Exploring the Role of Play in Human-Generative AI Interactions

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ABSTRACT

Generative artificial intelligence (AI) models are rapidly growing in both popularity and capability. Simultaneously, their user bases are expanding beyond the expert domain. Although the inherent variability of generative models can make productive use difficult, it may also lend itself to playful interactions that can help users without deep technical knowledge to learn how to work with them. To explore the role of play in human-generative AI interactions and its relationship to learning, we conducted a series of semi-structured interviews with creative practitioners who engage with generative models. Thematic coding analysis revealed that the participants interacted playfully with these models, that the models' support of experimentation and parameter control are conducive to play, and that playful interactions can lead to practical understanding through an iterative learning process.

KEYWORDS

generative AI, generative models, play, learning, constructivism, creativity

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1 INTRODUCTION

As technology continues to advance, the systems we interact with are becoming increasingly complex and may seem incomprehensible to many. This has led to discussions in expert communities about how to address the knowledge gap between users and complex technologies, particularly in the field of artificial intelligence (AI) [6]. Despite the widespread use of AI in various sectors, it is often perceived as difficult to use and understand [8], creating challenges for users to work with it effectively—especially for those without technical expertise [6]. This is a growing concern, as a number of AI systems are being made available to the general public with the intention of broadening their user base beyond expert communities. In this paper, we explore the practical understanding and use of generative AI models among non-expert users, and the role of playful interactions in their learning and decision-making.

1.1 Generative AI Models

From programming (e.g. Copilot[1]) to writing tasks (e.g. GPT-3[2]) and image generation (e.g. DALL-E[3], Midjourney[4], Stable Diffusion [17]), generative AI models are rapidly growing in both breadth of application and computational power. Part of these models' popularity might be attributed to their relative availability to a general audience: many function entirely within an internet browser window or other common platforms, such as Discord[5]. As a result, such models are becoming an increasingly mainstream technology [19], with contexts of use extending beyond the expert domain. Simultaneously, they pose unique challenges in terms of users' understanding, particularly for non-experts. Generative models are inherently designed to generate content that is variable and often divergent. If such a model is presented without clear indication of this variability, it is likely that users will experience difficulties in engaging productively with it, as results are not easily replicable [19] and patterns in responses to user input can thus be difficult to identify.

However, these qualities are also part of generative models' appeal. As identified by Weisz and colleagues, the variability of generative models provides an expansive space of potential outputs for users to investigate [19]. This can be advantageous in a number of creative processes—particularly in engineering and design, where users input design goals and parameters which are then used by the model to generate possible design options within a solution space [10]. Such processes are thus iterative [21] and have the potential to be collaborative, depending on the extent to which end users' interaction with generative models is supported [7]. In all cases, user-model interactions are characterised by a sense of exploration—either explicitly, where latent variables can be controlled, or implicitly, where several output artefacts are presented simultaneously for appraisal [19].

1.2 Generation, Learning and Play

Recent studies have shown that this exploration of outputs can support users in building domain-specific knowledge, specifically that of a technical nature [18, 20]. Explorative knowledge-building is an established topic in the educational sciences literature and is often aligned with a constructivist approach [4]. Constructivism refers to the educational standpoint that knowledge is developed through

[1]https://copilot.github.com
[2]https://platform.openai.com/playground
[3]https://labs.openai.com
[4]https://midjourney.com/
[5]https://discord.com/

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"contextually meaningful experience through which [the learner] can search for patterns; raise questions; and model, interpret, and defend their strategies and ideas" [9], enabled by interactions with and feedback from an entity [13]. Based on this definition and the findings of Ross and Weisz [18, 20], we propose that a user's exploration and interaction with a generative model might be characterised as an example of constructivist learning.

Constructivism, and its exploratory nature in particular, is also associated with learning through play [5], with some researchers proposing play as the ideal mode of constructivist learning [12]. Although definitions of play are multiple and varied, it is generally agreed upon that play consists of autotelic (i.e. inherently rewarding), intrinsically motivated and repeated behaviours [1, 2]. Reflecting on the processes identified in human-generative model interactions, we see a notable overlap with elements of play behaviours. This overlap has been alluded to in some recent work in the generative AI and HCI communities, referring to some users' creative processes as autotelic [14]. Our own informal observations of colleagues' interactions with generative models in creative workshop settings echo this description. However, the exact role of play in human-generative AI interactions remains unclear, as does the extent to which it influences users' knowledge-building (as in the constructivist perspective). To investigate this potential relationship, we explored the experiences of creative practitioners who engage with generative models. We sought to answer the following research questions:

- How do practitioners engage with generative AI models?
- How do they develop their practical understanding of these models?
- What are the enablers and barriers to playful interactions with generative AI models, and how do these interactions contribute to learning?

2 METHODOLOGY

We investigated the questions presented above through a series of interviews with creative practitioners who currently use generative models in their work. We recruited participants through a community snowball method, specifically targeting individuals who considered themselves relatively experienced with generative AI models and used them in personal creative work, but had neither a professional nor academic background in generative AI. In doing so, we aimed to explore how their interactions with generative AI contributed to their understanding of it, as opposed to formal technical or theoretical instruction, i.e. in line with a constructivist framing of learning. A total of four participants were recruited: two (P1, P3) from academia (PhD candidates), one (P2) from education (libraries professional), and one (P4) from the arts (new media artist).

2.1 Interview topics

Our interviews were semi-structured and explored the following topics:

Background and prior experience with generative AI. We asked the participants questions about their professional and/or academic background, and their previous experiences with generative AI, including the types of models used and context of use.

Process of artefact generation. We asked participants to verbally walk us through their process of generating an artefact, assisted by an example of their choice, either generated previously or during the interview.

Strategies and appraisal. We discussed participants' strategies for generating desired outcomes, their decision-making processes during generation, and their personal criteria for assessing generated artefacts.

Understanding and learning. Participants described their personal understanding of generative AI models, including model parameters and prompt formulation, as well as how they developed this knowledge.

2.2 Analysis

The interviews were transcribed verbatim from audio recordings and subsequently analysed through thematic coding, using ATLAS.ti. Our coding process was theory-driven, applying conceptual frameworks of play and constructivist learning from the literature. Specifically, we referred to Burghardt's five criteria of play behaviour [2], summarised as follows:

(1) Not fully functional in its form or context (i.e. not needed for survival);
(2) Autotelic (i.e. inherently rewarding);
(3) Structurally and/or temporally incomplete or exaggerated;
(4) Performed repeatedly in a similar (but not necessarily identical) manner;
(5) Initiated when (the player's) basic wellbeing needs are met.

These criteria were used to identify aspects of play behaviour in participants' descriptions, along with instances in which participants explicitly referred to play. (For clarity, when discussing criteria 1 through 5 in the following sections, we are referring to Burghardt's five criteria as summarised above, and in the order shown.) For identifying aspects of constructivist learning, we referred to Fosnot's definition as previously discussed [9].

3 RESULTS

We were able to identify various aspects of play behaviour according to Burghardt's criteria [2] in all participants' transcripts. Although it was difficult to pinpoint instances in which all five occurred simultaneously, criteria 2-4 were the most prevalent and were often identified together. Criteria 1 and 5 were less explicitly identifiable in participants' descriptions of their thoughts and actions. However, all of the participants stated that they engaged with generative models out of personal interest as opposed to a professional, financial, or other imperative, and that they did so outside of their usual working activities. We can therefore assume with a good degree of certainty that criteria 1 and 5 are satisfied in their interactions with generative models. Additionally, participants themselves explicitly described various aspects of their interactions as play.

More broadly, we have identified aspects of interactions with generative AI models that both enable and hinder play: exploration and parameter control, and predictability, respectively. Additionally, our findings suggest that the iterative nature of such interactions aids users' learning, and that these learning experiences can also be characterised as playful.

3.1 Experimentation

The concept of experimentation appeared frequently in participants' descriptions of playful behaviour, particularly in relation to criteria 3 and 4 (structurally and/or temporally incomplete; performed repeatedly). One participant made a direct link between experimentation and play, as follows:

> *"I think the playing around, you know, is... I think you just have to experiment, I would say maybe experiment a little bit more, play as experiment or experiment as play." (P2, libraries professional)*

Several participants described processes of rapidly cycling through different input options to compare their respective outputs, with one participant explicitly referring to the testing of personal hypotheses:

> *"...there are some hypotheses that you make, and you try—I mean, it's more like deduction, really. Like being a detective... " (P3, PhD candidate)*

Another participant described their workflow with image generation in a curious, question-oriented manner:

> *"...what you can then do is really start to play around with the prompt, and understand, OK, so if I move these [parameters] around, what happens? If I change this style word, what happens?" (P1, PhD candidate)*

This curiosity and desire to ask and answer one's own questions was a recurring phenomenon. Crucially, this desire appeared to be internally motivated—a key factor in playful behaviour, relating to criterion 2 (autotelic). One participant described their internal motivation for engaging with generative models as follows:

> *"...if computers can do this now, then I want to know what they're doing. So there's a little bit of a competitive thing there." (P2, libraries professional)*

In this particular quote we also see a reference to competition, which a number of play scholars have identified as a frame in which play behaviour can occur [3, 11].

3.2 Parameter control

When describing processes of experimentation in relation to play, participants also often referred to changing model parameters. One participant connected playing with image generation models to parameter control—and understanding those parameters' behaviour—as follows:

> *"[I would]...start playing around with that image. Then, I would try and understand the sort of very basic parameters that the system has." (P1, PhD candidate)*

Another participant described how being able to actively control model output made their interactions with generative models rewarding in themselves, as in criterion 2 (autotelic):

> *"And one of the things that makes it [a generative model] such a... like, an enigma and a puzzle and a pleasure, honestly a rewarding thing to work with, is because... I'm crafting this." (P2, libraries professional)*

In this instance the participant also expressed a sense of ownership over model output, connected to their active role in its creation. Here, the fact that the generative model remains puzzling in some ways appears to also contribute to an overall positive experience. The same participant went on to explicitly link play to parameter control, describing how this process intersects with divergent model output:

> *"...I'm kind of curating it too... I'll pick, you know, some of them have a matrix of images, some of them you'll have to redo a couple of times. And maybe you can even play with some parameters." (P2, libraries professional)*

In this case, play with regards to parameter control is part of a larger curatorial process with a number of iterations, relating to criterion 4 (performed repeatedly). Likewise, another participant indicated how the ability to make changes in model behaviour is conducive to play:

> *"...the opportunity is there because it's open, because we can tweak and play around with it... there's so many extensions coming out and there's such a vibrant community around it." (P3, PhD candidate)*

They also connected this ability to efforts from user communities, who expand generative models' functionalities beyond their original design.

3.3 Predictability

As previously mentioned, the enigmatic nature of generative models appeared to contribute positively to participants' experiences of interacting with them, and to the playfulness of these interactions. Conversely, highly predictable or linear relationships between input and output were seen as undesirable. One participant explained this as follows:

> *"...that, I will say, prevents me from playing as much. I do play... but the more accessible these tools get, I feel like they become... tighter... I feel like it takes the generative out of it and they just become models. Where it's just like, you put this in and it gives this." (P2, libraries professional)*

Here, the participant saw the divergent and probabilistic nature of generative model output as conducive to play, and improved model accuracy as a potential threat to this. The same participant elaborated on this with regards to their creative process:

> *"...the algorithms are trying to get more and more accurate, right? Like, if you put 'blue dogs' and it wants to make a blue dog. But I actually don't want to see the blue dog, I want to see some sort of weird metaphor for a blue dog." (P2, libraries professional)*

In this statement, the participant again expressed concern regarding increased accuracy of generative models, specifically regarding literal (figurative) interpretation of prompts. Another participant echoed this sentiment:

> *"...the work I find most interesting, that lies on the edge between figurative and abstract, is less easy to make with the more modern models going forward. It's getting more and more real, and also more and more boring, in a way." (P4, new media artist)*

Here, the participant flagged purely figurative model output as less interesting compared to more ambiguous content, which they also linked to increased model accuracy. Another participant, when describing their process of "playing around" with a generated image, explained how specific model parameters can compound this issue:

> *"So, the CFG scale... that's how close the prompt should be to your sentence. But it can also really ruin the generation process because then it's adding too much." (P1, PhD candidate)*

In this case, the model's increased adherence to a user's prompt hinders the participant's experience of play in the generation process.

3.4 Iteration

Several references were made by participants to the iterative, cyclical nature of their interactions with generative models. This was often connected to the process of building knowledge and competence with a model. One participant described such a process as follows:

> *"So just changing parameters and changing the amount of training and then trying it again, but with some insights on the previous examples, or the previous results that you had." (P3, PhD candidate)*

Here, the participant observed the effects of their actions on model output, drew conclusions from these effects, and applied this new knowledge to their next iteration. The same participant went on to describe their process of understanding model parameters as cyclical:

> *"And then you're like, understanding what the parameter does. I think it's a cycle, a little bit." (P3, PhD candidate)*

Some instances of learning through iteration also overlapped with play through experimentation (see section 4.1) and parameter control (see section 4.2). Revisiting another participant's description of playing with parameters, we can see this overlap clearly:

> *"...what you can then do is really start to play around with the prompt, and understand, OK, so if I move these [parameters] around, what happens? If I change this style word, what happens?" (P1, PhD candidate)*

In this case, control over model parameters and iterative experimentation with their effects on model output were directly connected to both understanding of the model and to play. Finally, one participant explained how iteration could extend chronologically beyond the generation of a single artefact (in this case, an image), using this artefact as a starting point for new variations:

> *"I occasionally have images that I can get a lot [of other images] out of, while still seeing the same starting image as their basis." (P4, new media artist)*

This suggests that iteration may occur at different levels and timescales in users' generation processes.

4 DISCUSSION

Our results offer some promising insights into the role of play in human-generative AI interactions and the learning experiences that these interactions can provide.

The interactions our participants described were often characterised as iterative, echoing the findings of Zeng and colleagues [21]. This involved repeating an action or partial process, often with slight variations based on their appraisal of the output generated by the previous iteration. In these interactions we therefore see criteria 3 (structurally/temporally incomplete) and 4 (performed repeatedly) represented quite clearly, with some participants explicitly referring to such interactions as play. Participants also linked these interactions to building a functional understanding of generative AI models by applying new information gained from one iteration to the next. This aligns with a constructivist framing of learning, i.e. interpreting feedback from one's interactions with an entity to construct one's own knowledge [13].

Additionally, we identified the ability to experiment with, and control the parameters of generative models as enablers of play. These modes of interaction were also discussed by participants in relation to knowledge-building, using terms such as "understand", "know", "hypotheses" and "deduction". From our results, we see the relationship between play and constructivist learning as discussed in the educational sciences literature [12] illustrated with particular clarity in human-generative AI interactions, and propose that specific qualities of these interactions (experimentation, parameter control and iteration) enable this relationship. By embodying and encouraging such interaction qualities, designers of generative AI models can support users' understanding of how these models function, and how to work with them.

We also noted that (increased) predictive accuracy of generative models was perceived by participants as a barrier to play. In particular, literal interpretations of prompts were seen as a hindrance to playful interactions and detrimental to the aesthetic quality of model output. There appears to be a 'biting point' of sorts between figurative and abstract model output that leaves space for ambiguity and metaphor. Our findings suggest that this space is not only important for creative applications, but can support play as well—and, by extension, may also support (constructivist) learning experiences, aligning with previous work exploring the relationship between ambiguity, metaphor and learning [15].

An unexpected finding concerned the role of intuition in working with generative models. Two of our participants (P3, P4) referred to intuition in describing their decision-making processes, contrasting it with rationality and identifying situations in which they relied on each. This relates to dual-process theories of reasoning, in which intuitive and logical thought processes are implemented variously depending on the nature of a task [16]. Although modes of reasoning were not within the scope of our study, this topic may merit further investigation in future work.

Finally, we recognise that the small sample size of our study, as well as our focus on creative applications of generative AI, limits the generalisability of our results. We plan to conduct further interviews to bolster our initial findings, and to develop larger-scale tools (such as a survey) for characterising playful interactions with generative AI, such that designers might support them.

5 CONCLUSION

In this paper, we presented a qualitative study investigating the role of play in human-generative AI interactions and its potential relationship to learning. We conducted a series of interviews with creative practitioners who engage with generative models, and identified several aspects of human-generative AI interactions that enable and hinder play: experimentation and parameter control, and predictability, respectively. We also found a significant overlap between interactions that were characterised as playful and that were related to knowledge and learning, with iteration being a key quality of learning experiences in this context. From these findings we propose that, in supporting experimentation, parameter control and iteration, designers of generative AI systems can aid users—particularly those without technical knowledge—in learning to work effectively with them. The findings of this study may have implications for the design and development of generative AI models in creative industries, as well as for the education and training of creative practitioners who use these models. Furthermore, this study contributes to the growing body of literature on the intersection of AI and creativity, shedding light on the experiences of those who engage with (generative) AI models in their creative work.

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