Design Science

Understanding how expertise shapes human-AI collaboration in graphic design with PatternPursuit

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Abstract

The increasing importance of co-creative tools in creative graphic design tasks has made it essential to understand how different levels of expertise shape the collaborative process between humans and computers. This paper presents a study with 30 participants to explore the impact of the PatternPursuit on the creative process, as well as on the collaborative experience and the user's perception of the system as a creative agent. PatternPursuit is an ideation system that uses pre-digital design work to produce graphic patterns for wrapping paper. The study involves two different groups of users interacting with the system; one group comprises design experts, and the other comprises non-experts. The results suggest that experts tend to see the system as a creative partner that challenges their objectives, while non-experts see it as a tool that broadens their skills and supports creative exploration. The findings can be used to develop effective co-creative systems that consider the target audience and their understanding of the creative process.

Keywords: Human-computer interaction, Creative process, Human-computer co-creation, User perception, Computational design

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1. Introduction

The increasing importance of intelligent systems today, especially in the context of creative processes, has fuelled the need to make systems that are based on stimulating human creativity more efficiently (Shneiderman 2002; Frich *et al.* 2019; Shireen 2020). Human-computer co-creative systems are characterised by the ability of computers to collaborate with humans in creating new ideas (Karimi *et al.* 2018; Kantosalo 2019). Currently, despite the vast contributions, according to Rezwana & Maher (2023), human-computer co-creative systems still present several challenges due to the unpredictable nature of human creativity and the different strategies and reasoning individuals use when developing creative artefacts. Given this unpredictability, it is expected that humans will vary in their level of control during the creative process, but also that the final result will be influenced by both the process followed and the objectives or experience (Shneiderman *et al.* 2006; Rezwana & Maher 2023; Rovira Martins *et al.* 2024). This leads us to the need to approach the development of human-computer co-creative tools not merely as a technical challenge, but as a process inherently

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characterised by subjectivity and uniqueness (Poon & Maher 1997). This is even more evident when these tools are applied to design, which is already a field with procedural nuances, making the balance between scientific rigour and creative practice even more difficult (Lawton *et al.* 2023). We therefore need to understand how different behaviours lead to distinct experiences (Lawton *et al.* 2023).

Considering the aspects mentioned above, we aim to understand how users' prior knowledge of design influences the perception of an ideation human-computer co-creative system, including the level of trust, the role the system adopts, the dynamics of the creative process and even the final result. Given the novelty of examining how expertise shapes human-computer co-creative interactions throughout a complete design workflow, we adopted an exploratory approach. Therefore, instead of testing pre-defined hypotheses to guide the study design and data analysis, we formulated the following research questions:

- RQ1: How does the level of design expertise influence the human-AI collaborative experience and the process during a design task?
- RQ2: How does the level of design expertise influence the user's perception of the computational partner in terms of trustworthiness and the role it adopts during the design process?
- RQ3: How does the level of design expertise influence the level of creativity in the final result and during a human-AI collaborative design task?

We used PatternPursuit, developed by Rovira Martins *et al.* (2024), as our study environment. We chose this system because it enables human-AI collaboration throughout the creative process, from exploring references to finalising a design artefact, within a structured yet flexible environment that reflects real-world design workflows. While we recognise the limitations of testing our hypotheses using a single system, PatternPursuit stands out as, to the best of our knowledge, the only available example that combines these characteristics with explainability strategies to improve users' trust in the creative process. These features support a deeper exploration of how the level of expertise influences the collaborative experience between humans and AI (RQ1) and the perception of the AI partner (RQ2).

Furthermore, the system initially provides users with visual references, specifically works by Portuguese graphic designer Sebastião Rodrigues, although it could operate with another set of references. This system uses conceptual and visual exploration techniques to decompose the works' elements into graphic raw materials, enabling the development of graphic patterns for wrapping paper (see Figure 1). This complete process of using Rodrigues' elements to create something new not only allows users to become deeply involved, supporting the analysis of the impact of the design experience on the level of creativity and the type of process during collaboration, but also makes it possible to analyse how it influences the level of creativity and the perception of the presence of references in the final result (RQ3). Although the system only explores the works of a single designer, it counters design fixation by allowing the user to explore different ideas (Jansson & Smith 1991; Son *et al.* 2024). We conducted a study with 30 participants to explore the mentioned aspects and present the findings as insights for designing effective human-AI co-creative systems, grounded in a deeper understanding of the target audience's diverse needs and their grasp of the human-AI creative process. In this paper, we make the following contributions:

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Figure 1. Graphic patterns for wrapping paper developed by the participants in this study using PatternPursuit.

- We demonstrate that expertise creates a fundamental division in the relationship between the process and the perception of the final result. In other words, while non-experts are motivated by originality and exploration, which is linked to the quality of the final result, experts operate on the basis of a dependency between agency and value, in which the validation of the final result is conditioned by their perception of control during the process.
- We have identified a dichotomy of interaction in which the same system plays opposing roles: for non-experts, it acts as a capability extender that fills skill gaps; for experts, it acts as a semi-autonomous partner that challenges authorship, highlighting the need for future systems to support explicit negotiation phases.

In addition to leading to new knowledge about the design of human-computer co-creative systems, this research also establishes a basis for future studies in this area.

2. Related work

2.1. Creative support systems

Creativity support tools, according to Frich *et al.* (2019), can be defined as digital systems that encompass one or more creativity-centred features and are used to positively influence one or more phases of the creative process. These tools have evolved in such a way that they have moved from the field of understanding how tools can help creativity in general (Shneiderman 2001) to the study of how these tools can be developed in a more specialised way and adapted to specific aspects and phases of the creative process (Davis, Wambsganss *et al.* 2024). One of these phases is ideation, characterised by divergent and convergent thinking, which are forms of searching in the design space of a specific domain (Frich *et al.* 2019). However, as the continuous accumulation of existing concepts expands these search spaces, it imposes a growing cognitive burden on human designers. Artificial Intelligence (AI) is increasingly employed to alleviate this limitation and enhance creativity (Sarica & Luo 2024). Currently, such systems are more effective at supporting the initial divergent ideation, while the convergent phase remains predominantly human-led (Chen *et al.* 2025).

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Supporting human creativity and stimulating new ideas can be done through real-time collaboration with artificial creative systems. We refer to these systems as human-computer co-creative systems, where the human and AI are considered creators during the creative process (Davis 2013). This differs from autonomous AI systems, which generate creative artefacts independently, and human creativity support systems (Davis, Deshpande *et al.* 2024). These systems, which have emerged in recent years (Jacob & Magerko 2015; Kantosalo 2019), have applications either for sketching (Davis *et al.* 2015; Karimi, Maher *et al.* 2019; Karimi, Grace *et al.* 2019; Ibarrola, Lawton & Grace 2024) or in the exploration of other disciplines, such as game design or design ideation (Yannakakis, Liapis & Alexopoulos 2014; Lucas & Martinho 2017; Koch *et al.* 2019).

Many recent examples of human-computer co-creative systems are in the field of drawing. In these systems, the interaction usually starts with a sketch by the user, and the computer partner contributes iteratively, promoting an alternating process until the final result is achieved. These include Drawing Apprentice (Davis *et al.* 2015), Collabdraw (Fan, Dinculescu & Ha 2019), DuetDraw (Oh *et al.* 2018) and Reframer (Lawton *et al.* 2023). There are cases (Ha & Eck 2017; F. Liu *et al.* 2019; Ge *et al.* 2021) in which the computational agent even explores the conceptual value of what is being designed, thereby making the computational contributions more appropriate. However, some examples (Sun *et al.* 2019; Li *et al.* 2020) adopt a task-divided co-creative approach (Kantosalo & Toivonen 2016), where humans and computers work on separate tasks during the process.

In the design field, we have the Arny system (Abdellahi, Maher & Siddique 2020), may AI (Koch *et al.* 2019) and CreativeConnect (Choi *et al.* 2024). Arny is based on emotional feedback to give answers to the human collaborator (Abdellahi *et al.* 2020). Besides considering the contributions to the task in question, it uses an interaction method to communicate perceptions and expectations similar to those of human-human collaboration; i.e., through facial expressions, a passive interaction channel is established between the agents. Koch *et al.* (2019) designed a system to support the design ideation process, with particular focus on mood board design. It uses a variant of machine learning methods known as cooperative contextual bandits. CreativeConnect (Choi *et al.* 2024) supports graphic designers' ideation process by helping to extract elements from reference images and suggesting a wide range of recombinations of these elements.

2.2. Influencing factors in the perception of creative systems

As mentioned, user perceptions of creative support systems may change due to the unpredictability inherent in human creativity and the different reasoning humans can adopt during the process (Rezwana & Maher 2023). However, other factors can influence users' perception of these tools.

The computational partner's role is a fundamental factor in the success of the collaboration (Bown 2015), and it can adopt various roles (Kantosalo & Toivonen 2016). For this reason, the positive experience of human-AI collaboration does not depend solely on the creative capacity of the artificial partner (Wegner 1997; Louie *et al.* 2020). The degree of similarity between the contributions of the user and the AI partner and how this communication is carried out also shapes the users' perception of the system (Rezwana & Maher 2023). In comparison, systems that produce results similar to the user's contributions can be perceived as more

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"pleasant" than systems that challenge the user with divergent or "provocative" contributions (Rezwana & Maher 2023). Moruzzi (2022) argues that agency and creativity are associated characteristics; if a system is considered creative, it will also be capable of having agentive capacity. However, to fully understand human-AI collaboration, it is crucial to distinguish between the machine's capabilities and the human's experience. For the computational partner, this agentive capacity is operationalised as autonomy, the ability to independently choose creative actions and determine when to contribute (Davis, Deshpande *et al.* 2024). Conversely, for the human user, the focus lies on the Sense of Agency (SoA), defined as the subjective awareness of initiating, executing and controlling actions within the environment (Jeannerod 2003; Pagliari, Chambon & Berberian 2021; Moruzzi 2022). A fundamental component of this experience is feeling in control throughout the creative process (Pagliari *et al.* 2021). Furthermore, as systems transition from mere tools into collaborative partners, user trust emerges as a critical dimension; successful interfaces must go beyond usability to actively cultivate trustworthiness and foster human agency (Carroll *et al.* 2026). In this sense, both the interaction and the process defined by the interface developed can limit the user's possibilities for exploration, influencing their level of creativity and agency (Heer 2019; Moruzzi 2022).

User characteristics can also be influential in the dynamics of acceptance, perception and response to technology (Davis 1989; Venkatesh *et al.* 2003). Studies suggest that people with different levels of design experience may have different expectations, preferences and levels of satisfaction when using AI tools (X. Liu, Maedche & He 2019; Liu & Huang 2025). For instance, in terms of the creative process, while experts tend to have an easier time projecting and anticipating what they can do in a design task, non-experts or less experienced designers tend to have more difficulty in this projection and even in exploring references (Bonnardel & Marmèche 2005; Kim *et al.* 2015).

The growing accessibility of these tools, alongside advances in computational creativity, has sparked debate about their impact on creative work. While some professionals consider these technologies important in supporting creative practices, others fear they will be replaced. It is therefore essential that the development of these systems goes beyond the technical aspects and considers the dynamics of human-computer interaction and the social dimension of collaboration (Gero, Long & Chilton 2023; Lim *et al.* 2024).

Given the aspects mentioned above, our study investigates human perceptions of collaboration with AI, considering the level of user expertise. This analysis considers the creative process, how the user perceives the computational partner, its effectiveness as an ideation system, the result and the perception of references. This research aims to answer growing questions regarding AI as a collaborative creator and to explore users' perceptions of interaction dynamics in co-creative tasks with AI agents. To the best of our knowledge, while research exists on how expertise shapes general tool expectations (Bonnardel & Marmèche 2005; Kim *et al.* 2015; X. Liu *et al.* 2019; Liu & Huang 2025), its specific influence on the perception of agency and trustworthiness throughout a complete human-computer co-creative design workflow remains underexplored. This study aims to contribute to this context by providing a comparison between professional and novice mental models in human-computer collaborative design.

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3. Methodology

3.1. PatternPursuit: a collaborative ideation system

PatternPursuit is a collaborative ideation system that enables the development of innovative graphic patterns (Rovira Martins *et al.* 2024). PatternPursuit promotes a human-computer co-creative process and takes advantage of pre-digital design work's conceptual and visual exploration to develop graphic patterns. Using this system as a study environment was particularly pertinent, as it reflects all stages of the actual graphic design process, including studying references, exploring forms and developing a final artefact. This factor allows us to study not only how users with different levels of expertise perceive a collaborative human-computer system, but also which stages of the process are most affected. Such cases are not common in the literature, so PatternPursuit proved to be a favourable environment for exploring the research hypothesis. Besides, graphic patterns are a fundamental element of graphic design, and the reasoning underlying its development process can be applied to other graphic design tasks. The restrictions associated with pattern creation challenge designers to find a balance between visual impact and functionality, understood in this context as the structural viability of a base unit to connect and repeat seamlessly into a continuous surface, a skill present in other graphic design tasks. In addition to the aspects mentioned above, the authors use Sebastião Rodrigues, a Portuguese graphic designer who reinvented and adapted international graphic design movements (Baltazar, Bártolo & Rosa 2021), as a case study. Sebastião Rodrigues was an ethnographic designer (Lisbon, 1929–1997), representing the "portugality" of the time through his own traditionalist modernism. Although the use of third-party works may raise copyright concerns from a commercial perspective, PatternPursuit's dataset-independent architecture offers a distinct advantage over other generative models (e.g., DALL-E). Unlike models trained on opaque, non-consensual datasets, this system can be implemented using a closed-loop approach with materials from, for instance, a company or a brand's archives. This allows designers to take advantage of AI-assisted design while maintaining strict compliance with copyright, demonstrating the system's viability for commercial practice.

The proposed hypotheses fall within the context of human-computer co-creative systems in graphic design, so it was considered appropriate to select a stable, representative process within the discipline that operates with a body of work of recognised value. These aspects offer a well-established theoretical and practical structure, providing resilience to potential disruptions introduced by the study or the system.

This system consists of five modules (see Figure 2), which enable an interactive process that users can monitor, adjust and directly influence. Initially, users interact with a gallery of works by Sebastião Rodrigues. Users can perform a semantic search via text input to explore the works conceptually. The system processes the user-entered concepts using the NLTK library (Bird, Loper & Klein 2009) and WordNet (Princeton University 2010) to identify semantically related words. The CLIP model (Radford *et al.* 2021) is used to associate the resulting words with the works in the gallery. The user is then presented with the Selected Gallery, which contains only works semantically related to the concepts entered. From this subset, users can select the works they find visually interesting to be

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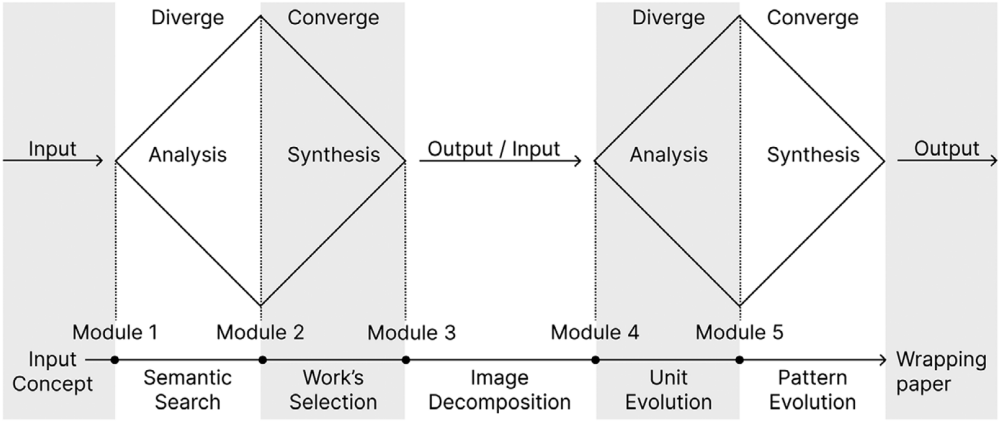


Figure 2. PatternPursuit workflow, showing the approaches used in each module and the methodological basis of each phase (Rovira Martins *et al.* 2024).

decomposed into graphical elements (regular and irregular shapes, textures or typography). To obtain them, this module uses image processing and computer vision algorithms, including k-means for colour quantisation (Dhanachandra, Manglem & Chanu 2015) and the MSER detector (Matas *et al.* 2004).

These decomposed elements, shown in the Decomposed Gallery, are the starting point for developing graphic patterns. Using Interactive Evolutionary Computation (Parmee, Abraham & Machwe 2008; Eiben & Smith 2015) the user iteratively develops the unit and then the complete graphic pattern. In both phases, the system acts as a partner and autonomously generates a set of candidate solutions. During the development of the unit, the system automatically generates various compositions using the decomposed elements in order to create the pattern unit. Next, during pattern development, it applies geometric transformations (such as translation, rotation and reflection) to the selected units to create different compositional structures. The user's role is to evaluate these machine-generated options via a point-and-click interface, selecting the most suitable ones to guide the next generation of the evolutionary process. Users have different functionalities that can help them to develop solutions more in line with what they want, for instance a solution archive or an expanded mode (see Figure 3) (Rovira Martins *et al.* 2024).

3.2. Participants

We invited 30 participants who took part in the study voluntarily. Most participants (23 out of 30) were recruited by the authors of this study via email invitation. The remaining seven participants were recruited through contact with a design studio. The selection criteria were defined in accordance with the study's need for a group of design experts and a diverse group of people from different areas who did not meet the criteria for the first group. As for the participants' ages, 19 were between 21 and 30, three were between 31 and 40, five were between 41 and 50, one was between 51 and 60 and two were aged 61 or over. Table 1 summarises each participant's profession and educational background.

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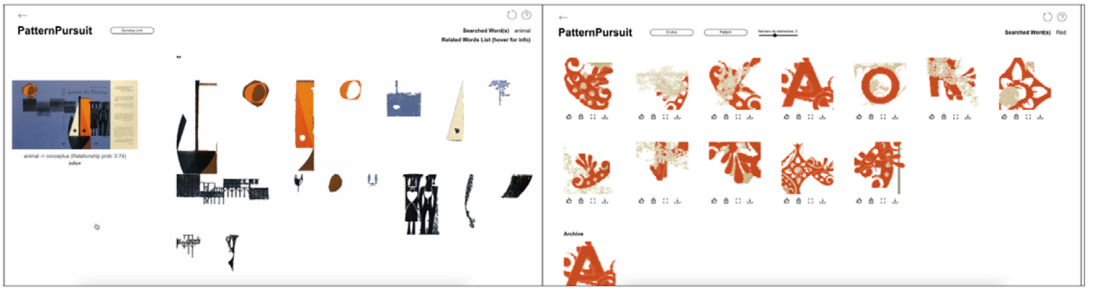


Figure 3. PatternPursuit system interface for the Decomposed Gallery and unit development modules.

Table 1. Information about the study participants

ID	Profession	Education	Years of experience
Non-experts			
P01	Management Controller	MSc in Management Control	None
P02	Music Teacher	BSc in Music	None
P03	Business Manager	BSc in Sociology	≤5 years
P04	Student	BSc in Design and Multimedia	≤5 years
P05	Architect	MSc in Architecture	≤5 years
P06	Architect	MSc in Architecture	None
P07	Researcher and Lecturer	MSc in Computer Engineering	≤5 years
P08	Researcher	MSc in Electrical Engineering	≤5 years
P09	Researcher	MSc in Design and Multimedia; MSc in Evolution and Human Biology	≤5 years
P10	Digital Designer	MSc in Graphic Design	≤5 years
P11	Student	MSc in Design and Multimedia	≤5 years
P12	Researcher	MSc in Computer Engineering	≤5 years
P13	Researcher and Lecturer	MSc in Computer Engineering	≤5 years
P14	Researcher and Lecturer	MSc in Computer Engineering	≤5 years
P15	Veterinary Physician	MSc in Veterinary Medicine	None
Experts			
P16	Designer	MSc in Design and Multimedia	11–20 years
P17	Designer	BSc in Design; MSc in Anthropology	21–30 years
P18	Designer	BSc in Communication Design	21–30 years

Continued

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Table 1. Continued

ID	Profession	Education	Years of experience
P19	Designer and Lecturer	PhD in Graphic Design	21–30 years
P20	Researcher	MSc in Design	6–10 years
P21	Designer and Lecturer	PhD in Design	21–30 years
P22	Researcher	MSc in Design and Multimedia	6–10 years
P23	Designer	PhD in Design	11–20 years
P24	Graphic Designer	BSc in Communication Design	21–30 years
P25	Graphic Designer	MSc in Graphic Design	6–10 years
P26	Product Designer	MSc in Design and Multimedia	6–10 years
P27	Motion Designer	MSc in Motion Design	11–20 years
P28	Researcher and Lecturer	MSc in Design and Multimedia	6–10 years
P29	Graphic Designer	BSc in Communication Design	6–10 years
P30	Researcher and Lecturer	MSc in Design and Multimedia	6–10 years

3.3. Level of expertise

Regarding experience in the design field, the group comprised 15 design experts and 15 non-experts. Each group was defined according to years of professional experience in the design field. The actual coding of design expertise and domain used the following conventions:

- Non-expert: individuals with less than 5 years of professional design experience. The 5-year threshold aligns with professional development models, marking the transition to a specialised level characterised by a consolidated mental model and workflows. This group encompasses both junior designers and professionals from unrelated fields (domain novices). Of the 15 non-experts, 11 had previously used design-related tools; of these 11, five had studied or worked in the design field for less than 5 years. It is important to note that the inclusion of participants from different backgrounds in this group was deliberate, as it allowed us to observe how people with different disciplinary perspectives interacted with the system, providing richer insights. Furthermore, this grouping stems from the premise that junior designers, although possessing academic training, are still in the early stages of consolidating their professional practice. Therefore, they share a similar cognitive flexibility and exploratory openness with domain novices when interacting with novel generative systems. This shared behaviour also occurs because, unlike experts who are accustomed to the authority and decision-making burden of authorship (Rock 1996), both junior designers and novices often experience a sense of relief when the AI assumes this responsibility.
- Expert: people with more than 5 years of professional experience in the field of design. Of the 15 experts, seven had between 6 and 10 years of experience, three between 11 and 20 years and five between 21 and 30 years. Beyond the temporal threshold, these participants were selected based on their active professional

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practice in design studios or academia, ensuring they possessed a consolidated design process and critical vocabulary typical of domain experts.

3.4. Protocol

The study used a mixed-methods protocol, consisting of a creative task followed by a structured quantitative questionnaire and a semi-structured qualitative discussion (see Figure 4). The interviews were conducted in person and recorded on audio and video; all interviewees gave their consent to participate in the study and verbal and written authorisation for audio and video recording during the interview. The questionnaire items were displayed on the screen to the participant. The discussion at the end gave participants the opportunity to freely elaborate on their experiences and challenges. Participants did not receive any compensation for participating in the study, but were highly motivated by the topic.

3.5. Data collection and instruments

The first part involved initial personal questions and a creative task. Participants were guided by a design brief: they were tasked with creating graphic patterns for gift wrapping paper. Although providing this concrete goal was essential to give users a starting point and prevent the paralysis of not knowing what to create, we deliberately kept the brief relatively open, without highly constrained requirements like a specific context. This trade-off aimed to encourage free exploration and allow us to observe how users naturally navigate the human-computer co-creative process. Within this brief, users could interact freely with the system until they developed one or more patterns that satisfied them (Rovira Martins *et al.* 2024).

The second part consisted of a structured quantitative questionnaire followed by a semi-structured qualitative discussion (see Supplementary Material). This

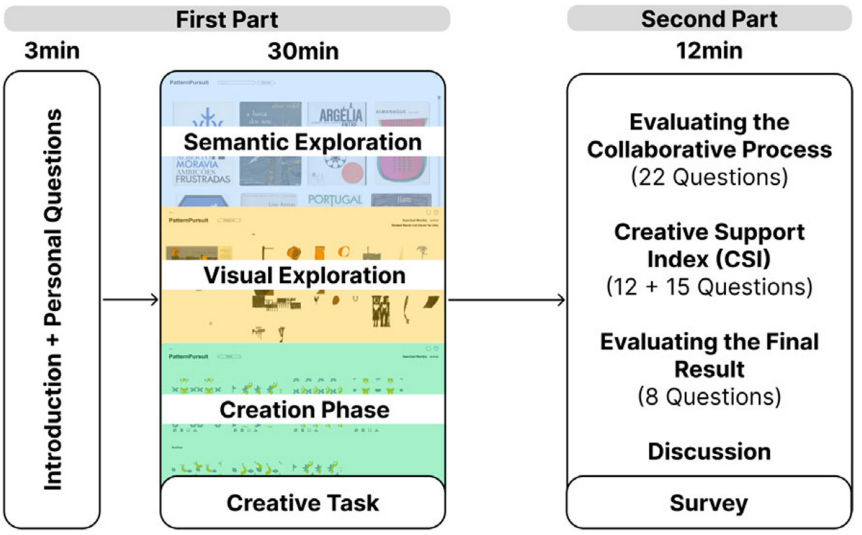


Figure 4. Structure of the tests conducted.

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part was subdivided into four different topics: (i) evaluating the collaborative process; (ii) Creative Support Index (CSI); (iii) evaluating the final result and (iv) general discussion.

Regarding the evaluation of the collaboration process, this assessed topics including Trustworthiness ("I felt the system was trustworthy"), Human Control ("I felt I had control over the process"), Freedom of Choice ("The system offered me freedom of choice"), System as an Idea Facilitator ("The system was effective as an idea facilitator"), Usefulness in Exploring Ideas ("The system was useful in exploring new ideas") and Perception of how users' skills and prior knowledge could have influenced the process. These items were measured on the defined 5-point Likert scale. Given that the main objective of this exploratory research was to study user perception within a broad context, encompassing the analysis of the artificial partner, the collaborative process and the creative impact, we opted to use single-item Likert scales to measure global perceptions such as trust and control. This methodological choice aimed to prevent participant fatigue, a practical constraint where single-item measures offer a viable alternative for overarching global constructs (Wanous, Reichers & Hudy 1997; Fisher, Matthews & Gibbons 2016). While this precludes a granular analysis of specific sub-dimensions, it provides a general overview of user perceptions that is aligned with the study's exploratory objectives. Other measuring factors, such as autonomy, contributions, the role the system played during the process and the quantity of ideas explored, were assessed using a multiple-choice answer format.

To evaluate the system's level of autonomy in terms of action and creative choices, we used categorical choice instrument based on the characteristics of autonomy of the five-pillar framework proposed by Davis, Deshpande *et al.* (2024): (i) Fully autonomous – the computer takes the initiative to act and chooses the creative action; (ii) Semi-autonomous – the computer does not take the initiative to act, but chooses its creative action and (iii) User directed – the user guides the computer and it behaves in a defined way.

Regarding the system's contributions, users had the following options (Davis, Deshpande *et al.* 2024): (i) Fully emergent – produces contributions that are highly variable, spontaneous and unpredictable and cannot be deduced; (ii) Partially emergent – produces contributions that are unexpected but deducible considering the initial conditions and the set of rules defined and (iii) Non-emergent – produces contributions that are predictable and deducible. We chose this structure because it allows us to assess the system's alignment with the user's creative expectations and its potential to promote unexpected solutions. The system's level of autonomy and the nature of its contributions were fixed, meaning the system behaved consistently across all participants. Therefore, the questions on these topics assessed the users' inferred perceptions of the system's behaviour, revealing how their level of expertise shaped their mental model of the AI's capacity for action.

When asked about the predominant role the system played during the creative process, we used the options established by Maher (2012) (Q13): (i) Enhance – the system provides knowledge and incentives to increase the user's creative capacity; (ii) Support – the computer provides techniques and support tools that can help human creativity and (iii) Generator – the computer generates creative ideas that the human being interprets, evaluates and can integrate into the final product.

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In the second subsection, participants answered a CSI questionnaire proposed by Cherry & Latulipe (2014), consisting of 12 questions to assess the tool's support for creativity, measuring the six dimensions of creativity: Collaboration, Enjoyment, Exploration, Expressiveness, Immersion and Results worth the effort. Also related to the CSI, participants directly compared two factors to understand which factors were most frequently mentioned by the user.

Finally, the participants evaluated the final results regarding value, novelty and quality to understand the level of creativity of the result, as proposed by Boden (2004). To ensure conceptual clarity within this specific graphic design task, these three parameters were defined to the participants. This provided a standardised evaluation baseline across users, as the task, while having a specific objective, was partially open-ended in terms of context. "Novelty" referred to the visual and conceptual originality of the generated pattern, assessing its capacity to produce unexpected results that depart from typical wrapping paper conventions. "Value" measured the professional utility and practical relevance of the pattern for its intended real-world application. "Quality" was evaluated based on the aesthetic success and visual cohesiveness of the overall composition. We specifically looked for a unified whole in the Gestalt sense, where the final design feels like a complete piece rather than a mere aggregation of separate parts. Participants also evaluated the level of recognition of the references, and the "key elements" they considered for recognition. In addition, the final segment was a semi-structured qualitative discussion. Here, participants were encouraged to describe what they enjoyed most and the challenges encountered, and to suggest improvements. The open-ended nature of this discussion allowed the interviewer to pursue interesting emergent themes for deeper exploration.

For data analysis, given the sample size ($N = 30$) and the ordinal nature of the Likert-scale data, we used non-parametric tests. The Mann–Whitney U test was employed to identify significant differences between the two independent groups (experts versus non-experts). Furthermore, to understand the relationships between variables (e.g., how control influences perceived value), we conducted Spearman's rank correlation coefficient analyses for each group separately. Statistical significance was defined at $p < 0.05$.

4. Results

4.1. Reflecting on the user's collaborative experience (RQ1)

This subsection focuses on the global collaboration experience and the dynamics between the parties during the creative process. Regarding the system's workflow, both groups considered that the phases of the system helped the creative process (Q14), with a relatively higher mean for non-experts (*mean* = 4.33 ± 0.87, *mode* = *median* = 5.00) compared to experts (*mean* = 4.00 ± 0.82, *mode* = *median* = 4.00), though this difference was not statistically significant ($p = 0.201$). Similarly, regarding the influence of prior knowledge (Q19), no significant difference was found ($p = 0.982$), with both groups reporting high confidence levels (*mean* = 4.00 ± 0.82 for experts; *mean* = 4.00 ± 0.89 for non-experts).

As observed in Table 2, the level of trustworthiness in using the system (Q8) was rated positively by both groups. This indicates that, regardless of the level of

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Table 2. User perception of the computational partner considering expertise. Bold values indicate statistical significance ($p \leq 0.05$)

		Non-experts			Experts			
ID	Parameters	Mean (SD)	Mode	Med.	Mean (SD)	Mode	Med.	p-value
Q8	Trustworthiness	3.87 ± 0.72	4.00	4.00	3.53 ± 0.96	4.00	4.00	0.397
Q9	Human Control	3.13 ± 0.72	3.00	3.00	2.53 ± 0.72	3.00	3.00	**0.050**
Q12	Freedom of choice	3.93 ± 1.12	5.00	4.00	3.00 ± 0.82	4.00	3.00	**0.026**
Q15	System as an idea facilitator	4.33 ± 0.47	4.00	4.00	3.87 ± 0.62	4.00	4.00	**0.042**
Q28	Usefulness in exploring ideas	4.40 ± 1.00	5.00	4.00	3.80 ± 0.91	4.00	4.00	0.068

experience, the system's interface helps to support user confidence, although non-experts emphasise it slightly more.

However, significant differences emerged regarding agency. Non-experts reported feeling more human control (Q9, $p = 0.050$) and freedom of choice (Q12, $p = 0.026$) than experts. Consistent with this, non-experts felt that the system played more of a facilitating role in generating ideas (Q15, $p = 0.042$) and was marginally more useful in exploring them (Q28, $p = 0.068$) than experts.

Behavioural data support these quantitative findings. Non-experts adopted a divergent exploration strategy, with the majority exploring "4 or 5" or "6 or more" ideas before deciding. In contrast, experts adopted a more convergent approach, exploring fewer distinct ideas ("2 or 3"), but reporting a higher frequency of returning to previous steps to modify things. This behaviour demonstrates a desire for refinement and specific control that the system's semi-autonomous nature may have constrained.

4.2. Reflecting on the user's perception of the computational partner (RQ2)

Considering the user's perception of autonomy, 80% of experts (12 out of 15) categorised the system as Semi-Autonomous, demonstrating a higher consensus. In contrast, non-experts were more divided, with the majority (60%, 9) perceiving the system as User-Directed, while 40% (6) saw it as Semi-Autonomous. This suggests that non-experts, relying on the system to bridge skill gaps, perceived the tool's utility as an extension of their own agency.

Regarding the system's role, 66.7% of experts (10) viewed the system as an Enhancer. Non-experts were more divided between Enhancer (46.7%, 7) and Generator (40%, 6), indicating that a significant portion of non-experts attributed the core creative act to the creative artificial partner.

Furthermore, we also analysed perceptions of the system's contributions. While 100% of the experts (15) rated the contributions as "Partially emergent", that is unexpected but deducible from a set of rules, 33.3% (5) of the non-experts perceived them as "Fully emergent" and 66.7% (10) as "Partially emergent". This indicates that while experts could identify the underlying logic of the generation, a third of the non-experts perceived the output as non-deducible novelty.

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Table 3. Creativity Support Index results considering user expertise

Parameters	Avg. factor counts		Avg. factor score	
	Experts	Non-experts	Experts	Non-experts
Collaboration	0.73 ± 1.1	0.27 ± 0.6	7.00 ± 1.6	6.46 ± 2.6
Enjoyment	1.87 ± 1.4	2.27 ± 1.0	7.40 ± 1.2	8.47 ± 1.7
Exploration	4.40 ± 0.7	4.20 ± 0.9	7.13 ± 1.8	8.33 ± 1.5
Expressiveness	3.60 ± 0.6	3.60 ± 1.3	6.33 ± 1.8	8.13 ± 1.5
Immersion	1.27 ± 0.9	2.13 ± 1.1	6.87 ± 2.1	7.67 ± 1.9
Results worth effort	3.13 ± 1.3	2.53 ± 1.5	7.93 ± 1.4	9.40 ± 1.0
CSI score (total)			**71.22**	**83.28**

4.3. Reflecting on the level of creativity (RQ3)

When calculating the Creative Support Index for expert and non-expert groups, it was found that the non-experts had a higher score (83.28) than the experts (71.22), indicating that the system was far more effective at supporting the creativity of novices ($p = 0.011$).

As shown in Table 3, non-experts considered the system particularly effective in Results Worth the Effort (9.40 ± 1.0) and Enjoyment (8.47 ± 1.7), suggesting that they felt rewarded during creative exploration. In contrast, experts gave the lowest ratings to Expressiveness (6.33 ± 1.8), highlighting that they felt the system did not allow them to be as expressive as they would have liked.

Regarding the final pattern, non-experts considered it to have significantly higher quality ($p = 0.005$) and value ($p = 0.046$) than the experts (see Table 4). Concerning novelty, although non-experts rated it highly, no significant difference was found compared to experts ($p = 0.086$).

Finally, the analysis of the balance between novelty and authorship (Q56) reveals a subtle but important distinction in perception. Experts perceived the final patterns as slightly more balanced (*mean* = 3.53 ± 0.81) than non-experts

Table 4. Evaluation of the final result considering user expertise. Bold values indicate statistical significance ($p \leq 0.05$)

ID	Parameters	Non-experts			Experts			p-value
		Mean (SD)	Mode	Med.	Mean (SD)	Mode	Med.	
Q51	Quality	4.67 ± 0.60	5.00	5.00	3.80 ± 0.91	4.00	4.00	**0.005**
Q52	Value	4.67 ± 0.60	5.00	5.00	4.07 ± 0.93	5.00	4.00	**0.046**
Q53	Novelty	4.67 ± 0.47	5.00	5.00	4.13 ± 0.88	5.00	5.00	0.086
Q54	Memory recognition	2.67 ± 1.45	1.00	3.00	2.73 ± 1.00	2.00	3.00	0.832
Q55	Side by side recognition	3.73 ± 1.29	5.00	4.00	3.27 ± 1.18	3.00	3.00	0.285
Q56	Balance (novelty vs authorship)	3.33 ± 1.07	4.00	3.00	3.53 ± 0.81	3.00	3.00	0.726

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(*mean* = 3.33 ± 1.07, $p = 0.726$). This result is revealing when contrasted with recognition (Q54). Although experts struggled to explicitly identify Sebastião Rodrigues' works in the final output (*mean* = 2.73 ± 1.00), their higher rating for balance suggests they value the overall structural equilibrium between the new composition and the source material, rather than merely looking for literal visual citations. In contrast, non-experts, lacking this depth of design nuance, may have struggled to perceive this abstract balance, focusing instead on obvious visual references, which led to a lower perception of equilibrium despite their higher overall satisfaction.

5. Discussion and research opportunities

The results demonstrate how users' level of expertise significantly shapes their experience and interpretation of collaboration with AI-assisted design tools. This validates the need for adaptable interfaces (Shneiderman 2002) and underscores how user groups conceptualise the same system differently.

5.1. RQ1: influence on the collaborative experience and process

The findings show that the level of design expertise dictates distinct creative strategies, leading to fundamental differences in the collaborative process. Non-experts favoured a divergent exploration approach, exploring more ideas, appreciating the system's ability to generate and extend ideas beyond their competence. This approach is quantified by their perception of the system being highly useful in exploring ideas (Q28, *mean* = 4.40). For this group, the system acted as a capability extender, with one participant noting, *"I consider myself an uncreative person, and the tool exceeded all my expectations"* (P08), illustrating how the tool successfully bridges the gap between low technical skill and high creative output.

Experts, in contrast, adopted a convergent refinement process, revisiting previous iterations more often to refine the results, expecting the system's contributions to be more in line with their vision. When asked specifically if their prior knowledge made them feel inhibited or confident (Q19), experts reported high confidence (*mean* = 4.00), matching non-experts. This indicates that their expertise did not act as an internal psychological barrier or a source of inhibition. However, this internal confidence stands in contrast to their significantly lower perception of freedom of choice (Q12, $p = 0.026$). This suggests that while their expertise made them feel capable of defining a creative direction, the system's semi-autonomous nature restricted their ability to execute that specific vision. Unlike non-experts, who felt supported by the tool, experts felt constrained because the system could not accommodate the type of control over the process that they were accustomed to in their professional activity. This confirms a greater need for negotiation phases and explainable system behaviour for experts to feel confident in incorporating contributions.

5.2. RQ2: influence on perception of the computational partner

One of the most significant divergences concerns the conceptualisation of the system's role: non-experts (60%) categorised the system as User-directed, while experts (80%) conceptualised it as Semi-Autonomous. This dichotomy is

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fundamental to understanding the dynamics of collaboration. The non-experts perceived the AI as an empowering tool. This User-directed view aligns with their perception of balanced control (Q9, *mean* = 3.13), which stands in significant contrast to the experts' perception of system control (*mean* = 2.53) and their feeling that the system helps them overcome skill limitations to produce high-quality work (Q51, *mean* = 4.67). Their focus is on the structured guidance provided by the tool.

Conversely, experts conceptualised the AI as a creative partner that challenges their objectives. Their Semi-Autonomous categorisation suggests they expect the AI to have its own creative agency, prompting them to find a "middle ground" between the computer's idea and their own expectations, mirroring human-human collaboration dynamics. This need for alignment confirms a strong requirement for negotiation phases and explainable behaviour for experts to feel confident in incorporating the AI's contributions. As one expert illustrated, the lack of this negotiation led to a sense of restriction: "I felt that it controlled many of the images it gave me, so I felt I was a bit limited" (P21). This vividly highlights the friction experts experience when a semi-autonomous system does not offer the precise control required to align the AI's contributions with their professional intent.

5.3. RQ3: influence on the level of creativity and final result

The collaborative process resulted in a significantly lower overall CSI score for experts (71.22) than for non-experts (83.28). This divergence confirms that the structured guidance, while successfully accelerating the creative capacities of non-experts, led to reduced creative satisfaction for experts. For the latter group, the difficulty in aligning the AI's output with their established domain knowledge contributed to a lower assessment of the system's effectiveness in key areas they valued, such as Exploration (*mean* = 7.13 vs. *mean* = 8.33) and Expressiveness (*mean* = 6.33 vs. *mean* = 8.13).

Regarding the final result, non-experts rated the patterns significantly higher in Quality ($p = 0.005$) and Value ($p = 0.046$). This disparity is clarified by our correlation analysis. For non-experts, a positive correlation was found between perceived Quality and Novelty ($r = 0.55, p = 0.032$). This suggests that non-experts conflate the originality of the generation with the quality of its design, maximising their satisfaction with the final result.

On the other hand, although experts also rated Novelty as moderately high (*mean* = 4.13), their perception of Value is correlated with Human Control ($r = 0.48$). This indicates that, for experts, the professional usefulness of the artefact is linked to their SoA, that is without control, they do not value the result, even if they recognise it as innovative. Unlike non-experts, who were satisfied with the surprise, experts distinguished between the novelty of the generation and its actual usefulness. While experts acknowledged that the system *"presents options that I had not seen before through the selection of different parts and alternative combinations. It reverses the logic of visualisation/interpretation"* (P17), this intellectual recognition of novelty did not translate into professional value without control. In contrast, non-experts embraced the lack of control as a creative feature, with one stating that although they had a definite initial idea, the unexpected results "opened up my horizons" (P02), confirming the strong correlation found between Novelty and Quality for this group.

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5.4. Implications and research opportunities

This divergence in findings highlights a key tension in co-creative systems: the same functionalities may be perceived as empowering or intrusive, depending on the user's expertise and expectations.

Although these conclusions are drawn from interactions with PatternPursuit, they offer relevant insights for the broader discussion on human-AI collaboration. We acknowledge that PatternPursuit operates fundamentally differently from widely used generative AI tools (such as text-to-image diffusion models), as it provides structured control over the recombination of existing visual materials through an iterative, step-by-step collaborative loop, rather than generating entirely new visual elements from scratch through one-shot prompting. This fundamental distinction in the creative workflow makes direct comparisons with other generative systems difficult. However, these results demonstrate that a user's domain expertise is a critical factor that influences their perception of control and autonomy. Ultimately, this study highlights that the level of expertise can lead users to perceive the same system differently regarding its role, its contributions, the creative process and the evaluation of the final result.

These findings contribute to the development of more effective co-creative systems by directly informing a framework of research opportunities:

- Adaptable idea exploration: Systems should support both divergent (idea generation) and convergent (idea refinement) thinking styles to allow users with different levels of expertise to follow the process they need.
- Negotiation phase: Systems must provide users with a way of negotiating with the computational partner after their contribution, through explainability techniques.
- Customisable Autonomy: Systems should contain different levels of autonomy, allowing users to either use the system entirely autonomously or with slight inclusion of the computational partner, in a co-creative manner, with balanced agency between the parties, or with the computer having greater control over the process.

By implementing this framework, future co-creative systems can better respond to their users' needs. Such systems could promote more successful interactions, where experts feel their knowledge is reinforced rather than jeopardised, and non-experts feel empowered to create without barriers.

6. Limitations and future work

This study presents preliminary insights into how user experience shapes collaboration between humans and AI in graphic design. However, the relatively small sample size and interview-based context limited the observation of behavioural nuances that might arise with prolonged or real-world use. Larger-scale studies with diverse user groups would help validate the findings and their generalisation.

Regarding data collection and evaluation, our methodology prioritised capturing users' subjective experiences and high-level strategies through qualitative, self-reported data. This approach extended to the evaluation of creativity, which relied on participants' self-assessment. While this may introduce potential bias, it was a deliberate choice, since computational creativity relies heavily on subjective human judgement (Jordanous 2012; Lamb *et al.* 2019), and capturing this personal

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validation was essential to understanding users' perception of autonomy and trust. Nevertheless, while this qualitative focus effectively addressed our research questions, future studies could expand on these insights by using multi-item scales and incorporating low-level system telemetry. Logging quantitative behavioural data, such as the number of semantic searches, evolutionary iterations or time spent per module, would offer a valuable opportunity to triangulate these subjective reports with objective interaction metrics.

As noted in the previous section, the end-to-end nature of PatternPursuit, encompassing everything from the initial exploration of references to the creation of the final artefact, adds a layer of complexity to direct comparisons with mainstream AI generators. Furthermore, comparison with other tools, such as Illustrator, would introduce significant evaluation biases, as results for non-experts would reflect their lack of proficiency in the software rather than their collaborative experience. Consequently, we chose to focus on evaluating how user expertise shapes the creative process and perceptions within a specific workflow. Observing the strategies of experts and novices in a uniform environment allows us to assess the collaborative differences influenced by expertise (Bonnardel & Marmèche 2005; Ozkan & Dogan 2013).

Future work should explore how these findings inform system design that adapts to different levels of experience. Investigating the impact of users' prior experience with AI and drawing on models of human creative collaboration can also foster the development of more effective and adaptable co-creative systems.

7. Conclusion

The increase in the daily use of human-AI creative tools in creative tasks has fuelled the need to make creative systems more efficient. Even with the vast contributions to computational creativity, the unpredictable nature of human creativity means that the strategies and reasoning they use, the level of control in the process and the final result can vary depending on their goal and experience. These aspects contribute to the fact that systems such as human-computer co-creative still present several challenges (Rezwana 2023). In this sense, it is important to understand how the same system can be perceived depending on the user's background, initial expectations and critical thinking. The study revealed insights into how expertise level influences users' perceptions and interactions with collaborative design systems.

We used PatternPursuit as a study environment because it provides users with a range of references, allows conceptual and visual exploration, serves as an ideation tool and facilitates the elaboration of a final result – graphic patterns for wrapping paper. Given these characteristics, we consider PatternPursuit a complete and viable system for exploring the hypothesis posed.

The results of this study highlight the differences in collaboration and perception between groups with different levels of knowledge. By comparing the experiences of non-experts and experts using PatternPursuit, we observe trends in how knowledge impacts the various aspects of the creative process. While non-experts felt empowered by the tool, experts felt constrained by the system's semi-autonomous nature. Our analysis reveals that, for experts, the perceived value of the final artefact is linked to their SoA, i.e., if they are unable to guide the process, they do not validate the result as useful, regardless of its novelty. This reinforces the

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conclusion that, for adoption by experts, co-creative systems must go beyond generating surprise and offer the necessary control to align AI contributions with the user's professional intent. These conclusions can be used to develop more effective co-creative systems that consider the target audience.

Supplementary material

The supplementary material for this article can be found at http://doi.org/10.1017/dsj.2026.10078.

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Declaration of generative AI

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Competing interests

The authors report there are no competing interests to declare.

References

Abdellahi, S., **Maher, M. L.** & **Siddique, S.** 2020. Arny: a co-creative system design based on emotional feedback. In *Proceedings of the 7th International Conference on Computational Creativity*, pp. 81–84. Association for Computational Creativity (ACC).

Baltazar, M. J., **Bártolo, J.** & **Rosa, V.** 2021 *Designers Portugueses (Vols. 3–Sebastião Rodrigues)*. Cardume Editores.

Bird, S., **Loper, E.** & **Klein, E.** 2009 *Natural Language Processing with Python*. O'Reilly Media Inc.

Boden, M. 2004 *The Creative Mind: Myths and Mechanisms*, 2nd Edn. Routledge; doi: 10.4324/9780203508527.

Bonnardel, N. & **Marmèche, E.** 2005 Towards supporting evocation processes in creative design: a cognitive approach. *International Journal of Human-Computer Studies* **63** (4-5), 422–435; doi:10.1016/j.ijhcs.2005.04.006.

Bown, O. 2015 Player responses to a live algorithm: conceptualising computational creativity without recourse to human comparisons? In *Proceedings of the International*

https://doi.org/10.1017/dsj.2026.10078 Published online by Cambridge University Press

Conference on Computational Creativity, pp. 126–133. Association for Computational Creativity (ACC).

Carroll, F., **Slattery, D. M.**, **Renaud, K.** & **Bauerly, K. E.** 2026 Understanding people: extensions of human–computer interaction. *Design Science* **12**; doi:10.1017/dsj.2025.10047.

Chen, L., **Song, Y.**, **Guo, J.**, **Sun, L.**, **Childs, P.** & **Yin, Y.** 2025 How generative AI supports human in conceptual design. *Design Science* **11**, e9; doi:10.1017/dsj.2025.2.

Cherry, E. & **Latulipe, C.** 2014 Quantifying the creativity support of digital tools through the creativity support index. *ACM Transactions on Computer-Human Interaction* **21** (4), 1–25; doi:10.1145/2617588.

Choi, D., **Hong, S.**, **Park, J.**, **Chung, J. J. Y.** & **Kim, J.** 2024 Creative connect: supporting reference recombination for graphic design ideation with generative AI. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pp. 1–25. ACM; doi: 10.1145/3613904.3642794.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* **13**(3), 319–340. Available at: http://www.jstor.org/stable/249008; doi:10.2307/249008.

Davis, N. 2013 Human-computer co-creativity: blending human and computational creativity. In *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, **9**(6), 9–12. Number: 6. https://ojs.aaai.org/index.php/AIIDE/article/view/12603.

Davis, N., **Hsiao, C.-P.**, **Singh, K. Y.**, **Li, L.**, **Moningi, S.** & **Magerko, B.** 2015 Drawing apprentice: An enactive co-creative agent for artistic collaboration. In *Proceedings of the 2015 ACM SIGCHI Conference on Creativity and Cognition*, pp. 185–186. C&C '15, Association for Computing Machinery; doi:10.1145/2757226.2764555.

Davis, N., **Deshpande, M.**, **Rezwana, J.** & **Magerko, B.** 2024 The five pillars of enaction as a theoretical framework for co-creative artificial intelligence. In *Proceedings of the 15th International Conference on Computational Creativity*. Association for Computational Creativity (ACC).

Davis, R. L., **Wambsganss, T.**, **Jiang, W.**, **Kim, K. G.**, **Käser, T.** & **Dillenbourg, P.** 2024 Fashioning creative expertise with generative ai: Graphical interfaces for design space exploration better support ideation than text prompts. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, CHI '24, Association for Computing Machinery; doi:10.1145/3613904.3642908.

Dhanachandra, N., **Manglem, K.** & **Chanu, Y. J.** 2015 Image segmentation using K -means clustering algorithm and subtractive clustering algorithm. *Procedia Computer Science* **54**, 764–771. https://www.sciencedirect.com/science/article/pii/S1877050915014143; doi:10.1016/j.procs.2015.06.090

Eiben, A. E. & **Smith, J. E.** 2015 *Introduction to Evolutionary Computing, Natural Computing Series*. Springer; doi:10.1007/978-3-662-44874-8.

Fan, J. E., **Dinculescu, M.** & **Ha, D.** 2019 Collabdraw: An environment for collaborative sketching with an artificial agent. In *Proceedings of the 2019 Conference on Creativity and Cognition*, pp. 556–561. C and C '19, Association for Computing Machinery; doi: 10.1145/3325480.3326578.

Fisher, G. G., **Matthews, R. A.** & **Gibbons, A. M.** 2016 Developing and investigating the use of single-item measures in organizational research. *Journal of Occupational Health Psychology* **21** (1), 3–23; doi:10.1037/a0039139.

Frich, J., **MacDonald Vermeulen, L.**, **Remy, C.**, **Biskjaer, M. M.** & **Dalsgaard, P.** 2019 Mapping the landscape of creativity support tools in HCI. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–18. CHI '19, Association for Computing Machinery; doi:10.1145/3290605.3300619.

https://doi.org/10.1017/dsj.2026.10078 Published online by Cambridge University Press

Ge, S., **Goswami, V.**, **Zitnick, C. L.** & **Parikh, D.** 2021 Creative sketch generation. In *9th International Conference on Learning Representations*. International Conference on Learning Representations.

Gero, K. I., **Long, T.** & **Chilton, L. B.** 2023 Social dynamics of AI support in creative writing. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pp. 1–15. ACM; doi:10.1145/3544548.3580782.

Ha, D. & **Eck, D.** 2017 A neural representation of sketch drawings. arXiv:1704.03477 [cs, stat]. https://arxiv.org/abs/1704.03477.

Heer, J. 2019 Agency plus automation: designing artificial intelligence into interactive systems. *Proceedings of the National Academy of Sciences* **116** (6), 1844–1850; doi:10.1073/pnas.1807184115.

Ibarrola, F., **Lawton, T.** & **Grace, K.** 2024 A collaborative, interactive and context-aware drawing agent for co-creative design. *IEEE Transactions on Visualization and Computer Graphics* **30** (8), 5525–5537; doi:10.1109/TVCG.2023.3293853.

Jacob, M. & **Magerko, B.** 2015 Viewpoints ai. In *Proceedings of the 2015 ACM SIGCHI Conference on Creativity and Cognition*, pp. 361–362. C&C '15, Association for Computing Machinery; doi:10.1145/2757226.2757400.

Jansson, D. G. & **Smith, S. M.** 1991 Design fixation. *Design Studies* **12**(1), 3–11. https://linkinghub.elsevier.com/retrieve/pii/0142694X9190003F; doi:10.1016/0142-694X(91)90003-F.

Jeannerod, M. 2003 The mechanism of self-recognition in humans. *Behavioural Brain Research* **142**(1-2), 1–15. https://www.sciencedirect.com/science/article/pii/S0166432802003844; doi:10.1016/S0166-4328(02)00384-4

Jordanous, A. 2012 A standardised procedure for evaluating creative systems: computational creativity evaluation based on what it is to be creative. *Cognitive Computation* **4** (3), 246–279; doi:10.1007/s12559-012-9156-1.

Kantosalo, A. 2019 *Human-computer co-creativity — designing, evaluating and modelling computational collaborators for poetry writing*, Helsingin yliopisto. Available at: http://cs.helsinki.fi/

Kantosalo, A. & **Toivonen, H.** 2016 Modes for creative human-computer collaboration: alternating and task-divided co-creativity. In *Proceedings of the 7th International Conference on Computational Creativity*, pp. 77–84. Association for Computational Creativity (ACC).

Karimi, P., **Grace, K.**, **Maher, M. L.** & **Davis, N.** 2018 Evaluating creativity in computational co-creative systems. In *Proceedings of the 9th International Conference on Computational Creativity*, pp. 104–111, ICCC. arXiv: 1807.09886.

Karimi, P., **Grace, K.**, **Davis, N.** & **Maher, M.** 2019 Creative sketching apprentice: supporting conceptual shifts in sketch ideation. In *Design Computing and Cognition '18* (ed. J. Gero), pp. 721–738. Springer; doi:10.1007/978-3-030-05363-5_39.

Karimi, P., **Maher, M. L.**, **Davis, N.** & **Grace, K.** 2019 Deep Learning in a Computational Model for Conceptual Shifts in a Co-Creative Design System. arXiv:1906.10188 [cs, stat]. Available at: http://arxiv.org/abs/1906.10188.

Kim, J., **Dontcheva, M.**, **Li, W.**, **Bernstein, M. S.** & **Steinsapir, D.** 2015 Motif: Supporting novice creativity through expert patterns. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pp. 1211–1220. CHI '15, Association for Computing Machinery; doi:10.1145/2702123.2702507.

Koch, J., **Lucero, A.**, **Hegemann, L.** & **Oulasvirta, A.** 2019 May AI? Design ideation with cooperative contextual bandits. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–12. ACM; doi:10.1145/3290605.3300863.

https://doi.org/10.1017/dsj.2026.10078 Published online by Cambridge University Press

Lamb, C., **Brown, D. G.** & **Clarke, C. L. A.** 2019 Evaluating computational creativity. *ACM Computing Surveys* **51** (2), 1–34; doi:10.1145/3167476.

Lawton, T., **Ibarrola, F. J.**, **Ventura, D.** & **Grace, K.** 2023 Drawing with reframer: Emergence and control in co-creative ai. In *Proceedings of the 28th International Conference on Intelligent User Interfaces*, pp. 264–277. IUI '23, Association for Computing Machinery; doi:10.1145/3581641.3584095.

Li, Z., **Wang, Y.**, **Wang, W.**, **Greuter, S.** & **Mueller, F. F.** 2020 Empowering a creative city: Engage citizens in creating street art through human-AI collaboration. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1–8. ACM; doi:10.1145/3334480.3382976.

Lim, J., **Leinonen, T.**, **Lipponen, L.**, **Kato, H.**, **Palresha, K.**, **Thomas, R.** & **Jaramillo, L.** 2024 Relational dynamics in human-AI co-creative learning. In *Proceedings of the 15th International Conference on Computational Creativity*. Association for Computational Creativity (ACC).

Liu, F., **Deng, X.**, **Lai, Y.-K.**, **Liu, Y.-J.**, **Ma, C.** & **Wang, H.** 2019 SketchGAN: Joint sketch completion and recognition with generative adversarial network. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 5830–5839. https://openaccess.thecvf.com/content_CVPR_2019/html/Liu_SketchGAN_Joint_SketchCompletion_and_Recognition_With_Generative_Adversarial_Network_CVPR_2019_paper.html.

Liu, X., **Maedche, A.** & **He, S.** 2019 Designing an AI-based advisory platform for design techniques. In *Proceedings of the Twenty-Seventh European Conference on Information Systems (ECIS)*, Stockholm-Uppsala, Sweden.

Liu, Y.-L. E. & **Huang, Y.-M.** 2025 Exploring the perceptions and continuance intention of AI-based text-to-image Technology in Supporting Design Ideation. *International Journal of Human–Computer Interaction* **41**(1), 694–706. doi:10.1080/10447318.2024.2311975.

Louie, R., **Coenen, A.**, **Huang, C. Z.**, **Terry, M.** & **Cai, C. J.** 2020 Novice-AI music co-creation via AI-steering tools for deep generative models. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1–13. ACM; doi:10.1145/3313831.3376739.

Lucas, P. & **Martinho, C.** 2017 Stay awhile and listen to 3buddy, a co-creative level design support tool. In *Proceedings of the Eighth International Conference on Computational Creativity*, pp. 205–212. Association for Computational Creativity (ACC).

Maher, M. 2012 Computational and collective creativity: Who's being creative? Human and computational creativity. In *Proceedings of the International Conference on Computational Creativity*, pp. 67–71. Association for Computational Creativity (ACC).

Matas, J., **Chum, O.**, **Urban, M.** & **Pajdla, T.** 2004 Robust wide-baseline stereo from maximally stable extremal regions. *Image and Vision Computing* **22**(10), 761–767. British Machine Vision Computing 2002. https://www.sciencedirect.com/science/article/pii/S0262885604000435; doi:10.1016/j.imavis.2004.02.006.

Moruzzi, C. 2022 Creative agents: rethinking agency and creativity in human and artificial systems. *Journal of Aesthetics and Phenomenology* **9**(2), 245–268. doi:10.1080/20539320.2022.2150470.

Oh, C., **Song, J.**, **Choi, J.**, **Kim, S.**, **Lee, S.** & **Suh, B.** 2018 I lead, you help but only with enough details: Understanding user experience of co-creation with artificial intelligence. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pp. 1–13. CHI '18, Association for Computing Machinery; doi:10.1145/3173574.3174223.

Ozkan, O. & **Dogan, F.** 2013 Cognitive strategies of analogical reasoning in design: differences between expert and novice designers. *Design Studies* **34**(2), 161–192. https://linkinghub.elsevier.com/retrieve/pii/S0142694X12000932

https://doi.org/10.1017/dsj.2026.10078 Published online by Cambridge University Press

Pagliari, M., **Chambon, V.** & **Berberian, B.** 2021 What is new with Artificial Intelligence? Human-agent interactions through the lens of social agency. https://osf.io/a6fmr

Parmee, I. C., **Abraham, J. A.** & **Machwe, A.** 2008 User-centric evolutionary computing: melding human and machine capability to satisfy multiple criteria. In *Multiobjective Problem Solving from Nature: From Concepts to Applications*, pp. 263–283. Springer; doi: 10.1007/978-3-540-72964-8_13.

Poon, J. & **Maher, M. L.** 1997 Co-evolution and emergence in design. *Artificial Intelligence in Engineering* **11**(3), 319–327. https://www.sciencedirect.com/science/article/pii/S0954181096000477; doi:10.1016/S0954-1810(96)00047-7.

Princeton University 2010 *About wordnet*. WordNet. Princeton University. Available at: https://wordnet.princeton.edu (Accessed: January 18, 2024].

Radford, A., **Kim, J. W.**, **Hallacy, C.**, **Ramesh, A.**, **Goh, G.**, **Agarwal, S.**, **Sastry, G.**, **Askell, A.**, **Mishkin, P.**, **Clark, J.**, **Krueger, G.** & **Sutskever, I.** 2021 Learning Transferable Visual Models From Natural Language Supervision. arXiv:2103.00020 [cs]. Available at: http://arxiv.org/abs/2103.00020.

Rezwana, J. 2023 *Towards designing engaging and ethical human-centered ai partners for human-ai co-creativity*, PhD Thesis, The University of North Carolina at Charlotte. https://search.proquest.com/openview/c77ad36ed43f8639fcdd17ef22d382b3/1?pq-origsite=gscholar&cbl=18750&diss=y.

Rezwana, J. & **Maher, M. L.** 2023 Designing creative ai partners with cofi: a framework for modeling interaction in human-ai co-creative systems. *ACM Transactions on Computer-Human Interaction* **30** (5), 1–28; doi:10.1145/3519026.

Rock, M. 1996 The designer as author. *Eye Magazine* **5** (20), 44–53.

Rovira Martins, J., **Cunha, J. M.**, **Martins, P.** & **Boavida, A.** 2024 PatternPursuit: pattern generation using libraries built on graphic decomposition. In *Proceedings of the 15th International Conference on Computational Creativity*. Association for Computational Creativity (ACC).

Sarica, S. & **Luo, J.** 2024 The innovation paradox: concept space expansion with diminishing originality and the promise of creative artificial intelligence. *Design Science* **10**, e11; doi:10.1017/dsj.2024.10.

Shireen, N. 2020 *Bridging the gap between design space exploration and generative design interfaces: an exploratory study*, PhD Thesis, Simon Fraser University.

Shneiderman, B. 2001 *Supporting Creativity with Advanced Information- Abundant User Interfaces*. SpringerLink; https://link.springer.com/chapter/10.1007/978-1-4471-0259-5_34.

Shneiderman, B. 2002 Creativity support tools. *Communications of the ACM* **45** (10), 116–120; doi:10.1145/570907.570945.

Shneiderman, B., **Fischer, G.**, **Czerwinski, M.**, **Resnick, M.**, **Myers, B.**, **Candy, L.**, **Edmonds, E.**, **Eisenberg, M.**, **Giaccardi, E.**, **Hewett, T.**, **Jennings, P.**, **Kules, B.**, **Nakakoji, K.**, **Nunamaker, J.**, **Pausch, R.**, **Selker, T.**, **Sylvan, E.** & **Terry, M.** 2006 Creativity support tools: report from a U.S. National Science Foundation sponsored workshop. *International Journal of Human-Computer Interaction* **20** (2), 61–77; doi:10.1207/s15327590ijhc2002_1.

Son, K., **Choi, D.**, **Kim, T. S.**, **Kim, Y.-H.** & **Kim, J.** 2024 GenQuery: supporting expressive visual search with generative models. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pp. 1–19. ACM; doi:10.1145/3613904.3642847.

Sun, L., **Chen, P.**, **Xiang, W.**, **Chen, P.**, **Gao, W.-y.** & **Zhang, K.-j.** 2019 SmartPaint: a co-creative drawing system based on generative adversarial networks. *Frontiers of Information Technology & Electronic Engineering* **20** (12), 1644–1656; doi:10.1631/FITEE.1900386.

https://doi.org/10.1017/dsj.2026.10078 Published online by Cambridge University Press

Venkatesh, V., **Morris, M. G.**, **Davis, G. B.** & **Davis, F. D.** 2003 User acceptance of information technology: toward a unified View1 *MIS Quarterly* **27**(3), 425–478. Available at: http://www.jstor.org/stable/30036540; doi:10.2307/30036540.

Wanous, J. P., **Reichers, A. E.** & **Hudy, M. J.** 1997 Overall job satisfaction: how good are single-item measures? *Journal of Applied Psychology* **82** (2), 247–252; doi:10.1037/0021-9010.82.2.247.

Wegner, P. 1997 Why interaction is more powerful than algorithms. *Communications of the ACM* **40** (5), 80–91; doi:10.1145/253769.253801.

Yannakakis, G. N., **Liapis, A.** & **Alexopoulos, C.** 2014 Mixed-initiative co-creativity. In *Proceedings of the 9th International Conference on the Foundations of Digital Games, FDG 2014 (Liberty of the Seas, Caribbean, April 3–7)*. Foundations of Digital Games.

https://doi.org/10.1017/dsj.2026.10078 Published online by Cambridge University Press