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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.<sup>1</sup> Computer-based tools, in particular, have enabled extended expressions, efficiency, and skills [37]. For instance, Adobe's Photoshop

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provides a set of tools ranging from assorted brushes to contextaware 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 paintbrushone 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 *artmaking* 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

<sup>&</sup>lt;sup>1</sup>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 humanmachine 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, 9, 100, 100, 100, 100, 100, 100, 100,
	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.<sup>2</sup> 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. 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,

<sup>&</sup>lt;sup>2</sup>https://dl.acm.org/

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 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 handtuned, 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** 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	[67]	43	38.7
			generation.			
		Curation	The tool suggests novel information or artifacts from existing	[75]	10	9.0
			sources.			
		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
s	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
ion		No Input	The user does not make an input to the tool.	[65]	2	1.8
Interact	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	Learning Algorithm	Algorithms trained on data (e.g., ML algorithms).	[93]	45	40.5
		Non-learning	Algorithms not trained on data (e.g., rule-based algorithms and	[143]	30	27.0
Technologies		Algorithm	optimization).			
		Software UI	Software UI that gives easier use and control (e.g., visual program-	[81]	25	22.5
			ming).			
		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	[66]	11	9.9
			or thermochromic ink).			
		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.

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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<sup>th</sup> 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, Voice-Cuts [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 cooccur 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 genera-tion* and *execution assistance*. For *curating* tools, all of them are supported 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

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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* 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.

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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 $\times$ 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 highquality 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 ( $\leq 10\%$  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 artmaking 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 artmaking tools (e.g., paintbrushes). As these conventional tools are more familiar, CST researchers might focus on these design. It

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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 designcentered, consolidating perspective to the understanding of artmaking CSTs. We taxonomized and coded 111 publications on artmaking 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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