The Intersection of Users, Roles, Interactions, and Technologies in Creativity Support Tools

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ABSTRACT

Creativity Support Tools (CSTs) have become an integral part of artistic creation. The range of CST technologies is broad—from fabricators to generative algorithms to robots. The interaction approaches for CSTs are accordingly broad. CSTs combine specific technologies and interaction types to serve a spectrum of roles and users. In this work, we tackle a comprehensive understanding of how the intersections of users, roles, interactions, and technologies form a design space for CSTs. We accomplish this by reviewing 111 art-creation CSTs from HCI and computing research and analyzing how diverse aspects of CSTs relate to each other. Our findings identify patterns for designing CSTs, which can give guidance to future CST designers. We also highlight under-explored types of CSTs within the HCI community, providing future directions that CST researchers can pursue given the current trajectory of technological advancement. This work contributes an integrating perspective to understand the landscape of art-creation CSTs.

CCS CONCEPTS

• **Human-centered computing → Interactive systems and tools**.

KEYWORDS

creativity support tools, art-making, literature review

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1 INTRODUCTION

Technological innovation has always led to changes in art-making.[1] Computer-based tools, in particular, have enabled extended expressions, efficiency, and skills [37]. For instance, Adobe's Photoshop provides a set of tools ranging from assorted brushes to context-aware selection tools. Many features mimic existing physical tools and infrastructure available to artists but some afford new capabilities for which there is no equivalent. As *technologies* evolve to support new forms of *interactions* and information processing, these capabilities have been integrated into Creativity Support Tools (CSTs) [38, 117, 118]. For example, many traditional CSTs lack 'agency.' However, new advances in artificial intelligence (AI) and machine learning (ML) have enabled CSTs to become more autonomous, allowing them to do tasks on behalf of the user. This has naturally led to new forms of interaction. An *intelligent* paintbrush–one that does not simply put paint on the material but renders objects in the appropriate style with simply an outline–does not operate like a standard paintbrush (digital or otherwise). Combinations of *technologies* and *interactions*, can expand the capacity of CSTs to serve a wider set of *roles*. For example, with advanced generative algorithms such as GAN [49, 101] or style transfer algorithms [45, 114], CSTs can serve the *role* of creating a portion of the artifact on behalf of the users. The combined changes in *technologies*, *interactions*, and *roles* has also led to an expanded range of supported *users* [38, 39]. For example, CSTs that autonomously generate artifacts lower the creation hurdle for users, allowing novices to create artifacts with minimum skills.

Our work builds on past reviews of CSTs [38, 39, 110]. We specifically seek to provide a framework for understanding the intersection of *technologies*, *interactions*, *roles*, and *users* in shaping *art-making* CSTs. By taking an integrative approach that considers various aspects of CSTs, we aim to map the design space for CSTs. Mapping this space has a number of benefits. For example, we can better identify what are effective design approaches for different types of CSTs. We can also learn what areas are under-explored, difficult, or not yet technologically viable. These gaps hint at future research directions: from those that require more attention; to emerging opportunities and challenges; to those that would be more plausible with technological advances.

In this work, we conducted a literature review of 111 publications that introduced novel art-making CSTs. From the analyzed papers, we identified various facets to model CSTs. These include a resource-based model for understanding CSTs and their placement in the creation process. Additionally, we identify dimensions of interaction approaches to better understand the models of interactions between the human and tools. Our analysis revealed a broad range of technologies by which CSTs are implemented. Finally, we connect these taxonomies to user types and usage scenarios.

Through the analysis, our work contributes a comprehensive understanding of the design space of art-making CSTs while giving hints at future research directions. We identify patterns that

[1] We use the term "art-making" to indicate a broad set of activities for making creative, aesthetic artifacts, from visual arts to music, stage play, visual designs, etc.

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are common within CSTs created by the HCI community. These patterns can inform future CST designers and allow us to identify under-explored CST types. For example, while critique tools were often built for novices, we found very few designed for experts. In some cases, we identify combinations that seem largely implausible. However, many types of CSTs may emerge due to technological advancement. We also found that there have been few tools for specific user populations like children or disabled users. Anticipating these 'possibilities' in the space can guide research efforts.

2 BACKGROUND AND RELATED WORK

Tools are an essential part of art-making [9] and are themselves shaped by advancing technologies [11]. Computing technologies have enabled a broader class of CSTs, and their development and study have become a fixture in the HCI community [117, 118]. The evolution of these tools in the research community has been extensively tracked [38, 39]. This work has provided a lens to study the trajectory of CST research and associated focus areas. We build on this work not only to map work within the research community but also to identify a design space for art-making CSTs.

Among past efforts to understand CSTs (broadly), a focus on *roles* is common. For example, Shneidermann [117] described the need for CSTs to support four role types: collect, relate, create, and donate. A more process-focused approach identified the parts of the creative process that CSTs can support: pre-ideation, idea generation, implementation, evaluation, and iteration [38]. Other efforts have found metaphorical categories for CSTs as different types of fitness equipment: 1) running shoes, which augment the artist's creation actions, 2) dumbbells, which help the learning of the artist, and 3) skis, which introduce new types of expressions [96]. Building upon existing taxonomies, our approach seeks to be more integrative as we consider roles in the context of other factors.

An alternative structure for the study of CSTs focuses on evaluation. For example, Garfield [44] proposed that CSTs can be evaluated with products' quality, such as novelty or appropriateness. Similarly, Carroll et al. [16] and Cherry et al. [21] introduced Creativity Support Index (CSI), evaluating CSTs in six criteria: exploration, collaboration, engagement, effort, tool transparency, and expressiveness. Others have taken a more critical view of CST evaluation, identifying a lack of clarity in evaluation goals, theoretical grounding, and expert participants [110]. Models of evaluation are of obvious importance. However, this only represents a facet of determining the effectiveness and appropriateness of CST development.

While the majority of previous work focused on individual aspects of CSTs (e.g., roles or evaluation techniques), the library of Mixed-Initiative Creative Interface (MICI) has taken a different approach [122]. MICI looks at the roles and interactions of autonomous and intelligent CSTs. Specifically, for each CST, the authors annotated how each role is served in which order by the tool and human. Despite rich relational information on roles and interactions, the work—which is limited to autonomous CSTs—does not draw comprehensive insights from these annotations.

It is worth emphasizing that CST research is extremely broad. Not all CSTs focus on art-making (e.g., those for inventions [48]). Art-making is a relatively unique and complex space for human-machine interaction. Values such as ownership, authenticity [30, 98], and the end-users intrinsic motivations (e.g., what is enjoyable?) [69] will shape the effectiveness and acceptability of new tools. The introduction of CSTs with cutting-edge technologies in the academic community—including those of AI—will invariably turn into commercial products, making this space even more complex. Thus, we are interested in understanding how technologies and interactions have shifted CSTs for art-making. The notion that technologies impact art-making is by no means a new one. We have long known that technological innovation in the arts has increased production efficiency and enabled diverse expressions [11].

Computing technologies have brought multifaceted changes to art-making CSTs. One change is in how CSTs interact with the users. For example, AI or ML has shifted CSTs to be more autonomous and unpredictable [26, 27, 93]. These advanced technologies and diversified interactions have also driven CSTs into a broader set of roles. For example, CSTs can adopt advanced recognition algorithms to automatically provide critiques [108, 119]. Generative algorithms allow CSTs to build artifacts on behalf of users [24, 52, 89, 93, 99, 131]. Art-making CST innovations have enabled new forms of interaction for more diverse users, from novices [73, 89] and experts [46, 74] to those with disabilities [97]. Taken together, these innovations represent an opportunity for synthesis.

In our work, we build upon past efforts in mapping CSTs. However, we have specifically targeted art-making CSTs for analysis. Because of this focus, we identify unique categories and features. Our work also seeks to better contrast different taxonomic categories for CSTs (i.e., roles, interactions, technologies, and users).

3 LITERATURE REVIEW METHOD

For our analysis, we implemented a sampling strategy and a coding process to identify and analyze papers for art-making CSTs.

3.1 Sampling

We first set the criteria that decide which CSTs to sample. While we focus on art-making CSTs, notions of 'art' and 'art-making' are the subjects of significant academic and philosophical debate [25]. We take a fairly broad definition, scoping "art-making" CSTs as *systems or tools used as part of the creative process that result in an artifact with aesthetic qualities*. In our definition, artifacts can take various forms. In music, gaming, creative writing, and film-making, artifacts can be demos and footage that are stored in digital formats. Artifacts can also be form-changing sculptures, sketches, and embroidery in domains such as sculpting, painting, and fiber-based art, respectively. In our model, artifacts can serve as components or instructions for larger creative 'result.' For example, a script (for animation) or dance movement annotations (for a dance piece) are also artifacts. While this definition is broad, there are CSTs that we exclude. Most often, these tools are unlikely to lead to the creation of an artistic product. For example, we do not consider tools for business decision making, crowd tasks (e.g., 'design a way to remember a person's name' [18]), or artifacts that do not consider aesthetics or artistic values (e.g., practical inventions [48]). Additionally, we limited the scope of this study to single-user interactions around art-making. Hence, we excluded CSTs that *only* supported the collaboration or communication between artists, but did not directly

Source	Publications
From Frich et al. [38]	[10, 20, 23, 24, 26–28, 42, 43, 51, 53, 57, 61, 65, 70–73, 92, 95, 100, 106, 128–131, 137, 138, 141, 144, 145]
Newly sampled.	[3, 6, 7, 19, 22, 29, 34, 41, 46, 47, 50, 54, 56, 59, 60, 62, 66–68, 74–79, 81, 84, 86–88, 97, 102, 105, 107, 112, 113, 115, 119, 120, 123, 126, 127, 132, 134–136, 139, 142, 143]
Exploratorily found.	[1, 8, 12, 17, 31–33, 35, 36, 40, 52, 55, 58, 63, 64, 80, 82, 83, 85, 89, 91, 93, 94, 99, 104, 108, 116, 124, 125, 133, 140]

Table 1: Reviewed publications according to sampling approaches.

support art-making (e.g., a system that redistributes responsibility and leadership in web-based art-making collaborations [90]).

With our criteria, we focused on surveying CSTs from research (specifically HCI). With this approach, we can investigate novel art-making CSTs that have not yet made their way into commercial tools. With novel academic tools, we can gain a sense of the reactions (and possibilities) inherent to technologies that are not yet commercially available. A second, more practical reason is that research papers are much more explicit in explaining the intended roles, designs, technologies, and users. With the descriptions in the paper, we could also decide whether the tool is within our criteria.

To begin our sampling, we leveraged the literature review of CSTs by Frich et al. [38]. One author identified those CST papers that fell within our inclusion criteria for art creation. This initial pass yielded 31 papers.

To expand this set, we identified post-2018 publications (the end year of Frich et al's survey). We targeted papers published between September of 2018 and October of 2020. To sample these, we took an approach similar to Frich et al. We used the author keywords 'creativity support tool' or 'creativity' to search and sample papers from the ACM Digital Library.[2] Unlike Frich et al., we did not filter papers with download or citation count. It is because bibliometric measures tend to be relatively small for all newer papers. Among this set, we identified 49 new papers that follow our criteria.

We also sought to include relevant papers that did not have author keywords of "creativity" or "creativity support tools." This was done by exploring publications that cite or are cited by our sampled papers. We also searched through proceedings of recent HCI conferences. These yielded additional 31 papers. In total, we considered 111 publications from 2009 to 2020 (Table 1).

3.2 Coding Process

Two authors analyzed sampled papers iteratively. We focused on 1) the purposed roles of the tool, 2) the interaction patterns between users and tools, 3) technologies used, and 4) intended user population. We targeted these factors based on previous work (Section 2), as they either drive changes in CSTs (technologies) or are impacted by those changes (roles, interactions, and users). Our analysis goal was to find patterns in, and between, these factors.

Our iterative approach involved multiple joint sessions of discussion and analysis. Each session added up to 10 papers. Papers for each session were randomly sampled from the papers that had not been reviewed yet. Before each session, the authors independently read, summarized, and coded sampled publications. Codes were developed over the course of the sessions. When appropriate, we also leveraged codes from existing work as a starting point.

[2] https://dl.acm.org/

If a new paper fit under an old code, this was used. Otherwise, we inductively generated codes as we went through the data. Section 4 describes which codes were based on previous work and which were inductively generated. In each session, the authors reviewed each other's summaries and codes. For generated codes, the authors tried to integrate differing codes into a single scheme. If necessary, codes were revised, removed, added, merged, or split. The updated coding scheme was used for the next rounds of discussions. Moreover, with the update of the coding scheme, the authors reviewed past codes and updated them with the new scheme. After analyzing the whole paper set, we identified additional higher-level structures.

4 CODES

Through coding, we structured taxonomies of roles, interaction approaches, technologies, and users of CSTs. Some codes were grounded in previous work, while some were inductively found during the coding process. In this section, we introduce details of each code in taxonomies. All codes are summarized in Table 2.

4.1 Roles of CSTs

We identified roles with two different taxonomies. First, ***resource roles*** indicate which type of resources, or benefits, each CST offers. These further divide into two types based on whether the resource was an 'idea' or something more tangible and skill-based, like 'labor' or 'expertise'. In contrast, ***process roles*** indicate in which part(s) of the art-making process the CST is intended to work. At a high-level, *process roles* include ***aiding ideation***, ***aiding implementation***, and ***aiding evaluation***. These are grounded on the creative process phases identified by Amabile [4, 5]. Our coding approach is similar to those of a CST's roles by Frich et al. [38] and the Library of Mixed-Initiative Creative Interfaces [122]. Based on previous work and our coding process, we further identified which more specific *process roles* exist under each high-level role.

4.1.1 Resource roles. We identify two types of *resource roles*: (1) those that help with ***skills***, and tend to support artists with expertise or labor efficiency; and (2) those that help with ***vision***, and target artistic vision or ideas. A simple example within the *skill* category is a tool that helps if an artist cannot implement an artifact due to the lack of expertise (e.g., they may not be able to sculpt well) or time (e.g., a complex pointillist piece). In contrast, *vision*-focused CSTs can offer an inspiring suggestion or create part of the artifact that the artist could not have brought up by herself. In our analysis, we did not find examples of CSTs that focused on both roles. This is not to say that a complex CST could not do both. For example, a full platform for image editing such as Photoshop might arguably offer both in different parts of the system. However, such scale did not exist in the academic examples we studied and, arguably, one might divide a monolithic CST like Photoshop into smaller features/components.

4.1.2 *Process roles.*

Our analysis identified a more complex set of *process roles*. Additionally, we found many CSTs with multiple process role codes.

Aiding ideation. The first high-level *process role* a CST might have is supporting the user's ideation process. Artists or designers tend to seek novel and inspirational ideas before or during creation. A specific instance of this role is ***idea generation***. For example, Karimi et al. [67] used sketch generation algorithms to inspire designers when they are doing a visual design task. A second code, ***curation***, plays a similar role but focuses on suggesting from existing information or artifacts. For example, Koch et al. [75] designed an intelligent mood board that curates contextually appropriate inspiration images for designers.

Aiding implementation. The second high-level process role is helping with the implementation of artifacts. Here, a CST augments or automates certain functions. One specific sub-category is ***execution assistance***. For example, Dynamic Brushes [63] help artists create procedural visual arts without programming knowledge. This is achieved by providing a custom interface that lowers required expertise. A second variant, ***producing*** was assigned to situations where artists let CSTs conduct most of the implementation tasks. In this role, the artists can allow the CSTs to make most of the creative or implementation decisions. Users who lack the expertise or labor to implement artifacts by themselves benefit from this category of CST. For example, Frid et al. [40] designed a music-producing system for video creators who don't necessarily know anything about composition. The ***understanding*** code was used for CSTs that help the user understand the current state of their artifact. This role is helpful when the implementation of creations can be complex. For instance, Progression Maps [17] help interactive narrative designers understand complex narrative structures through a visualization. This role is different from the other two specific roles in *aiding implementation* as it does not directly support the artist's implementation of the artifact. Rather, *understanding* helps with the sensemaking required for implementation.

Aiding evaluation. The third process role was in helping with the evaluation of created artifacts. Within this role, we identified one specific code, ***critique***. Here, the CST critiques or gives feedback intended to guide improvements to the artifact. For example, VoiceAssist [112] gives feedback on voice recordings, so that users can make improvements on room acoustics and background noise.

4.1.3 *Complementarity of Resource and Process Roles.*

There are situations where process and resource roles are strongly connected. For example, giving someone an 'idea' (a vision resource) often happens within 'ideation' (a specific process). While this may be more common, one can imagine situations where ideas are provided in other points in the artist's creative workflow (i.e., process). For example, when evaluating an artifact, the system can also provide ideas for improvements. Because of this, we treat resource roles and process roles as complementary. By splitting role types, we can distinguish between the *benefits* offered by the CST and *where/how* they are offered within the creative workflow.

4.2 Interaction Approaches Used by CSTs

Our analysis identified the interaction approaches used within CSTs. We found that a single tool can have multiple interaction behaviors corresponding to multiple functions. While the traditional types of interactions (e.g., mouse, voice, touch, direct manipulation, etc.) are part of this analysis, we are more concerned with the properties and intents of the interaction relative to the creative process.

4.2.1 *Input Directness.*

We categorize input directness in relation to whether a CST is receiving direct inputs or not. Here, ***direct*** inputs are closely relatable to the artifact or the change that is going to be made in the artifact. A simple example of a direct input is brush strokes on a digital canvas. Clearly, these directly relate to what is drawn on the canvas. It is important, however, to note that we distinguish between the idea of 'direct manipulation' and 'direct input.' A more subtle example of direct input is when the input becomes part of the artifact's final 'form.' For example, the recorded audio of a voice-actor can be recorded when producing a character animation. That voice is used to drive the expression in the character but is also a final part of the animation (as in Adobe's Character Animator and TakeToons [124]). We also consider the observation of the "current state" of the artifact as *direct* input. For example, a CST can take the current representation of the artifact as input and provide a critique of that work. While the art is not being *modified* by the CST, the input is nonetheless direct, as the input is the artifact itself. ***Indirect*** inputs are those that are more separated from the artifact. One example is natural language queries given by the user. These queries would be used to request various functions to the tool (e.g., searching or generating artifacts), but queries themselves are not artifacts. Another type of *indirect* input is a manipulation of parameters, like those for cameras, such as exposure levels. It is more of partial information about how the artifact should be, but not the representation of the artifact.

4.2.2 *Predictability of Impact.*

The second property of interaction is *predictability* of the CST when it is used. How well can the user model and anticipate what the tool will do? A ***predictable*** CST is one in which the CST behaves exactly according to the user's specifications or anticipation. An example of the former is a brush in virtual canvas, where users are certain that the lines will be created following their strokes. An example of the latter would be a fabrication tool that receives a blueprint from the user. While the blueprint may not be a complete specification (e.g., it may not contain scaffolding instructions), the user is nonetheless certain about the tool's behavior and what the final output will look like.

CSTs that are ***unpredictable*** are those that produce output that is difficult for the end-user to model. These tools are clearly not 'random'—the overall function is understood. We can take the example of the 'art-critic' CST that is constantly providing feedback on the art. The end-user is aware that critiques are being produced but can't accurately model what they will be. *Unpredictable* tools rarely require users to give very specific information on how the tool should behave. In fact, it is this ambiguity that makes them unpredictable. While tools can be *unpredictable* due to errors, we coded CSTs according to their intended behaviors. We also recognize that CSTs can be both predictable or unpredictable. For example, an unpredictable CST can become predictable given enough experience.

4.2.3 Output-Implementing/Influencing. The final aspect of our interaction codes is on the *output* of the CSTs. We identified differences in CSTs that support the artist by ***implementing*** the whole or a part of the artifact or by ***influencing*** the artist. We coded tools to be *implementing* if they directly create or generate a part of an artifact. An example is a generative algorithm that creates the visual design of products [108]. We also coded tools as *implementing* if they simulate the final artifact or some part of it. SimuLearn [140] is one example of this type of CST. The tool generates a simulation of how the 3D fabrication would change with the application of heat. We coded as *influencing* those CSTs that impact the artist, not the artifact. This includes feedback, critique, scaffolds, or analysis. The artist is intended to *react* to this information in modifying their behavior, and thereby, the artwork. In some cases, the CST's output is both *implementing* and *influencing*. This can happen in the cases of mixed-initiative systems. For example, in a tool that outputs inspirational metaphors for a word [47], the metaphor can be directly used in the user's writing or can influence artists to get inspiration and draw more ideas.

4.3 Technologies for CSTs

When considering the technologies used in CSTs, we focused on the aspects that provided core functionality or interaction support. We inductively identified six types among our sampled papers.

4.3.1 Learning algorithms. CSTs based on ***learning algorithms*** were those that were trained on data. They include many ML algorithms, ranging from Hidden Markov Model, neural networks, and Generative Adversarial Network [49, 101]. One use of these algorithms is to recognize and understand artifacts or user inputs. For example, Shtern et al. [119] used ML recognition algorithms to inspect the quality of music mastering. *Learning algorithms* were also used for generating artifacts. For example, McCormack et al. [93] designed a machine improviser that generates music that fits with what a human musician is playing. *Learning algorithms* were also used to learn users while they are using CSTs, so that tools can give adaptive support. For example, Drawing Apprentice [27] learns how to co-create with the user from user interactions.

4.3.2 Non-learning algorithm. CSTs that were not data-driven were classified as ***non-learning algorithms***. This type included hand-tuned, rule-based algorithms, or optimization algorithms. CSTs in this category often leveraged these algorithms for artifact exploration or search given some constraints. For example, Scout [125] suggests designs with a constraint resolver and a ranking function. Algorithms used in Scout were designed by researchers to assure the quality of the suggested designs. *Non-learning algorithms* are also used to manipulate the artifact in a controlled way. For example, DataQuilt [143] used GrabCut [111] and Canny edge detection [15] to extract specific parts of images. We coded *non-learning algorithms* separately from *learning algorithms* as they are different in how they are designed. This difference would possibly impact how CSTs with these algorithms would interact with the users. For example, *non-learning algorithms* are more often designed to perform deterministically according to the tool designer's intention. However, *learning algorithms* are often trained on data—both small and large—that leads to uncertainty in how the tool behaves.

4.3.3 Software UI. CSTs that were principally centered around ***software UIs*** often involved designs to improve user control of the CST. For example, Demystified Dynamic Brushes [81] helped artists understand the dynamic visual arts by showing relevant numerical parameters. These also helped the editing of dynamic arts by allowing easier manipulation within the UI.

4.3.4 Sensors. ***Sensors*** have been used in CSTs to expand the modality of the expressions. Their usage ranged from photo-sensing to audio-, depth- and gyro-sensing. For example, MoBoogie [53] allows users to create musical expressions with dancing moves, by sensing them with an accelerometer.

4.3.5 Fabricators. Some CSTs use new ***fabricators*** or materials (or leverage existing ones). For instance, ExpandFab [66] introduces a fabrication process of expanding objects using foam materials.

4.3.6 Robots. Though rare in our samples, some CSTs had mechanical or ***robotic*** infrastructure. This enabled the CSTs to interact in physical spaces. For example, Robovie [65] is a physical robot designed to give inspiring prompts on garden designs.

4.4 Users of CSTs

When classifying CSTs, we also focused on who they were targeted for. We built on the taxonomy of Frich et al. [38] for expertise and augmented this with codes for the populations that were the intended audience of the CST (i.e., general use or specific populations such as children or end-users with certain disabilities).

4.4.1 Expertise/Availability of Description. Our first set of user codes included four categories corresponding to expertise: novice, expert, all/both, or unspecified. CSTs for ***novices*** enabled creations that are not possible with the user's expertise. For example, ChordRipple [61] helps *novice* composers try radical chords with recommendations. Some CSTs are designed specifically for ***expert*** users. For instance, VoiceCuts [74] allows *experts* to interact with creative applications through vocal commands. For *experts*, as they have their ways of creating, it would be important to design a tool that embeds well into their practices. CSTs can also be designed to support ***both*** types of users, regardless of their expertise. For example, Joinery [145] supports both *novices* and *experts* in the fabrication of laser-cut assemblies. For *novices*, it democratizes the creation, and for *experts*, it provides rapid prototyping ability. Lastly, some CSTs did ***not specify*** target users. For instance, BodyAvatar [144] focuses more on describing the novel tool, without explicitly (or implicitly) indicating for whom the tool is designed.

4.4.2 Specific and General Populations. Finally, we considered whether the CSTs were focused on specific or general populations. CSTs for ***specific populations*** often had narrow use-cases in mind (e.g., children). For example, Zarei et al. [142] designed a tool that helps children create storytelling with embodied avatars. Another set of *specific population* CSTs are those built for end-users with some disability. For example, CreaTable [97] supports people with aphasia to create content with tangible interactions. Those CSTs that were either explicitly or implicitly for more ***general populations*** were labeled as such. One commonality in *specific populations* that distinguishes them from *general populations* is that they might

	Taxonomies	Codes	Definition	e.g.	#	%
Roles	Resource roles	Vision	The tool supports the user with artistic vision and ideas.	[47]	**63**	**56.8**
		Skill	The tool supports the user with expertise or labor efficiency.	[141]	48	43.2
	Process roles	Idea Generation	The tool suggests novel information or artifacts with computational generation.	[67]	43	38.7
		Curation	The tool suggests novel information or artifacts from existing sources.	[75]	10	9.0
		Execution Assistance	The tool augments the user's implementation actions.	[63]	**81**	**73.0**
		Producing	The tool automates implementation on behalf of the user.	[40]	14	12.6
		Understanding	The tool helps users understand the current state of creation.	[17]	19	17.1
		Critique	The tool helps users evaluate the created artifact.	[112]	10	9.0
Interactions	Directness	Direct	The user input is close to the artifact.	[124]	**89**	**80.2**
		Indirect	The user input is distant from the artifact.	[134]	82	73.9
		No Input	The user does not make an input to the tool.	[65]	2	1.8
	Predictability	Predictable	The user can predict which output will come out.	[85]	60	54.1
		Unpredictable	The user cannot predict which output will come out.	[22]	**76**	**68.5**
	Output	Implementing	The tool implements the whole or a part of the artifact.	[99]	**96**	**86.5**
		Influencing	The tool influences the user.	[112]	39	35.1
Technologies	Technologies	Learning Algorithm	Algorithms trained on data (e.g., ML algorithms).	[93]	**45**	**40.5**
		Non-learning Algorithm	Algorithms not trained on data (e.g., rule-based algorithms and optimization).	[143]	30	27.0
		Software UI	Software UI that gives easier use and control (e.g., visual programming).	[81]	25	22.5
		Sensor	Sensors that expand the modality (e.g., depth sensors).	[53]	23	20.7
		Fabricator	Fabricators or materials, or new ways of using them (e.g., XY-plotter or thermochromic ink).	[66]	11	9.9
		Robot	Robots in the physical space (e.g., robots that draw sketches).	[65]	3	2.7
Users	Users-Expertise	Novice	Users who are not fully trained in the art-making domain.	[61]	31	27.9
		Expert	Users who are enough trained in the art-making domain.	[74]	30	27.0
		Both	Tools support both experts and novices.	[145]	17	15.3
		Not Specified	Tools not specifying which user group is supported.	[144]	**33**	**29.7**
	Users-Specific	General Populations	Users other than specific populations.	[32]	**105**	**94.6**
		Specific Populations	Specific targeted users, such as children or users with a disability.	[97]	6	5.4

Table 2: Definitions, example CSTs (e.g.), counts (#), and percentages (%) of codes in each taxonomy. Resource roles are types of supportive resources provided by CSTs, and process roles are about which part of the creation process is supported. Directness is an interaction dimension of whether the user input is close to the artifact or not, while predictability is about whether the tool behavior is predictable or not. Output is about how the tool is contributing to the creation of artifacts. Technologies and users indicate which technologies are used, and who are the intended user population, respectively.

require special accommodations—either due to not-yet developed motor or cognitive abilities or disability.

5 CODING AND ANALYSIS RESULTS

Not all codes are equally likely among CSTs. Below, we provide the distribution of codes in each taxonomy. For taxonomies that allow multiple codes for a tool (process roles, interaction approaches, and technologies), we present co-occurrence statistics. Finally, we return to the main motivating question in how roles, users, technologies, and interactions intersect in the design space of CSTs. We include coding results in the supplementary material.

5.1 Distribution for Each Taxonomy

Our analysis on the distribution of codes for each taxonomy is presented in Table 2. For *resource roles*, we found that there were slightly more *vision*-offering tools (56.8%) than *skill*-offering ones (43.2%). For *process roles*, we found that the percentage of tools for serving *execution assistance* was the highest (73.0%), followed by *idea generation* (38.7%). The rest of the *process roles* had lower percentages, in the order of *understanding* (17.1%), *producing* (12.6%), *critique* (9.0%), and *curation* (9.0%).

For interaction approaches, there were slightly more tools that allow *direct* inputs (80.2%) than *indirect* ones (73.9%). Only two tools did not receive user inputs (1.8%) [3, 65]. With *predictability*, there are more *unpredictable* tools (68.5%) than *predictable* ones (54.1%). With *output* categories, there are over twice more *implementing* tools (86.5%) than *influencing* ones (35.1%).

For technologies, *learning algorithms* were most used (40.5%) whereas *fabricators* (9.9%) and *robots* (2.7%) were least common.

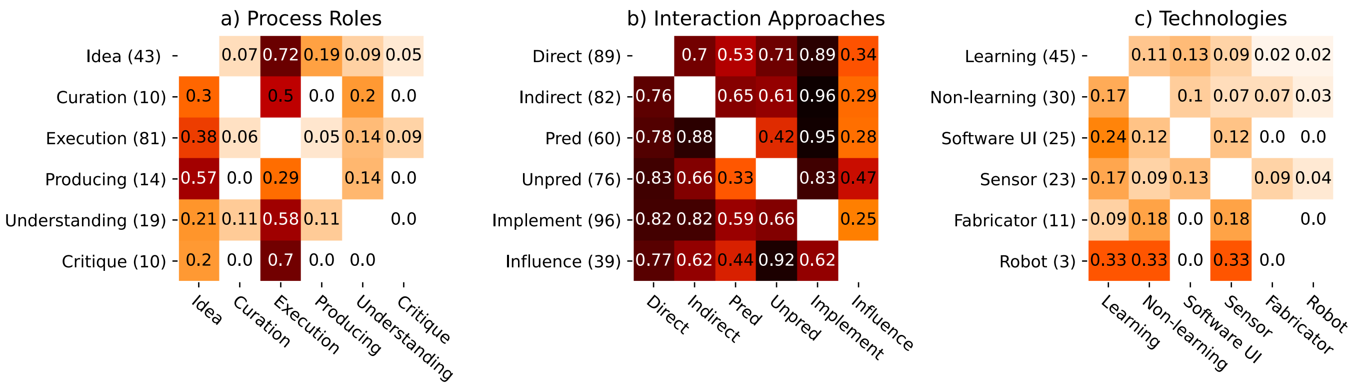

Figure 1: Co-occurrences of codes within each taxonomy. The number in each box indicates the ratio of tools that have the element in the column among all tools with the element in the row. On the y-axis, numbers in parenthesis indicate the number of CSTs with the code. In a), 'Idea' and 'Execution' stand for idea generation and execution assistance, respectively. In b), 'Pred' and 'Unpred' stand for predictable and unpredictable, respectively.

For users, with expertise and the availability of user description, 29.7% of tools did *not specify* user group, which was the highest among user groups. Tools for *novices* (27.9%) and *experts* (27.0%) were slightly less common. Fewer supported both experts and novices (*both*, 15.3%). Only six were for *specific populations* (5.4%).

5.2 Within-Taxonomy Analysis

Figure 1 summarizes the co-occurrence of codes within the CSTs.

5.2.1 Within Process Roles. In *process roles*, *execution assistance* co-occurred most frequently with other *process roles* ($\geq$ 50%, 3^{rd} column of Figure 1a) except for *producing*. *Idea generation* also showed relatively high co-occurrences with other process roles ($\geq$ 20%, 1^{st} column of Figure 1a). However, *producing* was an exception to this pattern, as it co-occurred more with *idea generation* (57%) than with *execution assistance* (29%). This different result in *producing* is likely due to the incompatibility of *producing* and *execution assistance*: tools with *execution assistance* tend to maintain user control while *producing* tools create on behalf of the user. For cases where they co-occur, separate functions supported each role. Additionally, the high co-occurrence of *idea generation* in *producing* tools would be because *producing* often requires creative decisions.

5.2.2 Within Interaction Approaches. We analyzed the co-occurrence in three dimensions of interaction approaches (Figure 1b). Within *directness*, more than half of tools were *direct* and *indirect* at the same time (55.9% of all tools). Compared to *directness*, the co-occurrence was relatively low for the dimension of *predictability* (22.5% of all tools). This indicates that *predictability* more clearly characterizes each tool compared to *directness*. Within the *output* dimension, while 21.6% of tools both support implementing and influencing, the rate of *influencing* tools co-occurring with *implementing* tools (62%) was higher than the co-occurrence of the other way around (25%). It is due to the imbalance of frequency within the *output* dimension. When one tool has both codes in one interaction dimension, it was often because the tool has multiple functionalities. For example, COCOCO [89] has an *unpredictable* function of generating a part of the music and a *predictable* function of recording the user's midi input. We also observed that *implementing* code co-occurred with all *directness* and *predictability* codes frequently (5^{th} column of Figure 1b). Similar to results within the *output* dimension, it would also be due to the high number of *implementation* tools. Another notable pattern was that *influencing* tools more co-occurred with *unpredictability* (92%) than *predictability* (44%). This result would be because many tools *influenced* artists with unexpected information or artifacts, such as critiques or inspirations. While it was rare for *influencing* tools only to be *predictable*, there were cases that the tool does *predictable* management for the user. For example, VoiceCuts [74] allowed users to select tools with voice commands in applications like Adobe's Photoshop. In this case, VoiceCuts would manage the selection of the tool as the user's vocal commands (in a *predictable* way), while not directly implementing on the artifact.

5.2.3 Within Technologies. Overall, technology types did not co-occur a lot (Figure 1c). This is principally because we focused on the 'core' technologies of the CST (often this was singular).

5.3 Cross-Taxonomy Analysis

We analyzed how CSTs have been designed by relating different taxonomies. Our core research questions for this analysis are:

- How each *role* intersects with different *interaction approaches* and *technologies*?
- How each *user group* intersects with different *roles*, *interaction approaches*, and *technologies*?

5.3.1 Role × Interaction and Technologies.

Resource Roles, Interaction Approaches, and Technologies. In Figure 2, we illustrate how *resource roles* relate to *interaction approaches* and *technologies*. For *directness* (Figure 2a), we found that *vision*-supporting tools slightly more often adopt *direct* inputs (82.5%) than *indirect* ones (68.3%). For *skill*-supporting tools, there were more tools with *indirect* inputs (81.2%) than those with *direct* inputs (77.1%), but the difference was small. We also found that a small number of tools support *vision* without receiving any

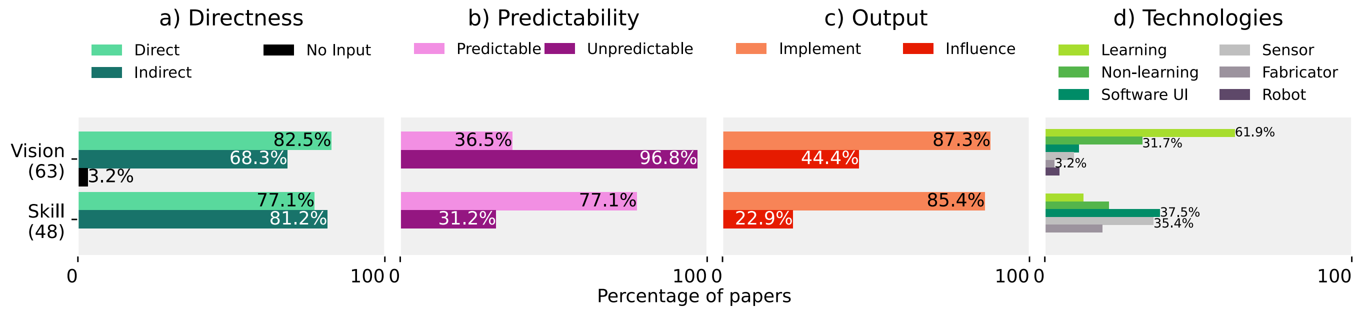

Figure 2: Percentage of interaction approaches (directness, predictability, and output) and technologies according to resource roles (items on the y-axis). On the y-axis, numbers in parenthesis indicate the number of CSTs with the code.

input from the user (n = 2, 3.2%). These tools function by prompting messages for inspiration without getting any input (e.g., "Tell me about your past creative experiences.") [3, 65]. With the *predictability* (Figure 2b), we found that tools for *vision* tend to be more *unpredictable* (96.8% for *unpredictable*, 36.5% for *predictable*). Tools that generate arts to give inspirations to the users are one type of *unpredictable* tools that support with *vision* [24, 26, 27, 52, 68, 78, 100, 106, 129, 131]. Tools for *skills* are shown to be more *predictable* (77.1% for *predictable*, 31.2% for *unpredictable*). One type of *predictable* tools for *skills* augments the user's implementation actions while following the user's controls, like how paintbrushes are used on a canvas [23, 62, 63, 72, 120, 130, 143, 144]. Rarely, there were cases where a tool for *vision* is only designed with *predictable* approaches. For example, UnicrePaint [41] allowed a *predictable* but inspiring and unprecedented way of creating visual arts, stamping physical objects on a digital screen. There were also cases that the tool offers *skill*-wise benefits only with *unpredictable* means. For example, in the fabrication of morphing material, SimuLearn [140] extends the user's *skill* by informing the user of how the morphing would be done, which is *not predictable* to the user. With ways of how *outputs* are contributing (Figure 2c), we found that more tools are supported with *implementing* than *influencing* for both *vision*-supporting and *skill*-supporting tools. This high occurrence of *implementation* across resources roles would be due to the prevalence of *implementation* among reviewed publications.

We also analyzed how resource roles and technologies relate (Figure 2d). For *vision*-supporting tools, learning (61.9%) and non-learning algorithms (31.7%) were the top two most used technologies. On the other hand, the top two technologies used for *skills* were UI (37.5%), and sensors (35.4%). We give specific cases of technology use in each role in the next section, with process roles.

Process Roles, Interaction Approaches, and Technologies. We analyzed how *process roles* intersect with *interaction approaches* and *technologies* (Figure 3). With input *directness* (Figure 3a), *direct* and *indirect* approaches are almost equally used in *idea generation* and *execution assistance*. For *curating* tools, all of them are suppported with *indirect* inputs. Curating tools received natural language-based queries [36, 46, 76, 77], preferences [75], or partial information [136]. However, *indirect* inputs were not a necessary condition for *curation*, as some also received an artifact as a *direct* input [76, 135]. On the other hand, *producing*, *understanding*, and *critique* were more supported with *direct* inputs. Among them, all *understanding* and *critique* tools adopted *direct* inputs, as, by definition, they require artifacts to be understood [17, 33, 34, 60, 76, 77, 79, 81, 86, 87, 102, 123, 140] or evaluated [28, 31, 32, 80, 108, 112, 119]. Tools that receive no inputs are found only in *idea generation* (4.7%), which were robots prompting for inspiration [3, 65].

With *predictability* (Figure 3b), most *process roles* (excepting *execution assistance*) are more supported with *unpredictability*. Among these, all *critique* tools were *unpredictable*, as they give information that is unexpected by the user to change the user's behavior. Moreover, while most curation tools are unpredictable, there was a case of a predictable curation tool. This tool, Color Builder [120], allowed users to curate colors by arranging color swatches. By positioning color swatches, the tool would curate intermediate colors between swatches in gradients, which is predictable interactions to the user. On the other hand, *execution assistance* was equally supported by both *predictable* (61.7%) and *unpredictable* tools (60.5%).

For the *output* (Figure 3c), similar to *resources roles*, all *process roles* except *critique* are more enabled with *implementation*. Among these roles, *curation* and *understanding* used *influencing* more than others (70.0% and 63.2%, respectively). For *curation*, the curated artifact can be either included in the final artifact or used to influence users, like for inspirations [22, 46, 75–77]. For *understanding*, tools that *influence* often support by showing the analysis [17, 33, 76, 77, 79, 81, 86, 87, 102, 123]. On the other hand, tools that *implement* for *understanding* helped the user create an alternative representation of the artifact. For instance, Knotation [23] allowed choreographers to document choreographic processes into diagrams so that they can better *understand* them. Apart from these roles, all *producing* tools *implemented*, as the definition indicates. One thing to note is that there were cases where the tool is supporting *execution assistance* only through *influencing*. One type of such tool only augments the user's actions without directly manipulating artifacts [51, 138]. For example, when drawing with a pen, DePENd guided the user's pen strokes with ferromagnetic forces [138]. We also found *critique* is more and all supported with *influencing* outputs, as it is to change the user's behavior.

With how *process roles* are supported by *technologies* (Figure 3d), *learning algorithms* were used frequently across different *process roles*. When we took a more specific look, *idea generation* was majorly supported with *learning algorithms* (58.1%), followed by *non-learning algorithms* (32.6%). These *algorithms* were often used

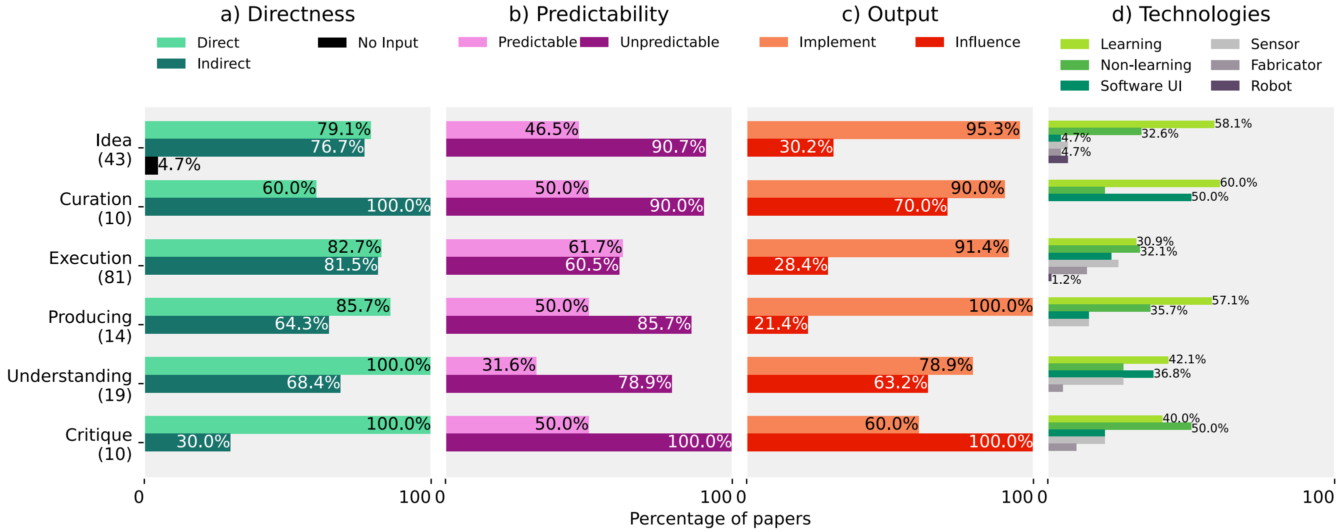

Figure 3: Percentage of interaction approaches (directness, predictability, and output) and technologies according to process roles (items on the y-axis). On the y-axis, the number of CSTs with the code is in the parenthesis. On the y axis, "Idea" stands *idea generation* and "Execution" is for *execution assistance.*

to generate artifacts or information that can inspire users [20, 26, 47, 67, 83, 89, 92, 99, 107, 108, 113, 125]. Also, compared to other roles, *idea generation* had the highest percentage of using *robots*. These robot tools either prompt inspiring messages to the user [3, 65] or draw inspiring sketches on physical paper [83].

Curation frequently used *learning algorithms* (60.0%) and *software UI* (50.0%). *Learning algorithms* were often used to collect and curate materials [22, 36, 46, 75–77, 135, 136], while *software UI* were used to effectively present curated results [22, 36, 73, 77, 120]. *Curating* tools did not use *sensors*, *fabricators*, and *robots*.

Execution assistance showed the most distributed use of *technologies*, but was most supported by both types of *algorithms* (30.9% for *learning* and 32.1% for *non-learning*). Often, *execution assistance* tools that use learning algorithms generated a portion of an artifact [12, 12, 33, 52, 83, 89, 99, 131], like generating and adding a snippet of music upon the tune that the user have created [89]. However, still, for *execution assistance* CSTs, the majority of controls were on the users. Usually, the tool generates a small portion of the artifact, and the user could post-edit what the tool generated. These were the most frequently appearing type of designs for AI-driven CSTs that use generative algorithms. Moreover, compared to other *process roles*, the percentage of *fabrication* (13.6%) was highest in *execution assistance*. ThreadPlotter [55] is one example of enabling *execution assistance* with a *fabricator*, which allows users to create punch needle embroidery with X-Y plotter.

Producing was mainly powered by generative algorithms from *learning* (57.1%) and *non-learning algorithms* (35.7%). However, with generative algorithms, more tools have been devised with *execution assistance*. Different from generative *execution assistance* CSTs, *producing* tools allowed minimum post edits from the user. Instead, there were cases where it allowed continuous interactions through generation, like improvising music together [93].

Understanding used *learning algorithms* (42.1%) in the highest percentage, followed by *software UI* (36.8%), *non-learning algorithms* (26.3%), and *sensors* (26.3%). For *understanding* tools that analyze, *algorithms* were often used for the analysis [33, 76, 77, 79, 86, 87, 123], *UI* for the effective presentation of analysis [17, 33, 77, 81, 87, 102], and *sensors* to capture the artifacts [64, 87].

Critique frequently used *non-learning algorithms* (50.0%) followed by *learning ones* (40.0%). *Algorithms* generated *critiques* by analyzing artifacts [31, 32, 80, 108, 112, 119, 132, 133, 137].

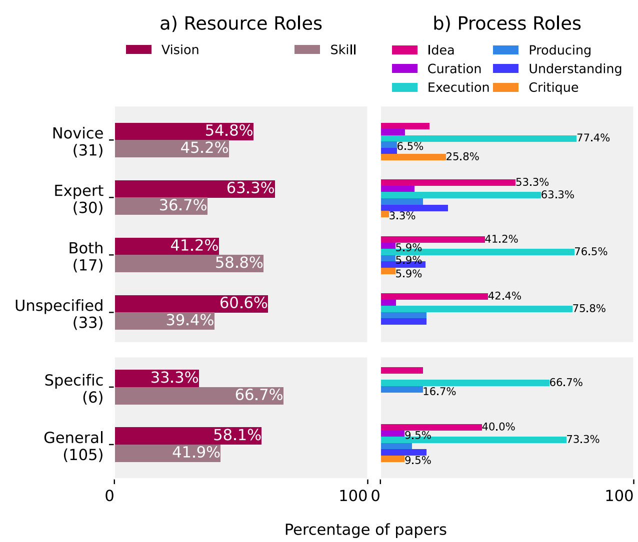

Figure 4: Percentage of roles according to user groups (items on the y-axis). On the y-axis, the number of CSTs with the code is in the parenthesis. In b), "Idea" stands for idea generation and "Execution" stands for execution assistance.

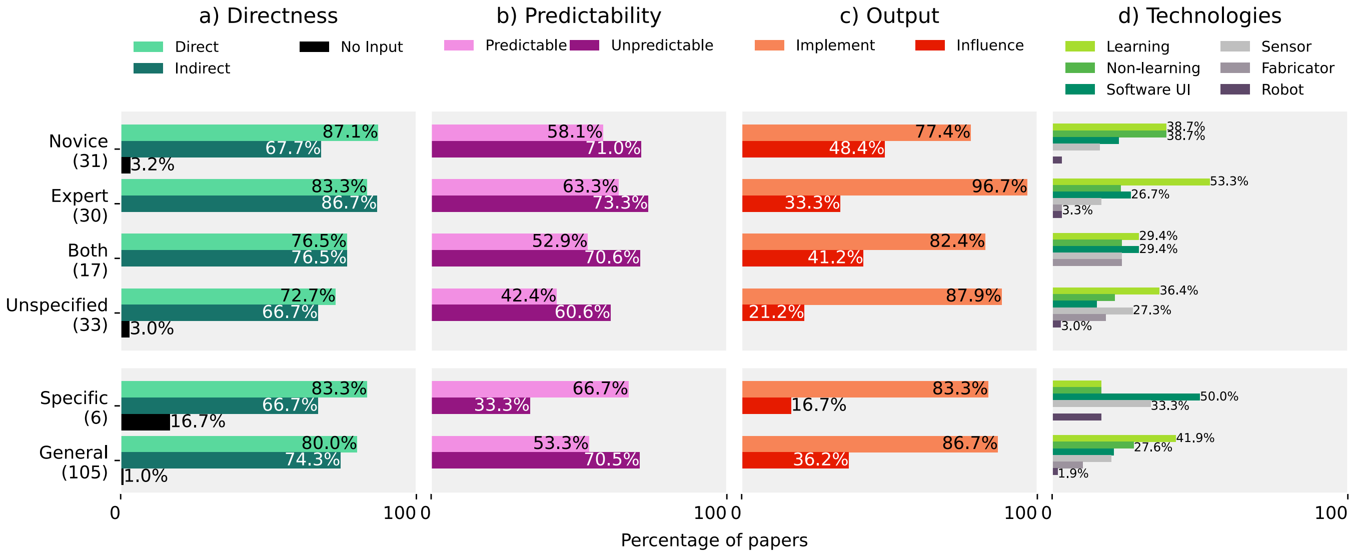

Figure 5: How each user group (on the y-axis) is supported with different interaction approaches (directness, predictability, and output) and technologies. On the y-axis, numbers in parenthesis indicate the number of CSTs with the code.

5.3.2 User × Role, Interaction, and Technologies.

Users and Roles. For *resource roles* (Figure 4a), tools that support *both* levels of expertise and those for *specific population* had more tools that support with *skills* than with *vision*. Other user groups were supported more by tools for *vision*. With *process roles* (Figure 4b), *novices* were supported with *critique* in a higher percentage (25.8%) than other groups. With this role, novices frequently got critiques on how they can accomplish more high-quality creation with extended expertise [28, 31, 32, 119, 132]. However, *novices* were less supported with *understanding* (6.5%), compared to other user groups. We also found that *experts* are more supported with the role of *idea generation* (53.3%) compared to other user groups. This type of tool often allowed expert users to explore more possible options by generating one or more of them [47, 67, 68, 83, 88, 100, 104, 108, 116, 125]. For *specific population*, we found that they were not supported with *curation*, *understanding*, and *critique*.

Users and Interaction Approaches. For *users* and *interaction approaches*, we found patterns with *novices* and *specific populations*. For the *directness* (Figure 5a), user groups other than *novices* and *specific populations* were similarly supported by *directness* and *indirectness* without large gaps (≤ 10% difference). On the other hand, *novices* and *specific populations* were more supported with *direct* inputs. With *specific populations*, we found that they had one case of receiving no input. It was a robot that prompts inspiring messages to children when creating titles for a drawing [3]. Even though there was one tool, due to a low number of tools for *specific populations* (n=6), it took 16.7%. For *predictability* (Figure 5b), the *specific populations* were the only group with more *predictable* tools, while other user groups were more with *unpredictable* tools. Those *predictable* tools for *specific populations* were designed to overcome their skill limits from not yet fully grown motor and cognitive skills (for children) or disability [19, 56, 84, 97, 142]. With *output* (Figure 5c), all user groups are more tend to be supported by *implementing* tools than *influencing* tools. Among them, *novices* were most supported with *influencing* compared to other user groups (48.4%), which is partly due to the high occurrence of *critique* tools in this population (which contribute through influencing).

Users and Technologies. On analyzing *users* and *technologies*, we found that *novices* got more support with *non-learning algorithms* than other groups. This would be relevant to high support of *critique* roles in *novices*, as *critique* tools frequently use *non-learning algorithms*. Moreover, *novices* were not supported with *fabricators* or *robots*. Compared to other user groups, *experts* were more supported with *learning algorithms* (53.3%), which mainly powered *idea generation* tools. On the other hand, tools for *specific populations* showed the most distinct distribution of technologies. They used *UI* (50.0%), *sensors* (33.3%), and *robots* (16.7%) in higher percentages compared to other users.

6 DISCUSSION

Our analysis reveals interesting patterns in the construction of art-making CSTs from the HCI community. We hypothesize on possible reasons certain CST categories are more or less common. Among our findings, we see that AI-CSTs represent a unique–and likely expanding–category.

6.1 Trends in CST Research for Art-making

The HCI community has built certain types of tools more than others. CSTs with *execution assistance* and *implementing* were those which were dominant in *process roles* and *output approaches*, respectively. We consider these as an extension of conventional art-making tools (e.g., paintbrushes). As these conventional tools are more familiar, CST researchers might focus on these design. It may simply be reasonable to imagine the translation of physical/conventional tools to digital versions. Another interesting observation in our data is that more tools support *vision* than *skills*. We also observed that *idea generation* was the second most frequent role in the *process* codes. One possible explanation is that vision CSTs are more broadly applicable. Skill-focused CSTs may be more 'niche' and less desirable to implement.

Within *technologies*, *learning algorithms* were the most dominant. CST creators frequently use them to suggest novel ideas, artifacts, and information. Given current trends in AI, it is likely that the HCI community will use *learning algorithms* more in the future. These technologies are rapidly advancing with more capabilities and more reliable output. For instance, recent ML algorithms can generate texts and images based on the user's natural language description [14, 109]. However, there is a question of whether these technologies would really introduce novel, creative, or artistic things or simply sample from the training data [13]. If they only sample from training data, the long-term effect of using these algorithms in CSTs would be detrimental. They might reinforce existing ideas but not lead artists towards under-explored, new ideas in art-making. We believe that care is needed in applying these algorithms in CST contexts. New ways of evaluating the novelty of CST output may help answer some of these questions [103].

Many CST papers did *not specify users*. Instead, they focused on describing opportunities introduced by new technologies and interactions. As a research community, we argue that CST researchers should be more deliberate in specifying the intended use. This will become increasingly important with novel AI technologies. Such tools are known to have significant biases. More specific acknowledgment of how a CST will be used and by whom may be vital in identifying and addressing unintended consequences.

6.2 How Roles Are Supported with Interaction Approaches and Technologies

With *resource roles*, *vision*-offering tools were more *unpredictable*, while *skill*-offering tools were more *predictable* (see Figures 2 and 3). This is expected, as contributing to artistic vision is more related to introducing inspiring ideas to users, which they could not have brought up themselves. At the same time, *technology* use was also different according to *resource roles*. *Vision*-offering tools use *algorithms* frequently, as they can find or generate novel ideas and artifacts. On the other hand, *skill*-offering tools more used *software UI*, *sensor*, and *fabricator*, which give better interfacing or means of construction. With *process roles*, we found that all roles except *execution assistance* tend to have more *unpredictable* tools than *predictable* ones. *Execution assistance* is equally supported with *predictable* and *unpredictable* approaches. Also, all *process roles* have *learning algorithms* within the top two most used *technologies*. However, they diverged along *directness* and *output*. *Critique* was the most noticeable among them, as *critique* CSTs are all designed to be *unpredictable*, *influencing*, and receiving *direct* inputs.

These findings reveal patterns of how CSTs can be designed for different *roles* with *interaction approaches* and *technologies*. In some cases, combining *roles*, *interactions*, and *technologies* would be inherently restricted. For example, *producing* less frequently co-occurred with *execution assistance* than with other process roles. Even when they co-occurred, they were actually enabled by separate functions. Moreover, all *producing* tools were *implementing*. This pattern is due to the nature of *producing*: *producing* tools do the majority of implementations on behalf of the user.

However, other patterns might have arisen as researchers focused more on one way of building CSTs. For example, the *skill*-supporting tools were more *predictable*. However, there were exceptions, like tools extending the user's *skill* with *unpredictable* simulation [140]. This exception is the evidence that researchers have employed a narrow focus when designing CSTs, while other approaches are possible. Another example is the use of *robots*. In the HCI community, the robot was rarely used to build CSTs (n=3). Moreover, while *robots* can enable tools to create physical artifacts, there was only one case a robot was used for *implementation*. This is a limited focus of our community—outside of the HCI/computing community, artists have been devising *robots* that *implement* artifacts by themselves or through collaboration with humans [2, 121]. The HCI researchers would be able to do a similar exploration while pushing beyond what has been done by other communities.

Some seemingly impossible patterns would be more feasible with technological advances. *Understanding* and *critique* tools using *indirect* input is one example. Designers of these tools have assumed that they must have artifacts to be analyzed. However, technological advances are introducing more expressive ways of making *indirect* inputs [14, 109], and they would increase the needs and feasibility for *indirect* inputs to be analyzed. For example, advanced generation models can produce content with natural language prompts [14, 109], which should be well-designed to get the intended results. Hence, CSTs would be able to analyze or give feedback on the user's prompts, so that they can be improved to draw desirable results.

6.3 Patterns in Supporting Users

Regarding how *users* get support, we found a few interesting patterns. First, *novices* were more supported with *critique* compared to other user groups. While *critique* is also valuable to *experts* (e.g., artists get feedback from colleagues), the CSTs we surveyed rarely supported *experts*. This may be due to the technical feasibility of giving *critique* that meets the expectation of *experts*. When *experts* receive *critique*, they would expect not only skill-wise *critiques* but also more subjective feedback. For example, one possible expert CST critique role might be to learn and predict how people interpret an art pieces. Such *critiques* would be more difficult for algorithms and machines to generate, as they tend to be subjective. On the other hand, *novices* would significantly benefit from *critiques* that can improve their expertise. These types of *critique* tools would be easier to be designed and programmed as they require less subjective decisions. Hence, one possible future direction would be expanding the user population of *critique* tools to *experts*. At the same time, *novices* were shown to be less supported with *idea generation* and *understanding*. This might be because CST designers assumed that novices might not try novel ideas or build complex artifacts. We would also be able to expand the range of tools for *novices*, supporting them with *idea generation* and *understanding*.

Another pattern we found was in *specific populations* CSTs. The few examples were *skill*-offering, *predictable* tools. This might be because researchers designed tools that can fill in the gap of the skill from disability or not yet fully developed motor or cognitive skills (for children). However, this pattern also might be due to the low number of tools for this population (n=6). Hence, we argue that this population requires more attention from CST researchers. It would be beneficial for these populations to have a broader diversity of tools. For instance, devising tools that can effectively help ideation for people with sensory disability (e.g., mood boards for the visually impaired) can be a valuable but under-explored topic in CST research. To accelerate research in this thread, we would be able to learn from accessibility or children-related research in HCI.

6.4 Present and Future of Generative AI-CSTs

Recent AI/ML algorithms generate content, introducing new design opportunities for CSTs. With those algorithms, CSTs can be more autonomous, making creative decisions on behalf of the users. When we looked into these types of tools in our reviewed papers, we could find these generating tools distribute among two *process roles*: *producing* (13 CSTs) and *execution assistance* (26 CSTs), with more CSTs in the latter. From this result, we saw that many CST researchers decided not to delegate all controls to these AI-CSTs. *Execution assistance* AI-CSTs are designed to allow a lot of user controls, from the specification on what to generate to post-editing. These design decisions would have been to defend the user's agency and sense of ownership while leveraging generative capabilities.

With producing tools, we found that some CSTs' interactions were more similar to those of humans. For example, some CSTs played a character in interactive narratives [57] or a participant chatbot in a radio comedy show [105], which was designed to mimic the interaction between humans (even though they are not perfect). Another example was a machine drum improviser that works with human performers [93]. More technical advances would render these types of human-like CSTs move viable. Hence, preparing for the future, it would be helpful to learn how interactions should be designed for these AI-CSTs.

6.5 Comparison to Previous Work

For some parts of our taxonomy (e.g., process roles and expertise), we build on previous work. However, with new papers, we modified these by merging, removing, and adding certain categories. For process roles, our taxonomy expands Frich et al. [38]'s taxonomy on the creative process (pre-ideation, idea generation, evaluation/critique, implementation, iteration, meta/project). Here, we excluded meta/project, a taxonomy on the management, as we focused on a single user's interaction with CSTs during the artifact creation itself. Iteration is excluded, as it largely included support for repeating other processes. For pre-ideation and idea generation, we considered them to broadly contribute to ideation and combined them within the *aiding ideation* category. Pre-ideation would be close to *curation* in our taxonomy. For the taxonomy of implementation, we tried to identify more specific implementation approaches, which can potentially have different interaction dynamics.

For our taxonomy of users based on expertise, we also built upon Frich et al. [38]. In addition to the novice/expert split offered in the earlier classification, we added the code *both*. In Frich et al., the code closest to *both* is "casual" but this did not feel appropriate to CSTs that could support both types of users. Frich et al. [38]'s *casual* more implies tools that are "easy to be used by broad users". However, we used *both*, to include cases that support both experts and novices by having *a low threshold and a high ceiling*.

6.6 Limitations and Future Work

We focused on surveying art-making CSTs from HCI and computing research. Our motivation was to understand how researchers in technological, human-centered fields have been designing CSTs. However, CSTs can be, and likely are, designed and developed outside of the community. Independent artists often devise unique CSTs to realize their artistic vision with new computing technologies. For such a community, the design patterns in roles, interaction approaches, and technologies would be significantly different from what we observed. Hence, studying other communities to investigate the commonalities and differences can be future work.

Our sampling approach introduces another limitation. First, we focused on tools that support the making of aesthetic artifacts with a single user. To understand the broader design implications of CSTs, considering other CSTs would be valuable future work. Moreover, as we did not filter recent papers with citation or download counts, our papers are more biased to recent work (the number of the published paper is increasing). One relevant future work can be adopting a sampling approach that balances publication across time and doing temporal analysis.

We coded each CST with the dimension of predictability, but only considering intended behaviors. The spectrum of predictability can be wider, including unpredictable behaviors like unexpected errors. We only considered intended behaviors, because many CST publications do not have full information on errors. Future work can consider this aspect of "acceptability to the user". Furthermore, a single tool makes scoped outputs, not all imaginable ones. Hence, we would also be able to consider "possibility by the tool", whether the CST can make a certain output or not. With these, researchers would be able to analyze CSTs more comprehensively with the user's expectation. They would distinguish various tool behaviors, including intended results, known errors, unknown errors, surprising but favorable results, desired but impossible behaviors, etc.

7 CONCLUSION

In this work, we studied how researchers in the HCI community construct art-making CSTs through the combined lens of roles, users, interactions, and technologies. Our work adds a more design-centered, consolidating perspective to the understanding of art-making CSTs. We taxonomized and coded 111 publications on art-making CSTs. Using our codes, we identified design patterns and design space of art-making CSTs. We also describe implications for future CST design. Furthermore, from the identified design space, we discovered under-explored types of CSTs and emerging CSTs. These analyses hint at future research challenges and opportunities in CST research. AI-CSTs in this category are expected to become more prevalent but are complicated with technological advances.

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REFERENCES

[1] Rinat Abdrashitov, Fanny Chevalier, and Karan Singh. 2020. Interactive Exploration and Refinement of Facial Expression Using Manifold Learning. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 778–790. https://doi.org/10.1145/3379337.3415877

[2] Ai-Da. 2021. Ai-Da Robot. https://www.ai-darobot.com/ai-da-home Accessed: January, 2021.

[3] Safinah Ali, Tyler Moroso, and Cynthia Breazeal. 2019. Can Children Learn Creativity from a Social Robot?. In *Proceedings of the 2019 on Creativity and Cognition* (San Diego, CA, USA) *(C&C '19)*. Association for Computing Machinery, New York, NY, USA, 359–368. https://doi.org/10.1145/3325480.3325499

[4] Teresa M Amabile. 1983. The social psychology of creativity: A componential conceptualization. *Journal of personality and social psychology* 45, 2 (1983), 357.

[5] Teresa M Amabile. 2012. Componential theory of creativity. *Harvard Business School Working Paper* 12, 096 (2012).

[6] Christopher Andrews. 2019. An Embodied Approach to AI Art Collaboration. In *Proceedings of the 2019 on Creativity and Cognition* (San Diego, CA, USA) *(C&C '19)*. Association for Computing Machinery, New York, NY, USA, 156–162. https://doi.org/10.1145/3325480.3325506

[7] Ilhan Aslan, Katharina Weitz, Ruben Schlagowski, Simon Flutura, Susana Garcia Valesco, Marius Pfeil, and Elisabeth André. 2019. Creativity Support and Multimodal Pen-Based Interaction. In *2019 International Conference on Multimodal Interaction* (Suzhou, China) *(ICMI '19)*. Association for Computing Machinery, New York, NY, USA, 135–144. https://doi.org/10.1145/3340555.3353738

[8] Thomas Ball, Shannon Kao, Richard Knoll, and Daryl Zuniga. 2020. TileCode: Creation of Video Games on Gaming Handhelds. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 1182–1193. https://doi.org/10.1145/3379337.3415839

[9] H.S. Becker. 1984. *Art Worlds*. University of California Press, USA. https://books.google.com/books?id=jXDyRK2EL5YC

[10] Luca Benedetti, Holger Winnemöller, Massimiliano Corsini, and Roberto Scopigno. 2014. Painting with Bob: Assisted Creativity for Novices. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology* (Honolulu, Hawaii, USA) *(UIST '14)*. Association for Computing Machinery, New York, NY, USA, 419–428. https://doi.org/10.1145/2642918.2647415

[11] Walter Benjamin. 1935. The Work of Art in the Age of Mechanical Reproduction, 1936.

[12] Guillermo Bernal, Lily Zhou, Erica Yuen, and Pattie Maes. 2019. Paper Dreams: Real-Time Human and Machine Collaboration for Visual Story Development. In *XXII Generative Art Conference*. Domus Argenia, Rome, Italy.

[13] Sebastian Berns and Simon Colton. 2020. Bridging Generative Deep Learning and Computational Creativity. In *Proceedings of the Eleventh International Conference on Computational Creativity, ICCC 2020, Coimbra, Portugal, September 7-11, 2020*, F. Amílcar Cardoso, Penousal Machado, Tony Veale, and João Miguel Cunha (Eds.). Association for Computational Creativity (ACC), New York, USA, 406–409. http://computationalcreativity.net/iccc20/papers/164-iccc20.pdf

[14] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. arXiv:2005.14165 [cs.CL]

[15] J. Canny. 1986. A Computational Approach to Edge Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence* PAMI-8, 6 (1986), 679–698.

[16] Erin A. Carroll, Celine Latulipe, Richard Fung, and Michael Terry. 2009. Creativity Factor Evaluation: Towards a Standardized Survey Metric for Creativity Support. In *Proceedings of the Seventh ACM Conference on Creativity and Cognition* (Berkeley, California, USA) *(C&C '09)*. Association for Computing Machinery, New York, NY, USA, 127–136. https://doi.org/10.1145/1640233.1640255

[17] Elin Carstensdottir, Nathan Partlan, Steven Sutherland, Tyler Duke, Erika Ferris, Robin M. Richter, Maria Valladares, and Magy Seif El-Nasr. 2020. Progression Maps: Conceptualizing Narrative Structure for Interaction Design Support. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376527

[18] Joel Chan, Steven Dang, and Steven P. Dow. 2016. Improving Crowd Innovation with Expert Facilitation. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing, CSCW 2016, San Francisco, CA, USA, February 27 - March 2, 2016*, Darren Gergle, Meredith Ringel Morris, Pernille Bjørn, and Joseph A. Konstan (Eds.). ACM, New York, USA, 1221–1233. https://doi.org/10.1145/2818048.2820023

[19] Julia Chatain, Olivier Bitter, Violaine Fayolle, Robert W. Sumner, and Stéphane Magnenat. 2019. A Creative Game Design and Programming App. In *Motion, Interaction and Games* (Newcastle upon Tyne, United Kingdom) *(MIG '19)*. Association for Computing Machinery, New York, NY, USA, Article 6, 6 pages. https://doi.org/10.1145/3359566.3360056

[20] Siddhartha Chaudhuri and Vladlen Koltun. 2010. Data-Driven Suggestions for Creativity Support in 3D Modeling. *ACM Trans. Graph.* 29, 6, Article 183 (Dec. 2010), 10 pages. https://doi.org/10.1145/1882261.1866205

[21] Erin Cherry and Celine Latulipe. 2014. Quantifying the Creativity Support of Digital Tools through the Creativity Support Index. *ACM Trans. Comput.-Hum. Interact.* 21, 4, Article 21 (June 2014), 25 pages. https://doi.org/10.1145/2617588

[22] Saemi Choi, Shun Matsumura, and Kiyoharu Aizawa. 2019. Assist Users' Interactions in Font Search with Unexpected but Useful Concepts Generated by Multimodal Learning. In *Proceedings of the 2019 on International Conference on Multimedia Retrieval* (Ottawa ON, Canada) *(ICMR '19)*. Association for Computing Machinery, New York, NY, USA, 235–243. https://doi.org/10.1145/3323873.3325037

[23] Marianela Ciolfi Felice, Sarah Fdili Alaoui, and Wendy E. Mackay. 2018. Knotation: Exploring and Documenting Choreographic Processes. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3174022

[24] Elizabeth Clark, Anne Spencer Ross, Chenhao Tan, Yangfeng Ji, and Noah A. Smith. 2018. Creative Writing with a Machine in the Loop: Case Studies on Slogans and Stories. In *23rd International Conference on Intelligent User Interfaces* (Tokyo, Japan) *(IUI '18)*. Association for Computing Machinery, New York, NY, USA, 329–340. https://doi.org/10.1145/3172944.3172983

[25] Stephen Davies. 1991. *Definitions of art.* Cornell University Press, USA.

[26] Nicholas Davis, Chih-PIn Hsiao, Kunwar Yashraj Singh, Lisa Li, Sanat Moningi, and Brian Magerko. 2015. Drawing Apprentice: An Enactive Co-Creative Agent for Artistic Collaboration. In *Proceedings of the 2015 ACM SIGCHI Conference on Creativity and Cognition* (Glasgow, United Kingdom) *(C&C '15)*. Association for Computing Machinery, New York, NY, USA, 185–186. https://doi.org/10.1145/2757226.2764555

[27] Nicholas Davis, Chih-PIn Hsiao, Kunwar Yashraj Singh, Lisa Li, and Brian Magerko. 2016. Empirically Studying Participatory Sense-Making in Abstract Drawing with a Co-Creative Cognitive Agent. In *Proceedings of the 21st International Conference on Intelligent User Interfaces* (Sonoma, California, USA) *(IUI '16)*. Association for Computing Machinery, New York, NY, USA, 196–207. https://doi.org/10.1145/2856767.2856795

[28] Nicholas Davis, Alexander Zook, Brian O'Neill, Brandon Headrick, Mark Riedl, Ashton Grosz, and Michael Nitsche. 2013. Creativity Support for Novice Digital Filmmaking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Paris, France) *(CHI '13)*. Association for Computing Machinery, New York, NY, USA, 651–660. https://doi.org/10.1145/2470654.2470747

[29] Florent Di Bartolo. 2019. Performative Meshes: Musical Expression in Visuals. In *Proceedings of the 9th International Conference on Digital and Interactive Arts* (Braga, Portugal) *(ARTECH 2019)*. Association for Computing Machinery, New York, NY, USA, Article 26, 7 pages. https://doi.org/10.1145/3359852.3359876

[30] Denis Dutton. 2003. Authenticity in Art. In *The Oxford Handbook of Aesthetics*, Jerrold Levinson (Ed.). Oxford University Press, UK, 258–274.

[31] Jane L. E, Ohad Fried, and Maneesh Agrawala. 2019. Optimizing Portrait Lighting at Capture-Time Using a 360 Camera as a Light Probe. In *Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology* (New Orleans, LA, USA) *(UIST '19)*. Association for Computing Machinery, New York, NY, USA, 221–232. https://doi.org/10.1145/3332165.3347893

[32] Jane L. E, Ohad Fried, Jingwan Lu, Jianming Zhang, Radomír Mech, Jose Echevarria, Pat Hanrahan, and James A. Landay. 2020. Adaptive Photographic Composition Guidance. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376635

[33] Camilo Fosco, Vincent Casser, Amish Kumar Bedi, Peter O'Donovan, Aaron Hertzmann, and Zoya Bylinskii. 2020. Predicting Visual Importance Across Graphic Design Types. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 249–260. https://doi.org/10.1145/3379337.3415825

[34] C. Ailie Fraser, Joy O. Kim, Hijung Valentina Shin, Joel Brandt, and Mira Dontcheva. 2020. Temporal Segmentation of Creative Live Streams. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376437

[35] C. Ailie Fraser, Julia M. Markel, N. James Basa, Mira Dontcheva, and Scott Klemmer. 2020. ReMap: Lowering the Barrier to Help-Seeking with Multimodal Search. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 979–986. https://doi.org/10.1145/3379337.3415592

[36] C. Ailie Fraser, Tricia J. Ngoon, Mira Dontcheva, and Scott Klemmer. 2019. RePlay: Contextually Presenting Learning Videos Across Software Applications. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*

(Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300527

[37] Jonas Frich, Michael Mose Biskjaer, Lindsay MacDonald Vermeulen, Christian Remy, and Peter Dalsgaard. 2019. Strategies in Creative Professionals' Use of Digital Tools Across Domains. In *Proceedings of the 2019 on Creativity and Cognition* (San Diego, CA, USA) *(C&C '19)*. Association for Computing Machinery, New York, NY, USA, 210–221. https://doi.org/10.1145/3325480.3325494

[38] Jonas Frich, Lindsay MacDonald Vermeulen, Christian Remy, Michael Mose Biskjaer, and Peter Dalsgaard. 2019. Mapping the Landscape of Creativity Support Tools in HCI. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–18. https://doi.org/10.1145/3290605.3300619

[39] Jonas Frich, Michael Mose Biskjaer, and Peter Dalsgaard. 2018. Twenty Years of Creativity Research in Human-Computer Interaction: Current State and Future Directions. In *Proceedings of the 2018 Designing Interactive Systems Conference* (Hong Kong, China) *(DIS '18)*. Association for Computing Machinery, New York, NY, USA, 1235–1257. https://doi.org/10.1145/3196709.3196732

[40] Emma Frid, Celso Gomes, and Zeyu Jin. 2020. Music Creation by Example. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376514

[41] Kaori Fujinami, Mami Kosaka, and Bipin Indurkhya. 2018. Painting an Apple with an Apple: A Tangible Tabletop Interface for Painting with Physical Objects. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 4, Article 162 (Dec. 2018), 22 pages. https://doi.org/10.1145/3287040

[42] Quentin Galvane, Marc Christie, Chrsitophe Lino, and Rémi Ronfard. 2015. Camera-on-Rails: Automated Computation of Constrained Camera Paths. In *Proceedings of the 8th ACM SIGGRAPH Conference on Motion in Games* (Paris, France) *(MIG '15)*. Association for Computing Machinery, New York, NY, USA, 151–157. https://doi.org/10.1145/2822013.2822025

[43] Jérémie Garcia, Theophanis Tsandilas, Carlos Agon, and Wendy E. Mackay. 2014. Structured Observation with Polyphony: A Multifaceted Tool for Studying Music Composition. In *Proceedings of the 2014 Conference on Designing Interactive Systems* (Vancouver, BC, Canada) *(DIS '14)*. Association for Computing Machinery, New York, NY, USA, 199–208. https://doi.org/10.1145/2598510.2598512

[44] Monica J. Garfield. 2008. *Creativity Support Systems*. Springer Berlin Heidelberg, Berlin, Heidelberg, 745–758. https://doi.org/10.1007/978-3-540-48716-6_34

[45] L. A. Gatys, A. S. Ecker, and M. Bethge. 2016. Image Style Transfer Using Convolutional Neural Networks. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, USA, 2414–2423. https://doi.org/10.1109/CVPR.2016.265

[46] Katy Ilonka Gero and Lydia B. Chilton. 2019. How a Stylistic, Machine-Generated Thesaurus Impacts a Writer's Process. In *Proceedings of the 2019 on Creativity and Cognition* (San Diego, CA, USA) *(C&C '19)*. Association for Computing Machinery, New York, NY, USA, 597–603. https://doi.org/10.1145/3325480.3326573

[47] Katy Ilonka Gero and Lydia B. Chilton. 2019. Metaphoria: An Algorithmic Companion for Metaphor Creation. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300526

[48] Karni Gilon, Joel Chan, Felicia Y. Ng, Hila Lifshitz-Assaf, Aniket Kittur, and Dafna Shahaf. 2018. Analogy Mining for Specific Design Needs. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, CHI 2018, Montreal, QC, Canada, April 21-26, 2018*, Regan L. Mandryk, Mark Hancock, Mark Perry, and Anna L. Cox (Eds.). ACM, New York, NY, USA, 121. https://doi.org/10.1145/3173574.3173695

[49] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Nets. In *Advances in Neural Information Processing Systems 27*, Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger (Eds.). Curran Associates, Inc., USA, 2672–2680. http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf

[50] Uttam Grandhi and Ina Yosun Chang. 2019. PlayGAMI: Augmented Reality Origami Creativity Platform. In *ACM SIGGRAPH 2019 Appy Hour* (Los Angeles, California) *(SIGGRAPH '19)*. Association for Computing Machinery, New York, NY, USA, Article 4, 2 pages. https://doi.org/10.1145/3305365.3329729

[51] Garth Griffin and Robert Jacob. 2013. Priming Creativity through Improvisation on an Adaptive Musical Instrument. In *Proceedings of the 9th ACM Conference on Creativity & Cognition* (Sydney, Australia) *(C&C '13)*. Association for Computing Machinery, New York, NY, USA, 146–155. https://doi.org/10.1145/2466627.2466630

[52] Matthew Guzdial, Nicholas Liao, Jonathan Chen, Shao-Yu Chen, Shukan Shah, Vishwa Shah, Joshua Reno, Gillian Smith, and Mark O. Riedl. 2019. Friend, Collaborator, Student, Manager: How Design of an AI-Driven Game Level Editor Affects Creators. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300854

[53] Megan K. Halpern, Jakob Tholander, Max Evjen, Stuart Davis, Andrew Ehrlich, Kyle Schustak, Eric P.S. Baumer, and Geri Gay. 2011. MoBoogie: Creative Expression through Whole Body Musical Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. Association for Computing Machinery, New York, NY, USA, 557–560. https://doi.org/10.1145/1978942.1979020

[54] Yuma Hamasaki, Seiichi Serikawa, and Yuhki Kitazono. 2019. Storage and Playback Device for Creative Dance with Kinect. In *Proceedings of the 7th ACIS International Conference on Applied Computing and Information Technology* (Honolulu, HI, USA) *(ACIT 2019)*. Association for Computing Machinery, New York, NY, USA, Article 28, 6 pages. https://doi.org/10.1145/3325291.3325383

[55] Shiqing He and Eytan Adar. 2020. Plotting with Thread: Fabricating Delicate Punch Needle Embroidery with X-Y Plotters. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference* (Eindhoven, Netherlands) *(DIS '20)*. Association for Computing Machinery, New York, NY, USA, 1047–1057. https://doi.org/10.1145/3357236.3395540

[56] Sean Hickey. 2019. Bricoleur: A Tool for Tinkering with Programmable Video and Audio. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI EA '19)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3290607.3312919

[57] Rania Hodhod and Brian Magerko. 2016. Closing the Cognitive Gap between Humans and Interactive Narrative Agents Using Shared Mental Models. In *Proceedings of the 21st International Conference on Intelligent User Interfaces* (Sonoma, California, USA) *(IUI '16)*. Association for Computing Machinery, New York, NY, USA, 135–146. https://doi.org/10.1145/2856767.2856774

[58] Megan Hofmann, Jennifer Mankoff, and Scott E. Hudson. 2020. KnitGIST: A Programming Synthesis Toolkit for Generating Functional Machine-Knitting Textures. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 1234–1247. https://doi.org/10.1145/3379337.3415590

[59] Ting-Yao Hsu, Yen-Chia Hsu, and Ting-Hao (Kenneth) Huang. 2019. On How Users Edit Computer-Generated Visual Stories. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI EA '19)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3290607.3312965

[60] Stacy Hsueh, Sarah Fdili Alaoui, and Wendy E. Mackay. 2019. Understanding Kinaesthetic Creativity in Dance. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300741

[61] Cheng-Zhi Anna Huang, David Duvenaud, and Krzysztof Z. Gajos. 2016. ChordRipple: Recommending Chords to Help Novice Composers Go Beyond the Ordinary. In *Proceedings of the 21st International Conference on Intelligent User Interfaces* (Sonoma, California, USA) *(IUI '16)*. Association for Computing Machinery, New York, NY, USA, 241–250. https://doi.org/10.1145/2856767.2856792

[62] Junko Ichino and Hayato Nao. 2018. Playing the Body: Making Music through Various Body Movements. In *Proceedings of the Audio Mostly 2018 on Sound in Immersion and Emotion* (Wrexham, United Kingdom) *(AM'18)*. Association for Computing Machinery, New York, NY, USA, Article 15, 8 pages. https://doi.org/10.1145/3243274.3243287

[63] Jennifer Jacobs, Joel Brandt, Radomír Mech, and Mitchel Resnick. 2018. Extending Manual Drawing Practices with Artist-Centric Programming Tools. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3173574.3174164

[64] Yunwoo Jeong, Han-Jong Kim, Gyeongwon Yun, and Tek-Jin Nam. 2020. WIKA: A Projected Augmented Reality Workbench for Interactive Kinetic Art. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 999–1009. https://doi.org/10.1145/3379337.3415880

[65] Peter H. Kahn, Takayuki Kanda, Hiroshi Ishiguro, Brian T. Gill, Solace Shen, Jolina H. Ruckert, and Heather E. Gary. 2016. Human Creativity Can Be Facilitated Through Interacting With a Social Robot. In *The Eleventh ACM/IEEE International Conference on Human Robot Interaction* (Christchurch, New Zealand) *(HRI '16)*. IEEE Press, USA, 173–180.

[66] Hiroki Kaimoto, Junichi Yamaoka, Satoshi Nakamaru, Yoshihiro Kawahara, and Yasuaki Kakehi. 2020. ExpandFab: Fabricating Objects Expanding and Changing Shape with Heat. In *Proceedings of the Fourteenth International Conference on Tangible, Embedded, and Embodied Interaction* (Sydney NSW, Australia) *(TEI '20)*. Association for Computing Machinery, New York, NY, USA, 153–164. https://doi.org/10.1145/3374920.3374949

[67] Pegah Karimi, Nicholas Davis, Mary Lou Maher, Kazjon Grace, and Lina Lee. 2019. Relating Cognitive Models of Design Creativity to the Similarity of Sketches Generated by an AI Partner. In *Proceedings of the 2019 on Creativity and Cognition* (San Diego, CA, USA) *(C&C '19)*. Association for Computing

Machinery, New York, NY, USA, 259–270. https://doi.org/10.1145/3325480.3325488

[68] Pegah Karimi, Jeba Rezwana, Safat Siddiqui, Mary Lou Maher, and Nasrin Dehbozorgi. 2020. Creative Sketching Partner: An Analysis of Human-AI Co-Creativity. In *Proceedings of the 25th International Conference on Intelligent User Interfaces* (Cagliari, Italy) *(IUI '20)*. Association for Computing Machinery, New York, NY, USA, 221–230. https://doi.org/10.1145/3377325.3377522

[69] Joseph Kasof, Chuansheng Chen, Amy Himsel, and Ellen Greenberger. 2007. Values and Creativity. *Creativity Research Journal* 19, 2-3 (2007), 105–122. https://doi.org/10.1080/10400410701397164 arXiv:https://doi.org/10.1080/10400410701397164

[70] Jun Kato, Tomoyasu Nakano, and Masataka Goto. 2015. TextAlive: Integrated Design Environment for Kinetic Typography. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 3403–3412. https://doi.org/10.1145/2702123.2702140

[71] Natsumi Kato, Hiroyuki Osone, Daitetsu Sato, Naoya Muramatsu, and Yoichi Ochiai. 2018. DeepWear: A Case Study of Collaborative Design between Human and Artificial Intelligence. In *Proceedings of the Twelfth International Conference on Tangible, Embedded, and Embodied Interaction* (Stockholm, Sweden) *(TEI '18)*. Association for Computing Machinery, New York, NY, USA, 529–536. https://doi.org/10.1145/3173225.3173302

[72] Rubaiat Habib Kazi, Kien Chuan Chua, Shengdong Zhao, Richard Davis, and Kok-Lim Low. 2011. SandCanvas: A Multi-Touch Art Medium Inspired by Sand Animation. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. Association for Computing Machinery, New York, NY, USA, 1283–1292. https://doi.org/10.1145/1978942.1979133

[73] Joy Kim, Mira Dontcheva, Wilmot Li, Michael S. Bernstein, and Daniela Steinsapir. 2015. Motif: Supporting Novice Creativity through Expert Patterns. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 1211–1220. https://doi.org/10.1145/2702123.2702507

[74] Yea-Seul Kim, Mira Dontcheva, Eytan Adar, and Jessica Hullman. 2019. Vocal Shortcuts for Creative Experts. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3290605.3300562

[75] Janin Koch, Andrés Lucero, Lena Hegemann, and Antti Oulasvirta. 2019. May AI? Design Ideation with Cooperative Contextual Bandits. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300863

[76] Janin Koch, Nicolas Taffin, Michel Beaudouin-Lafon, Markku Laine, Andrés Lucero, and Wendy E. Mackay. 2020. ImageSense: An Intelligent Collaborative Ideation Tool to Support Diverse Human-Computer Partnerships. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW1, Article 045 (May 2020), 27 pages. https://doi.org/10.1145/3392850

[77] Janin Koch, Nicolas Taffin, Andrés Lucero, and Wendy E. Mackay. 2020. SemanticCollage: Enriching Digital Mood Board Design with Semantic Labels. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference* (Eindhoven, Netherlands) *(DIS '20)*. Association for Computing Machinery, New York, NY, USA, 407–418. https://doi.org/10.1145/3357236.3395494

[78] Max Kreminski, Devi Acharya, Nick Junius, Elisabeth Oliver, Kate Compton, Melanie Dickinson, Cyril Focht, Stacey Mason, Stella Mazeika, and Noah Wardrip-Fruin. 2019. Cozy Mystery Construction Kit: Prototyping toward an AI-Assisted Collaborative Storytelling Mystery Game. In *Proceedings of the 14th International Conference on the Foundations of Digital Games* (San Luis Obispo, California, USA) *(FDG '19)*. Association for Computing Machinery, New York, NY, USA, Article 86, 9 pages. https://doi.org/10.1145/3337722.3341853

[79] Max Kreminski, Melanie Dickinson, Michael Mateas, and Noah Wardrip-Fruin. 2020. Why Are We Like This?: The AI Architecture of a Co-Creative Storytelling Game. In *International Conference on the Foundations of Digital Games* (Bugibba, Malta) *(FDG '20)*. Association for Computing Machinery, New York, NY, USA, Article 13, 4 pages. https://doi.org/10.1145/3402942.3402953

[80] Maria Larsson, Hironori Yoshida, Nobuyuki Umetani, and Takeo Igarashi. 2020. Tsugite: Interactive Design and Fabrication of Wood Joints. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 317–327. https://doi.org/10.1145/3379337.3415899

[81] Jingyi Li, Joel Brandt, Radomír Mech, Maneesh Agrawala, and Jennifer Jacobs. 2020. Supporting Visual Artists in Programming through Direct Inspection and Control of Program Execution. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376765

[82] Jiahao Li, Meilin Cui, Jeeeun Kim, and Xiang 'Anthony' Chen. 2020. Romeo: A Design Tool for Embedding Transformable Parts in 3D Models to Robotically Augment Default Functionalities. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 897–911. https://doi.org/10.1145/3379337.3415826

[83] Yuyu Lin, Jiahao Guo, Yang Chen, Cheng Yao, and Fangtian Ying. 2020. It Is Your Turn: Collaborative Ideation With a Co-Creative Robot through Sketch. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376258

[84] Lasse Lingens, Robert W. Sumner, and Stéphane Magnenat. 2020. Towards Automatic Drawing Animation Using Physics-Based Evolution. In *Proceedings of the 2020 ACM Interaction Design and Children Conference: Extended Abstracts* (London, United Kingdom) *(IDC '20)*. Association for Computing Machinery, New York, NY, USA, 314–319. https://doi.org/10.1145/3397617.3397842

[85] Jingyuan Liu, Hongbo Fu, and Chiew-Lan Tai. 2020. PoseTween: Pose-Driven Tween Animation. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 791–804. https://doi.org/10.1145/3379337.3415822

[86] Lucas Liu, Duri Long, Swar Gujrania, and Brian Magerko. 2019. Learning Movement through Human-Computer Co-Creative Improvisation. In *Proceedings of the 6th International Conference on Movement and Computing* (Tempe, AZ, USA) *(MOCO '19)*. Association for Computing Machinery, New York, NY, USA, Article 5, 8 pages. https://doi.org/10.1145/3347122.3347127

[87] Duri Long, Lucas Liu, Swar Gujrania, Cassandra Naomi, and Brian Magerko. 2020. Visualizing Improvisation in LuminAI, an AI Partner for Co-Creative Dance. In *Proceedings of the 7th International Conference on Movement and Computing* (Jersey City/Virtual, NJ, USA) *(MOCO '20)*. Association for Computing Machinery, New York, NY, USA, Article 39, 2 pages. https://doi.org/10.1145/3401956.3404258

[88] Daniel Lopes, João Correia, and Penousal Machado. 2020. Adea - Evolving Glyphs for Aiding Creativity in Typeface Design. In *Proceedings of the 2020 Genetic and Evolutionary Computation Conference Companion* (Cancún, Mexico) *(GECCO '20)*. Association for Computing Machinery, New York, NY, USA, 97–98. https://doi.org/10.1145/3377929.3389964

[89] Ryan Louie, Andy Coenen, Cheng Zhi Huang, Michael Terry, and Carrie J. Cai. 2020. Novice-AI Music Co-Creation via AI-Steering Tools for Deep Generative Models. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376739

[90] Kurt Luther, Casey Fiesler, and Amy Bruckman. 2013. Redistributing Leadership in Online Creative Collaboration. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work* (San Antonio, Texas, USA) *(CSCW '13)*. Association for Computing Machinery, New York, NY, USA, 1007–1022. https://doi.org/10.1145/2441776.2441891

[91] Sam Ross Lydia B. Chilton, Ecenaz Jen Ozmen. 2019. VisiFit: AI Tools to Iteratively Improve Visual Blends.

[92] Dimitri Masson, Alexandre Demeure, and Gaelle Calvary. 2010. Magellan, an Evolutionary System to Foster User Interface Design Creativity. In *Proceedings of the 2nd ACM SIGCHI Symposium on Engineering Interactive Computing Systems* (Berlin, Germany) *(EICS '10)*. Association for Computing Machinery, New York, NY, USA, 87–92. https://doi.org/10.1145/1822018.1822032

[93] Jon McCormack, Toby Gifford, Patrick Hutchings, Maria Teresa Llano Rodriguez, Matthew Yee-King, and Mark d'Inverno. 2019. In a Silent Way: Communication Between AI and Improvising Musicians Beyond Sound. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3290605.3300268

[94] K. L. Bhanu Moorthy, Moneish Kumar, Ramanathan Subramanian, and Vineet Gandhi. 2020. GAZED– Gaze-Guided Cinematic Editing of Wide-Angle Monocular Video Recordings. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3313831.3376544

[95] Brad A. Myers, Ashley Lai, Tam Minh Le, YoungSeok Yoon, Andrew Faulring, and Joel Brandt. 2015. Selective Undo Support for Painting Applications. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 4227–4236. https://doi.org/10.1145/2702123.2702543

[96] Kumiyo Nakakoji. 2006. Meanings of Tools, Support, and Uses for Creative Design Processes. *International design research symposium '06* 6 (12 2006), 156–165.

[97] Timothy Neate, Abi Roper, Stephanie Wilson, Jane Marshall, and Madeline Cruice. 2020. CreaTable Content and Tangible Interaction in Aphasia. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376490

[98] George E Newman and Paul Bloom. 2012. Art and authenticity: The importance of originals in judgments of value. *Journal of Experimental Psychology: General* 141, 3 (2012), 558.

[99] Changhoon Oh, Jungwoo Song, Jinhan Choi, Seonghyeon Kim, Sungwoo Lee, and Bongwon Suh. 2018. I Lead, You Help but Only with Enough Details: Understanding User Experience of Co-Creation with Artificial Intelligence. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3173574.3174223

[100] Antti Oulasvirta, Anna Feit, Perttu Lähteenlahti, and Andreas Karrenbauer. 2017. Computational Support for Functionality Selection in Interaction Design. *ACM Trans. Comput.-Hum. Interact.* 24, 5, Article 34 (Oct. 2017), 30 pages. https://doi.org/10.1145/3131608

[101] Taesung Park, Ming-Yu Liu, Ting-Chun Wang, and Jun-Yan Zhu. 2019. Semantic Image Synthesis With Spatially-Adaptive Normalization. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, USA, 2332–2341. https://doi.org/10.1109/CVPR.2019.00244

[102] Nathan Partlan, Elin Carstensdottir, Erica Kleinman, Sam Snodgrass, Casper Harteveld, Gillian Smith, Camillia Matuk, Steven C. Sutherland, and Magy Seif El-Nasr. 2019. Evaluation of an Automatically-Constructed Graph-Based Representation for Interactive Narrative. In *Proceedings of the 14th International Conference on the Foundations of Digital Games* (San Luis Obispo, California, USA) *(FDG '19)*. Association for Computing Machinery, New York, NY, USA, Article 100, 9 pages. https://doi.org/10.1145/3337722.3341858

[103] Alison Pease, Daniel Winterstein, and Simon Colton. 2001. Evaluating machine creativity. In *Proceedings of the ICCBR'01 Workshop on Creative Systems*. Springer, Germany, 129–137. ICCBR'01 Workshop on Creative Systems ; Conference date: 30-07-2001 Through 02-08-2001.

[104] Mengqi Peng, Li-yi Wei, Rubaiat Habib Kazi, and Vladimir G. Kim. 2020. Autocomplete Animated Sculpting. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 760–777. https://doi.org/10.1145/3379337.3415884

[105] Allison Perrone and Justin Edwards. 2019. Chatbots as Unwitting Actors. In *Proceedings of the 1st International Conference on Conversational User Interfaces* (Dublin, Ireland) *(CUI '19)*. Association for Computing Machinery, New York, NY, USA, Article 2, 2 pages. https://doi.org/10.1145/3342775.3342799

[106] Florian Pinel and Lav R. Varshney. 2014. Computational Creativity for Culinary Recipes. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI EA '14)*. Association for Computing Machinery, New York, NY, USA, 439–442. https://doi.org/10.1145/2559206.2574794

[107] Azzurra Pini, Jer Hayes, Connor Upton, and Medb Corcoran. 2019. AI Inspired Recipes: Designing Computationally Creative Food Combos. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI EA '19)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3290607.3312948

[108] Brian Quanz, Wei Sun, Ajay Deshpande, Dhruv Shah, and Jae eun Park. 2020. Machine learning based co-creative design framework. arXiv:2001.08791 [cs.HC]

[109] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Mark Chen, Rewon Child, Vedant Misra, Pamela Mishkin, Gretchen Krueger, Sandhini Agarwal, and Ilya Sutskever. 2021. DALL·E: Creating Images from Text. https://openai.com/blog/dall-e/ Accessed: January, 2021.

[110] Christian Remy, Lindsay MacDonald Vermeulen, Jonas Frich, Michael Mose Biskjaer, and Peter Dalsgaard. 2020. Evaluating Creativity Support Tools in HCI Research. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference* (Eindhoven, Netherlands) *(DIS '20)*. Association for Computing Machinery, New York, NY, USA, 457–476. https://doi.org/10.1145/3357236.3395474

[111] Carsten Rother, Vladimir Kolmogorov, and Andrew Blake. 2004. "GrabCut": Interactive Foreground Extraction Using Iterated Graph Cuts. In *ACM SIGGRAPH 2004 Papers* (Los Angeles, California) *(SIGGRAPH '04)*. Association for Computing Machinery, New York, NY, USA, 309–314. https://doi.org/10.1145/1186562.1015720

[112] Prem Seetharaman, Gautham Mysore, Bryan Pardo, Paris Smaragdis, and Celso Gomes. 2019. VoiceAssist: Guiding Users to High-Quality Voice Recordings. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3290605.3300539

[113] Ticha Sethapakdi and James McCann. 2019. Painting with CATS: Camera-Aided Texture Synthesis. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–9. https://doi.org/10.1145/3290605.3300287

[114] Lu Sheng, Ziyi Lin, Jing Shao, and Xiaogang Wang. 2018. Avatar-Net: Multi-scale Zero-Shot Style Transfer by Feature Decoration. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*. IEEE, USA, 8242–8250. https://doi.org/10.1109/CVPR.2018.00860

[115] Yang Shi, Nan Cao, Xiaojuan Ma, Siji Chen, and Pei Liu. 2020. EmoG: Supporting the Sketching of Emotional Expressions for Storyboarding. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376520

[116] Evan Shimizu, Matthew Fisher, Sylvain Paris, James McCann, and Kayvon Fatahalian. 2020. Design Adjectives: A Framework for Interactive Model-Guided Exploration of Parameterized Design Spaces. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 261–278. https://doi.org/10.1145/3379337.3415866

[117] Ben Shneiderman. 2001. *Supporting Creativity with Advanced Information-Abundant User Interfaces*. Springer London, London, 469–480. https://doi.org/10.1007/978-1-4471-0259-5_34

[118] Ben Shneiderman. 2007. Creativity Support Tools: Accelerating Discovery and Innovation. *Commun. ACM* 50, 12 (Dec. 2007), 20–32. https://doi.org/10.1145/1323688.1323689

[119] Mark Shtern, Pedro Casas, and Vassilios Tzerpos. 2018. Evaluating Music Mastering Quality Using Machine Learning. In *Proceedings of the 28th Annual International Conference on Computer Science and Software Engineering* (Markham, Ontario, Canada) *(CASCON '18)*. IBM Corp., USA, 126–135.

[120] Maria Shugrina, Wenjia Zhang, Fanny Chevalier, Sanja Fidler, and Karan Singh. 2019. Color Builder: A Direct Manipulation Interface for Versatile Color Theme Authoring. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300686

[121] Chung Sougwen. 2021. Sougwen Chung-Exhibition Highlights. https://sougwen.com/exhibitions Accessed: January, 2021.

[122] Angie Spoto, Natalia Oleynik, Sebastian Deterding, and Jon Hook. 2017. Library of Mixed-Initiative Creative Interfaces. http://mici.codingconduct.cc/

[123] Sarah Sterman, Evey Huang, Vivian Liu, and Eric Paulos. 2020. Interacting with Literary Style through Computational Tools. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376730

[124] Hariharan Subramonyam, Wilmot Li, Eytan Adar, and Mira Dontcheva. 2018. TakeToons: Script-Driven Performance Animation. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology* (Berlin, Germany) *(UIST '18)*. Association for Computing Machinery, New York, NY, USA, 663–674. https://doi.org/10.1145/3242587.3242618

[125] Amanda Swearngin, Chenglong Wang, Alannah Oleson, James Fogarty, and Amy J. Ko. 2020. Scout: Rapid Exploration of Interface Layout Alternatives through High-Level Design Constraints. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376593

[126] Haruki Takahashi and Jeeeun Kim. 2019. 3D Pen + 3D Printer: Exploring the Role of Humans and Fabrication Machines in Creative Making. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300525

[127] Cesar Torres, Jessica Chang, Advaita Patel, and Eric Paulos. 2019. Phosphenes: Crafting Resistive Heaters within Thermoreactive Composites. In *Proceedings of the 2019 on Designing Interactive Systems Conference* (San Diego, CA, USA) *(DIS '19)*. Association for Computing Machinery, New York, NY, USA, 907–919. https://doi.org/10.1145/3322276.3322375

[128] Cesar Torres, Wilmot Li, and Eric Paulos. 2016. ProxyPrint: Supporting Crafting Practice through Physical Computational Proxies. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems* (Brisbane, QLD, Australia) *(DIS '16)*. Association for Computing Machinery, New York, NY, USA, 158–169. https://doi.org/10.1145/2901790.2901828

[129] Cesar Torres and Eric Paulos. 2015. MetaMorphe: Designing Expressive 3D Models for Digital Fabrication. In *Proceedings of the 2015 ACM SIGCHI Conference on Creativity and Cognition* (Glasgow, United Kingdom) *(C&C '15)*. Association for Computing Machinery, New York, NY, USA, 73–82. https://doi.org/10.1145/2757226.2757235

[130] Theophanis Tsandilas, Catherine Letondal, and Wendy E. Mackay. 2009. Mus<i>Ink</i>: Composing Music through Augmented Drawing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Boston, MA, USA) *(CHI '09)*. Association for Computing Machinery, New York, NY, USA, 819–828. https://doi.org/10.1145/1518701.1518827

[131] Kento Watanabe, Yuichiroh Matsubayashi, Kentaro Inui, Tomoyasu Nakano, Satoru Fukayama, and Masataka Goto. 2017. LyriSys: An Interactive Support System for Writing Lyrics Based on Topic Transition. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces* (Limassol, Cyprus) *(IUI '17)*. Association for Computing Machinery, New York, NY, USA, 559–563. https://doi.org/10.1145/3025171.3025194

[132] Blake Williford, Abhay Doke, Michel Pahud, Ken Hinckley, and Tracy Hammond. 2019. DrawMyPhoto: Assisting Novices in Drawing from Photographs. In *Proceedings of the 2019 on Creativity and Cognition* (San Diego, CA, USA) *(C&C '19)*. Association for Computing Machinery, New York, NY, USA, 198–209. https://doi.org/10.1145/3325480.3325507

[133] Blake Williford, Matthew Runyon, Wayne Li, Julie Linsey, and Tracy Hammond. 2020. Exploring the Potential of an Intelligent Tutoring System for Sketching Fundamentals. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376517

[134] Erik Wolf, Sara Klüber, Chris Zimmerer, Jean-Luc Lugrin, and Marc Erich Latoschik. 2019. "Paint That Object Yellow": Multimodal Interaction to Enhance Creativity During Design Tasks in VR. In *2019 International Conference on Multimodal Interaction* (Suzhou, China) *(ICMI '19)*. Association for Computing Machinery, New York, NY, USA, 195–204. https://doi.org/10.1145/3340555.3353724

[135] Hui-Yin Wu, Francesca Palù, Roberto Ranon, and Marc Christie. 2018. Thinking Like a Director: Film Editing Patterns for Virtual Cinematographic Storytelling. *ACM Trans. Multimedia Comput. Commun. Appl.* 14, 4, Article 81 (Oct. 2018), 22 pages. https://doi.org/10.1145/3241057

[136] Anna Xambó, Johan Pauwels, Gerard Roma, Mathieu Barthet, and György Fazekas. 2018. Jam with Jamendo: Querying a Large Music Collection by Chords from a Learner's Perspective. In *Proceedings of the Audio Mostly 2018 on Sound in Immersion and Emotion* (Wrexham, United Kingdom) *(AM'18)*. Association for Computing Machinery, New York, NY, USA, Article 30, 7 pages. https://doi.org/10.1145/3243274.3243291

[137] Jun Xie, Aaron Hertzmann, Wilmot Li, and Holger Winnemöller. 2014. PortraitSketch: Face Sketching Assistance for Novices. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology* (Honolulu, Hawaii, USA) *(UIST '14)*. Association for Computing Machinery, New York, NY, USA, 407–417. https://doi.org/10.1145/2642918.2647399

[138] Junichi Yamaoka and Yasuaki Kakehi. 2013. DePENd: Augmented Handwriting System Using Ferromagnetism of a Ballpoint Pen. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology* (St. Andrews, Scotland, United Kingdom) *(UIST '13)*. Association for Computing Machinery, New York, NY, USA, 203–210. https://doi.org/10.1145/2501988.2502017

[139] Junichi Yamaoka, Kazunori Nozawa, Shion Asada, Ryuma Niiyama, Yoshihiro Kawahara, and Yasuaki Kakehi. 2018. AccordionFab: Fabricating Inflatable 3D Objects by Laser Cutting and Welding Multi-Layered Sheets. In *The 31st Annual ACM Symposium on User Interface Software and Technology Adjunct Proceedings* (Berlin, Germany) *(UIST '18 Adjunct)*. Association for Computing Machinery, New York, NY, USA, 160–162. https://doi.org/10.1145/3266037.3271636

[140] Humphrey Yang, Kuanren Qian, Haolin Liu, Yuxuan Yu, Jianzhe Gu, Matthew McGehee, Yongjie Jessica Zhang, and Lining Yao. 2020. SimuLearn: Fast and Accurate Simulator to Support Morphing Materials Design and Workflows. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '20)*. Association for Computing Machinery, New York, NY, USA, 71–84. https://doi.org/10.1145/3379337.3415867

[141] Tom Yeh and Jeeeun Kim. 2018. *CraftML: 3D Modeling is Web Programming*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3174101

[142] Niloofar Zarei, Sharon Lynn Chu, Francis Quek, Nanjie 'Jimmy' Rao, and Sarah Anne Brown. 2020. Investigating the Effects of Self-Avatars and Story-Relevant Avatars on Children's Creative Storytelling. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3313831.3376331

[143] Jiayi Eris Zhang, Nicole Sultanum, Anastasia Bezerianos, and Fanny Chevalier. 2020. DataQuilt: Extracting Visual Elements from Images to Craft Pictorial Visualizations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376172

[144] Yupeng Zhang, Teng Han, Zhimin Ren, Nobuyuki Umetani, Xin Tong, Yang Liu, Takaaki Shiratori, and Xiang Cao. 2013. BodyAvatar: Creating Freeform 3D Avatars Using First-Person Body Gestures. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology* (St. Andrews, Scotland, United Kingdom) *(UIST '13)*. Association for Computing Machinery, New York, NY, USA, 387–396. https://doi.org/10.1145/2501988.2502015

[145] Clement Zheng, Ellen Yi-Luen Do, and Jim Budd. 2017. Joinery: Parametric Joint Generation for Laser Cut Assemblies. In *Proceedings of the 2017 ACM SIGCHI Conference on Creativity and Cognition* (Singapore, Singapore) *(C&C '17)*. Association for Computing Machinery, New York, NY, USA, 63–74. https://doi.org/10.1145/3059454.3059459