RESEARCH-ARTICLE

Designing Interactions with Generative AI for Art and Creativity: A Systematic Review and Taxonomy

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Abstract

Generative Artificial Intelligence (GenAI) applications in artistic and creative domains have gained substantial attention of late. These intelligent interactive systems, shaped by innovations in Large Language Models (LLMs) and Vision Language Models (VLMs), are materially impacting digital creative domains. While initial work to understand this space has highlighted new models and architectures, we lack a holistic view of how interactive GenAI systems are designed for user interactions across various artistic and creative domains. In this paper, we present a systematic review of interactive GenAI system designs for art and creativity in the HCI literature (N = 189), and a detailed taxonomy of interaction paradigms with design components. We shed light on the communities of design focus and decompose the system interaction designs, mapping these characteristics to creative domains, user interaction patterns, GenAI technologies, detailing under-represented spaces, and future directions of designing interactions for GenAI creativity.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; **Interaction paradigms**.

Keywords

Generative AI, art, creativity, systematic review, taxonomy.

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1 Introduction

In recent years, generative artificial intelligence (GenAI) models such as Large Language Models (LLMs) and Vision Language Models (VLMs) have been attracting substantial attention and investment from industry and academia alike. GenAI applications in art and creative domains are (for better or worse) disrupting current practice; lowering the bar to content creation and implicating a new set of digital skills one must master as a digital creative. This growth is exemplified by the increasing uptake of GenAI technologies in commonplace digital design tools such as Adobe's Photoshop and its Generative Fill [4] and Autodesk AutoCAD's use of GenAI-augmented design tools [12].

A large number of GenAI products have been launched. These tend to be text-to-text and text-to-image intelligent systems developed on top of GenAI models—often exploiting existing technologies (e.g., ChatGPT[1]). Many such technologies do not make it past the prototype phase—e.g., see the "AI-graveyard"[2], a growing repository of failed AI-supported technologies. We also see a fast accelerating trend in research on GenAI in creativity, with an increasing number of academic papers in numerous creative domains—e.g., music [20], visual art [32], creative coding [10] and video [173]. The exceptional growth of GenAI applied to the artistic domain means that, as a field, it grows without informing itself. In this nascent experimental phase, we risk wasting effort, at a significant environmental cost [98]. With a detailed understanding of the present technologies that enable art and creativity, we might take stock and better orient our research, by understanding the

[1] ChatGPT: https://chatgpt.com
[2] AI Graveyard: https://dang.ai/ai-graveyard

shortcomings of the domain, and better sharpen our research focus. To address these challenges, we conduct a systematic literature review (SLR) of GenAI for art and creativity.

In this SLR, we collect and analyze papers that design and develop interactive intelligent systems powered by GenAI models across different art and creative domains. These systems can play a crucial role in enhancing creativity when their design aligns with the user's cognitive processes driving creative thinking [109]. It is therefore essential to understand creativity as an interactive and experiential process [9] in which user engagement plays a key role. We find commonalities and novelty in how these interactive systems facilitate end-users to generate creations through interacting with the system interfaces. We analyze these patterns to understand the current state of the art of this interaction design space and provide a taxonomy of interaction design components to support designers, making inferences from our analysis to inform future interaction designs for creative GenAI systems.

1.1 Research Questions and Contributions

To achieve our research goal, we have developed the following three Research Questions (RQs):

- `RQ-1`: Who are the creative GenAI systems designed for?
- `RQ-2`: How can users interact with the creative GenAI systems?
- `RQ-3`: How are the creative GenAI systems designed and built to facilitate user interaction?

In this SLR, our main contributions are threefold:

- `Dataset`: We have built an open-source dataset of 189 coded papers in HCI literature from 2008 to April 2024 that focus on designing and implementing interactive intelligent systems using GenAI models across art and creative domains for end-users.
- `Survey`: We conduct an SLR to find the trends in the interaction design of the above systems. We analyze end-user community groups, user interaction patterns, system interaction design paradigms, underpinning GenAI technologies, and input and output modalities.
- `Theoretical`: We provide a comprehensive taxonomy by identifying four paradigms commonly adopted in the system design of creative interactive GenAI systems—medium, tool, partner, and mediator—and analyze their representations in interface design.

2 Background and Related Work

We outline the background and key related work on surveys of GenAI and creativity, to clarify the key concepts that define our research scope, and discuss the research gap in current literature reviews.

2.1 Definitions of Art and Creativity

Art is an "essentially contested concept" [64], meaning it lacks a single, universally accepted definition, and evolves over time. Gallie [64] argues that reaching a consensus is inherently unattainable due to the dynamic and interpretive nature of such concepts. Similarly, creativity is also considered essentially contested, often described as a secondary quality attributed to a person or object. Colton et al. [43] use this framing to explore the debate on whether AI can be truly creative.

Coordinating various sources of framing, one widely accepted definition of *creativity* is as the ability to produce work that is both novel (original and unique) and appropriate (effective, useful, and relevant to the task at hand) [128]. Rhodes [126] proposes the "4P" conceptual model of creativity: person, process, press, and product. "Person" relates to a human's personality, intellect, habits, attitudes, and other factors that influence one's creativity. "Process" refers to the steps involved in generating ideas and creating artifacts, such as thinking, motivation, and learning. "Press" denotes the environment surrounding the individual, which can impact both the person and their mental processes. Finally, "Product" refers to the tangible outcomes of thought—ideas expressed and shared in visible forms, such as poems, paintings, or sculptures. Boden [18] highlights three pathways to surprise or novelty in the creative "process"—combination, exploration, and transformation. She further distinguishes art from crafts, stating that crafts often downplay the role of surprise and display minor novelty by exploratory creativity, whereas art more often integrates combinational and transformational creativity that elicits surprise.

Defining *art* itself can be equally complex, but it can be captured by *artwork*—an artifact created to be presented to an audience to fulfill an aesthetic function, communicate significant ideas, or evoke emotional responses from the audience [144]. Alperson [8] argues that creativity is a hallmark of artistic practice and plays a vital role in the arts but is not exclusive to them.

In our SLR, we prioritize intelligent interactive systems that facilitate art-making practices, and also include systems that support artistic and creative design, as distinct from purely functional product design.

2.2 Human-Computer Interaction (HCI) Literature on Creativity

Recently, Hsueh et al. [72] have investigated diverse understandings of creativity within HCI research, identifying four epistemic positions that underpin how creative work is understood: problem-solving, cognitive emergence, embodied action, and tool-mediated expert activity. They analyze "creativity support" from the perspective of human endeavor with machine assistance. "Computational creativity" extends this by encompassing autonomous creative agents, while "mixed-initiative creativity" combines the efforts of both human- and machine-initiated contributions.

2.2.1 *Creativity Support Tools (CSTs).*

Shneiderman et al. [138] define CSTs as tools that extend users' capabilities to make discoveries or inventions. These tools support various stages of creative process, from gathering information and generating hypotheses to refining and disseminating ideas [136]. To evaluate CST effectiveness, the Creativity Support Index (CSI) was developed, measuring six dimensions of creativity support: Exploration, Expressiveness, Immersion, Enjoyment, Results Worth Effort, and Collaboration [34]. CSTs often require extensive learning, but setting constraints can both simplify their use and enhance creativity (e.g., Polymetros [17], Painting with Bob [15], MakeWrite [106]). To collect one-off exploratory prototypes and have an overview of CSTs, Frich et al. [62]

first conduct a survey based on studies presenting CST prototypes in HCI literature to analyze the key characteristics that constitute CSTs. Some key categories are device types, complexity, maturity, and phases of creativity process support. Chung et al. [39] further identify patterns and gaps in the intersection of users, roles, interactions, and technologies, and emphasize the potential of advanced technologies like AI and ML to enhance CST capabilities.

2.2.2 Computational Creativity. In [44] Colton and Wiggins define the field of Computational Creativity as "the philosophy, science and engineering of computational systems" that exhibit behaviors perceived as creative by human audiences, incorporating a wide range of research methods including philosophical discourse, psychology and cognitive science, human-machine co-creative systems, and fully autonomous and independent creative agents. The field has gone through several phases over the last two decades. In the late 2000s and early 2010s, researchers emphasized the importance of the creative process, arguing that making the AI's generative process more transparent and communicative to audiences would enhance its perception as a creative entity [45, 111]. More recently, GenAI has gained increasing popularity, with researchers contending with how to make such systems explainable [157].

2.2.3 Mixed-initiative Creativity. Mixed-Initiative Creative Interfaces (MICI) emerge as a third paradigm between the two mentioned above, where humans and computers interact as collaborators in a tight feedback loop [53]. Mixed-Initiative Co-Creativity (MI-CC) emphasizes both human and computational initiatives contributing to the creative process [186]. This paradigm has been extensively applied to music and dance performance (e.g., eTu{d,b}e [48], LuminAI [96]), drawing and sketching (e.g., RoboSketch [113], Reframer [89]), and storytelling and gaming (e.g., TaleMaker [112]).

2.3 Definitions of Generative Artificial Intelligence (GenAI)

The term "generative" has long been associated with algorithmic approaches to art, dating back to the 1960s with techniques such as L-systems, Markov processes, and agent-based simulations. Earlier definitions of "generative art", particularly in the 1990s and 2000s, emphasized the human artist's role in guiding and controlling the process. Since the late 2010s, with the advent of Foundation Models (FMs), "generative art" has come to refer to art produced by AI systems trained on large datasets. Today, the term "generative" spans both historical algorithmic methods and contemporary AI techniques. In this SLR, we focus on interactive systems facilitating "generative AI" art and creative design, while drawing comparisons with rule-based generative art systems.

A modern definition of a GenAI system by Muller et al. [104] is "an AI system that uses existing media to generate new, plausible media". Distinguished from AI systems for decision-making or explanations, GenAI systems are capable of creating content in subjective domains, such as images, text, music, video, code, and various forms of design. These systems are powered by Foundation Models (FMs)—large-scale models pre-trained on massive, diverse datasets, often utilizing transformer architectures. Prominent examples include Large Language Models (LLMs) such as GPT, BERT, and T5, and Vision-Language Models (VLMs) like CLIP, DALL·E, and Flamingo, which are trained on multimodal datasets [28].

An earlier definition of GenAI that has existed before the emergence of FMs, encompasses probabilistic models that learn the joint distribution of data, as opposed to discriminative AI models focused on modeling the conditional distributions [181]. This includes earlier architectures such as Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and Variational Autoencoders (VAEs).

In this SLR, we adopt a broad view of generativity in AI systems, considering both definitions as valid and including papers that use GenAI technology either by the former or the latter definition, in order to ensure a comprehensive view of how GenAI systems have evolved over the years.

2.4 Reviews and Surveys on GenAI

Generative AI (GenAI) and AI-generated content (AIGC) have been reviewed across various modalities and application domains. Cao et al. [28] provide a comprehensive overview of generative models for unimodal and multimodal tasks, highlighting the impact of transformer-based architectures—such as CLIP—on text, images, and complex content generation. Zhang et al. [191] focus on the capabilities of GPT models (e.g., GPT-3, GPT-4), detailing their applications in multimodal contexts, including chatbots, text-to-image generation (e.g., DALL-E), and industry-specific sectors such as education, gaming, and media. Several domain-specific surveys delve deeper into specialized AIGC advancements. In the area of image synthesis and editing, Zhan et al. [188] categorize key approaches—such as GANs, diffusion models, autoregressive models, and NeRF—and evaluate them using benchmark datasets, metrics, and experimental results, highlighting their strengths and limitations. For music generation, Ji et al. [79] examine deep learning techniques across score generation, performance modeling, and audio synthesis, analyzing the evolution of these models and discussing their benefits and challenges.

Extensive research has explored more user-centered perspectives. For writing assistance, Lee et al. [90] propose a design space addressing key dimensions including task, user, technology, interaction, and ecosystem. Gao et al. [65] identify four distinct phases in the human–LLM interaction—planning, facilitating, iterating, and testing—and introduce a taxonomy of interaction modes that reflect how users engage with LLMs throughout language-based workflows. For drawing assistance, Qin et al. [114] categorize works by content type, user group, interaction mode, and underlying algorithm, revealing trends such as the rise of GAN-based techniques for light and color rendering. For designer-AI collaboration, Shi et al. [134] identify three overarching themes: AI assisting designers, designers assisting AI, and collaborative workflows, highlighting AI's role in user need discovery, idea visualization, design creation, and testing. Rezwana and Maher [124] further anatomize the creative processes of human-AI co-creative systems in mixed-initiative mode, advocating human-AI partnerships.

Despite these contributions, a gap remains in systematically analyzing system interaction design across artistic and creative domains. Existing studies touch on interaction design but lack depth and comprehensiveness. For instance, Hughes et al. [77] focus on specific GenAI models, and Bossema et al. [19] examine interactions in specialized user groups. Shi et al. [133] propose a taxonomy for human-GenAI interaction but provide only a high-level analysis, leaving space for a more detailed and systematic exploration of interaction design tailored to creative contexts.

3 Methods

We conducted a SLR following the PRISMA 2021 [122] guidelines, with additional practical guidance from Siddaway et al. [141], Silva and Frâncila Weidt Neiva [142]. We first consider the scope of the SLR by defining the requirements; then we describe the creation of the dataset; lastly, we present the qualitative and quantitative analysis.

3.1 Scope

We have identified three essential requirements (Req) for our SLR as follows:

- `Req-1`: **Art and creativity**. As mentioned in Section 2.1, we constrain our scope to art-making and creative design systems. To be more precise, we only consider such systems facilitating these two types of creative process—embodied action and system-mediated expert activity [72], because we are interested in the crafting of the creative "product" [126].
- `Req-2`: **GenAI**. As mentioned in Section 2.3, we include systems using both the modern GenAI models and the probabilistic models that model the joint distribution of data.
- `Req-3`: **System interface facilitating end-user interaction**. We only consider papers describing and illustrating system interfaces that facilitate end-user interaction.

3.2 Dataset Creation

We followed the SLR practice guide [141] to construct our paper dataset on GenAI for art and creativity, applying the steps of identification, screening, and eligibility. Additionally, we conducted reference snowballing based on Wohlin [177]'s guidelines. The process is presented in Fig. 1.

3.2.1 *Identification.*

Databases. To search for papers on GenAI for art and creativity, we chose the three major digital databases in AI, HCI, and computer science, i.e., the ACM Digital Library, IEEE Xplore, and SCOPUS. These databases provide extensive publication venues, e.g., CHI, UIST, IUI, C&C, ICCC, AIIDE, which contribute most to GenAI creative computing. We experimented with some preliminary search trials and decided to use generic truncated keywords, such as "generati*" and "creati*", as opposed to "generative" and "music", to ensure we captured variations without providing an exhaustive list of all the possible keywords. To abide by both the modern and expansive definitions of GenAI, we added other relevant keywords, such as "AI-generated content" and "generative model". The keyword "art" can lead to many false-positive results with keywords "state-of-the-art" or "state of the art", but none of the databases offers possible constraints to avoid them. Given the large number of search results, we chose to just search for abstracts.

Final Search Query. The Boolean search query and keywords used are as follows to ensure consistency across the three databases:

```
((AI OR "machine learning" OR "deep learning"
OR "neural network" OR "neural networks")
AND generati* OR AIGC OR "AI-generated content"
OR "AI generated content" OR "generative
learning" OR "generative model" OR "generative
models" OR "generative modeling") AND (art
OR creati*)
```

Limiting Search by Year. We chose not to set a starting date for our search, as we observed that the number of papers had only significantly increased in the past five years. However, we set December 31, 2023, as the cutoff point for our identification search phase, before entering the later snowballing phase in April 2024.

Filtering by Venues. Running the same search query, the ACM Digital Library returned 1,520 papers, while IEEE Xplore and SCOPUS yielded significantly higher results with 25,867 and 12,797 hits, respectively. To refine the results, we filtered by conferences and journals, excluding venues where fewer than 10% ($\leq$ 1) of the 12 most relevant papers (the smallest total number of papers across candidate venues) were deemed relevant, using this metric to eliminate irrelevant venues. Due to keywords limitation (e.g., "art" producing false positives like "state-of-the-art"), one author manually reviewed all papers from each venue rather than relying on relevance sorting. By the end of 2023, this process identified a total of **3,275** references.

3.2.2 *Screening and Eligibility.*

During the screening phase, 4 duplicate and 4 retracted papers were first removed. A quick review of titles and abstracts revealed additional papers that were clearly unrelated to GenAI, art, or creativity. Following the PRISMA 2021 guidelines [122], we established six eligibility criteria (EC), as detailed in Table 1, to exclude papers outside the scope of our SLR.

The eligibility screening took place in a spreadsheet, where the titles of all the candidate papers were listed, with every eligibility criterion of each paper to be evaluated as true or false. The fourth author screened 800 items and the rest went to the first author. If uncertainty arose about whether to include or exclude a paper after reviewing its title, abstract, and skimming its figures and captions, it was highlighted and passed to the fifth and last authors for a final decision. A large number of papers were excluded by EC-3, due to the false-positive search results retrieved by the keyword "art". EC-6 was also an important gate-keeping criterion, since many papers focus on the technical aspects without any regard for end-users. We first looked for user interaction, but ended up with user interface. Once we finished screening and eligibility check, we were left with N = **42** papers.

3.2.3 *Snowballing.*

Finally, we conducted a snowballing step and another round of screening and eligibility, following the guidance of Wohlin [177]. In forward snowballing, we used Google Scholar to retrieve the "Cited by" list of each included paper; while in backward snowballing, we read through the references list at the end of each paper to pick out the ones with a seemingly relevant title. Due to time limitations, we only went through one iteration of forward snowballing and backward snowballing, and identified N =

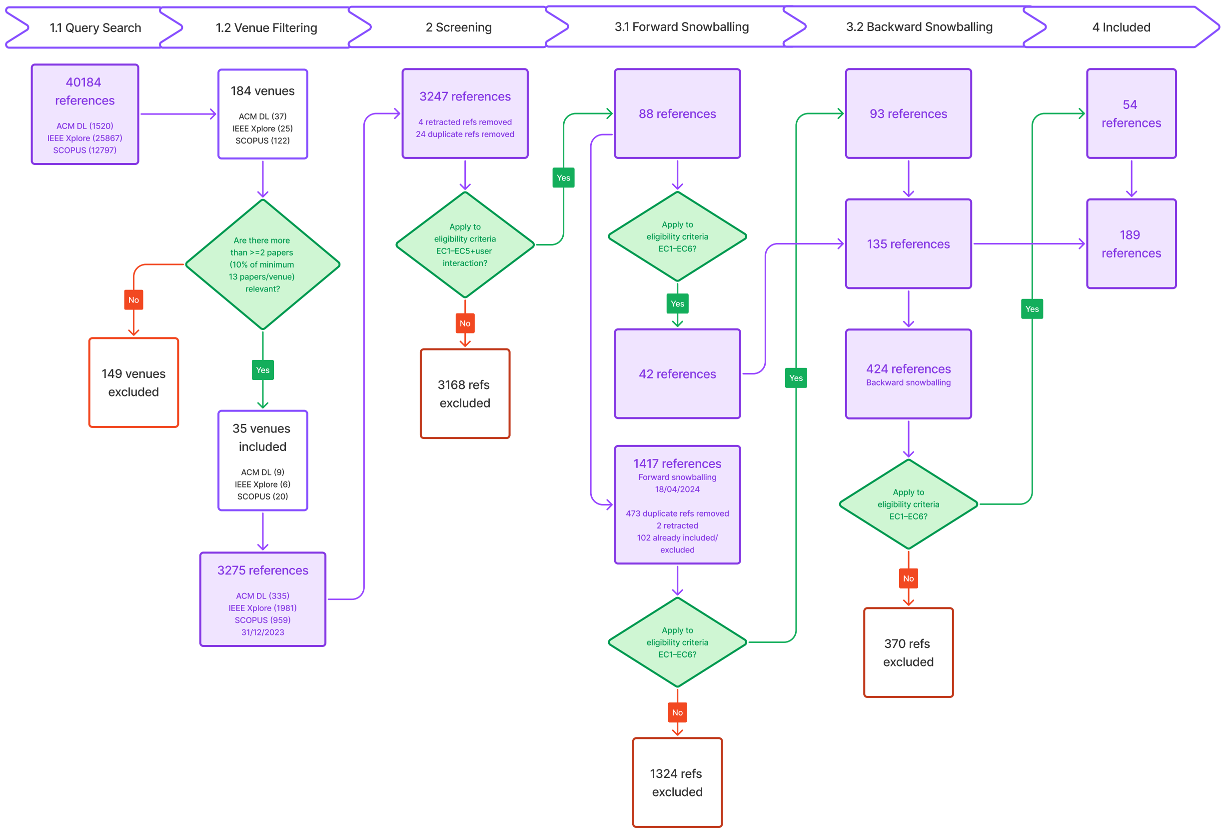


Figure 1: Dataset creation flow chart demonstrating the number of references in the flow of each step: identification, screening, eligibility, snowballing, and inclusion stages.

Table 1: Eligibility criteria (EC).

#	Description
EC-1	**Availability of text** – The full text of the paper must be available in English.
EC-2	**Peer-reviewed research** – The paper must describe peer-reviewed research.
EC-3	**AI art and creativity** – The paper must focus on creative processes in AI-assisted artistic expression and creative design.
EC-4	**Artifact** – The paper must include an artifact: inventions that can be "*new systems, architectures, tools, techniques, or designs that reveal new opportunities, enable new outcomes, facilitate new insights or explorations, or impel us to consider new possible futures*" [176].
EC-5	**GenAI or generative machine learning systems** – The paper must involve at least one GenAI or generative machine learning system. The artifacts themselves can be GenAI systems or powered by GenAI algorithms.
EC-6	**User interface** – The artifacts and GenAI systems in the paper must be for end-users and include a user interface that facilitates interaction.

147 new papers, wherein 93 from forward snowballing and 54 from backward snowballing. Adding to the 42 papers in the previous step, the final total number of papers in our dataset is N = **189**, and the publication years range from 2008 to 2024.

3.3 Analysis

We qualitatively coded the full text and figures of the N = **189** papers in our dataset spanning the 16-year period. For cases where multiple papers describe the same system, we pick the most elaborate one for coding. We also calculated Fleiss' kappa to assess Inter-Rater Reliability (IRR) and measure the level of agreement among the first four authors. Following this, we collected statistics on community groups and user participation. We then qualitatively analyzed system design (generative system UI components [22]), system implementation (inputs, GenAI models, outputs), and user interaction patterns. Finally, we calculated and analyzed the Pearson correlation coefficient among user groups, user interaction patterns, generative system UI components, and GenAI models.

3.3.1 Qualitative Analysis. To analyze the dataset, we created a codebook, based on the thematic analysis of an initial 20 samples in the dataset. The first two authors discussed the interaction diagram (see Fig. 2) to frame the structure and first-level categories of the codebook, and the first four authors discussed the subcategories and codes over a period of time. It is important to acknowledge that the development of this codebook, as well as the paper screening and analyses conducted, are influenced by the inherent biases of the researchers—the first three authors have a background in human-centered computing, two of whom have experience in creative design, and the fourth author has a background in LLM and knowledge graph. This codebook was generated iteratively with codes to answer our research questions and provide a holistic view of the design and implementation of the intelligent interactive systems within our dataset. Once the codebook was finalized (see Table 2), the first four authors coded a random sample of 17.5% (N = 33) of the papers in the dataset to reach an agreement. Upon agreement, the rest of the papers were assigned to the same authors for coding. After we finished coding all the papers, we collected representative examples and qualitatively analyzed how the systems are designed and built, and how users interact with the systems.

3.3.2 Quantitative Analysis. We calculated the number of papers targeting each community group—both in terms of system design and user study recruitment—as well as user participation across individual design thinking phases and the total number of phases. We also examined human-GenAI co-agency role pairs, both individually and by the number of role pairs presented (see Table 3, 4, 5). To capture the links across dimensions in the user-system interaction flow, we programmatically analyzed frequently co-occurring code combinations as frequent item sets, and illustrated them with codes connected by "+" in the Sankey diagram (see Appendix A Fig. 8). We also programmatically computed the Pearson correlation coefficients [16] between user groups and generative system UI components, between user interaction patterns and generative system UI components, and between user groups and GenAI models.

4 Findings

Before we present the findings of our analysis of the N = **189** papers, we need to clarify the scope of our dataset. As shown in Fig. 3, we collected papers on interactive GenAI systems applied to artistic and creative domains, which belong to generative systems and intersect with creativity support tools. Prior to the advent of GenAI, generative design tools came in the form of "procedural" tools, e.g., some of them are creativity support tools for parametric design and generative art, and others include procedural content generation (PCG) for games. As depicted in Fig. 4, the number of papers on GenAI art and creativity has consistently increased from 2008 to 2024 (our cutoff dates for search identification stage and forward snowballing stage are up to December 31, 2023, and April 18, 2024, respectively). Notably, there is a significant surge in 2023, with the count increase surpassing 20. This surge can be attributed to the newly launched digital platforms featuring LLM and VLM products in the prior year. For example, both ChatGPT and DALL·E[3] were launched in November 2022, and Midjourney[4] debuted earlier in July of the same year.

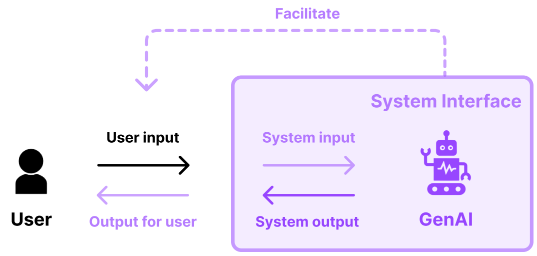
As shown in Table 2, the final codebook consists of 100 codes across 10 categories and 28 subcategories. For most of the subcategories, the codes are not mutually exclusive, i.e., more than one code can be applied to a paper except for the exclusive binary ones. The majority of the Inter-Rater Reliability (IRR) calculated with Fleiss' kappa [61] for each subcategory show substantial (0.61 to 0.80) and almost perfect (0.81 to 0.99) agreement among the first four authors, except for moderate agreement (0.41 to 0.60) for three subcategories and slight agreement (0.01 to 0.20) for one.

4.1 RQ-1: Who are the creative GenAI systems designed for?

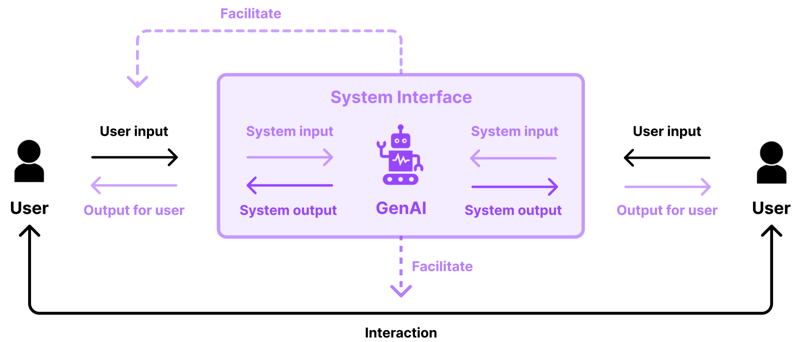
4.1.1 User Distribution in Communities. When coding the users' background and expertise, we noticed a difference between who the systems were designed for, and who were recruited as participants in the user studies. As demonstrated in Table 3, the largest group is the *Visual Artists/Designers*, comprising 25.40% papers, with 22.75% recruited in user studies. *General Public* follow at 22.22%, with 28.42% recruited as participants. *Musicians/Composers* represent 14.29%, and *Hobbyists/Non-professionals* make up 14.81%, with 11.64% involving user studies. Other notable groups include *Students/Educators/Researchers* (9.52%) and *Creative Writers* (12.17%), both having 9.52% involving user studies. Smaller groups include *Creative Coders* (1.06%), *Theatre/Film/Video Creators* (1.59%), and *Creative Arts Therapists* (0.53%), with similar proportions in user studies. The data highlights the engagement of diverse professions and hobbies with GenAI art and creativity systems, indicating significant interest in user-centered research and the application of these systems in both professional and personal contexts.

4.1.2 User Participation in the Design Thinking Phases. In Table 4, the dataset categorizes the frequency of applied codes based on the involvement of end-users across the different phases of the design thinking process, with a particular emphasis on the number of phases covered by each paper. Regarding individual phases, the *User Test* phase is the most represented, with 66.14% (N = 125) of papers incorporating the code focusing on evaluating or testing solutions with users. The next most frequent phase is *Empathize*, which appears in 20.11% (N = 38) of papers, reflecting a strong interest in understanding user needs. The phases of *Define* (7.41%; N = 14), *Prototype* (6.88%; N = 13), and *Ideate* (4.23%; N = 8) are less frequently represented, indicating that these phases see comparatively fewer instances of end-user involvement.

[3]DALL·E: https://www.dallefree.ai/
[4]Midjourney: https://www.midjourney.com/



(a) Single-user interaction



(b) Multi-user mediated interaction

Figure 2: Interaction diagram representing the flow of user and system input and output in single-user and multi-user scenarios.

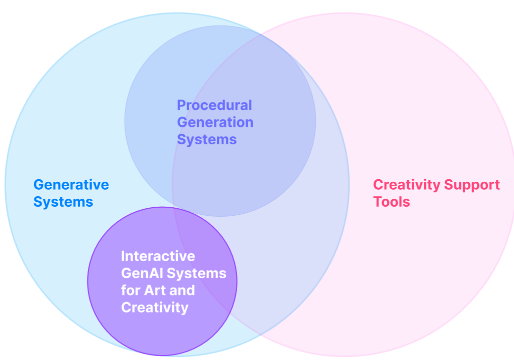


Figure 3: Purple circle representing the conceptual scope of our dataset, situated within Generative Systems and overlapping with Creativity Support Tools. (The relative positions and overlaps of the circles are illustrative and not drawn to scale; they do not represent precise paper counts or quantitative proportions.)

The second part of Table 4 outlines how many design thinking phases end-users are involved in each paper. A significant proportion of papers, 47.62% (N = 90), focus on a single phase of the process, predominantly User Testing. Meanwhile, 10.58% (N = 20) of papers address two phases, and 6.88% (N = 13) involve three phases. Papers covering four or five phases are relatively rare, accounting for only 1.06% (N = 2) and 2.12% (N = 4) of the total, respectively. This data suggests that most research tends to concentrate on one or two phases of the design thinking process, particularly *User Test*, with fewer papers exploring the entire design thinking framework.

Taking a closer look at these rare papers that cover all phases, Taheri et al. [151]'s paper is a noteworthy accessibility paper, since it takes an autoethnographic approach (cf. [121]) where one of the researchers, with mobility impairments, is a target user himself, and he participated throughout the whole research process as both user and researcher. Similarly, autoethnography of people interacting with GenAI is also considered by Ghajargar et al. [66] and covers all phases of the process. This is done within the realm of fiction, where authors reflect on their own experience of co-writing with GenAI; examining their own experience as writers and describing how they navigated the limitations of a GenAI as a writing partner.

Verheijden and Funk [167] conducted several rounds of user studies in their paper: firstly some designers shared their experience with existing GenAI design co-creation systems in the *Empathize* phase; then some participants tried an early version of the BrainFax prototype in the *User Test* phase; finally through discussions and feedback in the co-creation group sessions, participants helped identify key problems and areas for improvement to build a new prototype version, which involve the *Define*, *Ideate* and *Prototype* phases. Likewise, Wang et al. [173] co-designed with two professional journalists in a six-month period, during which the participants actively engaged throughout the creative process.

4.2 RQ-2-1: How can users interact with the creative GenAI systems? – GenAI as Tool, Partner, Mediator

4.2.1 Human–GenAI Co-agency Spectrum. In the pre-GenAI era, rule-based generative systems were predeterministic, with a set of inputs consistently triggering the same predefined outputs. Users had the most control and viewed the systems as inanimate tools

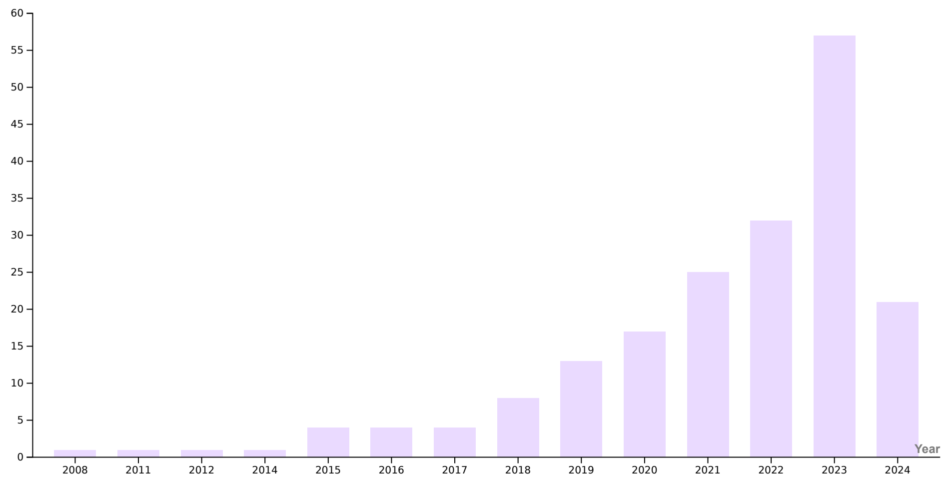


Figure 4: Frequency of N = 189 paper counts by year for GenAI art and creativity within dataset from 2008 to April 2024.

to assist with their generation tasks. The advent of GenAI systems reduces users' level of control, introducing more flexibility and unpredictability between what users want and what the systems create. Satyanarayan [130] redefine intelligence not as competence, the capacity to perform a task, but rather as agency, the capacity to act as a co-agent. GenAI can share the goals of humans and meaningfully contribute to their creative tasks, if "meaning" is understood as "a dimension of goal-oriented action or interaction". The individual agencies of human and GenAI blend together and both parties can be held accountable for their joint pursuits. The proportions of accountability vary in different scenarios, forming a spectrum illustrated in Fig. 5a.

4.2.2 Roles on the Human–GenAI Co-agency Spectrum. Palani and Ramos [110] discover perceived roles when participants work with GenAI in a user study: some participants think of GenAI only as a tool, some see it as a collaborator. Participants also perceived their own roles, such as the project manager or the main ideator. Both the roles of GenAI and humans evolve throughout the creative process. Romas further extended the perceived roles on a spectrum in his talk in CIX'24 [119] as illustrated in Fig. 5b, which we consider a reasonable categorization to describe the relationships of human and GenAI in their co-agency. In Table 5, we present in the order of increasing GenAI agency and decreasing human agency.

Tool–Protagonist. On one end of the human–GenAI co-agency spectrum is the *Tool–Protagonist* relationship, GenAI acts as a tool since users have a highly proactive sense of control using the interactive system. Users decide what they want, and they often tweak the generated artifacts at a detailed level. GenAI can be seen as an extension of human capabilities to perform the generative tasks that humans initiate. This is similar to how some users perceive rule-based procedural generation systems before the advent of GenAI, as GenAI carries more of an assistive and supportive role. 24.87% of the papers (N = 47) mention this relationship. For example, for art therapy, DeepThInk [56]'s AI Brush, Styling, and Filtering features are designed to enhance users' creativity and expressivity without taking over the entire art-making process. GenAI assists but does not dominate, letting users maintain control and ownership of their artwork. This is analagous to the therapeutic goals of art therapy, emphasizing the process of creation rather than the aesthetics of the final artifacts.

Oracle–Student. On the other end of the human–GenAI co-agency spectrum is the *Oracle–Student* relationship, which is the opposite of the Tool-Protagonist relationship. Here, GenAI contributes the most to the creation, while users primarily listen or observe. Only a few systems (3.17%, N = 6) adopt this relationship, typically presenting informative generation content or artistic performances to spectators. For example, spectators can watch the monitors and listen through speakers to real-time dialogues between the AI clones of Machiavelli (the Renaissance diplomat and philosopher) and Sun Tzu (the ancient Chinese military strategist and philosopher) in the art installation "Botorikko, Machine Created State" [82].

Equal Collaborators. In the middle of the human–GenAI co-agency spectrum is the *Equal Collaborators* relationship. In this relationship, both users and GenAI take initiatives in the creation of artifacts with their contributions split evenly [130]. 16.40% of the papers (N = 31) present systems that act as equal collaborators with the users. For example, the wheeled robot Cobbie [93] and the user take turns sketching, ensuring a balanced exchange of ideas. The user retains control over the creative process by deciding when to hand the pen to Cobbie. Cobbie generates sketches that are both visually and semantically connected to the user's input; the user can pause, resume, and provide feedback on Cobbie's sketches, helping refine the robot's output to better align with their needs.

Delegate–Manager. The *Delegate–Manager* relationship sits between the Tool–Protagonist and the Equal Collaborators relationships on the human–GenAI co-agency spectrum. In this relationship, GenAI acts as a delegate and users as its manager. The input of users is usually much simpler in this relationship, directing GenAI to do the actual work. Users can also steer GenAI if the intermediate generations are misaligned with their creative intent. This is the

Table 2: The final codebook is represented by 100 codes across 10 categories and 28 subcategories. The Inter-Rater Reliability (IRR) is calculated with Fleiss' kappa for each subcategory among the first four authors.

Category	Subcategory	Codes	IRR
User Distribution (Age: 4 – 72)	Profession/Hobby	Creative Arts Therapists; Creative Writers; Visual Artists/Designers; Musicians/Composers; Theatre/Film/Video Creators; Playful Art Spectators/Gamers; Creative Coders; Students/Educators/Researchers; General Public; Clients; Hobbyists/Non-professionals	0.752
	Skill Level	Novice; Intermediate; Advanced	0.825
	Gender	Male; Female, Non-binary	0.914
	Special Needs	None; Motor Disabilities; Blind and Low Vision (BLV)	0.869
User Study		Empathizing; Defining; Ideation; Prototyping; User Testing	0.912
End User Input		Visual; Auditory; Tactile; Haptic; Other Modalities	0.903
Input User Interface		Graphical User Interface (GUI); Natural User Interface (NUI); Tangible User Interface (TUI)	0.916
Generative system UI Components	Conversation	Chatbot	0.915
	Sketching/Drawing/Painting	Canvas	0.822
	Collage/Collection	Moodboard	0.646
	Divide-and-Conquer/Content Infilling	Focus Region in Context; Spatially Structured/Sequentially Guiding Editor	0.571
	Tweaking	Slider/Knob/Numeric Textfield	0.771
	Rating	Binary/Likert-scale Rating	0.106
	Interpolation	Interpolating Slider/Region/Graph	0.637
	Selection/Exploration	List/Grid; In-flow Options; Branching Nodes; Map/Earth	0.762
	Sequence Editing	Timeline/Storyline/Step Sequencer; Lanes/Tracks	0.678
	Other	Text Prompt; Storyboard; Histogram; Color Palette; Entity-Relation Graph; Coordinate Plane; Music Sheet; MIDI Controller; Musical Instrument; Microphone; Myo Sensor; Wheeled Robot; Robotic Arm; E-textile Sensor; etc.	0.481
System Input		Text; Image; Sketch; Video; Audio; Parameter; Other	0.808
GenAI Technology	Generative Neural Network	RNN; LSTM; CNN; GAN; VAE; Diffusion Model; Other	0.807
	Foundation Models	LLM; VLM; Other	0.811
	Other	ControlNet; Word2vec; Genetic Algorithm; Hidden Markov Model; Latent Dirichlet Allocation; (Adversarial Reward) Reinforcement Learning; etc.	0.660
System Output		Text; Image; Sketch; Video; Audio; 3D/XR; Other	0.782
Output for End-users		Text; Image; Sketch; Video; Music; Voice; 3D/XR; Other	0.791
User Interaction Patterns	Human–GenAI Co-agency	Tool–Protagonist; Delegate–Manager; Equal Collaborators; Expert–Client; Oracle–Student	0.690
	Users Crafting GenAI Model	Yes; No	0.505
	Exploration of the Latent Space	Unstructured Divergence / Trial and Error; Structured Exploratory Divergence; Semantically-meaningful Control; Unstructured Iterative Convergence; Constraining/Steering in Structured Convergence; Reusing Exploration History; Selecting Generated Options	0.690
	Artwork Creation Workflow	Mixed-initiative Co-creation; All at Once; Polishing / Detail-oriented Tweaking; Spatial Breakdown; Temporal Breakdown / Step-by-step	0.618
	Multi-user Collaboration	Synchronized Mediated Communication; Synchronized Mediated Collaboration; Asynchronized Mediated Communication; Asynchronized Mediated Collaboration; Balance Co-creation Dynamics; Multi-modal Media Complementation	0.937

most common relationship, with 53.97% of the papers (N = 102) falling into this category. For example, the generative.fashion [47] system is designed to support both divergent and convergent thinking in the creative process, helping designers explore and refine ideas. In the divergent phase, fashion designs are generated from text descriptions (Delegate–Manager) and can be dragged into the style-mixing area. During the convergent phase, users can use the style-mixing panel to selectively combine elements from three different designs (Tool–Protagonist).

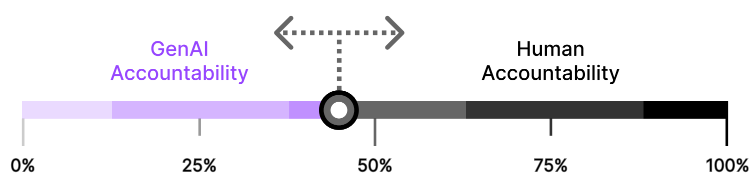
Expert–Client. The *Expert–Client* relationship is the opposite of the Delegate–Manager relationship, which sits between the Equal Collaborators and the Oracle–Student relationships. GenAI knows better than users what to do and takes the lead. Only 7.94% of the papers (N = 15) reflect this relationship, as systems are usually designed to let humans lead instead. For example, Mathemyths [189] is an AI partner that guides children in learning math through a question-feedback-scaffolding framework. It weaves mathematical terms into story plots and asks questions that prompt children to use these terms to continue the narrative. In this process, Mathemyths

Table 3: Frequency of applied codes for end-user groups mentioned within our dataset.

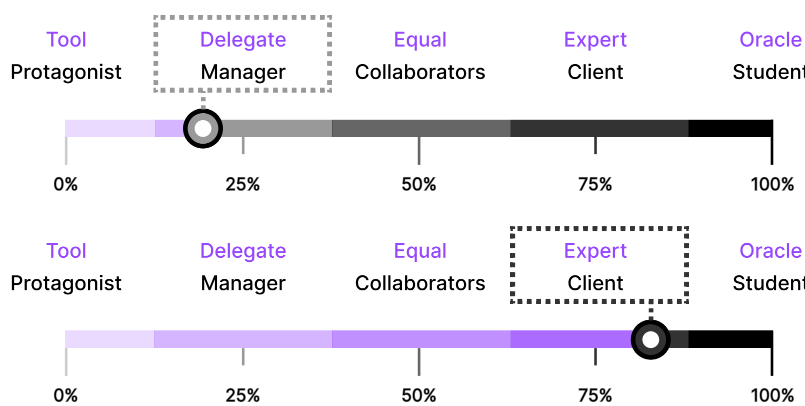
Profession/Hobby	Designed for communities	Recruited in user studies
Creative Arts Therapists	1 (0.53%)	1 (0.53%)
Creative Writers	28 (14.81%)	18 (9.52%)
Visual Artists/Designers	48 (25.40%)	43 (22.75%)
Musicians/Composers	29 (15.34%)	12 (6.35%)
Theatre/Film/Video Creators	6 (3.17%)	4 (2.12%)
Playful Art Spectators/Gamers	15 (7.94%)	4 (2.12%)
Creative Coders	2 (1.06%)	1 (0.53%)
Students/Educators/Researchers	4 (2.12%)	18 (9.52%)
General Public	42 (22.22%)	53 (28.42%)
Clients	2 (1.06%)	2 (1.06%)
Hobbyists/Non-professionals	32 (16.93%)	23 (12.17%)

Table 4: Frequency of applied codes for end-user participation in the design thinking phases within our dataset.

Phases of design thinking	Papers with code	Number of phases involved	Papers with code
Empathize	38 (20.11%)	5 phases	4 (2.12%)
Define	14 (7.41%)	4 phases	2 (1.06%)
Ideate	8 (4.23%)	3 phases	13 (6.88%)
Prototype	13 (6.88%)	2 phases	20 (10.58%)
User Test	125 (66.14%)	1 phase	90 (47.62%)



(a) Human–GenAI co-agency spectrum.



(b) Role pairs on the human–GenAI co-agency spectrum.

Figure 5: Human–GenAI co-agency and the roles of human and GenAI along the spectrum.

acts as the expert, generating prompts to engage the children—a reversal of typical chatbot interactions, where users provide prompts and delegate tasks to AI. In addition, when a math term is used, Mathemyths provides an in-context explanation, taking the role of an oracle while children listen as students.

Multiple relationships of human–GenAI co-agency. The majority of the systems (76.72%, N = 145) only focus on one relationship and 12.17% of the systems (N = 23) mention two relationships, e.g., CharacterChat [131], a chatbot designed to assist writers in creating fictional characters, functions not only as an expert scaffolding the

Table 5: Frequency of applied codes for perceived roles of GenAI and human within our dataset.

Roles on human–GenAI co-agency spectrum	Papers w/ code	Number of relationships involved	Papers w/ code
Tool–Protagonist	47 (24.87%)	5 relationships	0 (0%)
Delegate–Manager	102 (53.97%)	4 relationships	1 (0.53%)
Equal Collaborators	31 (16.40%)	3 relationships	2 (1.06%)
Expert–Client	15 (7.94%)	2 relationships	23 (12.17%)
Oracle–Student	6 (3.17%)	1 relationship	145 (76.72%)

creative process but also as a delegate within its structured workflow. It provides rule-based prompts to help writers define character attributes and, if users prefer not to fill in the details themselves, it can offer suggestions in response to follow-up requests. However, systems reflecting three or more relationships are very rare, e.g., Wordcraft [187] involves four different relationships: as a delegate, it can be assigned specific tasks such as generating text, rewriting passages, or providing stylistic edits; as an equal collaborator, it can engage in a back-and-forth process with the human writer, where GenAI gives suggestions and the user decides when to incorporate them; also, it can offer expert guidance through rule-based prompts, helping the writer define character attributes or plot points like CharacterChat [131]; finally, it can act as an oracle to answer the human writer's questions about grammar, style, or content.

4.2.3 Multi-user Collaboration. In total, only 5.82% of the systems (N = 11) facilitate multi-user interaction. Table 6 highlights different types of multi-user interactions, focusing on various modes of communication and collaboration. Synchronized Mediated Communication (3.70%) refers to real-time, immediate exchanges between users, while Synchronized Mediated Collaboration (2.65%) involves simultaneous teamwork supported by a system that enables continuous coordination. An example is the We-toon system [87], which facilitates real-time collaboration between writers and artists in webtoon sketch revisions. We-toon uses GAN-based image synthesis to improve communication by allowing writers to visually convey feedback, addressing the challenges of relying on textual descriptions. In contrast, Asynchronized Mediated Communication (1.59%) and Asynchronized Mediated Collaboration (2.12%) take place when users interact or contribute at different times. SAGA Shakeri et al. [132] exemplifies this by enabling users to collaboratively create stories asynchronously with GPT-3, a feature particularly useful for participants in different time zones or with conflicting schedules. Balancing Co-creation Dynamics (1.59%) involves fostering more equitable participation among collaborators, alleviating power imbalance in shared tasks, while Multi-modal Media Complementation (1.59%) incorporates various forms of media (e.g., text, images, video) to enrich interactions and foster more effective communication. These categories illustrate how users collaborate and communicate in mediated environments.

4.2.4 Interaction Paradigms – GenAI as a ***Tool****,* ***Partner****, and* ***Mediator****.* The above results can be categorized into three interaction paradigms, reflecting how users perceive and engage with GenAI: as a tool, a partner, or a mediator. Each paradigm corresponds to a shift in user perspective—from first-person to second-person to third-person. In the Tool–Protagonist human–GenAI co-agency relationship, users perceive themselves as the sole creative actors and view GenAI as a **tool** that extends their capabilities. In this mode, users only need to attend to their first-person perspective, focusing on their own creative ideas while leveraging GenAI to actualize them. In more collaborative co-agency relationships, GenAI is no longer deemed as a human extension, but as an independent agent capable of contributing creatively. Co-creation in this context requires both the human and GenAI to interpret and respond to each other's contributions. Users perceive another creative actor alongside themselves, and they have to negotiate with GenAI from a second-person perspective, similar to how they would collaborate with a human **partner**. In multi-user collaboration scenarios, users perceive more external entities as creative actors, and co-create with both GenAI and other users. Here, GenAI often mediates between different users to share the accountability of their co-creation, thus relieving the burdens of each user to be held accountable when their own creations face judgments and critiques from their peers. In these scenarios, users' main goal is to communicate and collaborate with each other, so they see GenAI as a **mediator** from a third-person perspective while they co-create and negotiate among themselves.

Table 6: Frequency of applied codes for multi-user interaction within our dataset.

Multi-user Interaction	Papers with code
Synchronized Mediated Communication	7 (3.70%)
Synchronized Mediated Collaboration	5 (2.65%)
Asynchronized Mediated Communication	3 (1.59%)
Asynchronized Mediated Collaboration	4 (2.12%)
Balancing Co-creation Dynamics	3 (1.59%)
Multi-modal Media Complementation	3 (1.59%)

4.3 RQ-2-2: How can users interact with the creative GenAI systems? – GenAI as Medium

4.3.1 GenAI as a Creative ***Medium****.* Ted Cohen describes a creative medium as being composed of three layers: its *physical material*, the *metaphysical construction* afforded by the material, and the *message conveyed* by the creative *representation* (e.g., shapes and forms) and *expression* that employ both the physical material and the metaphysical construction [68]. For example, consider a painter using watercolors: the physical materials are the pigments in paints, the water, and the watercolor paper; the metaphysical construction is the 2D space on the paper surface where pigments and water blend; the message conveyed depends on the exploited *properties*

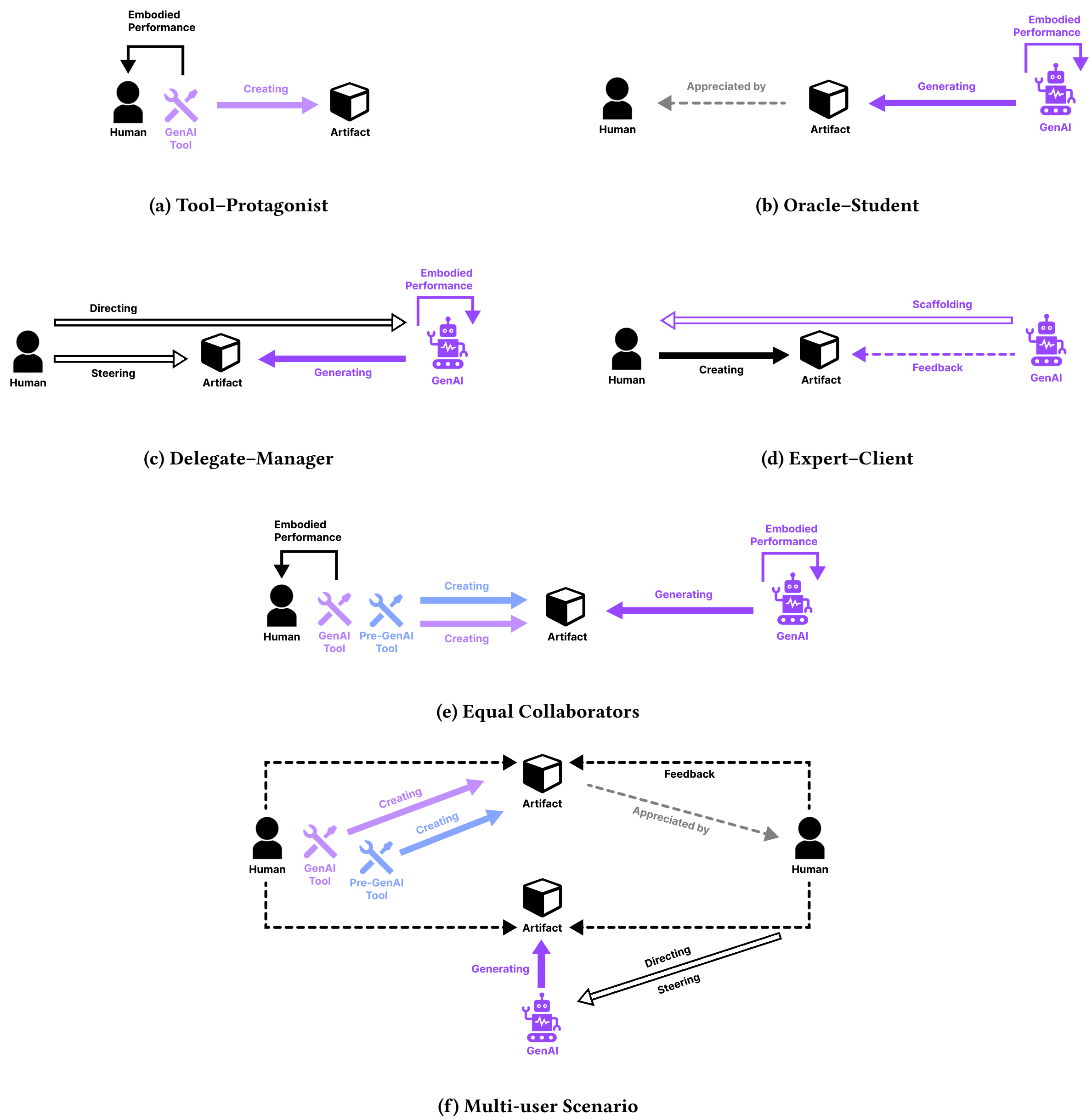


Figure 6: Diagrams of human–GenAI co-agency roles.

of the materials and the creative intent and skills of the artist, e.g., leveraging the fluidity of watercolor to reproduce a 3D natural landscape of a storm on the sea – the painter's understanding of the physical materials and how they interact in the constructive space (such as washes, layering, splattering) enable them to define what message is conveyed by the artwork.

Besides this idea, Dourish and Mazmanian [55] propose viewing "information as a material on its own" and "interaction as the locus of material properties", which invites a similar three-layer interpretation of GenAI systems as a creative **medium**: the models trained by the curated datasets as the *digital material* (data as the *material substances*, cf. [165]), the latent space as the *metadigital construction*, and the *message* is conveyed by users interacting with the GenAI system to produce creative content in certain forms or styles – the users' exploitation of the system *properties* and traverse in the latent space via shaping and reshaping their inputs and manipulating the outputs, allow them to expressively communicate their creative intent.

Furthermore, as Jung and Stolterman [81] note, "interaction design can be considered at the level of fabricating new computational materials". In this light, the interface of a GenAI system can be seen as its *material surface* (cf. [165]), encompassing perceivable attributes such as color, shape, and *texture*—"the feel, appearance, or consistency of the surface" [127].

To clarify these concepts further, we provide a comparison between traditional creative media and GenAI as a creative medium in Table 7.

4.3.2 Users Crafting the Creative Medium. Users can only leverage the existing expressivity of the medium if they have no access to the model training stage. For some artists in need of highly personalized expressivity, they tend to either fine-tune existing models [117], or train their own [30]. In our SLR, we coded whether user interaction would craft the GenAI models of interactive systems, shaping the digital and metadigital layers. In total, 6.88% of the systems (N = 13) allow end-user interaction to shape the models, 10 directly and 3 indirectly. Most of the direct GenAI model crafting comes in music and dance on the fly, also known as interactive machine learning, where user inputs continuously influence parameters of the model, e.g., when users play music, Spire Muse's listening module prioritizes key features—rhythm, timbre, melody, and harmony—which directly influence the subsequent matching algorithms of the music searching agent and shape the co-creative agent's behavior [156]. An example of indirect GenAI model crafting is TaleBrush [40]: with the Continuous-value Control – Language Model (CC-LM) architecture, user interaction can influence the CC model (GeDi), which in turn fine-tunes the LM (GPT-2).

Another unique example of users shaping the material surface of the creative medium is the 1001 Nights [148] game, which allows player-guided AI (GPT-4) to narrate tales where specific keywords materialize as in-game items, impacting the story and gameplay against an AI-controlled character. The authors propose the term "AI-Native games" to categorize such experiences where GenAI is essential to the core mechanics, differentiating them from traditional AI-based games that are "designed around AI". This could elicit novel gameplay that cannot exist without GenAI – players implement real-time generated content not predefined by developers to shape the game world, blurring reality and fiction.

4.4 RQ-2-3: How can users interact with the creative GenAI systems? – Creative Process

4.4.1 Artwork Creation Workflow. The workflow of interacting with GenAI to create artwork describes how users engage with GenAI to produce, edit, and refine outputs, as detailed in Table 8. *Mixed-initiative co-creation* (23.28%) allows both humans and GenAI to dynamically contribute throughout the process, as in systems like eTu{d,b}e [48] and RoboSketch [113], fusing human input with AI generation. *All-at-once* generation (24.34%) simplifies the process by providing outputs instantly after user input, common in chatbot interfaces like CALYPSO [194], where users have no direct control over the generated content. *Spatial breakdown* (13.23%) involves editing specific content areas separately, typically in image generation tasks, while *temporal breakdown* (16.40%) follows either a sequential editing or a step-by-step approach, allowing users to guide the process over time, both aligning with sequentially guiding editor designs. Finally, *polishing/tweaking* (25.40%) focuses on refining content after its initial creation, and other workflows (2.17%) represent less common ways of interaction and adaptation, e.g., live improvisation of embodied performances.

4.4.2 Exploration of the Latent Space. For creative GenAI systems, exploration of the latent space can be a source of surprise, as combinatorial and transformational creativity usually comes from an unexpected combination or rule-transformation of various existing sources [18]. GenAI, trained on large datasets, already has the ingredients for creativity—it is up to the users to find the combinations and transformations that express their creative intent via the system data. This is often achieved by deeply exploring the latent space and selecting from numerous diverse generations. However, a large proportion of current interaction design leads users to quickly converge on a narrow range of ideas and iterate around suboptimal options, known as the *fixation problem* [146]. To describe the divergent and convergent phases in users' creative exploration process, we refer to the terminology from Suh et al. [146]'s work, in their "structured multi-output" solution to address the fixation problem: "*Structured* denotes the presence of dimensions relevant to the task or domain in guiding the response generation and *unstructured* denotes their absence". For some systems, the divergent and convergent phases go together; other systems support a separate divergent phase and a convergent phase. We coded whether users are provided with structured guidance in their diverging and converging process (see Table 9) and compared some examples in Table 10.

4.5 RQ-3-1: How are creative GenAI systems designed to facilitate user interaction?

Interestingly, our finding that GenAI can act as a medium, tool, partner, and mediator echoes Candy [26]'s finding on the roles digital technologies play in four types of creative processes. In our dataset, GenAI systems are often designed as media and tools when they contribute very little to the human-GenAI co-agency accountability; with higher co-creative agency, they are often designed to take the roles of partners and mediators.

4.5.1 Designing Interfaces as Medium and Tool. In the simplest image generation scenario [71]: when users type text prompts in the textfield, they try different keywords to leverage the Vision-Language Model of the system; users input image descriptions in natural language, and the VLM is trained by mappings of image and natural language labels—they match without the need of any conversion. In this simplest scenario, the medium *properties* in the latent space are exposed to the users through the interaction of their own keyword exploration, without further clues provided. In a parameter-control scenario for image generation: users manipulate parameters with sliders, knobs, or numeric textfields; the parameters expose the properties of the VLM, and the tools are external add-ons to control the underlying properties. In a more complex scenario with a structured interface layout like the coordinate plane in the Luminate [146] system: it allows simple overarching text prompts, choosing one parameter for each axis of the coordinate plane to generate intermediate results that trade off the two selected properties, and choosing multiple parameters along X-Y axes to generate diverse intermediate results that coordinate among more various properties.

Table 7: Comparison between Traditional Creative Media and GenAI as a Creative Medium

Layers	Traditional Creative Media	GenAI as a Creative Medium
Physical / Digital material	Physical materials like watercolor paints, water, and paper.	Trained models, datasets, and algorithms.
Metaphysical / Meta-digital construction	The 2D space on the canvas where paint and water blend.	The latent space in GenAI, the internal structure and data processing space.
Message conveyed by creative expression and representation	The message conveyed through the artist's skill and interaction with materials, e.g., painting a storm; The artist's understanding and use of material properties, such as layering, blending, and splattering.	The user's interaction with the GenAI system to shape inputs and manipulate outputs to express creativity, adjusting the system's interface to influence the generated content and styles.

Table 8: Frequency of applied codes for artwork creation workflow within our dataset.

Artwork creation workflow	Papers with code
Mixed-initiative co-creation	44 (23.28%)
All at once	46 (24.34%)
Spatial breakdown	25 (13.23%)
Temporal breakdown	31 (16.40%)
Polishing/Tweaking	48 (25.40%)
Other	4 (2.17%)

Table 9: Frequency of applied codes for latent space exploration within our dataset.

Latent space exploration	Papers with code
Unstructured Divergence	34 (17.89%)
Unstructured Convergence	53 (27.89%)
Structured Divergence	56 (29.47%)
Structured Convergence	64 (33.68%)

In watercolor painting, we can find similar scenarios with the above three: children playing with paints with their hands—directly exploiting medium properties; children learning to paint with a brush—using tools as external addons to manipulate medium properties; children learning to paint on canvas, watercolor paper, and raw rice paper with increasing absorption properties—using different art media to leverage the different material properties for artistic representation and expression. In the third scenario, the same paints and level of proficiency will result in different art styles, because the *substrates* of the material surfaces differ in their ability to absorb water and color.

Based on the literal meaning of substrates—"the surface or material on or from which some living organisms grow", Maudet et al. [101] coin the concept of *graphical substrates*—"the underlying structures onto which the designer 'grows' a layout". They also point out that designers built their substrates on user-defined concepts, content properties, and context constraints, mapping them to spatial and temporal properties in their design representations. Carter and Nielsen [31] propose designing generative system UI representations with new *interface primitives* or UI components to explore the latent space and go beyond that to cater for our cognitive transformation, as representations of subject matter principles have been acting as substrates to shape our thinking. The coordinate plane in the Luminate [146] system compellingly exemplifies such a substrate: it represents the partial underlying structures in the latent space onto which users "grow" their creative writing with their own concepts and properties, under the principle of reifying the divergent phase in the creative process.

4.5.2 Designing Interfaces as Partner and Mediator. Is the metaphor of tools operating on media the one-size-fits-all interaction design paradigm? In 1997, a key debate unfolded between direct manipulation and interface agents: the former emphasized user control and predictability through visual interfaces, while the latter advocated delegating tasks to agents to manage increasing system complexity and accommodate user inexperience [139]. Notably, the concept of *agents* predates modern AI, originally proposing that agents could act independently on users' behalf, guided by their preferences.

While agents imply autonomy, they do not inherently entail *anthropomorphism* – a concept that also predates AI and was debated as early as 1992, when researchers examined the value and drawbacks of endowing computers with human-like characteristics [54]. Anthropomorphism has long been intertwined with the definition of intelligence: the landmark Turing Test published in 1950 [161], incorporated anthropomorphism into its game setting: an imitation game in which an investigator evaluates a machine's ability to exhibit human-level intelligence through typewritten conversation.

Designing autonomous agent systems raises critical questions of how to design the independent entities in comprehensible ways, e.g., when delegating a task to an agent, "to whom or to what are we delegating the task? What is the nature of this entity, and how do we communicate with it? What is the nature of the distinction between delegation and agency, and how does it affect representations in the interface?" As agent systems grow more autonomous and intelligent, anthropomorphic designs, especially chatbots using first-person pronouns, often feel like natural design choices, perhaps because this aligns with how we have historically conceptualized intelligence. But are chatbots the definitive forms of agent interfaces? Is delegation the ultimate role AI should fulfill?

As analyzed in Section 4.4.2, chatbots primarily support an unstructured divergent-convergent process, and without AI prompting alternative ways of thinking in other human–GenAI co-agency relationships (Section 4.2.2), users can become tunnel-visioned, limiting themselves to a narrow subset of the possibility space (the fixation problem) [146]. Ben Shneiderman, a proponent for human-centered AI, further opposes anthropomorphism and the use of "I"

Table 10: Examples of Simultaneous vs. Sequential, Unstructured vs. Structured, and Diverging vs. Converging Design Thinking Phases in the Creative Process.

Design Thinking	UI design	UI components	Example papers w/ code
Simultaneous Unstructured Divergence/Convergence	Users interact with an input panel, a generation trigger, and an output panel, providing inputs (e.g., voice, text, or images) and activating generation via a send command.	Text Prompt Field	0-Sketch-Paint [71]
		Chatbot	Mathemyths [189], KuiLeiXi [179], Jibo [6], CALYPSO [194], 1001 Nights [148]
Sequential Unstructured Divergence & Unstructured Convergence	Systems initially generate output variations based on user inputs (divergence), but no structured guidance is provided to help diversify these inputs.	List/Grid	CREA.Blender [115], IteraTTA [182], OwnDiffusion [178], LangRecol [175], PromptMagician [59], CreativeConnect [36], GANCollage [171])
Sequential Structured Divergence & Unstructured Convergence	Systems provide structured guidance for constructing inputs, while outputs are displayed in an unstructured layout.	In-flow Options	Metamorpheus [170], GenQuery [143], AIStory [69]
		Timeline/Storyline/Step Sequencer	Cococo [97]
		Interpolating Slider/Region/ Graph	PromptPaint [38], Mixplorer [85]
Simultaneous Structured Divergence/Convergence	Systems provide structured interfaces that guide users in exploring diverse ideas (divergence) while refining outputs at the same time (convergence).	List/Grid in Sheet	DreamSheets [7]
		Branching Nodes	Spellburst [10], Calliope [164], WorldSmith [46]
		Focus Region in Context	Reframer [89], StoryDrawer [190]
Sequential Structured Divergence & Structured Convergence	Systems with structured interfaces for exploring diverse ideas (divergence) and saving them in a structured history panel for iterative refinement (convergence).	Structured/Guiding Editor + List/Grid in History Panel	3DALL-E [94]
		Coordinate Plane	generative.fashion [47], Luminate [146],
		Plot View	Cells, Generators, and Lenses [86]

in chatbots, raising concerns about misleading users with deception and misrepresentation [140].

Artists and creators with machine learning expertise understand that GenAI systems are fundamentally powered by generative models. When granted access to the training process, they can shape these models and co-create with the systems in flexible ways. Consequently, interfaces can embody any of the four metaphorical paradigms—medium, tool, partner, and/or mediator. However, when the inner mechanisms of a system are opaque to users, their experiential perceptions can differ significantly. For instance, although Reframer [89] presents itself as a tool in the UI, it can simultaneously draw and edit sketches alongside the user, acting as an independent agent in a mixed-initiative co-creation mode. This unexpected autonomy can lead to confusion, especially when users anticipate a passive, controllable tool but instead encounter a proactive creative actor capable of modifying or overriding their input. A common solution to this confusion is to introduce an agent avatar that visually represents the co-creative actor—an embodiment of the partner interaction paradigm. This approach can also be extended to multi-user settings, where users discuss and collaborate over *intermediates* created by the GenAI agent avatar that serves as a co-creative mediator between users.

4.5.3 Components of the Generative System User Interfaces. Pre-GenAI systems and GenAI systems share many common UI components [22] in their UI design, as listed in Table 11. We present them under the structure of the interaction paradigms: medium, tool, partner, and mediator. We also visualize this taxonomy in a series of design cards[5] as design resources for scaffolding design ideation and workshops (Fig. 7). It is intriguing and worth noting

[5]Design cards: https://genai4creativity.github.io/designing-genai-interactions-for-art-and-creativity/

that GenAI systems inherit nearly all UI design from pre-GenAI (e.g., procedural generation) systems, except for text prompts.

On the one hand, rule-based procedural design tools such as those used by animators or architects follow deductive logical reasoning, i.e., algorithms and constraints. They are deterministic and predictable, ensuring that the generated content consistently adheres to predefined rules and parameters. Generative system UIs for such systems typically embody this approach by allowing users to manipulate attribute vectors or sliders that control specific parameters. On the other hand, GenAI systems are inherently inductive, relying on patterns learned from example training datasets that pair text descriptions with textual, visual, or audio data. So, text prompts in generative system UIs directly leverage the creative medium properties of large FMs, making this interaction both native to GenAI and coherent with users' creative intent.

Why has the UI design of generative systems changed so little? We suggest several possible reasons. Firstly, recombining existing design elements reduces the learning gap for users. Secondly, despite the huge difference in the underlying mechanisms, users perceive the systems in similar ways: controlling parameters to navigate in a multi-dimensional space for rule-based procedural generation and in a high-dimensional latent space for GenAI systems. The small perceivable differences are: precise and deterministic control vs. inaccurate and randomized control, jargon vs. natural language, slow rendering with local GPU vs. fast generation with trained models (particularly evident in the case of local constraint-solving or 3D model synthesis tools).

4.5.4 User Groups – Generative System UI Components Mappings. The correlation between user groups and generative system UI components are demonstrated in Appendix B Fig. 9. The numbers in the heatmap represent the Pearson correlation coefficients [16] from -1 to 1, with the red color meaning positive correlation and the blue color meaning negative correlation. Moderately high correlations were observed between user groups and UI components, particularly with respect to users' domains. As discussed in Section 4.5.3, *Timeline* and *Lane/Track* elements are commonly used to afford sequence editing. Interfaces designed for musicians and composers are highly likely to incorporate *Lane/Track* features (with a correlation of 0.63) and *Timeline/Storyline/Step Sequencer* features (0.34). *Timeline/Storyline/Step Sequencer* features are also prevalent for the theatre and film and video creators (0.33).

In addition, *In-flow generation options* are frequently applied in tools designed for writers (0.39), illustrating that interaction designs that empower users to generate content fluidly in alignment with their ideas and workflow are popular for supporting writers' creative processes. Moreover, we observed that *Branching Nodes* are commonly used for creative coders (0.34), likely due to the programmers' preference for tracking versions and variations over time, making this node-link feature critical for understanding generation provenance. For playful art spectators and gamers, *Earth/Map* features are frequently incorporated (0.27), likely for navigation purposes in game settings.

We found that *Canvas* elements, which offer a high degree of creative freedom, are more often designed for visual artists and designers (0.29), but are less common for musicians and composers (negative correlation of -0.25). This reflects the natural differences in workflows: while visual artists benefit from flexible, diffuse environments, music creation is inherently more structured due to its chronological nature, resulting in more temporally oriented UI design. Similarly, more structured UI components such as *Timeline/Storyline/Step Sequencer* features are less commonly found in interfaces for visual artists and designers (-0.25).

4.5.5 Generative System UI Components – User Interaction Patterns Mappings. In this section, we explore the relationship between system interaction design elements and users' interaction and usage patterns. Specifically, we aim to investigate whether the UI components designed in these systems are utilized by users as intended. Similar to the previous analysis, we calculated the Pearson correlation coefficients between the UI component variables (represented on the vertical axis in Appendix B Fig. 10) and user interaction patterns (represented on the horizontal axis). The UI component variables were extracted from the system interfaces described in the papers, while user interaction patterns were derived from the evaluation and user study sections.

Among the correlation coefficients, a notable observation is that users often employ a step-by-step approach (*Temporal Breakdown*) in their workflows. This is highly correlated with the *Spatially Structured or Sequentially Guiding Editor* UI component (coefficient = 0.39), indicating that this UI component is closely followed by users in practice. Additionally, the *Spatial Breakdown* interaction pattern – where users modify generated content piece by piece, particularly in image generation tasks where different areas of the image are edited separately – shows a relatively strong correlation with the *Focus Region in Context* UI component (coefficient = 0.34). This suggests that interaction elements designed to guide users' attention to specific content areas are well-aligned with users' spatial modification practices.

In terms of significant negative correlations, we found that *Tangible User Interfaces* are less likely to incorporate *Semantic Control* features (correlation = -0.32), indicating that these two interaction design elements are rarely used together.

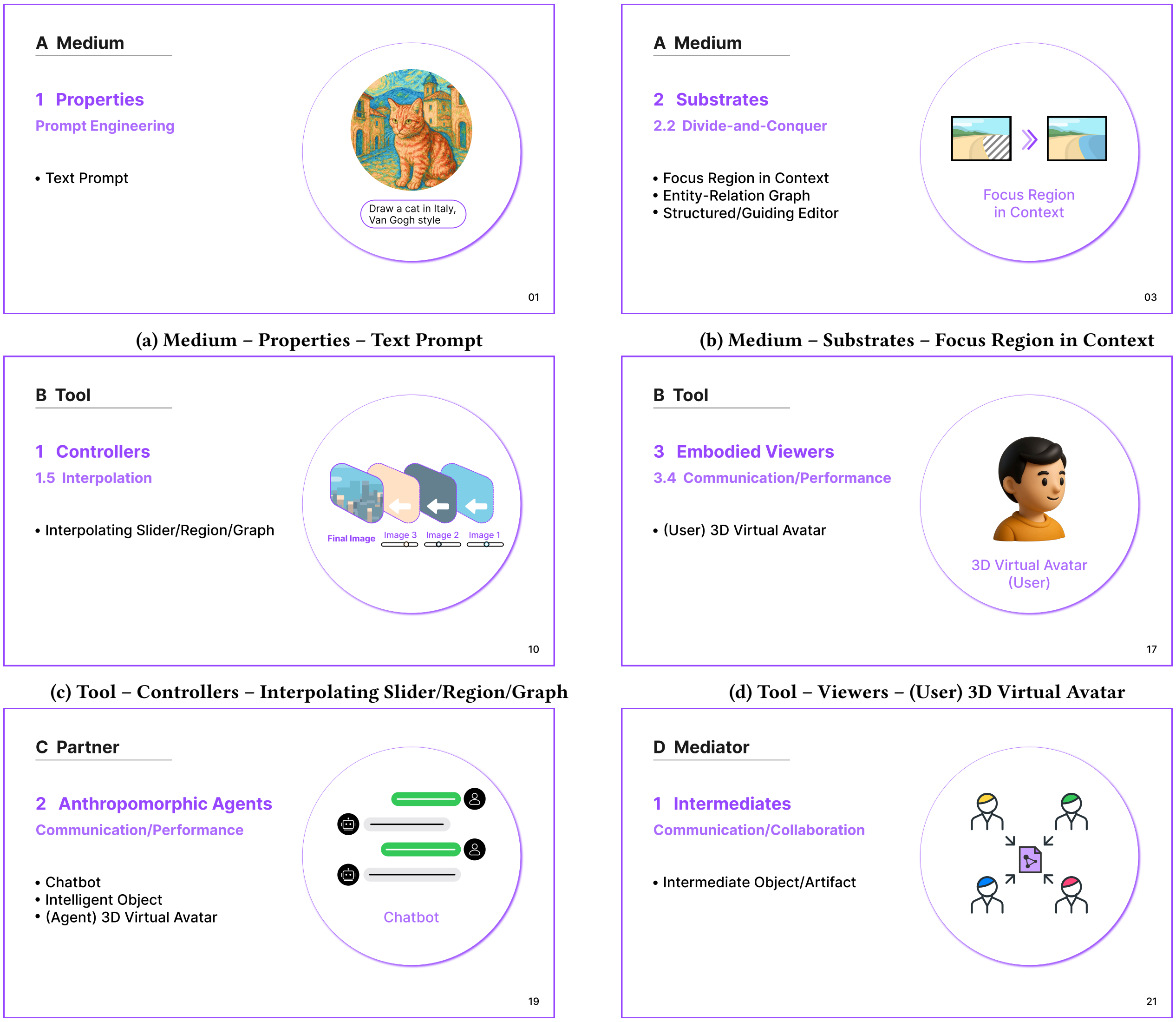
4.6 RQ-3-2: How are the creative GenAI systems built to facilitate user interaction?

4.6.1 Inputs-Models-Outputs. To illustrate the trend of how the systems are built, keeping the linkage of the connected system components as in Fig. 2, we present in a holistic Sankey diagram with six levels of nodes (see Appendix A Fig. 8). In this Sankey diagram, the most significant input-output flow involves visual text input through the graphical user interface, which is processed by an LLM to produce text output. The second most common flow is visual sketch input via the graphical user interface, processed by GANs and CNNs to generate sketches and images. The third most prominent flow involves visual text and image input through the graphical user interface, processed by LLM, VLM, and diffusion models to produce text and image output. The distribution of different GenAI models in our dataset is presented in Table 12. We can see that LLMs are the most prevalent, appearing in 33.33% (N = 63) of the papers, followed by VLMs at 16.93% (N = 32); among generative neural networks, diffusion models (15.34%, N = 29) and GANs (13.76%, N = 26) are the most commonly employed.

Table 11: Taxonomy and Example UI Components of generative systems in GenAI and pre-GenAI times.

Interaction paradigm	UI function	UI affordance	UI component code	GenAI systems	Pre-GenAI (e.g., procedural generation) systems
Medium	Properties	Prompt Engineering	Text Prompt	0-Sketch-Paint [71]	n/a
	Substrates	Exploration/Selection	Coordinate Plane	generative.fashion [47] Luminate [146]	FilmFinder [139]
			Map/Earth	Promptify [21] Wander 2.0 [149]	Minecraft [103]
			Branching Node	Spellburst [10] Calliope [164]	Touch Designer [51]
		Divide-and-Conquer	Focus Region in Context	Cococo [97] Reframer [89] PromptCharm [174]	[88]
			Entity-Relation Graph	XCreation [185] PlantoGraphy [75]	Dungeon Architect [42]
			Structured/Guiding Editor	3DALL-E [94] Bio sketchbook [192] Cells, generators, and lenses [86]	Unity [163]
		Sequence Editing	Timeline/Storyline/Step Sequencer	[108] TaleBrush [40] Wander 2.0 [149] PColorizor [153]	Logic Pro [11]
			Lane/Track	Calliope [20] Mixboard [129] ExpressEdit [158] LAVE [172]	After Effects [2]
		Drawing/Painting	Canvas	Drawcto [52] Magical Brush [70] DeepThInk [56] ChatScratch [33]	Photoshop [3]
Tool	Controllers	Tweaking	Numeric text field/ Slider/Knob	MMM-C [155] crea.blender [115] Prompt Paint [38] Hafez [67]	Shader Graph [162]
		Holistic Tweaking	Histogram/Histograph	Comicolorization [63]	Photoshop [5]
		Sketching	Sketch	DualFace [76]	Kitty [83]
		Coloring	Color Palette/ Swatches	Colorbo [84]	Photoshop [3]
		Interpolation	Interpolating Slider/Region/Graph	[24] Artinter [37] Mixplorer [85] Prompt Paint [38]	Motion Palette [73]
		Preference	Binary/Likert-scale Rating	Creative PenPal [125] Utopian or Dystopian [116] Spire Muse [156] Say Anything [150]	[92]
	(Embodied)	Tangible Control	Musical Instrument	Air guitar [58]	UnitKeyboard [152]
			MIDI Controller	Electronic Music Controller [100]	[160]
			E-Textile Sensor	Latent Organism [95]	[1]
		Motion Tracking	Myo Sensor	Air guitar [58]	[159]
			Depth Camera	Musicking robots [166]	[35]
	Viewers	Exploration/Selection	List/Grid	FlatMagic [183] Dream Sheets [7]	Design Galleries [99]
			Room/Vitrine/Cabinet	Calliope [164]	VRChat [169]
			In-flow Options	ABScribe [123] Spellburst [10]	IntelliSense [168]
		Collection/Collage	Moodboard	BrainFax [167] DesignAID [25] Creative Connect [36]	Miro [102]
		Visual Storytelling	Storyboard	Gennie [80] Codetoon [147] ChatGeppetto [49]	Music Collage [184]
	(Embodied)	Communication/ Performance	(User) 3D Virtual Avatar	LuminAI [96]	VRChat [169]
Partner	Agents	Physical Collaboration	Robotic Arm	Dream Painter [27]	[159]
			Wheeled Robot	Cobbie [93]	Lego Mindstorms [91]
	(Anthropomorphic)	Communication/ Performance	Chatbot	COSMIC [193] GenAssist [78] 1001 Nights [148]	[54]
			Intelligent Object	Mirror Ritual [118]	Sand Playground [57]
			(Agent) 3D Virtual Avatar	LuminAI [96]	Virtual human presenter [107]
Mediator	Intermediates	Communication/ Collaboration	Intermediate Object/ Artifact	Artinter [37] Cococo [145]	Figma [60]
	Agents	Same as in Partner			
	(Anthropomorphic)	Same as in Partner			

4.6.2 User Creative Domains – GenAI Models Mappings. In the heatmap (see Appendix B Fig. 11) depicting the correlation between user creative domains and GenAI models, *LLMs* are frequently used by writers (with a high positive coefficient of 0.38) but seldom used by musicians or composers (with a low negative coefficient of -0.31), who adopt *RNNs*, *VAEs*, other generative neural networks, and foundation models other than LLMs and VLMs. This derives from the distinct ad-hoc GenAI models of music generation systems, such as Coconet generating musical counterpoint in Bach Doodle [74] to harmonize user-created melodies in the style of Bach, and the Musical Speech transformer especially trained for converting speech into musical compositions [50]. Visual artists and designers



(a) Medium – Properties – Text Prompt

(b) Medium – Substrates – Focus Region in Context

(c) Tool – Controllers – Interpolating Slider/Region/Graph

(d) Tool – Viewers – (User) 3D Virtual Avatar

(e) Partner – Agents – Chatbot

(f) Mediator – Intermediates – Intermediate Object/Artifact

Figure 7: Example Design Cards for the Taxonomy of Interaction Paradigms. Each card summarizes one UI affordance of the paradigms using concise text and an example UI component to support design ideation and reflection. The complete set of cards is available for download at genai4creativity.github.io.

are positively correlated with *GANs*, *diffusion models*, and *VLMs*, as they use these models to generate visual artifacts. The relatively high coefficients of *CNNs* with clients and therapists result from papers describing visual art commissions [37] and art therapy [56].

5 Reflections

This SLR aims to better understand the building blocks of current interactive GenAI systems by decomposing them from end-user input, user interface, and system input, to GenAI model, system output, and output presented for end-users, and by analyzing how interface design facilitates user interaction. We now reflect on the findings of our review through the lenses of debates around several key concepts in our framing to answer the research questions.

5.1 Human–GenAI Co-agency Spectrum vs. Human-Centered AI

5.1.1 Appropriating along the Co-agency Spectrum. Human–GenAI co-agency envisions a new framework for understanding and designing GenAI systems through the lens of agency, advocating for design as the delegation of constrained agency, creating interfaces that allow for dynamic reconfiguration of the balance of agency between humans and AI. In our SLR, we notice the majority of the

Table 12: Frequency of applied codes for GenAI models within our dataset.

GenAI Technology	Models	Papers with code
Generative Neural Networks	RNN	17 (8.99%)
	LSTM	7 (3.70%)
	CNN	19 (10.05%)
	GAN	26 (13.76%)
	VAE	7 (3.70%)
	Diffusion	29 (15.34%)
	Other	4 (2.17%)
Foundation Models	LLM	63 (33.33%)
	VLM	32 (16.93%)
	Other	10 (5.29%)

GenAI systems (>50%) act as the role of delegates and users as managers. Here, GenAI performs most of the work while users provide simple directions. This might result from the prevalence of chatbot design, leading to a trend toward automation with oversight. Most systems (~78%) focus on a single human–GenAI co-agency relationship, with a few (~10%) reflecting two. Systems with three or more relationships are rare, indicating a lack of flexibility in the system design—this is perhaps due to most systems being ad hoc for a specific task in their early stage of prototyping. This lack of multi-role adaptability points to an important design opportunity: enabling context-aware, role-shifting interfaces that allow users to scale their level of involvement or delegate more to the AI as needed. Such flexibility would not only support a broader spectrum of user needs and creative processes but could also foster more meaningful collaboration toward truly co-creative partnerships.

5.1.2 Concerns about Human-AI Power Dynamics. Human-centered AI originally agreed with the one-dimensional spectrum and tends to favor one side of the co-agency spectrum, where users account for more than 50% co-agency [135]. This leads to designing GenAI systems primarily as creativity support tools, potentially overlooking the benefits and discoveries that could arise from exploring the other side of the spectrum, where AI systems hold greater agency. The dilemma of Reframer [89] reveals the need to design appropriate interaction paradigms to accurately reflect the agency of the systems and align with user perceptions.

Shneiderman [137] later critiques the uni-dimensional human-computer automation trade-off, and expands the design space to a two-dimensional one by decoupling human autonomy from computer autonomy, promoting simultaneous high human control and high computer automation. Muller and Weisz [105] further apply this dual-axis framework to more complex contexts beyond consumer and medical products, emphasizing the importance of dynamically shifting initiative between humans and AI systems, which aligns with our finding. It also supplements the "human-versus-AI" perspective with a "human-plus-AI" perspective – varying degrees of collaboration between humans and AI, ranging from low-intensity collaboration (like a music box) to high-intensity collaboration (like a digital camera).

In addition, we notice that only a small number of systems (<7%) allow user interaction to craft GenAI models. This could be a positive indicator that communities are shifting from the tech-savvy to the general public. However, the gap in the power dynamics between the system creators and end-users is still concerning—the end-users might be expelled from co-constructing and shaping GenAI as they are only facing a black box. We hope that advancement in explainable AI for the arts (XAIxArts) will help bridge this divide by providing clearer insights into co-creative process over various time spans, AI glitches and errors, and practice-based meaning-making beyond the AI's decision-making processes and functionalities [23], thus equipping end-users with the necessary knowledge to participate in the model-crafting process.

5.2 Designing GenAI as Medium and Tool vs. Partner and Mediator

5.2.1 Structured Medium – Substrates. Substrates are useful conceptualizations for creative system interface design, as they present the underlying structures of the medium, facilitating constrained creativity by organizing and contextualizing tool interaction across pre-GenAI and GenAI systems. In the pre-GenAI application StyleBlocks [101], substrates are derived from properties of concepts, content, and context, enabling dynamic layouts in both space and time. Its tools leverage graphical substrates to customize and dynamically reorganize layouts.

The GenAI system TaleBrush [40] reifies this structure for more advanced storytelling: TaleBrush uses stacked tracks as substrates, where the X-axis represents narrative sequence and the Y-axis visualizes abstract story dimensions, such as character fortunes or plot surprise levels. Users interact with this structured medium through brush sketching, directly manipulating these layers to shape narratives. Similarly, as a recent example of substrate reification, PatchView [41] adopts this metaphor by visualizing the latent space of generative models through the "Magnet Space", where "Magnets" represent concept dimensions and "Dust" particles represent generated outputs. By dragging "Dust" markers closer to certain "Magnets", users manipulate the underlying structure, effectively reshaping the AI's output. These systems illustrate how substrate-based design can make abstract or latent computational spaces legible and explorable, bridging the gap between user intention and AI generation through meaningful interface metaphors. Together, these systems highlight how GenAI tools can be designed as instruments with modular, inspectable, and extendable parts—fostering a more transparent and empowering user experience.

5.2.2 Designing Tools – Instrumental Interaction. The design model of *instrumental interaction* [13] and its design principles *reification, polymorphism, reuse* [14] provide a nuanced framework for designing tools that extend user capabilities through reified and manipulable interface objects. In our dataset, Cells, generators, and lenses [86] exemplify this approach: "cells" are reified objects of input prompt units that can be assembled and reused; "generators" are reified entities of GenAI models that can keep track of linked cell inputs, parameter changes, and generated outputs; "lenses" provide polymorphic views of generated content. This design decomposes complex GenAI interactions into reusable, composable instruments, improving transparency and user agency. Similarly, "Magnets" in PatchView [41] reify the concept dimensions that can be reused and controlled to form different latent "Magnet Spaces", and "Dust particles" reify the relevant positions of generations in the "Magnet

Space". "Dust particles" are polymorphic as both generation output markers and input controllers for users to correct AI behavior.

By turning AI internal mechanisms into visible and interactive constructs, these systems allow users to develop intuitions about AI behavior with modular, inspectable, and extendable parts, effectively engaging in a dialogue with the models' underlying logic. This resonates with pre-GenAI systems that have already applied instrumental interaction – e.g., Object-Oriented Drawing [180] adopts and extends this design model by objectifying graphical attributes into UI elements called "Attribute Objects", bypassing the mediated tools and embedding them into polymorphic objects of interest, enabling direct hands-on interaction through touch gestures.

5.2.3 "When is a Tool a Tool?" The boundary between tool and partner becomes blurred in creativity support tools where AI demonstrates initiative, adaptability, and responsiveness. Reframer [89] raises the question of defining the boundary of the tool and the partner paradigms. The authors find that the perception of AI as a collaborator arises when the system demonstrates agency, engages in real-time interaction, offers mixed-initiative suggestions, and adapts to the user's goals. Designing in a tool paradigm hinders users from making the most of this system and causes confusion when the "tool" starts to prune their drawings. Designing in accordance with the system behaviors can be crucial in providing a consistent understanding and experience to users.

5.2.4 "AI as Social Glue". Besides individual user scenarios, GenAI systems are increasingly situated in collaborative contexts, where their function extends beyond content generation to social mediation. As an example of designing GenAI as a mediator, Cococo [145] reveals how GenAI positively influences social dynamics during multi-user collaborations, facilitating common ground, providing a psychological safety net, and accelerating creation progress. However, the study also notes potential drawbacks, such as AI potentially limiting the depth of human collaboration and introducing additional decision-making overhead. The study highlights the double-edged nature of the mediator role, informing us designing GenAI for multi-user settings requires careful calibration – balancing support with space, and ensuring the AI acts as a facilitator rather than a filter. This opens up a broader design question: how might we craft systems that recognize and adapt to group dynamics, and what new roles might AI play in distributed agency ecosystems?

5.3 Generative System UI Design in Pre- vs. Post-GenAI Eras

5.3.1 The only fundamentally novel interface primitive – text prompts. Text prompts represent a fundamental shift in the way users interact with creative systems. By expressing their creative intent through natural language, often in a single textual prompt, users delegate the execution to the generative models. This marks a leap from conceptualization to realization, bypassing hands-on craftsmanship in the embodied exploration of both traditional creative media and digital media that simulate the textures of traditional ones. This shift redefines the creative process of art-making and creative design. For lay people without formal creative training or art skills, it opens up exciting opportunities to actualize their creative ideas with minimal barriers. However, for creative practitioners who often derive meaning, inspiration, and serendipity through direct sensory engagement and texture exploration via directly manipulating creative media, this is cutting out an important part of the process. Skipping the art-making effort has somehow transferred the "work" in "artwork" to crafting AI models: artists shift their focus to curating datasets, fine-tuning, and training models [29]; meanwhile, users often echo aesthetic patterns learned from training data without their original thinking, potentially leading to cycles of stylistic repetition.

5.3.2 Where should designing interactions with creative GenAI go next? Our review raises questions such as whether the dominant metaphor of tools manipulating media is sufficient to capture the evolving dynamics between users and intelligent systems, and whether AI anthropomorphic agents are the ultimate solution to metaphorize intelligent entities beyond human control and exhaustion. Carter and Nielsen [31] argue that effective interfaces for AI driven creative systems should address more than simple usability issues and aim to reify deep principles about the subject matter, enabling users to think and create in new ways. Ramos et al. [120] suggest an alternative metaphor of "infinite library" to design image generation systems, inspired by Borges' story of "Babel's Library". This library envisions an infinite number of interconnected hexagonal galleries, each containing 640 books written from a 25-character set. Within this vast library, every conceivable story exists within the finite permutations of the sensical books, yet the librarians are hopelessly lost in their endless search. This metaphor provokes the idea that image generation models may provide a computational mapping of near-infinite possibilities of meaningful embeddings or generate a near-infinite number of image variations in which a wide range of novel and meaningful visual content exists.

These researchers also propose using AI for human intelligence augmentation [31, 154], e.g., the aforementioned Luminate [146] system reifies the divergent phase of design thinking by generating intermediate results from flexible keyword inputs mapped along X and Y axes. However, treating AI merely as a source of outputs—what some call "stochastic parrots"—we risk overlooking opportunities to design novel interface primitives and interaction paradigms that leverage the power of AI to explore new forms of creativity and expand the boundaries of human cognition. Instead of simply automating or simulating creativity, well-designed interactive GenAI systems could catalyze reimagining how we interact with information, fostering a deeper, more synergistic relationship between human and machine intelligence.

5.4 Limitations

We identify several limitations with our SLR. Due to time constraints and the rapid growth of GenAI literature, we conducted only one round of snowballing to collect papers, resulting in a dataset skewed toward LLMs and VLMs. We would like to acknowledge that during the coding process, each paper was treated as a single instance, with a system as the basic unit. All UI components and user interaction patterns associated with each artifact were coded together. However, we recognize that some designs may have more specific user interaction strategies that are not fully captured by this approach. Consequently, some correlations in our analysis may have been magnified. This method does not fully reflect a one-to-one relationship between individual UI components and specific user interaction patterns. We encourage future research to explore these more detailed one-to-one/one-to-more relationships to gain a deeper understanding.

Additionally, our primary goal was to capture the range of interactive designs, so user studies and evaluations were not strict selection criteria in our SLR. We also focus the analysis on the systems creating artworks or artifacts, instead of fully covering the embodied performing systems. As a result, for some papers, we were unable to extract detailed user interactions and feedback. We would like to emphasize the importance of providing well-documented user feedback and embodied interactions in future studies. Such insights could significantly inform future research, as understanding not only how interactions are designed but also how users perceive and engage with these designs is equally critical. For the classification of GenAI Technology, our approach is generally based on summarizing the models mentioned across all the reviewed papers, and the categories we present are relatively broad. While this approach provides a general overview, there is room for further refinement. We encourage future research, particularly from experts with specialized knowledge in GenAI models, to offer more detailed categorizations and explore these models in greater depth. This could enhance understanding of the specific characteristics and applications of each model.

6 Conclusions

In this paper, we have provided a comprehensive SLR and taxonomy for designing interactive GenAI systems across various art and creative domains. To support the practical application of this taxonomy, we created a set of design cards that illustrate each interaction paradigm with visual and textual summaries (see Fig. 7 for examples). The complete set of cards can be downloaded from our project page at genai4creativity.github.io. Due to the exceptional growth of this domain, it is vitally important that we begin to map its nuances so that we might better equip designers in meeting the creative needs of professionals and non-professionals alike. Through a review of 189 papers, we have been able to better understand the focus of the field, delineate a set of interaction design paradigms, and understand the user interaction patterns explored by designers. We reflect on what these might mean, compare them to the existing literature, identify shortcomings, and potential under-explored areas, suggesting potential future research directions.

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A Sankey Diagram

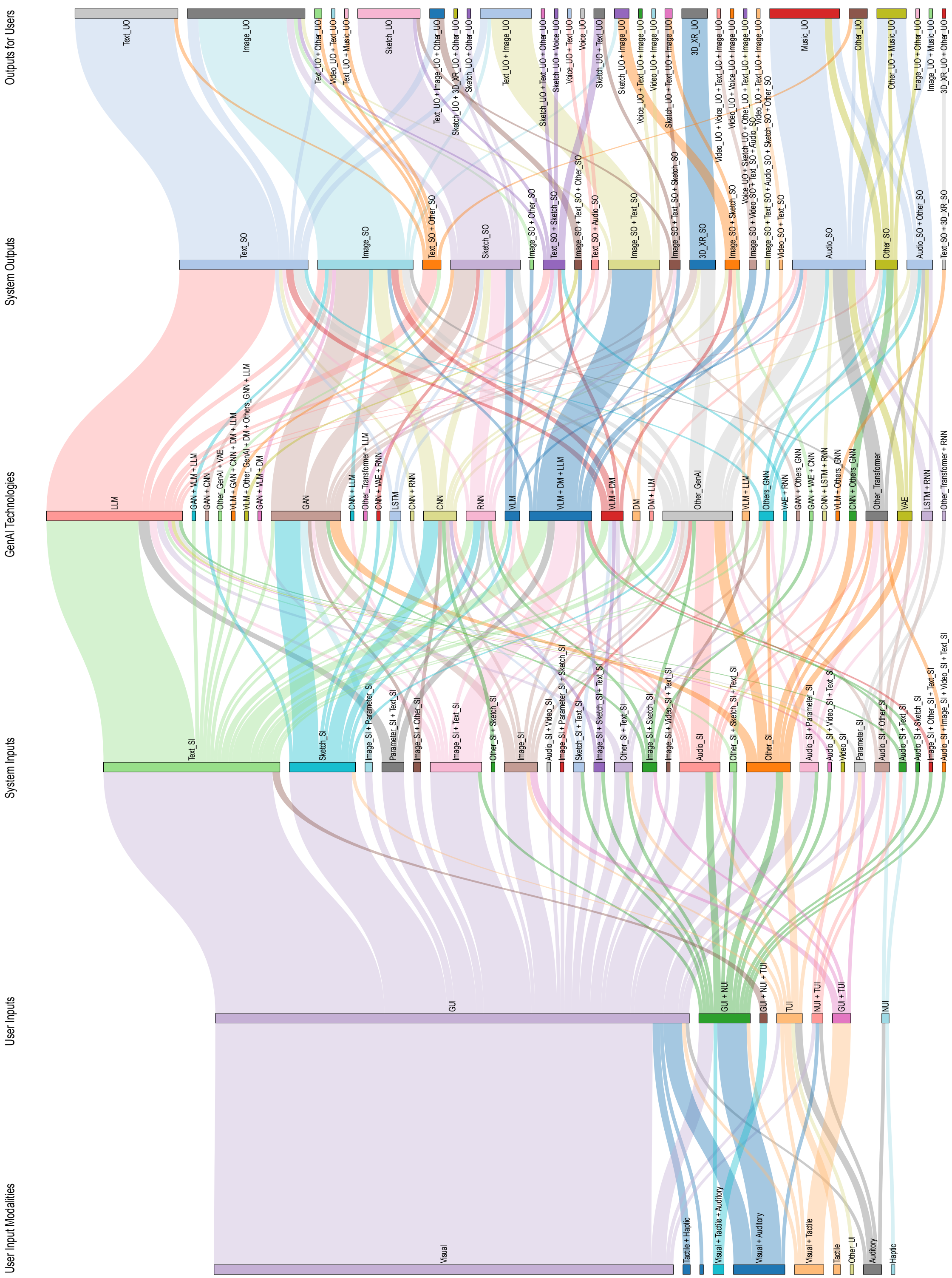

Figure 8: Sankey diagram showing the flow from user input, user interface, and system input, to GenAI model, system output, and output for users. Codes connected by "+" are frequent item sets, representing combinations of codes that frequently appear together.

B Correlation Heatmaps

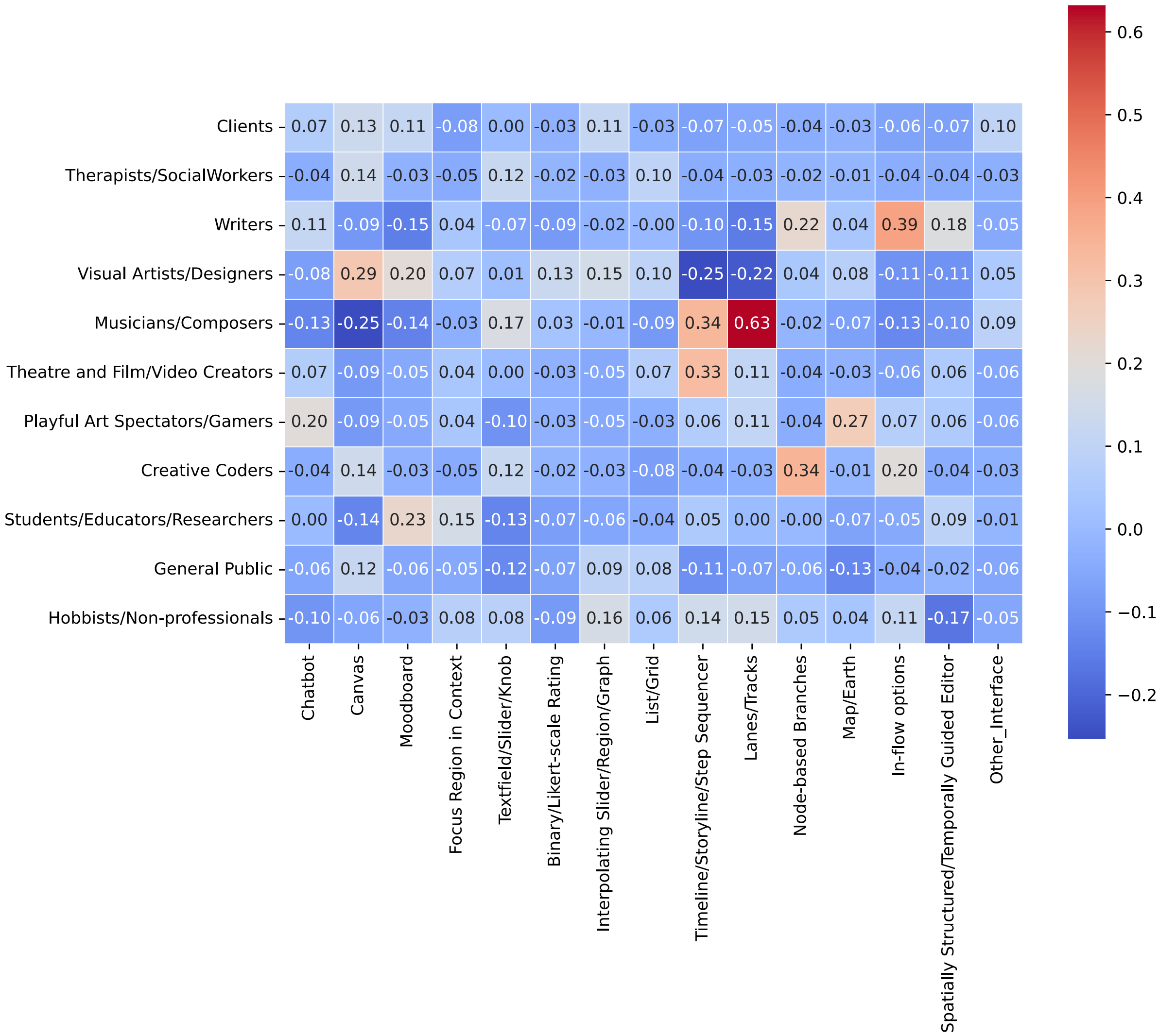

Figure 9: Correlation heatmap between user groups and generative system UI components.

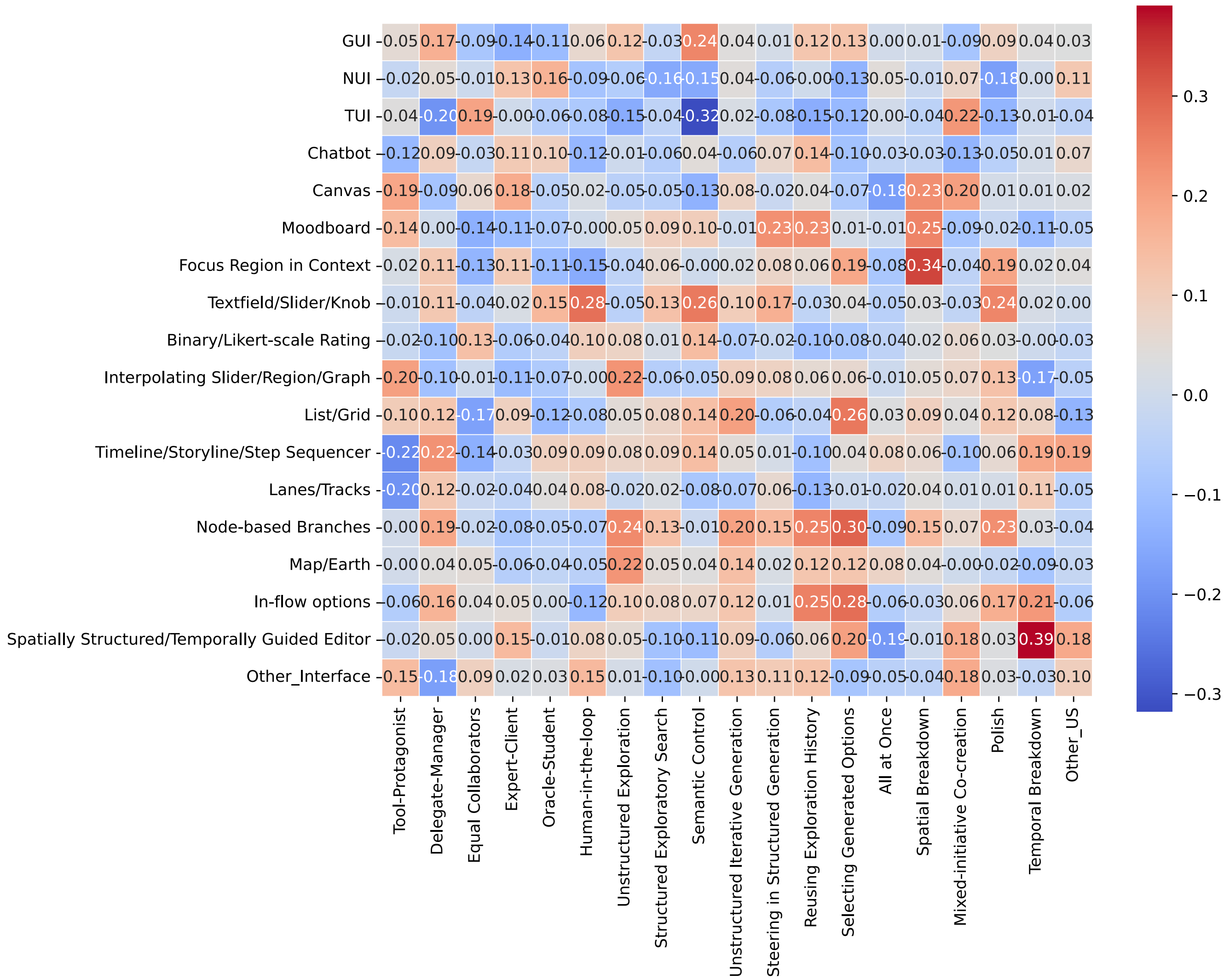

Figure 10: Correlation heatmap between generative system UI components and user interaction patterns.

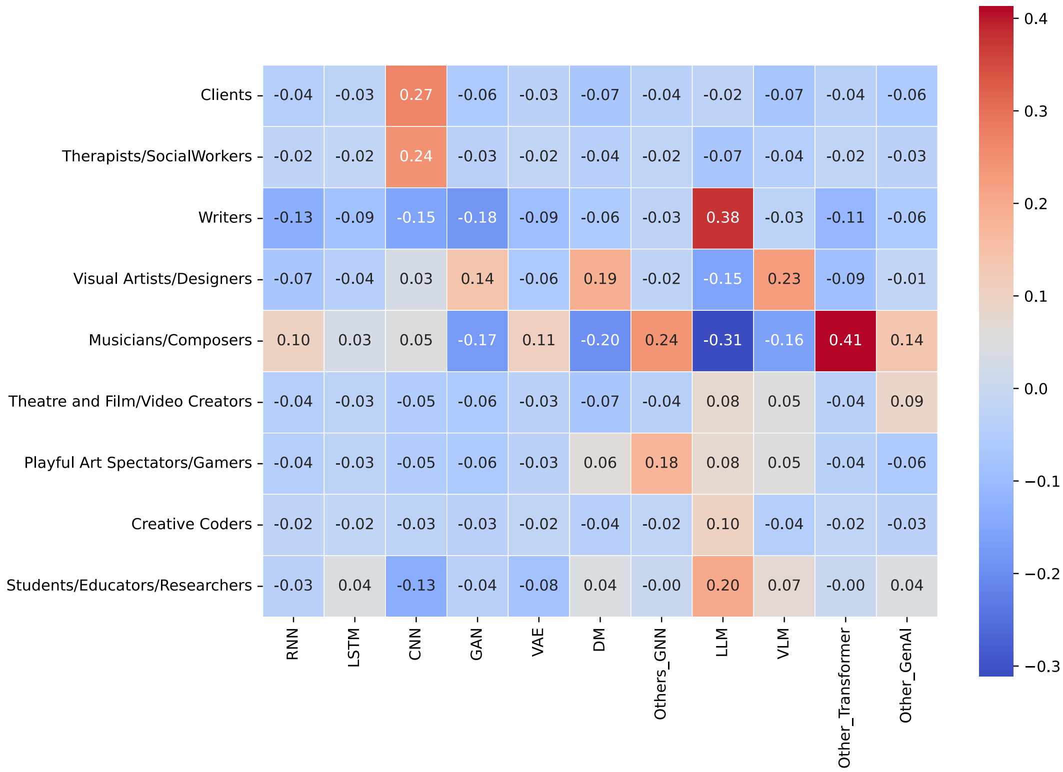

Figure 11: Correlation heatmap between user creative domains and GenAI models.