ideation, exploration, and refinement. Studies were **excluded** if they didn't use any AI tools, focused solely on technical model development without human interaction, addressed non-creative fields such as the medical domain, or did not focus on the creative process.

We used ACM Digital Library for the literature review, gathering papers published between 2010 and 2026 using the following search terms **("designer" OR "non-designer" OR "novice designer") AND ("AI tool" OR "generative AI" OR "artificial intelligence") AND ("creative process" OR "design process" OR "human–AI co-creation" OR "human-AI co-design") AND ("ideation" OR "concept generation" OR "visual exploration" OR "refinement")**. This time frame was selected because of the rise of AI applications in the creative domain since around 2010 [21]. We used the ACM Digital Library because it is a comprehensive repository of computing literature where most of the creative work has been published [22].

A total of 471 papers were retrieved from the search using the above key phrase. After that, the title and abstract were screened for all the papers to determine relevance; during the title and abstract screening, papers were excluded if they did not involve AI-supported creative work, did not include human interaction with an AI system, or were unrelated to visual and digital design, and 52 full-text articles were retrieved. Finally, after the full-text review and filtering out papers that were not aligned with our research goal, 22 papers were selected as the final corpus. These final 22 papers specifically focus on the digital and visual design contexts. In this work, we primarily investigate co-creative AI for design tasks, where the principal medium of creative expression is digital and visual design. Therefore, we did not include the existing literature on design disciplines where physical embodiment and materiality play a central role.

The final corpus included articles summarized in a spreadsheet, capturing the title, publication year, study context, participant characteristics, creative phase, interaction modality, key findings, and limitations. We then conducted an inductive thematic synthesis to identify recurring patterns across studies. This was then utilized for analysis and synthesis. The analysis found four themes presenting our findings relevant to our research question.

4. Results

In this section, we describe the four themes we found from our systematic literature review analysis.

4.1. Creative Phase Support

The review highlights a clear difference between ideation (divergent thinking) and refinement (convergent thinking). Most empirical studies show that AI is particularly effective in the *ideation phase*, supporting brainstorming, inspiration, and creating an early draft, while relying on human judgment for final decision making [23]. Systems such as AIdeation [16], Creative Sketching Partner (CSP) [15], DesignAID [24] and GenQuery [25] mostly help with the early ideation phase through iterative generation, inspiration methods, and visual search, also expanding the design space and reducing design fixation. For instance, CSP shows that dissimilar inputs encourage transformational creativity, while inputs that are quite similar encourage combinatorial refinement [15]. DesignAID [24] also supports both divergent exploration and convergent refinement available through its dual interaction mode, which supports the ideation workflow. Autospark [26] shows enhancement early ideation with vague ideas, analogical inspiration, and sketch-based exploration. Lee et al. provide a phase-specific role of AI modalities, meaning prompt-guided interaction supports early ideation, and sketch-guided interaction supports the refinement phase [27].

Conversely, systems like Sketchflex [8] and AdaptiveSliders [19] concentrate on the *refinement phase*, where users try to control, change, and align the outputs with their intention. These tools provide fine-grained manipulation, like semantic sliders and region-based editing, that let users iteratively improve specific attributes without having to regenerate all of the results.

Overall, these results confirm that AI support should transition from inspiration in ideation to precision control in refinement.

4.2. Interaction Strategies across Creative Phases

The second theme concerns interaction strategies across creative phases, which strongly influence the quality of co-creation and user engagement. Traditional systems rely on text-based prompts, whereas multimodal interaction enhances collaboration. During the *ideation phase*, interaction design transitions from linear text-centric prompts to more explanatory and expressive forms. Systems like ImaginationVellum [28] enable spatial interaction through sketching, layout, and direct manipulation, where layout, proximity, and composition affect the AI results and support ideation or exploration. Similarly, Inkspire [29] suggests a sketch-driven interaction model that enables a sketch-to-design-to-sketch feedback loop, which is a more natural and flexible way to simulate than text-based prompts. Using this approach suggests that ideation is enhanced by interaction strategies that emphasize ambiguity, visual expression, and iterative exploration. Similarly, RoomDreaming [30] introduces a human-in-the-loop control for iterative exploration, which helps designers to conduct preliminary design exploration, while CreativeConnect [20] supports idea generation through reference recombination and keyword-based exploration.

Alternatively, in the *refinement phase*, the interaction paradigm creates a more systematic and structured approach. Systems like FusAIn [31] introduce “composition as prompts”, where users make visual attributes by using pen-based interaction, enhancing the precise control over output. Also, GenQuery [25] creates precise intent expression through iterative query refinement and image-based alternation, allowing both divergence and convergence, but placing greater focus on control in the later phase. Also, Promptify [32] presents an interactive paradigm for prompt exploration that integrates LLM-based prompt suggestions, visual clustering, and iterative feedback loops, this assist to user aligning their output with their intention. Additionally, multimodal and hybrid interaction strategies provide a transition between the exploration and refinement phases. Autospark [26] gives a structured interaction workflow for generating, evaluating, and refining ideas, enhancing collaboration through prompt crafting, emotional alignment, and interpretation of outputs, bridging the ideation and refinement phase. Paratrouper [33] extends this with multi-modal interaction strategies that support concurrent exploration and iterative enhancement, enabling users to transition between ideation and refinement. Lee et al. introduce an innovative solution that integrates 3D sketching with 2D generative AI, enabling a smooth transition between representation and iterative refinement [34].

Overall, these results show that phase-dependent, open-ended, and multimodal interaction improves ideation, whereas controllable interaction improves refinement.

4.3. User Control and Alignment

User control and alignment are important factors to consider because it determines the extent to which users may direct AI and influence the final product. During the initial *stages of ideation*, users usually begin with unclear or unfinished concepts and use AI to generate options and provide ideas. However, users face challenges in expressing their design intention in the ideation phase as they cannot easily write prompts, and that creates a gap between what the user wants and what the AI generates [26]. Novice users face more difficulty in formulating prompts and controlling fine-grained spatial details, which makes it even more challenging for them to clearly express their creative ideas [8]. Moreover, unclear parameter ranges and unintended changes by latent space entanglement reduce the user control over the system [19]. As users struggle to formulate prompts that precisely align with their desired outcomes, prompt-based systems frequently go through iterative trial-and-error [32] and provide visual feedback and prompt suggestions to improve user-AI communication by making the creative process simpler and more controllable [8, 32].

In the *refinement phase*, control and alignment become more critical, as users must make small and exact modifications rather than generate broad concepts. However, modifying one portion of an image can also change other parts, resulting in frustration and repeated trial and error [19]. This control is also used differently by designers and non-designers. Rough and basic controls, like rapid sketches or prompt suggestions, are typically preferred by non-designers or inexperienced users due to their ease of use and less cognitive effort, while experienced designers want fine-grained control to maintain their original design purpose [8].

Overall, these results indicate that effective co-creation relies on precise alignment with user intent through iterative control while preserving usability.

4.4. Impact of User Expertise

Finally, the last theme shows the influence of user expertise on co-creation processes. In early ideation, *novice designers* mostly rely on AI for inspiration and idea generation, benefiting from structured support like keyword discovery and recombination, but *expert designers* adopt a more planned approach to strategically dealing with the design space [20, 24]. In refinement, it is more clear that *expert users* use controls more effectively for aligning their output with their intentions, while *novice users* struggle to use more precise control and get their desired output [8]. Additionally, experienced designers guide, evaluate, and refine AI outputs actively, while final evaluation and controls heavily rely on human judgment and expertise [9].

According to our literature review, most existing studies do not compare the interaction patterns of designers and non-designers, which highlights a critical research gap. Regardless of substantial investigation into human–AI co-creation, there is limited understanding of how different user groups interact with AI across creative phases.

5. Discussion

In this paper, we explore how users with different design expertise use AI tools in different co-creative phases through a systematic literature review. After several rounds of filtering to extract papers relevant to our research aim, we identified 22 papers and synthesized the final corpus into four themes. The

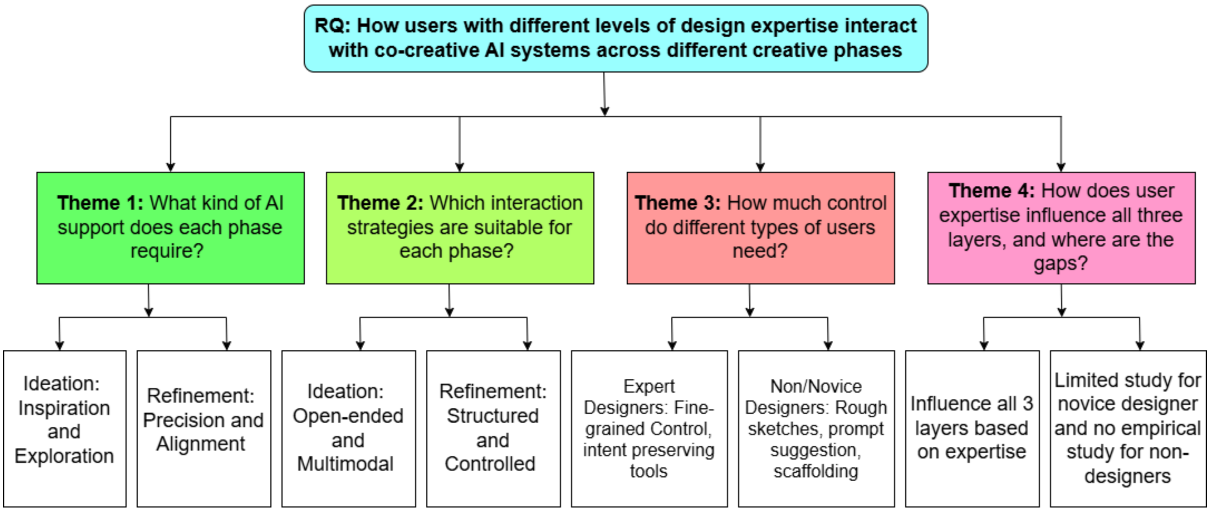

Figure 2: Summary of the Findings including Design Implications

four themes provide insights into the research question and also demonstrate what the field lacks. We present a summary of the key findings in (Figure 2).

The first theme *(Theme 1: Creative Phase Support)* establishes what kind of AI support each phase requires. During ideation, the AI must function as a generative partner, opening design space by proposing new ideas, producing different options, offering analogical inspiration, and reducing design fixation, but always preserving control over selection [16, 15]. During refinement, AI should operate as a precise and controlled agent, assisting the user with small changes, recognizing intent, and controlled iterations without spreading unintentional changes through the entire design [19, 8]. So, AI was found to be most useful in the early ideation, whereas in the refinement phase, AI becomes more useful when users have fine-grain control over it. HCI researchers should focus on developing a phase-aware system where users will get two distinct AI behavior modes, one for ideation and another for refinement, which enhances creativity and decision-making throughout the entire workflow.

The second theme *(Theme 2: Interaction Strategies across Creative Phase)* establishes which interaction mode fits in each phase. While ***Theme 1*** establishes what kind of phase-specific supports required, and ***Theme 2*** asks which interaction strategies deliver that support. In the ideation phase, benefits from open-ended, multimodal interaction, sketch-driven input, spatial composition, and visual input, which allows designers of different levels of expertise to communicate flexibly, avoiding premature verbal precision [29, 28]. The refinement requires well-defined, controllable interaction, such as semantic sliders, region-based editing, and composition-as-prompts, which allow designers precise control and make specific changes without unexpected results [19, 31]. So HCI researchers should focus on developing a phase-specific multimodal interaction strategy for different user groups. Where users can adjust modalities based on their intent and task environment, which supports exploratory interaction in ideation and a precise control mechanism in refinement, while combining the modalities to enhance engagement and creative outcomes.

The third theme *(Theme 3: User Control and Alignment)* establishes how much control each expertise level needs. Controls are not uniform across expertise levels, which means expert users require fine-grained controls that capture nuance and exact intent without distortion, while novice or non-designers rely more on rough sketches, prompt suggestions, and keyword transformation, etc. [8, 7]. These represent two fundamentally different design control problems; a single interface or interaction mechanism cannot effectively solve this issue for both expert precision and novice exploration. Another common challenge found across all studies is the misalignment between AI outputs and user intentions. Existing research shows that AI often fails to capture users' true intent [35], requiring constant input and human supervision to get the expected output. So, developing a transparent, user-adaptive AI system with interactive feedback loops, real-time interpretable controls, and intent-aware mechanisms reduces trial and error while balancing control and usability based on user expertise.

The fourth and final theme *(Theme 4: Impact of User Expertise)* shows that different levels of designer expertise do not just influence a single factor of co-creative interaction. It also reshapes the system itself, meaning what AI support is effective in each phase of the creative process (Theme 1), what type of interaction is appropriate and accessible (Theme 2), and which control mechanisms best support users' needs (Theme 3). So this theme shows that AI is used differently by users with varying expertise at different stages of the creative process. The themes also reveal that there is limited research on ”novice designers” and no empirical study has been found in our literature for non-designers. Most of the existing research largely focuses on design experts using AI. Future research must ask: What AI support is effective for non-designers during these phases? What interaction strategies and control mechanisms are effective for users with different design expertise? Exploring these questions can help in developing co-creative AI systems that cater to the needs and requirements of users with different expertise.

These four themes provide insights into the research question. It is clear that the use of a co-creative AI system that draws on different users' expertise and phases creates distinct requirements for AI in terms of function, interaction, and control. Overall, the findings suggest design implications of developing co-creative AI systems. First, phase-awareness in co-creative AI systems must recognize that different users have different interaction needs within the same phases. Themes 1 and 4 indicate that a phase-aware system needs to consider with whom it is co-creating. Second, theme 2 shows that the co-creative AI system should move from a single modality to a multimodal interaction strategy; future systems should focus on phase-specific multimodal interaction strategies where AI can adapt its interaction strategies based on users' phase-specific needs. Third, themes 3 and 4 suggest ways to mitigate the control alignment problem by developing intent-aware mechanisms and user-sensitive AI systems that support expressive precision for expert designers and intent articulation for non-designers. This paper serves two key purposes: one is to provide an analytical lens on existing work, offering guidance on how each finding is applied across different user levels and phases. And the other is to provide a roadmap for a future co-creative AI system design process that not only understands the creative phases but also adjusts its behavior, interactions, and control mechanisms appropriately to support different user groups in the digital and visual design context.

5.1. Limitations & Future Work

Overall, the results show that co-creative AI can help people be more creative and improve their creative potential during different phases if they have access to the right interaction strategies and control tools. However, this study has several limitations. First, we only considered one database, which may exclude relevant papers from other sources. Second, our final corpus is small, which may limit the generalization of results. However, we argue that this work remains an initial step towards answering our research question and may help practitioners and researchers in the relevant domains. Third, no user study was conducted, which may limit the validation of findings through real user interactions. As a part of the future work, we will expand the literature search to include additional databases to improve the generalization of the findings. Additionally, we plan to conduct a user study with designers and non-designers to understand their interaction strategies across creative phases. We planned to focus on digital and visual design art tasks that allow both designers and non-designers to engage in ideation and refinement activities. The final task selection will be guided by pilot testing to ensure it is accessible for both designers and non-designer groups while providing a meaningful opportunity for human-AI co-creation.

6. Conclusions

This paper presents a systematic literature review (SLR) of 22 human-AI co-creation research studies across user expertise levels and creative phases with a focus on the digital and visual design context. We analyze and synthesize our results into four themes. Through the four themes, we demonstrate that AI effectiveness, interaction strategies, and control requirements differ depending on both the creative phases and users' expertise. Synthesis of the findings not only provides the analytical lens of the existing work but also guides future HCI researchers on how these findings are implemented for future co-creative AI systems based on creative phases and user expertise. Developing a phase-aware, interaction-adaptive, user-sensitive AI system is both the most important open problem this review surfaces and the most concrete direction for future HCI research in computational creativity.

References

[1] J. Rezwana, M. L. Maher, Designing creative ai partners with cofi: A framework for modeling interaction in human-ai co-creative systems, ACM Transactions on Computer-Human Interaction 30 (2023) 1–28.

[2] L.-Y. Chiou, P.-K. Hung, R.-H. Liang, C.-T. Wang, Designing with ai: An exploration of co-ideation with image generators, in: ACM DIS '23, 2023, pp. 1941–1954.

[3] O. Shaer, A. Cooper, O. Mokryn, A. L. Kun, H. Ben Shoshan, Ai-augmented brainwriting: Investigating the use of llms in group ideation, in: CHI '24, 2024.

[4] J. Tholander, M. Jonsson, Design ideation with ai-sketching, thinking and talking with generative machine learning models, in: ACM DIS '23, 2023, pp. 1930–1940.

[5] S. Wadinambiarachchi, R. M. Kelly, S. Pareek, Q. Zhou, E. Velloso, The effects of generative ai on design fixation and divergent thinking, in: CHI '24, 2024, pp. 1–18.

[6] J. D. Weisz, J. He, M. Muller, G. Hoefer, R. Miles, W. Geyer, Design principles for generative ai applications, in: CHI '24, 2024, pp. 1–22.

[7] F. Nouraei, A. Siu, R. Rossi, N. Lipka, Thinking outside the box: Non-designer perspectives and recommendations for template-based graphic design tools, in: Extended Abstracts of the CHI, 2024, pp. 1–9.

[8] H. Lin, Y. Ye, J. Xia, W. Zeng, Sketchflex: Facilitating spatial-semantic coherence in text-to-image generation with region-based sketches, in: CHI '25, 2025, pp. 1–19.

[9] X. Tang, J. Windham, B. Bush, Pre-ai and post-ai design: Balancing human creativity and ai tools in the industrial design process, in: AIFE '24, 2024, pp. 100–108.

[10] X. Hu, Y. Xing, X. Cai, Y. Zhao, M. Cook, R. Borgo, T. Neate, Designing interactions with generative ai for art and creativity: A systematic review and taxonomy, in: ACM DIS '25, 2025, pp. 1126–1155.

[11] L. Candy, E. Edmonds, Modeling co-creativity in art and technology, in: C&C '02, 2002, pp. 134–141.

[12] N. Davis, Human-computer co-creativity: Blending human and computational creativity, in: AIIDE-13, volume 9, 2013, pp. 9–12.

[13] R. K. Sawyer, S. DeZutter, Distributed creativity: How collective creations emerge from collaboration., Psychology of aesthetics, creativity, and the arts 3 (2009) 81.

[14] A. H.-C. Hwang, Too late to be creative? ai-empowered tools in creative processes, in: CHI extended abstracts, 2022.

[15] P. Karimi, J. Rezwana, S. Siddiqui, M. L. Maher, N. Dehbozorgi, Creative sketching partner: an analysis of human-ai co-creativity, in: IUI '20, 2020, pp. 221–230.

[16] W.-F. Wang, C.-T. Lu, N. Ponsa i Campanyà, B.-Y. Chen, M. Y. Chen, Aideation: Designing a human-ai collaborative ideation system for concept designers, in: CHI '25, 2025, pp. 1–28.

[17] N. Kadenhe, M. Al Musleh, A. Lompot, Human-ai co-design and co-creation: A review of emerging approaches, challenges, and future directions, in: Proceedings of the AAAI Symposium Series, volume 6, 2025, pp. 265–270.

[18] J. Frich, M. Nouwens, K. Halskov, P. Dalsgaard, How digital tools impact convergent and divergent thinking in design ideation, in: Proceedings of the 2021 CHI conference on human factors in computing systems, 2021, pp. 1–11.

[19] R. Jain, A. Goel, K. Niinuma, A. Gupta, Adaptivesliders: User-aligned semantic slider-based editing of text-to-image model output, in: CHI '25, 2025, pp. 1–27.

[20] D. Choi, S. Hong, J. Park, J. J. Y. Chung, J. Kim, Creativeconnect: Supporting reference recombination for graphic design ideation with generative ai, in: CHI '24, 2024.
[21] N. Anantrasirichai, D. Bull, Artificial intelligence in the creative industries: a review, Artificial intelligence review 55 (2022) 589–656.
[22] Association for Computing Machinery, Acm digital library, 2026. URL: https://www.acm.org/publications/digital-library, retrieved May 20, 2026.
[23] J. Li, H. Cao, L. Lin, Y. Hou, R. Zhu, A. El Ali, User experience design professionals' perceptions of generative artificial intelligence, in: CHI '24, 2024, pp. 1–18.
[24] A. Cai, S. R. Rick, J. L. Heyman, Y. Zhang, A. Filipowicz, M. Hong, M. Klenk, T. Malone, Designaid: Using generative ai and semantic diversity for design inspiration, in: CI '23, 2023, pp. 1–11.
[25] K. Son, D. Choi, T. S. Kim, Y.-H. Kim, J. Kim, Genquery: Supporting expressive visual search with generative models, in: CHI '24, 2024, pp. 1–19.
[26] L. Chen, Q. Jing, Y. Tsang, Q. Wang, R. Liu, D. Xia, Y. Zhou, L. Sun, Autospark: Supporting automobile appearance design ideation with kansei engineering and generative ai, in: UIST '24, 2024, pp. 1–19.
[27] S. W. Lee, T. H. Jo, S. Jin, J. Choi, K. Yun, S. Bromberg, S. Ban, K. H. Hyun, The impact of sketch-guided vs. prompt-guided 3d generative ais on the design exploration process, in: CHI '24, 2024, pp. 1–18.
[28] N. Marquardt, A. Roseway, H. Romat, P. Panda, M. Pahud, G. Ramos, S. M. Drucker, A. D. Wilson, K. Hinckley, N. Riche, Imaginationvellum: Generative-ai ideation canvas with spatial prompts, generative strokes, and ideation history, in: UIST '25, 2025, pp. 1–19.
[29] D. C.-E. Lin, H. B. Kang, N. Martelaro, A. Kittur, Y.-Y. Chen, M. K. Hong, Inkspire: Supporting design exploration with generative ai through analogical sketching, in: CHI '25, 2025, pp. 1–18.
[30] S.-Y. Wang, W.-C. Su, S. Chen, C.-Y. Tsai, M. Misztal, K. M. Cheng, A. Lin, Y. Chen, M. Y. Chen, Roomdreaming: Generative-ai approach to facilitating iterative, preliminary interior design exploration, in: CHI '24, 2024.
[31] X. Peng, J. Koch, W. E. Mackay, Fusain: Composing generative ai visual prompts using pen-based interaction, in: CHI '25, 2025, pp. 1–20.
[32] S. Brade, B. Wang, M. Sousa, S. Oore, T. Grossman, Promptify: Text-to-image generation through interactive prompt exploration with large language models, in: UIST '23, 2023, pp. 1–14.
[33] J. Leong, D. Ledo, T. Driscoll, T. Grossman, G. Fitzmaurice, F. Anderson, Paratrouper: Exploratory creation of character cast visuals using generative ai, in: CHI '25, 2025, pp. 1–20.
[34] S.-J. Lee, J. Yoon, S.-H. Lee, J. H. Lee, S.-H. Bae, 3d sketching+ 2d generative ai for car exterior design, in: UIST Adjunct '25, 2025, pp. 1–14.
[35] P. Vaithilingam, M. Kim, F.-C. Acosta-Parenteau, D. Lee, A. Mhedhbi, E. L. Glassman, I. Arawjo, Semantic commit: Helping users update intent specifications for ai memory at scale, in: UIST Adjunct '25, 2025, pp. 1–18.