



Drawing Conversations Mediated by AI

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ABSTRACT

In this pictorial paper, we present a series of drawing conversations held between two humans, mediated by computational GAN models. We consider how this creative collaboration is affected by the hybrid inclusion of more-than-human participants in the form of watercolour and artificial intelligence. Our drawing experiments were an extension of our search for new ways of seeing and telling, which includes a reflection of the extent to which more-than-human elements took part in our creative process. We discuss our tendencies to form strange interpretations and assign meaning to the unpredictable and ambiguous spaces we created with them. We further speculate on the characteristic material agencies they revealed in our interactions with them. Finally, we contend how such collaborations are already and always embedded and embodied in our ways of seeing and knowing in design and creativity research.

Authors Keywords

Artificial Intelligence, Creativity, Drawing, Ambiguity, Interpretation, More-than-human

CSS Concepts

- Human-centered computing~Interaction Design

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Image 1. Humans and AI interpret each other's visuals by taking turns

INTRODUCTION

The HCI and design research community have long appreciated collaborative forms of speculative experimentation and art-based activities [2,20,21,22,23,66], while valuing drawing in particular as a form of knowledge production and sense-making [6,18,27,34,35,38, 39, 41,42,45,48,49,54,57,61,62,66]. Alongside this body of work, emerging more-than-human approaches [12,13,20,32,33,46,51,53,64] acknowledge relationships between humans and non-humans as interdependent, where non-human perspectives can point to novel insights and new design opportunities. This pictorial paper contributes to discussions relevant to these design inquiries, showing experiments in speculative watercolour drawing mediated by artificial intelligence (AI). Our paper presents our reflections on the extent to which more-than-human elements took part in our co-creative process and on our tendencies to give meaning to the ambiguous and seemingly unfinished spaces created with them.

We present a selection of drawings and AI-generated images, together with our interpretations as we tried to make sense of what we were experimenting with. We are deliberate in our selection of images – they have been chosen to support narrative sense in this pictorial – and we invite readers/viewers to also consider what other interpretations they might invite.

BACKGROUND

Our engagement is initiated as *Drawing Conversations* [66], exercises for collaborative speculation through drawing (image 4). Inspired by ideational drawing, surrealist games of exquisite corpse and art-based creative correspondences [8,15,22,23,44], *Drawing Conversations* invites speculative spaces by the merging of drawings created by two different people, where interpretations reflect the interrelated connections between the disciplinary perspectives of those who take part. *Drawing Conversations* emerged as a further development of *Fluid Speculations* [66], where drawing with watercolour is used for engaging with ambiguity in early ideational design processes. When used as a material for drawing, as shown in image 2, and not only for adding colour, watercolour's fluid, at times imprecise and evocative strokes can defy accuracy but invite narrative. An unpredictable material, watercolour can prompt forms to merge and mutate, inviting multiple interpretations in the space between what is drawn and what is left out. Arguably, watercolour can become a more-than-human 'partner' [31] through its visual suggestions of



Image 2: Watercolour drawing of an early videophone, from *Fluid Speculations* [66]

potential forms that invite free associations about what *could be* [66]. In this pictorial, we extend more-than-human participation to the inclusion of AI, which, like watercolour, brought in ambiguous possibility spaces that we might have not thought of otherwise. Today, computational models such as Generative Adversarial Networks (GANs), Convolutional/Recurrent Neural Nets (CNNs/RNNs), and Generative Pre-Trained Transformers (GPTs) appear to have imaginations of their own as they newly contribute to creative processes by adding layers of interpretation and generativity [3]. This capability of humans and artificial entities to imagine and perform alongside one another has given rise to new concepts and theories of creativity including computational creativity [8,9,11,15,16,26,38,50], post-anthropocentric creativity [52,55], and digital craft-machine-ships [1,3,10]. These theories focus not on whether or not the AI is intelligent but rather on how including more-than-human agents in creative processes may give rise to new approaches for creative expression and sense-making in art and

- We each draw an artefact of our choice
- We show each other our drawings
- We both create evolutions that go from your drawing into my drawing, or from my drawing into yours. Ideally, one of these drawings is strange
- We make stories about what the newly drawn artefacts would do

Image 3: Instructions for Drawing Conversations



Image 4: Drawing Conversations.

design. Digital artist and researcher Dr. Nettrice Gaskins, for instance, applies deep learning algorithms to portraits of human subjects, synthesizing image features and patterns to create new aesthetic vocabularies that are beyond human thought [28]. In a similar fashion, our experimental inquiry focuses on the hybrid, creative, and material interplay between watercolour and pre-trained AI models through Drawing Conversations. In other words, Drawing Conversations mediated by AI draws pleasure from playing with watercolour's ambiguity while intervening in the uncertainty of the computational model. By creating implementable yet contradictory outcomes, our fluid interpretations respond otherwise to dominant and instrumental logics of computation.

FEEDING WATERCOLOUR DRAWINGS INTO GAN MODELS

For the activity of computational (or computationally-aided) drawing, there are already readily accessible AI-driven software tools that intervene in one's creation. For example, Google's Auto Draw [68] turns any individual's hand-drawn doodle into neat clip art, while Sketch-RNN [69] completes one's unfinished drawing of an object based on its training of other similarly human-drawn objects. In a more indirect fashion, StyleGAN [40] or BigBiGAN [24] models generate visual outcomes that contain learned features and patterns derived from original datasets. For example, StyleGAN, which is trained on images belonging to a specific art style such as cubism, can turn any given input image into that approximate art style. We, on the other hand, utilised the BigBiGAN model via the software RunwayML [70], that is trained to generate a proximal representation of any input image by learning its visual features. As such, BigBiGAN is modelled on the ImageNet dataset [19] consisting of 14 million annotated two-dimensional photographs of objects and the images we used as input were our own watercolour drawings of objects. Already ambiguous due to the fluid and imprecise materiality of watercolour, our drawings were processed by the BigBiGAN model – extracting visual features and patterns, and generating new images that at times looked like photographed objects or parts of those objects, as shown in image 5. This helped us reflect on the specific materiality of the model's computational logic and architecture.



Image 5: How BigBiGAN interpreted the watercolour drawings of a hairdryer and a camera

AMBIGUITY, DEFAMILIARIZATION, UNCERTAINTY

A series of interrelated definitions are recurrent in this pictorial. Ambiguity and uncertainty are terms frequently and interchangeably used to characterize artistic and creative processes in design research and HCI and, as Soden et al. [60] point out, they are ‘conceptually overloaded’. The term defamiliarization is also often used in design research and here we briefly contextualise these terms for our experiments. While we are not aiming to create an exhaustive list of possible definitions, we present our thinking behind them and the curiosities they helped us elicit in our creative process.

Ambiguity

Ambiguity represents more than one possible state of affairs and, according to cognitive psychologist Barbara Tversky, it enables diversity of interpretations, one of the foundations of creative thought [62]. Ambiguous sketches and ideas can prompt multiple interpretations in the space between what is visible and what is left out [34,63], while inviting possibility and narrative. In design research, ambiguity has been recognized as a valuable resource [7,29,30,39,56,58,65,66] that can invite interpretative flexibility [30]. It means that different interpretations might suggest new relationships with designed artefacts or reveal subjectivities that tell of our complex relationships with designs and technologies. In our exploration, we encountered ambiguity in the merged and mutated watercolour drawings we created through our Drawing Conversations and in the partially abstract yet partly concrete low resolution images generated by the AI model. Our interpretations of the AI-generated images revealed how each of us projected our imaginaries onto them and our tendencies to find meaning through their ambiguous outcomes. A question that lingered was whether the model’s outcomes were ambiguous only to us or whether ambiguity was the combined result of uncertainty inherent in pre-trained datasets and models.

Defamiliarization

Defamiliarization was introduced to the design research and HCI community by Bell et al. [4], referring us to literary styles that use language in ways that render ordinary and familiar objects in unfamiliar formats. They suggest that using such techniques in the narratives around domestic technologies can induce us to challenge our perceptions of the unquestionably familiar and provide a lense to help us see design practices in a new light. Playing

with visual rather than literary tools to render representations of artefacts in unfamiliar formats, watercolour drawing can be used to such an end. As with much surrealist work, which produces defamiliarization through materials understood as incompatible with what they represent [71], watercolour can also produce estrangement. The application of a material that is ambiguous and of fluid boundaries can produce defamiliarization when used to represent industrial design artefacts, often illustrated in thin, straight and precise lines that evoke manufacturing accuracy [66]. This understanding of defamiliarization also extends to AI models that are capable of generating new and unfamiliar visual outcomes from a database of familiar objects, portraits, and landscapes. We wanted to know to what extent our interpretations of the AI outputs change our familiar relations with the drawn watercolour objects, thereby questioning how the computational model shapes our human ways of seeing and the way we are seen in relation to one another.

Uncertainty

Uncertainty is associated with risk, doubt, instability, and unpredictability. In HCI, uncertainty has been attended to through tools for modelling it or reducing its effects [17,43] or through methods for better understanding how to design *for* uncertainty [36]. Other engagements with uncertainty have explored potential directions that might improve our relationship to wider social, political contexts [60]; or support a dialogue between the humanities and computer science disciplines [25]. While ambiguity relates to modes of human expression and interpretation (for example, we might refer to an ambiguous phrase, poem, drawing or artefact); uncertainty is associated with material behaviour or phenomena that might partially reveal information. Uncertain is the opposite of certain, which in some languages (such as Spanish, Italian, Catalan or Portuguese) is often used as synonymous with truth.

We encountered uncertainty through our work with a fluid and at times unpredictable material that moved as pigment and water suggested shapes and accidental forms. The process of not being in total control of what the drawings might look like was one of uncertainty. In our process, we further troubled our encounters with uncertainty through the inclusion of AI. In a recent article by Benjamin et al. [5], the authors position uncertainty as a defining material attribute of machine learning (ML) processes (here we understand ML as a subset of AI and use the terms interchangeably). In particular, the authors point to the tendency of engineers in framing

ML tools as capable of curbing uncertainty i.e., tools that take complex or uncertain phenomena as input and generate outputs in more or less “unambiguous” or certain terms. Challenging that notion, the authors argue how most ML outputs can be said to characterize “thingly uncertainty.” According to them, thingly uncertainty goes beyond human uncertainty *about* an artefact by engaging in an algorithmic process of loosening an artefact’s scripted qualities (a process of defamiliarization). In that process, it may allow the model’s artificial agency and materiality to be partially discernible. In our Drawing Conversations mediated by AI, we were curious if we might be able to discern the material agency of the AI model by discovering “thingly uncertainty” in the generated outputs.

FIRST AI MEDIATED DRAWING CONVERSATIONS

As with the original Drawing Conversations, we gave ourselves a loose set of instructions:

- We each draw an artefact of our choice
- We each use our drawing as input source for BigBiGAN, which then produces an image
- We show each other this new image, without revealing our original drawing
- We each draw our interpretation of the AI produced image
- We show each other the original and AI mediated drawings, and reflect on the comparisons

Image 6: Instructions for our first AI mediated Drawing Conversations

As shown in our images, the GAN model’s output images were of limited resolution and ambiguous. Our interpretations of those images reflect how we gave meaning to what we saw, regardless of how clearly defined they were.

To identify each image, we wrote the initials of the author who did the drawing, then AI to indicate when the drawing was processed through BigBiGAN, and added the initials of the author who drew an interpretation of that generated image. In another round, we fed the drawn interpretation of the BigBiGAN image back to the BigBiGAN model, as shown in image 8 on the following page.

Paulina draws a teapot and feeds this image into the BigBiGAN.

We call this drawing PY



PY

The BigBiGAN model produces an image of a rounded shape on a white background.

We call this image PY-AI



PY-AI

Anuradha interprets PY-AI as a peanut, which is what she draws.

We call this drawing PY-AI-AR.



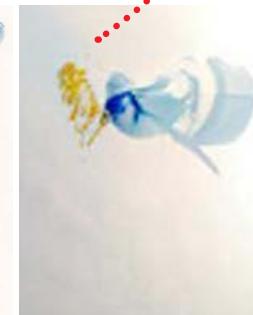
PY-AI-AR

Anuradha feeds the drawing of a drill into the BigBiGAN



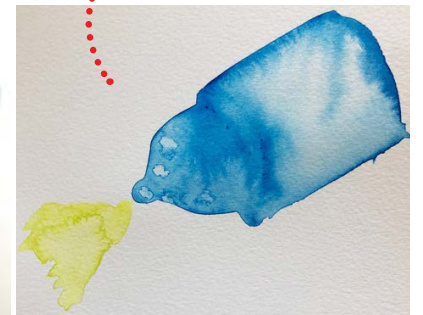
AR

The BigBiGAN model produces an ambiguous image of blues and yellows.



AR-AI

Paulina interprets AR-AI as a baby bottle spilling milk.

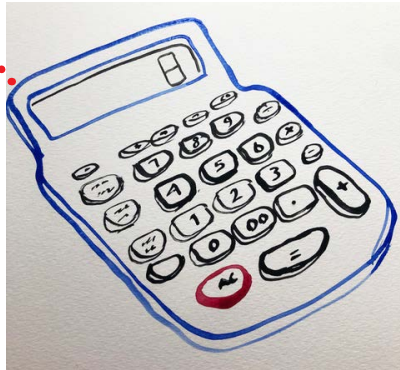


PY-AI-AR

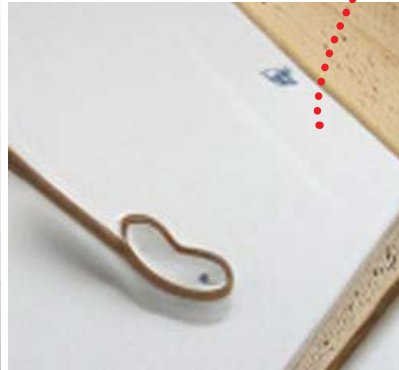
Image 7: First AI mediated Drawing Conversations

Paulina draws a calculator.

The BigBiGAN model interprets the calculator drawing and produces an image.

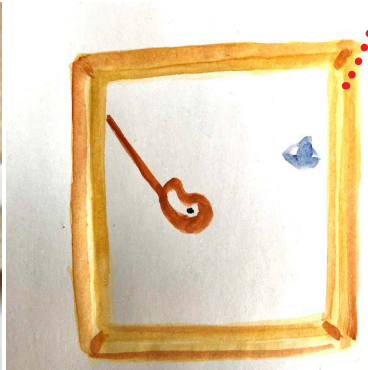


PY



PY-AI

Anuradha sees the BigBiGAN's interpretation of the calculator drawing, and draws 'a peanut inside a picture frame'.



PY-AI-AR

Anuradha's drawing of 'a peanut inside a picture frame' is fed into the BigBiGAN model, which produces an image resembling a screen.



PY-AI-AR-AI



AR



AR-AI



AR-AI-PY



AR-AI-PY-AI

Anuradha draws a microscope.

The BigBiGAN model interprets the microscope drawing and produces an image

Paulina sees the BigBiGAN's interpretation and draws 'a dog under a red blanket with holes'

Paulina's drawing of 'a dog under a red blanket with holes' is fed into the BigBiGAN model, which produces an image the authors interpreted as a ring with black ink or a raven's wings.

Image 8: First AI mediated Drawing Conversations

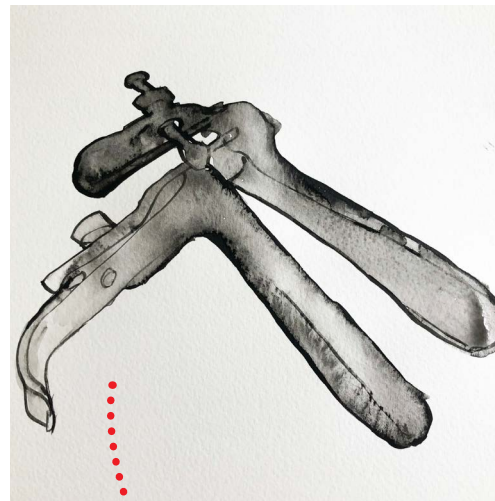
We surprised ourselves with how the BigBiGAN model was transforming our drawings into something we could not have anticipated and that was at times difficult to decipher, yet we were able to give meaning to these strange images. While we experienced the ambiguity of watercolour as evocative, fluid and suggestive, the ambiguity in the images produced by the BigBiGAN model was unevenly or uncertainly spread, at times with only concentrated areas of the image closely resembling a particular texture or a part that could be recognisable.

SECOND AI MEDIATED DRAWING CONVERSATIONS

In a second round of exercises, we followed a similar sequence to the original Drawing Conversations, in which we created evolutions from one author's drawing into the drawing created by the other author, with the added mediation of the BigBiGAN model.

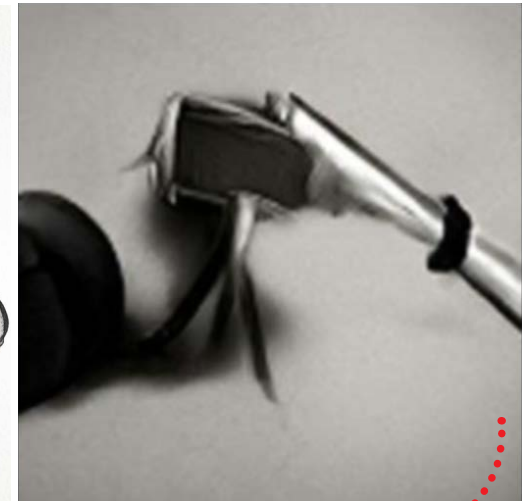
- I draw an artefact of my choice.
- I input this drawing into BigBiGAN, which interprets it and shows me that interpretation.
- I show you the BigBiGAN interpretation, without revealing my original drawing.
- You draw an artefact based on this BigBiGAN interpretation.
- We both create drawn evolutions between my original drawing and your drawing of the BigBiGAN interpretation.
- We speculate about what the newly drawn artefacts might be.
- We input one of these mutated drawings to BigBiGAN, which then creates another interpretation of it.

Image 9: Instructions for second AI mediated Drawing Conversations



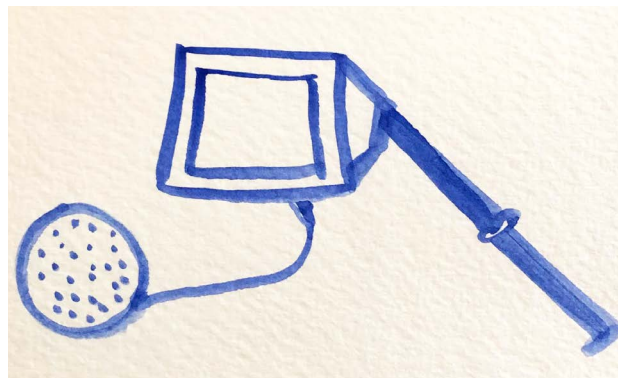
PY

Paulina draws a speculum and feeds this drawing into the BigBiGAN



PY-AI

The BigBiGAN model interprets the drawing of the speculum, producing an image resembling a metal item with a dark square area.



PY-AI-AR

Anuradha sees the BigBiGAN's interpretation of the drawing of a speculum (without seeing the original drawing) and draws an artefact of a monitor on a long stick, connected to a speaker or microphone through a cable

Image 10: Second AI mediated Drawing Conversation

Both authors create evolution drawings between drawing PY and drawing PY-AI-AR. What follows is a series of drawings that integrate both human and AI interpretations.



Image 11: Evolutions from drawing PY, a speculum, into drawing PY-AI-AR (see image 10). The result were strange combinations that resembled specula with screens, phones with ladles, screens with legs, tools. These drawings were then input into the BigBiGAN model, resulting in a new set of strange images (image 12).

We fed the evolution drawings back to the BigBiGAN model. At this point it was difficult to see if there was any resemblance to any of the drawings.



Image 12: How the BigBiGAN model interpreted the evolution drawings.

DISCUSSION

Ways of Seeing , Ways of Knowing, Ways of Interpreting

As humans, we cannot escape seeing things in particular ways and giving meaning to them: the images the AI created, however ambiguous, were interpreted by us as metal tins, screens with legs, a dog with a blanket, raven's wings. We filled in the gaps between what was rendered and what was left out and interpreted them as artefacts and their functionalities, even if they were still uncanny and strange. Our experiments with drawing, watercolour, visual dialogues and AI prompted us to reflect on our tendencies to interpret unfinished spaces in ways that were at times surprising to ourselves but that also reflected our own situated standpoints, disciplinary perspectives and personal imaginaries.

When Anuradha drew what was meant to resemble a handheld drill machine, the AI model processed the drawing and then generated an ambiguous image of blues and yellows. Paulina could have read this image in a number of ways, but in response, she chose to draw her interpretation of that image as a baby bottle spilling milk. While we could not comprehend why the AI generated that particular image, it was a lot easier to comprehend why Paulina may have interpreted that image as a baby bottle by drawing associations to her research interests and worldviews, affected by her age, gender, and social class. It also came to show that what we chose to draw was a manifestation of the things we were captivated by at that particular moment – an ongoing improvisation at work. In that improvisation, the AI model played a role in defamiliarizing us from what we already knew about these objects by opening up new possibility spaces where Anuradha's watercolour drawing of the drill could be reinterpreted as Paulina's baby bottle and merging entanglements in between – oil-like milk spills from drill-like bottle machines? We thus contend that ambiguous AI-generated images, not unlike watercolour, cater very well to “interpretative flexibility” as discussed by Gaver et al. [30] – a designerly way of knowing and exploring taken-for-granted relationships with deeply familiar artefacts and technologies.

However, it is quite difficult to separate human interpretation from that of the ambiguity and unpredictability of the materials themselves i.e. fluidity of watercolour and the BigBiGAN model uncertainty. When Paulina drew a vaginal speculum in grey watercolour and fed this image to the BigBiGAN model, the resulting image looked like another tool

made out of metal. Could we then speculate that the BigBiGAN model is trained partly on images resembling medical tools or that include parts of metal specula in that dataset? Or, do we, human authors and readers, carry the memory of our own predetermined image ‘datasets’ that feed our pattern recognition, which then makes us associate that image with metal characteristics? We reckon this kind of loose speculation on the materiality of the BigBiGAN model can be seen to demonstrate ‘thingly uncertainty’ [5]. Here, the focus shifts from what we think *about* vaginal specula to the possibility of expanding our ways of seeing and knowing specula through loose characteristics *of* similar specula-like objects, unfolded in part by AI.

Despite how we interpreted and speculated alongside watercolour and AI, we believe there was something more significant going on with the dialogical process of sharing our interpretations and imaginations with each other and recognising our human differences [42]. Coming from different though interrelated disciplinary backgrounds, we each entered this process with our own set of biases around art materials and practices around AI. Paulina has extensively explored industrial design drawing and drawing with watercolour but is relatively new to AI systems while Anuradha has a working understanding of machine learning and neural nets but is newly familiar to watercolour drawing. This affected and shaped how we navigated the unknown with the mediums we experimented with: each of us was more familiar with one type of ambiguity and unpredictability than the other. On the one hand, we were curious to find out what things might look like when drawn in watercolour and processed by AI, and on the other, we were also influenced by each other's perspectives as we were keen to find out how we incorporated our drawings into each other's. This merging of perspectives, materials, and intelligence (human and artificial) was fruitful in that it reflected the nature of collaborative work. What is it that we do when we exchange ideas and brainstorm? We share media, images, representations, metaphors, illustrations that move back and forth between us, being interpreted by each other, in different iterative ways. This coming and going of interpretations and meaning making facilitated creative dialogues and helped us see each other's way of seeing, knowing and interpreting. These partial understandings have the potential for creating spaces for human vulnerability and failure in design processes.

More-than-human hybrid creative agency

While it is debatable if watercolour or AI can be considered more-than-human partners in our experiments, it is useful to imagine ourselves designing and creating as if they were [13, 33, 51, 64]. The act of decentering from the human perspective can enable us to re-imagine things and open room for new opportunities. While watercolour and AI might not be a natural combination, they are materials frequently used for the generation of creative research outcomes. Putting them to work together has allowed us to appreciate their creative agency, separately and together, in lending value and insights to our design process. While combining watercolour and AI generated highly ambiguous and varied outcomes, they each evoked different responses and learning from us. This relates to our human (in)ability to adapt to each material and its generated outcomes – a matter of differently negotiating control and confronting our non-mastery of these materials. For instance, we found that while watercolour can be endlessly adapted, composed, and mastered to some degree, AI cannot be mastered in the same endless fashion (GANs generate the same fixed output when given the same latent vector as input). Then again, we also found out that deterministic AI processes are somewhat reversible [67] and can provide exhaustive depth (within the probability distribution of the training dataset), but watercolour cannot afford that reversible or exhaustive quality. Getting to such an understanding requires, however, a different kind of decentering – one that is tied to a ‘deep hanging out’ (coined by Anthropologist Renato Rosaldo cited in [14:5]) with materials and embracing a vernacular material consciousness.

Richard Sennett [59] writes that material consciousness is one that craftspeople are commonly engaged with, where consciousness and curiosity towards the material derive from a continuous dialogue with it in the process of making, and that often results in investing inanimate things with human qualities. Anthropomorphism might have started with our humanizing language that described watercolour as bleedy, evocative, subversive, ambiguous, and AI as impenetrable, intelligent, and creative. Here, we encountered another form of material consciousness, referred to by Sennett as the contrast between the natural and the artificial [58:136], where different values are given to different materials. Did we value watercolour and AI differently? Did these values change as we put them to work together? As this discussion stands, our answer to both these questions is a resounding yes. Rather than dichotomising watercolour and AI as natural or artificial entities, the hybrid combination of the two

has allowed us to understand their materiality as already embedded and embodied within our human ways of seeing and knowing. By inserting ourselves as human collaborators (rather than the other way around) in this multifaceted socio-material condition, we expose ethicopolitical concerns about our human wants for control, efficiency, and accuracy that come at the cost of ignoring what material agencies are conveying to us in our design processes. Our paper reflects on this concern by attempting to extend and enhance our abilities to attend to the unfamiliar, ambiguous, or uncertain through embedded and embodied processes of pattern recognition and free association with more-than-human counterparts.

CONCLUSION

The combination of seemingly discordant materials can stimulate defamiliarization, ambiguity and creativity and has been extensively used by both surrealists and designers [22,29,48,66,71]. Our inclusion of watercolour and AI was an extension of our search for new ways in which we might retell the familiar in unfamiliar forms and find spaces we would have not thought of otherwise. As we embraced material consciousness, we engaged with unlikely combinations that were partly led by us the authors, but also by watercolour and AI. In this process, we encountered our tendencies to give meaning to ambiguous outcomes, while also appreciating the possibilities in the materials we included in our work that affected our ways of seeing and interpreting, and that were situated from each of our own perspectives. We hope our work will inspire researchers and practitioners in our community to further experiment with methods that enable collaborative engagement with unknown spaces, tools and materials.

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