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Extending human creativity with AI

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ABSTRACT

The development of generative AI has led to novel ways that technology can be integrated into creative activities. However, this has also raised concerns about how human creators will be affected, and what impact it may have on creative industries. As a result, there has been research into how we can design AI tools that work with human creators, rather than replacing them. In this paper we review approaches utilized to build AI tools that facilitate human creativity and allow users to engage fully and authentically in the creative process. These include leveraging AI models to help us shed light on elements of the creative process, building interfaces that encourage exploration of ideas, and designing technological affordances that can support the development of new creative practices.

In recent years, our relationship to technology has undergone significant changes. The scope of what computing is used for has greatly expanded, and as a result the way that we use technology, particularly within the creative sphere, is also expanding. As AI models are increasingly able to generate artifacts, we are beginning to see changes to existing paradigms of artistic production (Du Sautoy, 2019; Vear & Poltronieri, 2022). This raises concerns about how AI creativity can coexist with human creativity, and whether it might be used to replace human creators (Caporusso, 2023; Fisher, 2023; Vinchon et al., 2023). Since AI models also require large sets of training data that may be acquired without the original creators' permission or any compensation for the use of that data, there are concerns about the question of artistic ownership, and whether copyrighted works should be accessible to AI models as training data (Sturm et al., 2019; Vear & Poltronieri, 2022; Vinchon et al., 2023). Already we are starting to see creators push back against this, with the development of tools, such as Nightshade, that can alter the underlying data in a digital artifact in ways that make it unable to be used as training data for these models (Heikkila, 2023).

Creativity has often been evaluated by assessing the novelty and usefulness of the ideas and artifacts generated during the creative process (Boden, 2004; Runco & Jaeger, 2012). However, it is also important to acknowledge that engaging in the creative process has intrinsic value for humans, independent from the artifacts that are produced (Acar et al., 2021; Benedek et al., 2020; Csikszentmihalyi, 2013; Keenan-Lechel et al., 2023; Warr et al., 2018). Part of what makes participating in the creative process enjoyable is the idea of 'flow experiences', which are characterized by immersive engagement in the process itself, irrespective of the eventual outcome (Csikszentmihalyi, 1999). Creativity can therefore be understood as an experiential process, driven by intrinsic motivation and defined by practices of intentional creation or curation (De Pisapia & Rastelli, 2022; Hertzmann, 2022; Runco, 2023). Because of this, authentic engagement in the artistic process is still important to many creators (Kaila et al., 2023). Currently, there are many open questions of how integrating AI tools into creative workflows can affect the ability of human creators to have meaningful agency within the creative process (Huang & Sturm, 2021). Additionally, the black box nature of many generative tools has the potential to remove key experiential aspects of the creative process that allows for intentionality and self-expression (Dahlstedt, 2021). Many of the concerns about AI creativity are therefore addressing a mismatch between the functionality of these technologies, and the types of experiences that are aligned with human needs and desires (Allred & Aragon, 2023; Batista & Hagler, 2022; Vinchon et al., 2023).

However, computational creativity support tools do have the potential to be useful in facilitating creativity when they are aligned with the underlying cognitive processes of creative thinking (Amitani & Hori, 2002). It is therefore important to focus on understanding creativity as an experiential process in order to identify the underlying mechanisms that lead to the emergence of creativity (Runco & Bower, 2023). This can then inform the design of AI tools that are able to align with our understanding of what it means to engage in creative practices in an authentic and meaningful way. In order to examine this, we reviewed literature within the fields of Creativity Research, Creative Cognition, AI, and HCI, in order to identify how AI tools can be integrated into the

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creative process in ways that allow users to still exercise intentionality and expressivity. Research in this area includes computational modeling of creative processes, and designing technological affordances that encourage creative exploration of ideas and which can support the development of new creative practices. In this paper, we will explore these ideas by first examining how we can draw meaningful parallels between theories of creative cognition and AI, how computational models can learn how to create meaningful representations of ideas, and how generative AI models can be leveraged for human-AI co-creativity.

Modeling creativity

Creativity involves engaging in a process of exploration and discovery that enables us to generate new ideas and artifacts (Keenan-Lechel et al., 2023; Martin & Wilson, 2017). Therefore, in order to understand creativity, we need to examine the processes by which new ideas are generated. A key component of creativity involves abstraction, the process of learning how to make sense of information by identifying the conceptual components which are relevant for the construction of meaning (Atkinson & Barker, 2023; Root-Bernstein & Root-Bernstein, 2013). Within individual domains, this leads to the development of different forms of symbolic knowledge, structures of thought, and generative rules, and the way in which we explore and develop new ideas within a given domain is shaped by these organizing principles (Boden, 2004). For example, research into the process of auditory grouping reveals that the human brain is able to make sense of sound based on features such as pitch, timbre, and amplitude (Bregman, 1994). From these, we see the emergence of organizing principles of musical structure that allow us to perceive musical components such as rhythm, melody, and harmony (Jackendoff & Lerdahl, 2006). Musical notation provides a means of symbolically representing these concepts, which composers are then able to use to generate new musical artifacts (Levitin, 2006).

We can therefore begin to bridge the conceptual divide between AI creativity and human creativity by drawing parallels between these components of creative cognition, and the types of information processing that are utilized within AI (Mateja & Heinzl, 2021; Saunders & Gero, 2002). AI models are also able to learn and represent knowledge, identify patterns and knowledge structures, and use these to make useful and appropriate connections and inferences (Catarau-Cotutiu et al., 2022; Russell, Norvig & Davis, 2010). When AI models are being trained on a set of artifacts from a particular domain, they utilize a process known as representational learning, in which the model learns how to identify and represent features of the data that allow it to identify patterns and generalizable rules that describe the data in a meaningful way (Boden, 2004; Vear & Poltronieri, 2022). As a result, AI tools have the potential to support human creativity by providing explicit representations of relevant knowledge, knowledge structures, and generative rules at different levels of representational abstraction (Boden, 2004). In order to build AI tools that can be incorporated into the creative process, it is therefore necessary to consider how individuals draw on their understanding of the domain in order to construct meaning and generate new content.

Associative thinking and analogy

Two important cognitive mechanisms involved in creativity are associative thinking (Beaty & Kenett, 2023; Runco & Bower, 2023) and analogical reasoning (Chesebrough et al., 2023; Root-Bernstein & Root-Bernstein, 2013). The associative theory of creativity posits that new ideas are developed by leveraging associative relationships stored in memory in order to draw connections between ideas that previously seemed unrelated (Beaty & Kenett, 2023). This can be modeled computationally by constructing a network graph in which concepts are represented as individual nodes, and associations between concepts are indicated by drawing a connecting edge between the corresponding nodes within the network (Kenett et al., 2014). The edges linking sequentially connected nodes can then be chained together to create longer associative paths within the relational structures of the network. Using this framework, associative thinking can be understood as a process in which the relational structure of the concept network is utilized in order to explore connections between more distantly related concepts (Kenett, 2019; Olson et al., 2020).

This allows us to analyze the development of different types of relational structures that exist between concepts within the associative network, which is a core component of analogical reasoning. Analogical reasoning involves identifying instances where there are similar patterns in the relationships between concepts, even if the concepts themselves are not similar (Chen et al., 2017; Root-Bernstein & Root-Bernstein, 2013). Analogies allow us to leverage these structural similarities to create a mapping between the concepts in the original context, and those in the novel context (Breitman et al., 2007). By examining the conceptual relationships that exist in one setting, we can then draw on the similarities between their relational structures to infer possible new connections that could be drawn between concepts in the other setting (Gilon et al., 2018). Both associative thinking and analogizing work by exploiting existing relational structures between concepts to explore different ways in which it is possible to generate new connections (Gentner, 1983; Holyoak et al., 2023). Because AI is capable of computationally modeling the relational structure of data, AI tools can be used to identify analogies by analyzing network structures for similar relational patterns (Catarau-Cotutiu et al., 2022). For example, search engines have been developed that leverage analogical reasoning to support innovation in product design. These are trained on product descriptions in order to extract relational information about elements of a product design and its functions which can define a 'problem schema' (Hope et al., 2017). The designer can then use the tool to search for examples of products that have a similar problem schema to gain inspiration for possible design solutions. By constructing abstract representations of relational data, these models can be used to search through large sets of data to identify new conceptual connections that can be generated.

Tacit knowledge

A great deal of creative activity is also shaped by implicit, or tacit knowledge about the domain (Boden, 2004). Harold Cohen, the creator of the art system AARON, pointed out that the reason why simulating creative expertise on machines is so difficult is because they utilize different ways of perceiving and understanding information (Cohen, 1999). In describing his process of teaching AARON to paint, he found that the key to recreating human expertise was to identify the visual aspects that had the greatest impact on human perception, and translate these into an information format the machine could understand and interpret. In the case of AARON, this involved being able to distinguish and choose between levels of brightness and color relationships within the artwork. However, the challenge is that tacit knowledge such as this can be difficult to articulate and describe in a systematic way. Humans working within a domain develop procedural knowledge through experience, but might not be explicitly aware of the underlying 'rules' that shape this procedural knowledge.

AI models, however, are able to learn from unstructured data in order to identify generalizable rules without needing them to be explicitly coded into the system by a human user (Boden, 2004; Russell et al., 2010). AI models can therefore be used to explicitly identify generative rules or structures that humans either perceived implicitly, or were not aware of, and help to identify important conceptual components of creativity for a given domain (Legaspi et al., 2007). For example, an AI model trained on paintings was able to extract different patterns of brightness and darkness to identify how artists used strategies of shading and color to create a sense of illumination (Stork, 2023). Another AI model which was trained on recordings of music performances was able to capture information about how musicians achieve expressivity in performance by examining how artists introduced slight variations to the timing, dynamics, and articulation of individual notes (Widmer, 2002). The model was able to generate a set of rules for predicting which expressive variations should be applied to individual notes. When tested on a different set of recordings, the accuracy of the model's predictions were above that of random chance. This indicated that the model was indeed capturing generalized tacit knowledge about how to expressively perform music, rather than stylistic elements specific to the performers whose recordings it was trained on.

Representation mapping

An important consideration when computationally modeling creativity is that the underlying data representations used by AI models might not be aligned with salient aspects of human perception, which has the potential to introduce constraints into the user workflow (Pardo et al., 2019). A solution to this is using machine learning techniques to create a mapping between the underlying parameters of the model, and representations that reflect human understanding of the domain (Mishra et al., 2021). One area of application for this is digital music production tools. In digital music, sound effects are created by increasing or decreasing the amplitudes of specific frequency ranges. The tool SocialEQ supports the user in this process by learning how these parameters correspond with individual words that describe qualities of sound (Pardo et al., 2019). The mapping process involves SocialEQ generating different combinations of amplitudes across the frequency spectrum, which a human user evaluates based on how well the sound effect matches the descriptor word. Using this feedback, the model learned the appropriate set of parameters that corresponded with the descriptor word, enabling the user to then apply the sound effect to their music. This illustrates how AI can be used to bridge different conceptual paradigms used by computers and humans to help users to execute their creative intentions.

Creativity support

One way of conceptualizing creativity is as the intentional process of cultivating novelty (Weisberg, 2015). In research on the development of creativity in children, Karmilioff-Smith found that this requires conscious awareness of relevant knowledge constructs in order to generate new ideas through intentional variation (Boden, 2004). This facilitates 'what-if' thinking (Shneiderman, 2000) by enabling an individual to consider different possibilities for recombining and transforming these concepts (Boden, 2004). The technological affordances of computational creativity support tools can therefore provide users with explicit representations of domain knowledge that facilitate intentional exploration of different creative possibilities (Olteţeanu et al., 2019).

Ideation support

AI computational support tools can not only help users to execute their creative intentions, but also to explore new ideas. When an AI model is trained on a set of artifacts, it extracts information about features of the artifacts that differentiate them from one another, which allows the model to encode information about each artifact in the form of a feature vector (Elgammal et al., 2017). It is then possible to map the high-dimensional feature space to a lower dimensional space that captures meaningful dimensions of variation by preserving the relative positioning of individual feature vectors (Roberts et al., 2018). This allows the AI to create a representation of the feature space as a visual spatial mapping that the user can then explore. Spatial mappings are useful because they encode similarity between individual artifacts in terms of the distances between their corresponding feature vectors within the higher-dimensional space (Falomir & Olteţeanu, 2019; Hart et al., 2017; Hebart et al., 2020). This results in a representation of the feature space that aligns with human perception of the similarities and differences between artifacts and enables the user to explore variations in an intentional manner (Green et al., 2023; Hamanaka et al., 2008; Wu et al., 2021). As the cognitive process of spatial reasoning has been shown to play a role problem-solving and abstract thinking, creating a 'map' of the possibility space can support creative exploration through strategies of 'active divergence' (Vear & Poltronieri, 2022). We can see this demonstrated in the interface for Audealize, seen in Fig. 1, which takes the individual descriptor words used for SocialEQ, and creates a 2-D map in which distances between words on the map represents how similar their sounds are to one another (Pardo et al., 2019). Users can click on a word to apply the corresponding audio effects, but can also explore by selecting other words that are nearer or farther from the original descriptor. By mapping the high-dimensional space of the audio parameters to a 2-dimensional map, the interface provides a representation of the audio concepts that can be navigated in a way that aligns with human perception of sound.

AI models are also able to generate new outputs that are not contained in the training data, by leveraging their high-dimensional representation of the feature space to interpolate the features values of any theoretical point within the space (Elgammal et al., 2017; Roberts et al., 2018). One example of this can be seen in a tool which helps composers to explore different possibilities for chord progressions by interacting with a 2-dimensional slider (Nichols et al., 2009). The model was trained on examples of chord progressions, through which it was able to extract generalized information about relationships between chords and principles of functional harmony. When provided with a melodic line, the model uses this knowledge to generate an accompanying chord progression. The slider then allows the user to navigate within a grid, whose axes represent dimensions of variability within the latent space. By using the slider to make changes to the underlying parameters of the model, the user can generate different possible chord progressions that could accompany the melody.

Because spatial mappings preserve meaningful relationships between the underlying features, the axes of the lower-dimensional mapping are able to capture perceptually salient dimensions of variability. This means that as the user explores different points within the map, the underlying feature values change in ways that create meaningful variation (Roberts et al., 2018). As a result, the user can connect their exploration of the map with meaningful changes to the generated outcomes, allowing them to intentionally direct their exploration to align

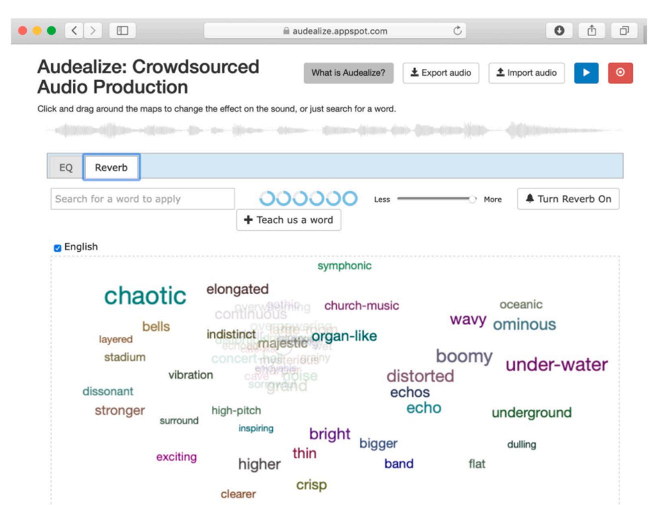

Fig. 1. The Audealize interface (Pardo et al., 2019). Proximity of words on the map reflects the similarity in their sounds. Users have the option to click on a word to implement its corresponding audio effects or explore by selecting words closer or farther from the original descriptor.

with their goals (Davies et al., 2014; Shneiderman, 2000). An example of this is NSynth Instrument, a tool created by Google Magenta that allows users to explore the space of musical timbre (Roberts et al., 2018). Timbre describes the characteristics of a sound that are separate from pitch, and can be heard in the way that different instruments have distinct qualities of sound. NSynth was trained on short recordings of notes being played by different types of instruments and synthesizers to learn features of the audio signals that corresponded with differential elements of timbre. By modeling the latent structure of these features, NSynth was able to take high-dimensional data about musical timbre and create a 2-dimensional grid that allowed the user to explore different combinations of timbral features.

Another benefit to reducing the dimensionality of the high-dimensional feature space with spatial mapping is that it allows the user to navigate between different combinations of parameters. We see this in the music production tool 'Mixploration', which was designed to be used for audio mixing in music production (Pardo et al., 2019). The process of audio mixing involves making adjustments to the volume and sound effects of individual tracks, which are layered together to create a song. Each track, and each audio change that can be applied to that track, introduces another parameter that can alter the overall sound of the song. Most mixing tools represent these parameters as separate points of interaction, which encourages the user to think about each parameter as independent from the others. The Mixploration interface, however, provides the user with a 2-D map in which each point represents a different combination of settings across all the tracks. This allows users to explore variations across not only individual parameters, but different combinations of parameter values (Pardo et al., 2019). A similar interface is used in the Google Magenta tool MusicVAE sequencer, seen in Fig. 2, which provides users with a spatial mapping interface for exploring musical variations produced through different ways of blending short rhythmic and melodic sequences. Additionally, with MusicVAE users can not only explore different points on the map but also draw paths through the space that allow them to hear how the sequence is dynamically transformed as the underlying parameters are changed (Roberts et al., 2018). The ability of AI models to generate new artifacts through interpolation allows users to explore variations on an individual idea or explore different ways that concepts can be blended together. This approach allows the user to make inferences about the possibility space beyond what is captured in the artifacts that already exist.

Personalization

Another important consideration when designing human-centered creativity support tools is the ability for AI to support creative experimentation through personalization (Hwang, 2021). Creativity support tools that allow users to externalize their ideas help them to organize and identify relationships between those ideas, and identify potential gaps to be explored (Shneiderman, 2002; Terry & Mynatt, 2002). Computational tools not only support externalization but can also be designed to allow users to engage in dynamic interactions with digital artifacts that support the meta-cognitive activities involved in creative experimentation (Keenan-Lechel et al., 2023; Schraw & Moshman, 1995). For example, the tool 'Knotation' allows choreographers to create and interact with their own visual representations of choreographic ideas at different levels of abstraction (Ciolfi Felice et al., 2018). When integrated into the choreographic process, the interactive nature of the tool was found to support the process beyond simply serving as a means of documentation. Because the tool allowed flexible creation and manipulation of personalized representations, users found that it helped them to become aware of new choreographic possibilities. As a result, tools that support dynamic personalization can help users become more intentional in their decision-making processes (Ribeiro et al., 2017). Another example of this is the Macroscopic Composition Supporting System (MACCS), which is designed to support music composition (Amitani & Hori, 2002). With this tool, individual phrases from within the composition can be represented as separate digital artifacts in order to spatially map them onto a 2-dimensional visualization that captures how similar they are to one another. This allows composers to visualize the amount of musical variation within the piece and identify sections that are potentially too repetitive. In doing so, MACCS supports the process of deliberate creativity, in which the creative decisions that an individual makes when developing an artifact are informed by the context of the 'emergent whole' (Brandt, 2023). When used to create interactive representations that can dynamically evolve in a way that is personalized for the user, AI tools can therefore facilitate iterative, reflective working processes that frequently occur in creative domains.

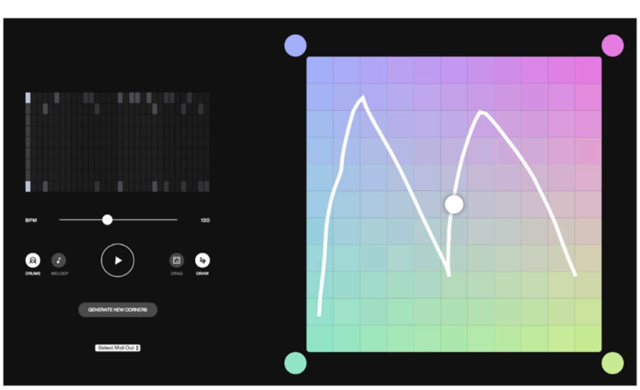

Fig. 2. MusicVAE Sequencer (Roberts et al., 2018). The interface provides the user with a 2-D interpolation palette for blending short rhythmic and melodic sequences in diverse ways.

Co-creativity

AI models are able to infer generative rules that outline how to construct artifacts that are appropriate for the given domain. As a result, it is possible to build generative AI agents that are able to engage in a co-creative process with the user by generating new content that can be incorporated into the creative artifact (Micchi et al., 2021). Here we see a blurring of the lines between what differentiates a tool from a collaborator, as both the human user and the AI agent are able to exert a degree of influence over how the creative process unfolds (Pepperell, 2002). This introduces a shift in perspective away from the action-response interaction paradigm that exists with many non-generative tools, as the system is able act as a creative partner, not just a passive tool (Vear & Poltronieri, 2022).

Novelty and variation

An important part of the creative process is experimentation and iterative exploration of variations (Terry & Mynatt, 2002). Because of their information processing capabilities and the large amount of data at their disposal, AI models can support this process by generating artifacts that serve to highlight different possible directions for creative exploration. As we have seen in previous examples, AI models can provide users with interactive tools for exploring different variations that are possible by changing parameters. However, as the complexity of the problem space increases, trying to explore all different possibilities of parameter combinations becomes difficult, and more targeted means of exploring variations are needed (Gilon et al., 2018). In this case, the ability of AI models to learn the rules and conventions of a domain can be leveraged in order to generate artifacts which are contextually appropriate for the problem space that the user is exploring. For example, the Google Magenta tool 'Continue' is able to analyze a musical sequence provided by a user and extend it by generating additional bars of music that are contextually appropriate (Abolafia, 2016).

As a result, generative AI tools can generate examples that help the user to better understand the range of possibilities available within the problem space (Koch et al., 2019; Kulkarni et al., 2014). One example of this is DesignAid, a tool that supports ideation in the design process (Cai et al., 2023). With DesignAid, the user provides short phrases that describe their ideas, which DesignAid then uses to search for related ideas. This is done by leveraging a Large Language Model (LLM) to create a semantic embedding, which is a feature vector that maps the phrase to an abstract high-dimensional space whose structure encodes information about contextual meanings and similarities between words (Mikolov et al., 2013). The model then searches for other semantic embeddings that are close by to identify related ideas that the designer might find useful. By generating examples of related ideas, this encourages the user to engage in a broader exploration of the idea space and has the potential to provide inspiration for new creative directions (Epstein et al., 2022; Wilf, 2023).

Generative AI tools can also be designed to support the process of 'near-term experimentation' in which users are able to iteratively explore and evaluate different creative possibilities (Jing & Yang, 2015; Terry & Mynatt, 2002). For instance, the ALYSIA app supports users in a co-creative songwriting process by generating ideas for song lyrics, and melodies that could accompany them (Ackerman & Loker, 2017). When using the app, the user can input an initial set of lyrics to which ALYSIA will respond by generating suggestions of additional lyrics that match the theme of the song. As the songwriter chooses and tweaks these suggestions, adding them into the piece, ALYSIA's generation of subsequent lyrics takes these into account. It can then generate a melody by using a prediction model that has been trained to learn meaningful relationships between a song's lyrics and its rhythmic and harmonic features, in order to create a melody that fits the given lyrics and make 'sense' musically (Ackerman & Loker, 2017). By conditioning the generated artifacts on content provided by the user, generative AI tools can employ strategic, contextually informed approaches to exploring novelty and variation in order to generate solutions which are more likely to be relevant for the user's goals. Another example of this is the Creative Sketching Partner (CSP), an AI partner that takes as input user sketches of design ideas to then generate variations on the sketch that incorporate new design ideas, or re-contextualize the design task (Karimi et al., 2020). Users were able to increase the creativity of their final design by using these variations as inspiration for incorporating new design features or altering existing features. Because these tools are informed by content provided by the user, they are able to generate variations that can introduce novelty while still aligning with the user's creative intentions. For example, the tool 'ChordRipple' helps composers explore different harmonic possibilities by analyzing the chord progressions in a musical sequence written by the user, and then generating different possible variations that would still make sense within the musical context (Huang et al., 2016). To do this, the AI model is trained on a data set of chord sequences to learn the latent space of chord progressions, and then makes suggestions based on the chords the composer is already using by identifying alternative chords that are different, but still close to the original chord within the latent space. Because the AI model captures tacit knowledge about functional harmony, i.e. the role that chord progressions play in shaping the musical structure of a piece, it is able to identify which alternative chord variations are appropriate given the musical context of the piece in order to support a more targeted exploration of the harmonic space.

Interaction paradigms

Within these co-creative systems, both the human user and the AI play a role in shaping the creative process and the development of the creative artifact (Boden, 2004; Vear & Poltronieri, 2022). When working with an AI that can exercise a degree of agency within the creative process, the interactions between the user and the AI are part of a participatory sense-making process in which the user learns how to construct a meaningful interpretation of the AI's actions (Davis et al., 2016; De Jaegher & Di Paolo, 2007). AI tools geared towards supporting human creativity therefore need to support interactions that allow the user to identify actions available to them which will allow them to execute their creative goals (Davis et al., 2017; Deshpande et al., 2023). These interactions determine the degree to which the user is embedded in the creative process, which in turn impacts their ability to intentionally encode meaning into the artifact they are creating (Lawton et al., 2023; Wu et al., 2021). This is the motivation behind much of the work currently being done to create 'steerable' AI tools that provide the user with greater control over the generative process (Das & Varshney, 2022; Louie et al., 2022). Some strategies for designing steerable tools include giving the user the ability to adjust parameters that will influence the features of the generated output, and the ability to then evaluate and curate these outputs (Compton, 2019; Secretan et al., 2008). This can involve creating 'hyperparameters' that represent more abstract concepts, such as novelty, or emotional sentiment (Chakrabarty et al., 2022; Karimi et al., 2020). For example, ALYSIA incorporates an 'explore versus exploit' parameter that allows users to specify how much novelty they want in the melodies being generated. Selecting a lower level of novelty prompts the app to generate melodies that are more similar to what is seen in the training data, while selecting a higher level of novel will yield more unique melodies. The user is then able to curate the selection of generated melodies and decide which ones they want to use for their song (Ackerman & Loker, 2017). With this approach to co-creation, the focus is less on being able to generate a single, static artifact, and more about how to facilitate the process of creative experimentation by generating a range of different ideas (Cassion et al., 2021; Vear et al., 2022; Wu et al., 2021).

In addition to generating variations and extensions of the user's ideas, AI tools can also be designed to generate artifacts that outline a set of creative constraints to provide the user with a 'problem' to solve. The choreographic support tool 'Scuddle', for example, generates a set of abstract representations of body positions to serve as high level reference points that create a general framework for the choreographer to work within (Carlson et al., 2011). Similar to the way that John Cage used the I Ching and 'Chance Procedures' to create a set of conditions that he could then creatively interpret, artifacts generated by AI can also support creative experimentation by introducing constraints and parameters, while still allowing the user to exercise artistic agency (Cromwell, 2023; Feiten et al., 2023; Tromp & Sternberg, 2022). By generating artifacts which represent ideas at different levels of abstraction, the tool is able to leave room for artistic interpretation. This is another way that it can spur the user to experiment with variations in their ideas, rather than only through creating explicit examples of alternatives (Church et al., 2012). As a result, co-creative AI tools can introduce novelty into the creative process both through the generation of new content, and as a result of the interpretative and evaluative process that the user must engage in, in order to create meaning from the AI's output (Thelle, 2023; Tromp, 2022).

The introduction of generative AI tools also opens the door to developing new forms of creative expression (Vear & Poltronieri, 2022). For example, the 'Paint with Music' tool, developed by Google, offers a novel approach to musical creation by enabling a user to generate music through the process of painting with a digital brush (Doury & Buttet, 2021). By using machine learning to learn a mapping between brush strokes and musical notes, this tool is able to juxtapose two different artistic practices that are defined by different types of sensory perception. By fusing the act of painting with the act of creating music, 'Paint with Music' is an example of how AI tools can allow us to transcend existing paradigms of creative domains to create novel experiences that facilitate creativity (Ritter et al., 2012).

Discussion

Whether or not creativity is a uniquely human attribute does not negate the fact that creativity is an experiential process, and for humans, there is value in the process as much as in the products (Csikszentmihalyi, 2013). Understanding creativity as an experiential process gives us a framework for further development of computational creativity systems that do not replace human creativity, but rather can be integrated with it. Therefore, one potential benefit of AI tools is to support people in engaging in meaningful creative practices by improving accessibility to the creative process through providing functionality that lowers the barrier to entry, as seen with SynthEQ and ALYSIA (Ackerman & Loker, 2017; Pardo et al., 2019). Additionally, the consequences of these new technologies are not limited to their impact on the creative processes of individuals. The way we conceptualize and practice creativity is embedded within the larger societal context, therefore the development of new creative practices and forms of expression will also have broader cultural implications (Csikszentmihalyi, 1999; Glăveanu, 2015; Negrotti, 1987). As the use of AI tools can lead to new ways of generating, developing, and evaluating creative ideas, it is important that future research for computational creativity support examines how to facilitate meaningful interactions with these systems through the development of Explainable Computational Creativity (Llano & Yee-King, 2020). Explainable AI models can provide transparency into the underlying decision-making processes that shape the AI's behaviors and outputs, which can preserve the ability of the user to exercise creative agency when interacting with these tools. Research in this area can identify possible directions for future development of technologies that preserve the artist's embeddedness in the creative process, while also leveraging AI capabilities to explore new forms of creative expression. With this approach, there is an opportunity to design AI tools that intentionally engineer user experiences which can serve as a catalyst for creative exploration and discovery.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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