Too Late to be Creative? AI-Empowered Tools in Creative Processes

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ABSTRACT

The present case study examines the product landscape of current AI-empowered co-creative tools. Specifically, I review literature in both creativity and HCI research and investigate how these tools support different stages in humans' creative processes and how common challenges in human-AI interaction (HAII) are addressed. I find these AI-driven tools mostly support the generation and execution of ideas and are less involved in the early stages of co-creation. Moreover, HAII challenges identified in other fields receive little attention in the creative domain. Based on a synthetic analysis, I elaborate on how future tools can leverage the "non-human" quality of AI to achieve innovation through a more human-centered, collaborative journey.

KEYWORDS

creativity, human-AI interaction, creativity support tool

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1 INTRODUCTION

Producing creative ideas has long been considered as one of the humans' unique capabilities. Even with the state-of-the-art technology, the common consensus acknowledges that the vision of AI attaining creativity *independently* remains years beyond sight. However, the potential of human-AI co-creativity has received much attention and interest among scholars and practitioners. In fact, abundant AI-empowered tools have already been adopted and applied by content creators of all kinds. The present case study takes a market research approach, surveying AI-supported tools for creative work, and, based on their functionality and technological capacity, I classify them into four types (the Editors, the Blenders, the Transformers, and the Generators). Furthermore, the present product analysis for these tools is driven by two key questions:

(1) How do these tools support different stages of users' creative processes?
(2) How do these tools address common challenges of human-AI interaction (HAII)?

To tackle the first question, I review previous literature and synthesize common action items in humans' creative work process into four stages and identify where the functions of these tools fit into users' creative journey. Accordingly, I pinpoint certain areas that have less been attempted by co-creative AI. Secondly, drawing from recent HAII work, I discuss whether and how these tools respond to three categories of problems (divergent, convergent, and collaborative issues) in human-AI co-creativity.

2 A LOOK INTO THE CREATIVE MIND: STAGES OF CREATIVE PROCESS

Creativity has been viewed as one of the most complex but least understood topics in human psychology. To date, researchers have reached little agreement on even the most fundamental inquiries for creativity, including its definition and essential constructs [33, 41]. Existing research has approached creativity as a form of intelligence, personality, learning, and more [11, 14, 16]. Since designing creativity support tools has come to the interest of HCI researchers, the conceptual foundation of creativity *per se* is likewise indefinite [13]. Here, instead of wrestling with its meaning, I turn to a specific area of creativity research that is much more clearly formulated: the stages of the creative process. The line of work has largely been grounded on investigating how individuals approach and tackle creative problems, ranging from how experts produce creative masterpieces to how laymen address simple, context-free creative questions (e.g., generating novel ways to make use of a piece of brick) [33].

The Q&A Stage. Through a systematic review, I synthesize and summarize stages of the creative process in Table 1 elaborated in previous literature. While individual scholars have offered their unique and/or domain-specific proposals, they commonly suggest that a creative process typically embarks on understanding the creative problem itself. During this initial stage, creators would gather relevant information (e.g., secondary research, observation, survey) and perform goal-setting, while the order of these actions may differ case-by-case. For instance, designers may receive a very definitive request from clients and thus collect only relevant information that advises what is feasible and practical under the given project specifics; on the other hand, a creative process may start with a broad, open-ended question, which requires initial research to narrow down the scope before a practical goal can be set.

The Wandering Stage. Building on the prior work, the second stage of the creative process involves a substantial amount of "mind wandering." This is when creators start to initiate and play around with some scattered, premature pieces of thoughts —they may not

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be complete enough to directly address a creative problem, but they serve as the nutrients for more formal ideas later on. During this stage, even though a person is not consciously producing workable ideas, their brain continues to search for concepts and opportunities that can fuel the formation of creative strategies. Specifically, researchers refer to this experience as *incubation* and emphasize the power of "letting an idea sit" [41]. In fact, even at some of the most studious design institutes, taking a break or a quick shower is "taught" as a technique to spark creativity [21].

The Hands-On Stage is when creators actually start to work on solving a problem. This process is often initiated by generating a large number of possible ideas (i.e., solutions to the creative problem) [30]. Several design disciplines refer to this process as brainstorming and utilize a variety of techniques to drive such activities (e.g., 180-degree thinking, ideation grids) [15, 21, 23, 34, 43]. With an initial set of possible solutions, creators may evaluate (screening out the good from the best), combine multiple compatible ideas, and select a small set of "candidates" to work on further revision and improvement.

The Camera-Ready Stage. In the final step of the creative process, creators finalize and execute ideas into presentable, "client-facing" formats, allowing them to "sell" their ideas to their intended audience. During this stage, creators leverage professional skill sets, tactics, and tools to externalize intangible concepts into concrete forms.

Worth noting, distinct stages may overlap with one another, and users may go through several stages iteratively, revisiting certain procedures a couple of times. Regardless, studies and reviews have revealed that common action items emerge in each section of the creative process (as listed in Table 1). In the next session, which covers common challenges in HAII, I reflect on difficulties users may encounter when they intend to carry out these specific activities throughout the creative process.

Table 1: Action items in the four stages of creative process

Stage	Action Items	Relevant theoretical framework
The Q&A Stage	Find the problem	[2, 7, 23, 33, 34]
	Framing and (re)defining problems and goals	[2, 5, 15, 41, 43]
	Acquire relevant information and knowledge	[2, 5, 7, 21, 23, 33, 34]
The Wandering Stage	Exploring data and possible strategies	[2, 43]
	Constructing opportunities & concept search	[23, 34, 43]
	Incubation	[5, 33, 45]
	Take time off	[7, 41]
The Hands-On Stage	Generate ideas	[5, 7, 15, 21, 23, 33, 34, 41, 43]
	Combine and cross-fertilize ideas	[33, 41]
	Developing solutions & insight	[43, 45]
The Camera-Ready Stage	Evaluate and judge ideas	[23, 34, 41]
	Select the best ideas	[5, 15, 33]
	Externalize and implement ideas	[15, 21, 23, 33, 34]
	Elaborate and sell ideas, build acceptance	[5, 7, 15, 41, 43, 45]

3 CHALLENGES IN HAII: APPLYING TO THE CREATIVE PROCESS

Besides solving problems at each stage of the creative process, the use of AI-driven tools introduces additional, AI-specific challenges to their users. Across domains, researchers have identified unique challenges in HAII, as the complexity of the technology is nothing like other computer-supported cooperative (CSCW) tools [31]. Reviewing existing work, I summarize common issues to address in HAII; specifically, given the context of human-AI co-creativity, I categorize these challenges into three classes and map them to the aforementioned four stages of the creative process.

3.1 Divergent Challenges

The first type of HAII challenges arise when users apply the technology to perform generative tasks, where AI involves in creating and/or delivering certain products [48, 53]. UX design is a field that has widely adopted AI in this type of task [6]. Specifically, the purpose of applying AI aims to produce a greater number of design alternatives and/or to offer a wider variety of resources, intending to inspire and augment human creativity. By taking in inputs from creators (e.g., design guidelines and constraints) and tracking end-users' data (e.g., behavioral data, such as views, clicks), AI facilitates to achieve goals set by its designers and developers, while creating a personalized experience for its end-users. Previous literature has suggested that the "capability uncertainty and output complexity" of AI has made it particularly difficult for humans to work with [26, 50, 52]. That is, designers and users cannot comprehensively envision the outputs, including both working errors and end products, of AI before it is fully built and deployed.

During one's creative process, generative tasks may include (1) acquiring relevant information during the Q&A Stage, (2) laying out premature concepts during the Wandering Stage, (3) generating and brainstorming ideas during the Hands-On Stage, and (4) externalizing ideas and transforming them into presentable forms in the Camera-Ready Stage. Previous studies examining the use of AI by design practitioners have revealed that designers could seldom predict what type of outputs (e.g., ideas being generated or information being collected) an AI assistant would offer; on the flip side, given the wide variety of outcomes that AI could possibly offer, building prototypes during early design processes became much more laborious, while the value of rapid prototyping (before building complete machine learning models) has decreased significantly [50].

3.2 Convergent Challenges

The second set of challenges concerns how AI guides users to make decisions, such as selecting the best option out of numerous alternatives or identifying trends from massive data. This type of human-agent teamwork has received substantial attention in clinical and military settings [1, 44]. Due to the high risk, high stake nature of these tasks, users typically express greater demand for transparency, explainability, and interpretability of AI [29, 46]. Recent studies investigating how physicians exploited AI in cancer diagnoses and clinical on-boarding have specifically sought the need to address "AI point-of-view," which concerns where AI sourced its data, what it was algorithmically optimized for, and which types of biases it was subject to [3, 20].

Throughout humans' creative processes, convergent decision-making is also applied extensively [4]. Starting from the first stage, creators need to narrow down the scopes and select clear goals for their creative work. Following, they have to screen and filter out concepts or information that are less relevant to the task at hand. When the process of idea generation embarks, creators go through a series of steps to evaluate, combine, and select ideas. Ultimately, they have to settle on a small set of ideas (and often a single option) to proceed with final, audience-facing execution. Though building machine learning models to perform decision-making has been studied and applied more extensively, the inhuman ways of AI "reasoning" set great obstacles for users to understand how decisions are made, adding additional barriers for trust and acceptance in HAII.

3.3 Collaborative Challenges

Finally, when humans and AI work *together*, challenges for coordination and cohesion exist —as in any teamwork. To begin with, whether AI and other computer-mediated agents should work *for* or work *with* humans has long been debated in relevant fields, such as human-robot interaction [19, 35]. Namely, the role of AI in teams is often unclear, and individual team members may hold different opinions toward this matter. Besides the technological capability to co-work efficiently, an emerging line of research, which studies human-machine partnerships in the future of work, has posited that the design of AI "teammates" should also take into consideration the psychological experience and personal values (e.g., self-worth) of individual users [3, 42]. Some common internal struggles when collaborating with AI include the above-mentioned issue of trust, as well as the perceived self-efficacy in teams, [3, 24, 46]. When AI has become more capable of performing sophisticated tasks, some of which can hardly be achieved by humans, users' self-doubts and perceived threats of job replacement are now more salient than ever. Moreover, whether users can work smoothly with CSCW tools and agents differ greatly from individual to individual [32, 35]. For instance, a recent review has suggested personality traits as determinants of success or failure of human-robot teamwork [10]. In this regard, accommodations for individual users should as well be addressed when it comes to the design of AI-empowered collaborative tools.

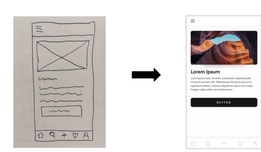
Last but not least, it is important to acknowledge that, when users apply CSCW tools, they are seldom solo players. Thus, how these tools mediate human-human teamwork should also be taken into account. This is particularly relevant to the context of co-creativity, as creators seldom work alone in modern work environments. Recent work has revealed the positive effects of AI and robots strengthening social synergy in teams [17, 36]. However, up to date, the topic area has been under-explored.

4 AI CO-CREATIVE TOOLS IN THE MARKET

To extensively search for AI-empowered co-creative tools, I first conducted web scraping using Python, capturing all web pages (in English) yielded by the search terms of "AI" and "creativity" in the past five years (2017 - 2021). I adopted this web scraping approach instead of performing a more formal research method (e.g., a systematic review using a research database) since abundant consumer products may not have been studied or discussed in scholarly articles. I then manually went through the scrapped results and identified any creativity support tools mentioned on these web pages, resulting in a total of 42 unique tools. To understand the functionality and capacity of these tools, I visited each product's official site, reviewed their demos, tutorials, instructions, etc., and tried out all the tools. I summarize their key functions in Appendix (Table 3). In particular, I performed product evaluation through two perspectives: (1) I noted whether these tools offer functions supporting action items in each stage of the creative process. (2) In a previous review, [37, 38] laid out eight functionalities that can effectively augment the usefulness of creativity support tools; I, therefore, inspected whether these AI-empowered products possess any of these features. Based on this analytic practice, I identified four major categories of AI co-creative tools —*the Editors, the Transformers, the Blenders, and the Generators.* I further elaborate on each category below.

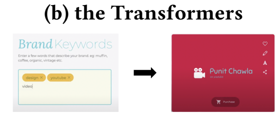
(1) **The Editors** facilitate various execution processes, allowing users to carry out content editing at ease. For example, Luminar applies cutting-edge computer vision techniques to identify, remove, and replace the background in an image or a video clip.
(2) **The Transformers** alter and convert content from one form to another; these include but are not limited to transforming hand-drawn sketches to digital images (e.g., Uizard) and converting visual templates of web UI to front-end code (e.g., Sketch2Code).
(3) **The Blenders** combine two or more creative elements to breed new ideas and outputs. Most of these tools are built using GAN (generative adversarial network), featuring *Deep Art* as one of the most famous examples. The tool requires users to select an image and a style as inputs; together, it will "blend" the style to the selected image to create a new visual output.
(4) **The Generators** produce ready-to-use creative outputs based on guidance and/or constraints inserted by users. For instance, the Brandmark tool relies on users to insert keywords describing a brand's characteristics, based on which it would generate logos to represent the brand's identity.

(a) the Editors



(b) the Transformers

(c) the Blenders



(d) the Generators

Figure 1: Examples for the four types of AI co-creative tools

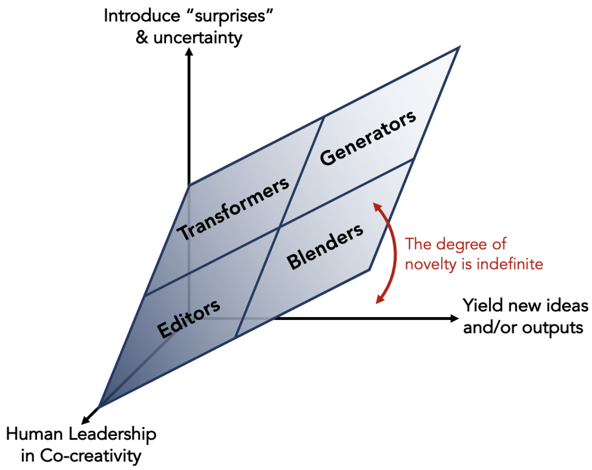


Figure 2: The relationship among the four types of AI co-creative tools

Together, the four categories of AI co-creative tools not only serve distinct functions, but their roles in human-AI co-creation also differ by three dimensions: whether they yield new ideas/outputs, whether they introduce novelty and uncertainty to creative products, and whether humans take the lead in the creative process. I illustrate the relationship among the four types of tools in Figure 2. I first group these tools by whether they yield new ideas (i.e., the *Blenders* and *Generators*) or not (i.e., the *Editors* and *Transformers*. Applying the Editors type of tools, users already have clear, planned directions for how they would attempt a creative product or solution, while the functions of these tools simplify the execution procedures. In this regard, users lead the creative dialogue and the tools serve as facilitators, bringing limited novelty to the table. On the other extreme, the Generators embrace greater voices in a human-AI co-creativity, brewing new ideas autonomously and can indeed introduce unexpectedness to the creative process. When applying these tools, users would insert some design requirements (i.e., determine certain parameters) at the beginning, then they would wait and see what the tools yield. Before getting the generative outputs, users, in fact, cannot really intervene in the working process of these tools. On the other hand, the roles of Blenders and Transformers are less definite. For instance, a Blender can introduce a whole new experience when merging different content types (e.g., Rosebud AI creates playful animation by blending static images with video clips). By contrast, the result of adding Starry-Night-like paint strokes to a scenic photograph is rather predictable. Nonetheless, users are likely to take greater control over the Transformers, as they typically would already have some ideas, sketches, or drafts at hand when attempting to convert content from one type to another.

4.1 RQ1: How do AI co-creative tools support each stage in the creative process?

To examine the first research question, I compare the action items in each stage of the creative process to the functions offered by each AI co-creative tool. As illustrated in Table 2, the majority of tools offer supporting functions that map to the later stages of the creative process, particularly to aid users with idea generation and execution. Each type of co-creative tool also demonstrates strengths for facilitating specific stage(s) during the creative process. To begin with, **the Generators** offers functions to support idea generation and can be most helpful during the Hands-On Stage when users are trying to brainstorm a large number of ideas and possible solutions. Following, **the Blenders** can be the most helpful when users already have some initial ideas in mind (e.g., what base visual or which artistic style they would like to work with), while these applications can be used to inspire additional ideas or to combine multiple existing ideas. After determining a shortlist of idea(s) to move on with, **the Transformers** mostly support the final stage of the creative process, during which creators already have a clear blueprint of their design and ideas and simply need to digitize or re-program it for the final execution. Finally, **the Editors** can support actions taken during the third and/or final stages of the creative process, such as investigating a close-to-finish look of a prototype or polishing a piece of client-facing content.

4.2 RQ2: How do AI co-creative tools address common HAII challenges?

As shown in the table in Appendix (Table 3), the majority of these tools demonstrated no sign of addressing these common challenges in HAII, as their functions can rarely be mapped to the list of divergent, convergent, and collaborative problems as mentioned in Section 3. A limited number of these applications embedded interactive machine learning (iML) in their platforms. Specifically, iML allows users to tweak model parameters and examine their impact on the model outcomes in real time, which is typically done through interactive panels and/or visualization [12]. For instance, after blending an image with a style, Art Breeder shows various interactive sliders, allowing users to adjust several dimensions of the training model and explore the visual outputs synchronously. Such interactive panels can be helpful for addressing the degree of

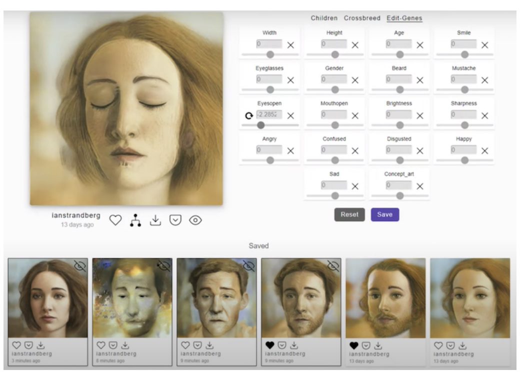
Table 2: AI co-creative tools supporting action items in the four stages of creative process

	Tools offering relevant functions
The Q&A Stage	
The Wandering Stage	
The Hands-On Stage	
The Camera Ready Stage	

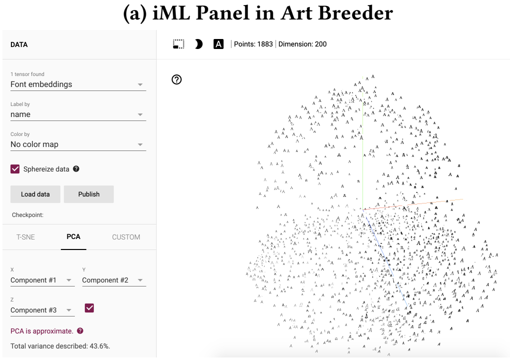
uncertainty while informing AI point-of-view (i.e., what the models are optimized for). Besides, Khroma is the one and only tool that allows users to download and examine the training data used on the platform. While this function demonstrates an attempt to address the transparency issue of this AI-driven tool, users without any data science or machine learning training may need further guides to decipher the usefulness of the piece of resource.

Furthermore, I noticed the limited set of tools which do attempt to address HAII challenges similarly requires certain ML knowledge and are lack of "layman terms" to account for novice users without relevant background. For instance, the interactive panel in Font Visualizer allows user to select the training and visualize methods (e.g., PCA or t-SNE) without any further explanations, assuming those who wish to further explore the model —or simply wish to know how the tool works —possess domain knowledge. While in previous research [49], designers working in data-drive environments often admitted that they neither owned nor intended to pursue expertise in this knowledge space.

Finally, when examining whether these AI-empowered tools contain the eight key features of creativity support tools, I realized despite the Generators being the most complex tools and the least human-led set of tools, they offered the fewest exploratory functions compared to other types. As mentioned above, users' inputs are typically demanded at the early stage, but the ways to involve seldom exceed "sit-and-wait" during the working process of these tools —while users are often uncertain what to expect for the outcomes. Therefore, creators' engagement and intervention often take place only after an creative output has been produced. At this point, few clues are informing what users can do, besides trials and errors, to improve or attempt desired outcomes from these tools.



(a) iML Panel in Art Breeder



(b) iML Panel in Font Visualizer

Figure 3: Examples of interactive panels in existing AI-empowered creativity tools

5 SYNTHETIC ANALYSIS: THE SWOT OF CURRENT AI CO-CREATIVE TOOLS

In this section, I integrate takeaways from the above literature and product reviews and perform a synthetic analysis on today's AI co-creative tools. In particular, I conduct a SWOT analysis, a technique commonly used in marketing and management science to understand the strength, weakness, opportunity, and threat in the current landscape of the technological products.

5.1 Strength: Strategizing Human-AI (Non-)Creative Task Assignment

Throughout the current analysis, I repeatedly see the imbalance of functions and tools available to support the first half versus those supporting the second half of the creative process. In particular, a number of these tools describe their value propositions as taking charge of the laborious work, allowing users to allocate their cognitive resources more wisely and focusing on solving the "real" creative problems. Apparent examples include content editing tools —instead of refining images pixel by pixel or altering footage frame by frame, applications such as Let's Enhance or Sequel allow users to perform editing work and add special visual effect with just a few clicks. More recently, tools such as Uizard can even greatly shorten the time spent on creating prototypes. Similarly, instead of sketching out all possible combinations of design elements, the concept of Autodesk's generative design proposes such onerous job can be performed through computational simulation. In consensus, the goal shared by these tools is to encourage human creators to focus their time and energy on bringing a "good" idea to the next level of innovation. In other words, to support humans' creativity, a substantial portion of these tools have continuously improved their technological capability in order to serve *non-creative* tasks as much as possible.

Conceptually, the intention of this work distribution model (i.e., humans focus on creative work, and AI take care of non-creative tasks) seems reasonable and helpful, but when I project this framework to the full creative process, some warning signals require second thoughts. To begin with, it is debatable whether spending most of their time on ideation and problem-solving is indeed the most efficient and effective approach to human creativity. Fundamentally, this strategy undermines the value of the Wandering Stage in the creative process, particularly overlooking the importance of incubation (i.e., let the ideas sit while one performs less mentally taxing tasks) [37, 38]. Furthermore, literature in craftsmanship and fine art has repeatedly found that artists often get inspiration when they engage in some repetitive, tedious work [39]. Given that we are not at all close to resolving the puzzle of human creativity, it may be reckless to jump to the conclusion that carrying out laborious tasks adds no value to innovation, and even the simplest, lowest-level tasks in one's creative process may, from time to time, bring surprises to the table.

5.2 Weakness: Shying away from HAII and Workplace Reality

Perhaps one of the most concerning findings is the scarcity of attempts made to address common HAII challenges in these co-creativity tools. Due to a lack of insights into how the tools work, what level of complexity to expect in the output, and how machines optimize their behaviors, users have little choice but to be more hands-off during the interaction experience. This particularly occurs when users are interacting with the Generators. Moreover, when generative outcomes turn out to be unsatisfying, there is often limited guidance for how improvement can be made systematically. Even though some tools do offer, for instance, iML panels for users to explore possible solutions, they may require domain knowledge or raise additional concerns for information overload. For example, while Font Visualizer shows all typefaces generated based on users' inputs, it can be challenging for users to find just one desirable font to use. An emerging line of research has offered various proposals for how AI systems should couple with good UX/UI design to more effectively communicate their capability [46, 47, 51]. I encourage future design and development of these co-creative tools should also take these proposals into practice. Indeed, by addressing common HAII challenges, studies in other domains (e.g., clinical training) have found co-work between humans and AI can be carried out more smoothly and effectively.

Another noticeable deficiency is the absence of consideration for collaborative challenges in HAII. Not only do these tools lack customizable functions, assuming all users demand identical creative outputs, they also offer limited support for teamwork. By definition, an intelligent system should be able to learn and improve itself over time. Placing this expectation into the human-Ai co-creative workflow, without offering support that tailors to individual creativity, it is questionable whether these current "AI-empowered" tools have leveraged the full potentials of machine learning and whether the type of support they provide is significantly different from non-AI tools. Moreover, it is apparent that these tools are not designed for collaboration among multiple human users —on most, if not all, of these AI-driven platforms, changes made on work are not updated in real-time, nor do they allow inputs from various devices simultaneously. Together, I encourage the production of future AI co-creative tools to take further consideration for how the creative work is attempted in actual workplaces and work scenarios.

5.3 Opportunity: Breaking Misconception & Going beyond the Creativity Domain

As emphasized throughout the current paper, the creative process encompasses far more than coming up with new ideas and making them look nice. The tendency to overlook activities that do not directly generate or execute ideas is also reflected in today's AI co-creative tools. Since computer-generated art was introduced a few decades ago, scholars commonly suggest though machines can produce artistic outputs, they lack the ability to evaluate and distinguish the mundane from the groundbreaking masterpiece [33]. Recently, the rise of concerns for accountability, responsibility, and fairness in HAII have also put a pause on whether AI should participate in goal-setting [8]. As a result, I see these apparent gaps in AI's involvement in the creative process. Here, I challenge the common belief and ask whether the "non-human" ways of AI reasoning and behaving remain inappropriate under the context of seeking creativity.

Previous literature has argued that machines cannot evaluate creative products nor define goals for innovation since there is no universal agreement on how creativity can be measured, resulting in ambiguity for which metrics these algorithmic models should optimize [18, 27]. However, recent work has shown that, even without AI systems understanding and seeking creativity as the target for optimization, their very distinct approaches to "thinking" can introduce intriguing perspectives that may fall out of humans' sights; for instance, when a machine learning model was demanded to calculate the "surprisingness" of different windows shapes, it concluded that having no shape at all is the most surprising [25]. In this study, I also see *Visual Eyes* as a unique case, which provides support during the early Q&A stage. The tool takes UX templates as inputs and produces heatmaps predicting where viewers may pay attention to, offering helpful information beyond humans' knowledge space. On the other hand, popular work in creativity research often discusses the difference between the "Big C" creativity (i.e., defining a completely new problem space for creativity problem-solving) and the "little c" creativity (i.e., solving an existing problem in a new way) [28, 40]. In this regard, I see the data-driven, non-human mind of AI offering much potential in re-defining and re-positioning the early stages of the creative process. Similarly, when it comes to evaluating creative work, AI may not "comprehend" nor base on the meaning of creativity to select great content, but it can identify outstanding pieces that may not otherwise be noticed by humans.

5.4 Threat: Guarding the Territory of Human Creativity

The concerns that machines may ultimately replace humans' unique identity in the creative space have long existed alongside the constant (re)introduction and improvement of creativity support tools, and relevant work has shown that such perceived threats can often lead to users' reluctance in adopting these applications [9, 22]. Based on the present product analysis, these internal struggles of users have not been addressed through the affordances of current AI co-creative tools. Alternatively, a large portion of these products targets *non-designers*, reducing the risk of depriving a user's creative role. However, this approach overlooks the omnipresence of creativity in today's work content, and employees (e.g., strategists, planners) who are not professional creators nor designers may also be heavily involved in producing creative work. As a result, it does not fundamentally resolve the push-back from human users.

Resonating with the call of human-centered AI, I propose that human-machine partnerships should be determined by users themselves. Currently, as shown in the conceptual model (Figure 2), whether humans take the lead in co-creation with AI depends on the functionality of the tools. Nonetheless, I posit that users should hold the autonomy in deciding whether they would prefer AI to work *with* or work *for* them, inputting such role assignments as one of the initial parameters to kick-start co-working processes with AI. To achieve this goal, future AI co-creative tools should minimize singularity in their functions (i.e., allowing room for different functions to overlap) and better inform users how their models work users and how intervention can be implemented. For instance, if a tool can merge the functions of a Generator and a Blender, it leaves greater autonomy for users who wish to take the lead and decide what images and styles should be blended together; on the other hand, if users hand leadership to AI, it can also autonomously select materials (based on pre-determined parameters or its data-driven point-of-view) to blend and generate new content, and even self-evaluate a set of initial generative outputs to pick the greatest piece.

6 LIMITATION & FUTURE RESEARCH

The present research surveyed the current market landscape by focusing on AI-empowered products featuring creativity support as their main value proposition. However, this approach is likely to overlook AI tools with other primary features (e.g., enhancing productivity, streamlining teams' workflow), while they may also facilitate innovation of creative professionals through other indirect means. Moreover, while the current analysis centers on the functions, usability, and experiences of individual users, it remains unclear how these tools may support an entire creative team. While today's innovative work is often conducted through collective efforts, I encourage future research to further explore the topic.

7 CONCLUSION

To conclude, the present case study shows that future AI co-creative tools should further explore the possibilities to offer support at various steps (especially the early stages) of the creative process, since producing creative work requires more than generating and executing ideas. Furthermore, I encourage designers and developers of these tools to address common HAII challenges, informing how users can interact, intervene, and determine roles in human-machine partnerships. Through leveraging the "non-human" quality of AI, I expect these supportive tools can introduce one-of-the-kind insights, that would not be achieved by the sole force of humans.

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A APPENDIX: DESCRIPTIONS OF AI CO-CREATIVE TOOLS

Table 3: Descriptions of AI Co-Creative Tools (Continued on next page)

Product	Target user and purpose	Description and key features	Output	Address HAII challenges	Searching	Visualizing	Relate	Thinking	Exploring	Composition	Reviewing	Disseminating
Let's Enhance	Content creator, e-commerce	**Editing**: Auto-improve photo quality	Image			v			v			
Luminar (SkyAI)	Not specified	**Editing**: Replace and/or add visual effect to background or foreground of images	Image			v			v	v	v	
Remove.bg	Content creator, e-commerce	**Editing**: Auto-remove or replace photo background	Image			v			v		v	
Deep Angel	Not specified	**Editing**: remove faces from photos	Image			v			v			
Sequel	Not specified	**Editing**: Replace and/or add visual effect to background or foreground of videos	Video			v		v	v	v	v	v
Artbreeder	Entertainment	**Blending** images and style	Image	Interactive ML		v	v	v	v			v
Dream Gen-er-a-tor.png Deep Dream Generator	Not specified	**Blend** images and style	Image			v	v					v
DeepArt	Not specified	**Blend** images with selected styles	Image			v	v		v		v	v
Style Transfer	Developer experienced with TensorFlow	**Blend** images and style	Image	Users can twig the model parameters		v					v	
Go Art	Not specified	**Blend** images and style	Image			v	v					v
Visionist	Not specified	**Blend** images and style	Image			v	v					v
Instapainting (AI Painter)	Not specified	**Blend** images and style	Image			v	v					

Product	Target user and purpose	Description and key features	Output	Address HAII challenges	Searching	Visualizing	Relate	Thinking	Exploring	Composition	Reviewing	Disseminating
Font Map	Not specified	**Blend** any two typefaces to create new fonts	Typography			v	v					
Rosebud AI	Content sharing on social media	**Blend** images with video to make animation	Animation, short video			v	v				v	v
NSynth: Sound Maker	Not specified	**Blend** different sound effects to make new sounds	Audio			v	v		v			
Khroma	Not specified	**Generate** color palette based on your selection of colors	Color palette	Interactive ML + data available for download	v	v			v		v	
AutoDraw	Non-designer	**Generate** icon or drawing as you draw on screen	Image			v		v				v
Uibot	Not specified	**Generate** UI design template automatically (does not take any user inputs)	UI template			v						
This person does not exist	Not specified	**Generate** human face automatically (does not take any user inputs)	Image			v						
Font Joy	Not specified	**Generate** fonts based on users' selected parameters (e.g., font family)	Typography			v	v				v	
Font Visualizer	Not specified	**Generate** fonts based on users' selected parameters (e.g., font family)	Typography	Interactive ML		v	v	v	v		v	
Brandmark	Small business owner	**Generate** brand logo and business car based on keywords of a brand	Image and UI template			v		v	v	v	v	v
René by Jon Gold	Not specified	**Generate** graphic design template based on users' selected parameters	UI template			v			v	v	v	
Color Mind	Not specified	**Generate** color palette automatically (users can edit individual colors later on)	Color palette			v					v	
Playground.ai	Professional content creator, small business owner	**Generate** shapes and color palette design (can couple with developers for more advanced product design)	Graphic or product design			v		v	v	v	v	
Generative Design by Autodesk	Professional designer	**Generate** simulation of possible design outputs based on design guides input by users	Graphic or product design	Show simulation to address the output complexity		v		v	v	v	v	
Design.AI	Small business owner or marketing agency	**Generate** image, audio, or video content based on users' specified parameters	Image, video, audio, markup, speech			v		v	v		v	v
ML Lab by Runway ML	Not specified	**Generate** image based on keywords input by users	Image			v	v	v	v	v	v	v
Magenta Studio	Not specified	**Generate** short music clips based on inputs using an interactive panel	Music	Interactive ML		v	v	v	v			
Quick Draw	Not specified	**Generate** text as users draw on screen	Text			v						
Sketch RNN	Not specified	**Generate** icon or drawing as you draw on screen	Image			v						
Handwriting	Not specified	**Generate** handwriting as you write on screen	Image/Text			v						
MuseNet	Not specified	**Generate** music based on selected musicians' styles	Music			v	v					
Fronty	Not specified	**Transform** image to editable web page	UI template			v		v	v	v	v	v
Uizard	UX design for non-designer	**Transform** hand-drawn sketches to digital forms	UI Template			v		v	v		v	v
Artyline	Professional content creator	**Transform** sketch to digital forms using AR convertor	UI template			v	v	v	v	v	v	v
Zecoda	Front-end designer, novice developer	**Transform** sketch to front-end code	Front-end code								v	
TeleportHQ	Novice web designer/developer	**Transform** GUI-based UI design to front-end code	Front-end code			v		v	v	v	v	
Sketch2Code	Novice web designer/developer	**Transform** hand-drawn sketch to HTML code	Front-end code			v					v	
Cartoonify	Not specified	**Transform** photographs into sketches	Image			v						
Visual Eyes	UX/UI designer	**Inform** attention heatmap per image/UI uploaded by users	Predictive heatmap			v		v		v		