Why or Why Not: Barriers of Adopting Generative AI in Human-AI Co-Creativity

ANONYMOUS AUTHOR(S)

Advances in generative AI (GenAI) have offered a wide range of compelling opportunities for creative professionals, inspiring the generation of novel ideas and facilitating content production. However, when it comes to adopting GenAI in their innovative processes, creators express much hesitation. In this position paper, we thus elaborate on common obstacles that stop creators from embracing the forefront of GenAI based on our prior and ongoing work as well as our participatory experiences in this research field. Together, we discuss possible approaches to addressing these challenges and where we see potential in the future of human-AI co-creativity.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**; **Interaction design**.

Additional Key Words and Phrases: generative AI, creativity, human-AI co-creation, idea generation, content production

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1 INTRODUCTION

In 2016, Autodesk announced that *generative design* will depict the future of creativity. With cutting-edge artificial intelligence (AI), intelligent machines can help human creators with assembling, re-mixing, simulating, producing, and even assessing a wide range of possible design elements, while designers can just focus on the "hard questions" during creative problem-solving. Together, this collaborative paradigm is proposed to generate more innovative design in a more efficient and cost-effective fashion. However, while more than half a decade has passed since this vision has been proposed, what has pulled content creators, designers, and artists back from this creative utopia? The current position paper posits three key areas for researchers and practitioners to re-consider when leveraging the potentials of generative AI (GenAI) to realize human-AI co-creativity of the next generation. In particular, these key concerns include:

(1) To consider appropriate time points when GenAI should involve in creators' work processes.
(2) To communicate AI capacity and offer interpretability and explainability to its behaviors.
(3) To learn from the differences between professional and amateur creators as inspirations for creativity assessment to improve the performance of GenAI.
(4) To take a holistic view toward user experiences during human-AI collaboration, particularly when users may hold defensive attitudes towards creativity-support tools.

2 THE CREATIVE TRAJECTORY: WHEN SHOULD AI HELP?

To begin with, humans' creative production comes with step-by-step processes, instead of yielding novel products out of the blue. Though individual differences exist in such processes and different disciplines have proposed domain-specific workflows, previous research (see a review in [8]) has found they can generally be segmented into four key stages, including (1) defining problem space, (2) incubating (or mind wandering), (3) executing ideas, and (4) presenting final products. In a recent case study examining current AI-empowered creativity support tools in the consumer market [anonymized for review], we remark that the majority of these existing tools target to support the later two stages of the creative processes. In other words, even though GenAI has promising potentials to yield novel ideas, currently, the technique is more often used in content execution, when the primary ideation phase has already passed and the goal when applying these tools is often to implement ideas that have already been generated by humans alone. At this time, we see limited space and freedom for GenAI to offer out-of-the-box inspirations, as creators are already too far down in the creative trajectory. By contrast, when creators are still brainstorming for ideas (particularly in Stage (1)), the oftentime unpredictable output of GenAI can introduce "healthy chaos" or randomness into creative processes, which is said to enhance innovation [9]. In this regard, we posit that before designing and focusing on what and how a GenAI application can augment creative production, scholars and practitioners should also consider *when* the technique can offer the greatest assistance. **Specifically, we propose future design of GenAI tools for creativity support should target at facilitating the earlier stages of creative production.**

3 MENTAL MODELS OF AI: HOW TO TRUST A NON-HUMAN BRAIN?

Through participation in workshops with artists and designers, we collected qualitative feedback regarding why these users may be hesitant to adopt GenAI in the first place, and much has to do with the "non-human" nature of how AI process information (i.e., data) and perform decision-making. As we introduced in the previous section, human creators follow a piecemeal approach to assemble their creative content, which is fundamentally distinct from the oft-referred "black box" nature of AI. Moreover, for machines to process text, image, and other multi-modal data and generate dynamic output, the front load of machine learning often require extensive pre-processing to handle the input data. As a result, the format of data that is fed into an AI model is often remote from how humans perceive them in the real world. For instance, as numerous architects pointed out during one of our previously participated workshops, they found it less appealing to take in GenAI product for architecture design as "the models 'think' in a 2D way, while in architecture, everything should be conceived in 3D." Together, the differences between humans and machines' "thinking style" have held these creators back from relying them during work processes. Along the same vein, recent work in human-centered AI and human-agent teamwork has dedicated much effort to explore how to effectively communicate the unique, non-human ways of "AI thinking" to its users, possibly through UX or interaction design [1]. **Here, we echo on this line of human-AI interaction design practices and emphasize that offering explainability and interpretability is as well important for users to adopt GenAI in their creative workflow.**

4 ASSESSING CREATIVITY: WHOM SHOULD AI LEARN FROM?

Harold Cohen's computer program AARON [3] was one of the very early art pieces which adopt computational approaches to experimenting with the potentials of *machine creativity*. When this concept is first proposed, the greatest critique arguing machine's incapability to perform *evaluation* of creative outcomes. That is, even thought an artificial program can yield a large number of "candidate" products, it cannot effectively distinguish the truly creative ones from the ordinary. In the case of AARON, the artist resolved this issue through a collaborative workflow, where the AI application generated a set of work and they would choose outstanding pieces from the batch regularly. However, we may ask why machines *cannot* possibly assess creativity —a prominent challenge with this topic concerns the lack of measurement for creativity. A common belief holds that, even for humans, there are no universally acknowledged standard for creativity assessment, leaving no benchmark or predictive parameter for AI to adopt. Realizing this issue, we took a step back and conducted a longitudinal mixed-methods study to examine how creatives identify, evaluate, and seek creative content on digital platforms. When we plotted the work deemed as "creators" based on their stylistic similarity on an t-SNE map (Figure 1), we found professional creators, regardless of their disciplines, tended to converge on how and what they considered as creative work, while the amateurs demonstrated greater randomness in their evaluative decisions. Not only do such findings resonate with qualitative or behavioral studies conducted in prior psychology research (see the Four-C model of Creativity by [6]), but if we can systematically decompose how amateur creators develop and land on consensuses for creative decisions, learning from this process can possibly inform effective and quantifiable solutions to creativity assessment. **Therefore, we recommend researchers and developers can learn from how professional versus amateur creators differ in their viewings, ideating, and working patterns to inspire future GenAI applications.**

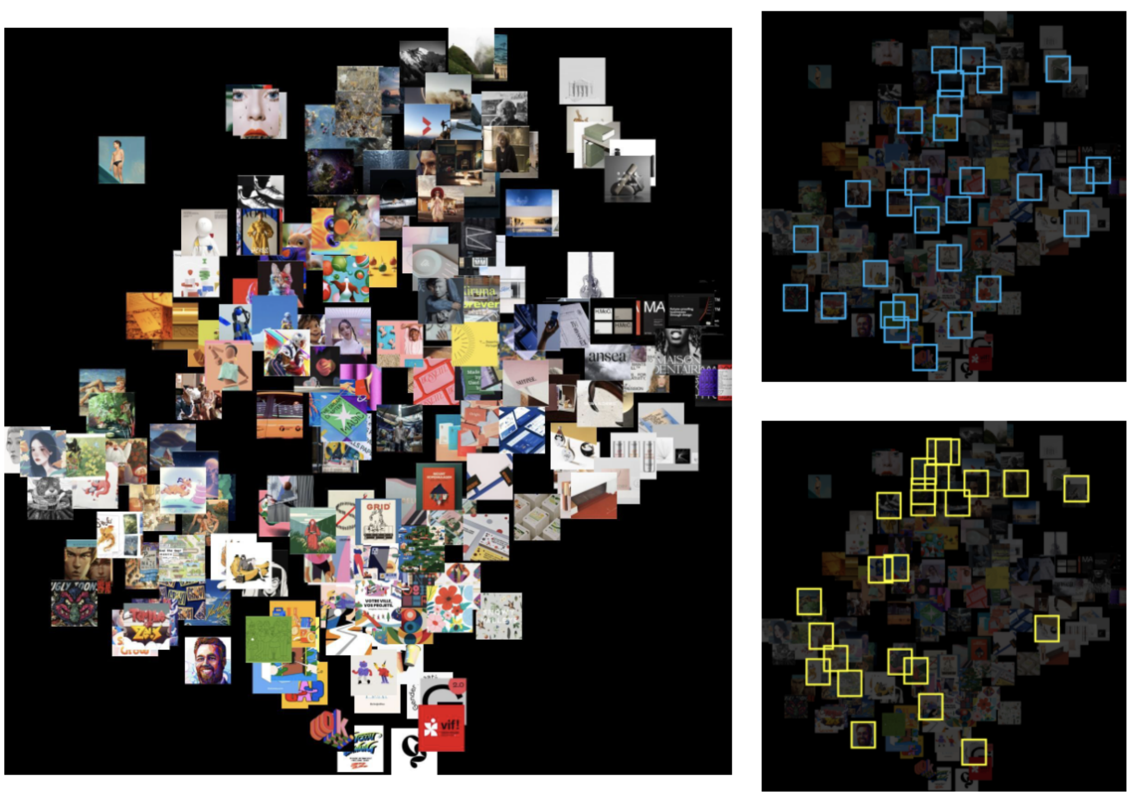

Fig. 1. Creative content identified by amateur (top-right, highlighted in blue outlines) and professional creators (bottom-right, highlighted in yellow outlines) in a longitudinal study tracking their content viewing behaviors across one month. Images are arranged based on their stylistic similarity on a t-SNE map.

5 COLLABORATION OR COMPETITION: IS CREATIVITY AS THE LAST TERRITORY OF HUMANITY?

Last but not least, whether users adopt GenAI to produce creative work is not solely driven by their usability. Instead, qualitative interviews have found designers and artists often undermine the value of AI applications as they consider creative craftsmanship and content production should be "pure human work" and the ability to produce creative pieces is uniquely possessed by humans [2, 8]. On the other hand, mass media often depict AI has this superpower that will replace human labors and eventually overtake the entirety humankind [4, 5]. Together, we often see creators demonstrating defensive attitudes, attempting to protect their unique roles in the cultural domain. Indeed, in our previous work [anonymized for review] asking human subjects to work on creative ideation tasks with two versions of chatbots – one offering creative, informative ideas, while the other providing low-quality, cliché ideas, we found although participants may report positive user experiences with the creative bot in the first place, they were less willing to cooperate and collaborate when they encountered it again in subsequent tasks. Then, taking an opposite route, we may ask whether computer-supported tools should simply focus on facilitating lower-level tasks that do not necessarily demand creative insights. Interestingly, various work has found that creators can as well come up with groundbreaking ideas when they hone in on trivial components during creative production [7], and studies using neuroimaging techniques did not found significant differences in neural responses and activities when humans were generating ideas (compared to the resting states of mind or when they were performing other mundane tasks). In this regard, it does not seem effective to determine the role of AI in collaboration with humans solely through the types of tasks it can serve. **Instead, we suggest taking a more holistic view to this problem and highlight that creative production is *not* just about a person or a team's capability of producing creative work, but the working and collaborative experiences of users can also play a critical role in adopting GenAI in their work processes.**

6 LOOKING FORWARD: GENAI IN THE FUTURE OF HUMAN-MACHINE CREATIVE PARTNERSHIP

To conclude, in the current paper, we outline four common challenges for scholars and practitioners to take into account when researching and designing future GenAI tools for human-AI co-creativity. We first propose that the design of GenAI techniques should consider appropriate time points to offer support, while, specifically, we posit that early involvement during users' creative processes can possibly yield more fuitful collaboration. Secondly, we recommend GenAI developers to refer to recent human-AI interaction design practices (specifically those concerning interpretability and explainability of AI), making the attempt to communicate the non-human fashion of AI processing and its limitation. The third, when it comes to improve GenAI for performing better assessment of its generative outcomes, we recommend seeking inspirations through studying the differences between professional and amateur creators. Finally, in light of the protective attitudes held by creators, we propose the design of future GenAI should take a more holistic view towards users' experiences during the work processes, aiming for comfort and harmony in human-AI collaboration.

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