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Creative Expertise and Generative AI in Visual Design Practice

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Abstract

The rapid proliferation of generative artificial intelligence (GenAI) and the increasing democratisation of such technologies have prompted critical debates among scholars and practitioners about their implications for creative practice (Cui, et al, 2025; Grassini & Koivisto, 2025; Matthews, et al, 2023; Nairn, et al, 2024). While these tools promise unprecedented efficiency in the production of creative work (Campbell, et al, 2022a; Cui, et al, 2025; Hartmann et al, 2025), they have also raised concerns about the rise of what some have termed 'AI slop'—outputs that are derivative, unoriginal, and reinforce prevailing cultural norms (Matthews et al, 2023; Smith & Southern, 2025). Furthermore, scholars widely argue that generative AI lacks intrinsic creativity; rather, it operates through what has been described as synthetic creativity, drawing upon existing cultural and aesthetic data within the zeitgeist to generate new iterations (Runco, 2023). In this sense, AI does not innovate so much as it replicates patterns from its training material, producing novelty only through recombination (Desmar, et al, 2025; Grassini & Koivisto, 2025; Pedota, et al, 2025).

Introduction

The rapid proliferation of generative artificial intelligence (GenAI) and the increasing democratisation of such technologies have prompted critical debates among scholars and practitioners about their implications for creative practice (Cui, et al, 2025; Grassini & Koivisto, 2025; Matthews, et al, 2023; Nairn, et al, 2024). While these tools promise unprecedented efficiency in the production of creative work (Campbell, et al, 2022a; Cui, et al, 2025; Hartmann et al, 2025), they have also raised concerns about the rise of what some have termed 'AI slop'—outputs that are derivative, unoriginal, and reinforce prevailing cultural norms (Matthews et al, 2023; Smith & Southern, 2025). Furthermore, scholars widely argue that generative AI lacks intrinsic creativity;

rather, it operates through what has been described as synthetic creativity, drawing upon existing cultural and aesthetic data within the zeitgeist to generate new iterations (Runco, 2023). In this sense, AI does not innovate so much as it replicates patterns from its training material, producing novelty only through recombination (Desmar, et al, 2025; Grassini & Koivisto, 2025; Pedota, et al, 2025).

Consequently, the creative use of generative AI technologies demands a particular kind of expertise. Human creators (designers, artists, and scholars) must act not only as collaborators but also as critical evaluators and cultural gatekeepers, bringing their aesthetic judgment, disciplinary knowledge, and technical skill to bear on the outputs these systems produce (DiStefano, et al, 2025; Nairn, et al, 2026). This dynamic introduces new modes of creative labour that rely on negotiation, interpretation, and curation rather than pure invention (Garcia, 2024; Nairn, et al, 2026). Such practices do not necessarily represent an entirely new skill set but rather an adaptation and recontextualisation of long-established creative competencies within an emerging technological landscape.

It is against this backdrop that this article explores how experts engage with generative AI tools when responding to creative briefs. Adopting a collaborative autoethnographic approach (Chang, 2021), we document and analyse how participants, academics with visual design expertise who are also experienced creative practitioners in fields such as web design, graphic design, advertising design and visual effects, navigate the affordances and limitations of these systems. Our focus lies on the points of friction that emerge during this collaboration: how creative judgment is exercised, how decisions are made, and how these creative individuals adapt to using GenAI as part of their creative process. By examining these creative encounters, we aim to illuminate how human expertise continues to inform, challenge, and extend the creative possibilities when using generative artificial intelligence.

Process and ecological models of creativity

Classic creativity research provides useful tools for understanding where GenAI might fit within creative work and where expertise may remain essential. Much of this foundational scholarship is explicitly human-centred, conceptualising creativity as a cognitive, affective and experiential process located within the individual. Creativity itself remains a complex and multidimensional concept that extends beyond the generation of what Beghetto, et al. (2004) summarise as "the combination of novelty and usefulness" (p. 91). For Young (2003), creativity is a product of a five-stage model: immersion, digestion, incubation, illumination and verification—as key phases in idea development. Breaking down this model, creators first gather raw materials, then explore relationships among them, allow subconscious processing, experience a moment of insight, and finally refine ideas so that they are workable and on brief. Comparatively, Cropley (2006), much like other scholars in the field (see for instance Campbell, 1960; Puccio & Cabra, 2011; Simonton, 1999; Ward et al, 1999), perceives creativity as a two-stage process: idea generation and idea evaluation. The former sees a creative person brainstorming in intuitive, often non-linear ways, in what Landa (2010) refers to as avoiding "conscious choices" (p. 100), while the latter is when the creative person undertakes a deliberative assessment of which ideas best address the problem at hand. These models make clear that creativity is both productive and selective (Barker, 2019). Similarly, agency-based frameworks used in creative industries describe ideation as a movement between unrestrained brainstorming and later stages of evaluation, where practitioners determine the relevance and novelty of emerging concepts (Barker, 2019; Garcia, 2024). These traditions position creativity as a process that depends on meaningful interpretation, human judgment, and the capacity to see relationships across diverse experiences. Importantly, because these influential models are grounded in human experience and judgement, the emergence of GenAI raises questions about whether (and potentially how) creative processes might shift when non-human systems begin contributing to idea generation and refinement.

Beyond the individual cognition emphasised in these earlier models, creativity also operates within cultural and institutional systems. Csikszentmihalyi's (2014) systems model is foundational in this regard. It argues that creativity emerges through interaction among the creator (the individual producing the idea), the domain (the symbolic system of knowledge, norms and aesthetic traditions), and the field (the gatekeepers who evaluate whether a creative idea is accepted into the domain). According to Csikszentmihalyi, creativity is inherently relational and socially mediated; ideas become 'creative' only when recognised as such by cultural authorities, such as creative directors, clients, critics, or consumers. Of particular note, this model emphasises that experts, then, are those who can navigate the domain and field effectively. They know how to read a brief, how to pitch ideas to clients, how to push boundaries without jeopardising relationships, and how to mobilise their own cultural capital to secure approval (Nairn et al, 2026). As Desmar et al. (2025) discuss, human creatives with their expertise and experience are, therefore, uniquely capable of interpreting complex emotions, cultural nuance, and client-specific needs. The introduction of GenAI into this ecology, thus, has the potential to reconfigure aspects of this expertise—not necessarily by replacing human capacities as some scholars suggest (Coffin, 2022), but by altering how ideas are produced, evaluated and justified. How creative practitioners negotiate AI-generated material within existing systems of approval, and how this may reshape professional expertise, are questions our research seeks to examine.

Artificial intelligence, generative systems and creative work

Traditional forms of AI have long been understood as systems built to respond to fixed inputs and perform predefined tasks intelligently (Desmar et al, 2025; Marr, 2023). Generative AI, however, introduces a different paradigm. It is trained on vast datasets and learns the patterns embedded within them so that it can produce new material that mirrors the examples to which it has been exposed (Marr, 2023). Scholars argue that this capacity to identify and recombine patterns in text, images, and sound represents a significant shift because it allows GenAI to construct new knowledge from existing cultural material, a property previously reserved for humans (Pedota et al, 2025). This development has led some to describe AI as a set of "disruptive technologies" capable of solving problems and executing tasks that were once inseparable from human intelligence (Ford et al, 2023, p. 2). In analysing the creative process, Nairn et al. (2026) found that participants repeatedly described GenAI as a catalyst or "flow facilitator" that sustained creative momentum, expanded associative links, and made it easier to test and discard unpromising creative ideas, demonstrating the efficiency, inspiration, and influence GenAI can have as a disruptive technology.

Core to GenAI is that, rather than simply filtering existing content, it now generates synthetic images and text that carry the stylistic DNA of prior work while appearing to be new (Binns, 2024; Srdarov & Leaver, 2024). Described loosely as 'happy accidents' (Epstein, et al, 2022), the creativity of GenAI can typify divergent thinking common to creative people. Divergent thinking refers to the ability to generate multiple, varied ideas, while convergent thinking refers to the selection and refinement of ideas based on criteria such as meaning, relevance, and strategic fit. Humans excel at divergent thinking because they draw on embodied experience, emotional memory, and cultural knowledge (Grassini & Koivisto 2025). Like humans, GenAI systems perform well on some divergent-like tasks because they can rapidly generate many variations, which aligns with practitioners' descriptions of GenAI as helpful for overcoming the 'tyranny of the blank page' and moving from inertia into creative momentum (Osadchaya et al, 2024; Nairn et al, 2026).

Yet, GenAI is viewed as problematic when it comes to another facet typical of creative processes, and that is convergent thinking. Convergent thinking entails selecting the most meaningful or appropriate idea based on contextual cues. It draws on tacit knowledge, aesthetic sensibility, problem-finding ability, and strategic judgment (Grassini & Koivisto 2025). GenAI lacks the lived experience held by humans that can form meaningful associations (Wingström, et al, 2022), leading the technology to imitate the appearance of creativity while lacking its experiential and intentional depth (Runco, 2023, 2025). In fact, Atkinson and Barker (2023) and Nairn et al. (2026) found that, although GenAI enabled rapid idea generation and accelerated iteration, it also introduced new "stylistic biases" (Atkinson & Barker, 2023, p. 1064) and expectations that more can be produced with fewer resources. Several of Nairn et al.'s participants likened the look of outputs to Canva templates or stock design, highlighting how GenAI reproduces dominant visual conventions rather than consistently pushing beyond them.

Furthermore, GenAI tools retain the character of a black box, where the inner workings are inferred from inputs and outputs rather than observed directly (Ajunwa, 2020). This opacity has significant implications for creative practice, since it becomes difficult to know exactly which cultural materials and representational patterns inform the 'synthetic creativity' of the system (Binns, 2024; Srdarov & Leaver, 2024). Studies that probe GenAI behaviour by systematically prompting image generators, for instance, show clear tendencies to reproduce classed, raced, and gendered ideals, such as white, middle-class, heteronormative bodies and families (Srdarov & Leaver, 2024). These findings reinforce broader concerns that GenAI may entrench existing cultural hierarchies rather than expand the imaginative range of creative work.

Despite AI's growing sophistication, scholars consistently argue that it lacks qualities fundamental to human creativity. Runco (2023, 2024) emphasises that GenAI does not possess intentionality, intrinsic motivation, or authenticity, which are psychological attributes essential to genuine creative expression. An AI system does not choose to innovate, nor does it possess the self-awareness required for meaningful artistic communication. Grassini and Koivisto (2025) similarly argue that AI systems lack sensory grounding because they do not experience the world through embodied perception. Even when AI appears to excel at producing novel combinations, these outputs arise from statistical optimisation rather than conscious vision or purposeful experimentation. As a result, much AI-generated novelty remains what Runco (2023, p. 1) terms "pseudo-creativity," contingent on human interpretation and contextualisation to become meaningful.

The limitations of GenAI in producing reliable or contextually appropriate creative outputs, therefore, reinforce the continued importance of expert judgement in creative processes. Matthews et al. (2023) report that experienced creatives can quickly identify weaknesses in AI-generated images, including anatomical distortions, inconsistent lighting, odd spatial relationships and degraded detail in areas such as hands or typography or what Smith and Southerton (2025) refer to as AI slop. These issues are not simply technical glitches. They can compromise the uniqueness of a brand (Desmar, et al, 2025), trigger negative affect in audiences (Bakpayev et al, 2022), or inadvertently communicate meanings that contradict the intended message or intentionally mislead through hallucinations (Park & Nan, 2025). In this sense, GenAI's shortcomings illuminate, rather than diminish, the need for skilled practitioners who can evaluate outputs, mitigate risks and ensure coherence between creative ideas and their strategic goals.

Human–AI co-creativity and modes of collaboration

Despite marked concerns over whether GenAI is beneficial or problematic to the creative process, recent scholarship on co-creativity explores how humans and AI systems can work together. Cui et al. (2025) proposed the co-creativity loop, which consists of three interconnected stages: co-inspiration, co-generation, and co-calibration. In co-inspiration, AI functions as a means of brainstorming by expanding "the creative possibility space" (p. 174). These generative outputs can help creatives avoid fixation and explore unfamiliar conceptual or stylistic directions. In co-generation, human creators and AI systems engage in a reciprocal process of iteration, where "humans provide strategic direction and creative constraints while AI generates multiple design variations based on this guidance" (pp. 174-175). In co-calibration, AI outputs are evaluated and refined to align with strategic goals, cultural norms, or brand guidelines (Cui et al, 2025). Implied in this model is that, because AI may generate visually plausible yet semantically inconsistent results, human calibration remains essential to producing meaningful creative work (Matthews et al, 2023).

In exploring how creatives and GenAI can collaborate, Dell'Acqua et al. (2023) delineate specific roles which they term the centaur and the cyborg. In centaur arrangements, humans and AI divide labour, "allocating responsibilities based on the strengths and capabilities of each entity" (p. 16). In cyborg arrangements, AI becomes more tightly integrated into the practitioner's thinking, influencing choices throughout the process. In practice, creative workflows often move between these configurations. Matthews et al. (2023) and Nairn et al. (2026) all report that experts use GenAI extensively during early ideation and prototyping, yet continue to rely on manual methods and human-only discussion at critical decision points. These hybrid workflows illustrate that creativity in the age of AI is neither wholly human nor wholly machinic but emerges through dynamic and negotiated interaction between the two.

Accordingly, current research suggests that GenAI can support creative abilities through speed, variety, and inspiration (Schetinger et al, 2023; Gao et al, 2023; Matthews et al, 2023; Nairn et al, 2024, 2026). However, the depth, intentionality, and contextual sensitivity that characterise human creativity continue to depend on human judgment and experience (Runco, 2023; Grassini & Koivisto, 2025). As generative systems become more accessible and widely adopted, the literature underscores the need to understand not only what GenAI can produce but how human expertise shapes and elevates the creative outcomes that arise from human–machine collaboration (Nairn et al, 2026).

Method

This study examines how human expertise shapes creative outcomes within human–machine collaboration, focusing specifically on the second iteration of a broader multi-stage research project. While the research programme began with an initial experiment using a tightly constrained creative brief and a two-hour production window, this article does not address the findings of that first iteration; those results are presented in Nairn et al. (2026). Instead, we concentrate exclusively on the expanded methodological design and execution of the second iteration, which was informed by lessons learned earlier in the project.

Two co-lead researchers guided the study: one participated as a practitioner-researcher alongside the other four creative professionals, and the second oversaw methodological consistency and procedural integrity. As creative practitioners with substantial industry experience and as academics teaching visual design, all participants brought established expertise to the collaborative exploration of generative AI. As a collaborative ethnography, our aim was to combine our “lived experiences on” using GenAI, and then “collaboratively analyze and interpret” the data “for commonalities and differences” (Hernandez, et al, 2017, p. 251) to gain a holistic view of how GenAI can influence the creative processes of experts.

Figure 1: AI-generated packaging by participants

For this second iteration, the creative brief was substantially extended in both scope and duration in comparison to the first iteration. Participants were presented with a fictional scenario in which a Swedish university had isolated a naturally occurring Scandinavian grain hybrid, scientifically termed Nord Grain Zero. While the scientific designation was fixed, participants were tasked with developing a new consumer-facing identity for a cereal derived from the grain. The brief required the creation of a product name, logo, optional mascot, packaging (see figure 1), a poster campaign, and a 15–20 second digital advertisement. Unlike the first iteration, where only OpenAI tools were permitted, participants in this stage were free to use any generative AI tools appropriate to their creative aims. In practice, they engaged with a range of systems, including Gemini, Dall-E, Adobe Firefly, Runway, Sora, Midjourney, Suno, Canva AI, and others, enabling a broader examination of cross-platform creative affordances. The timeframe was expanded to ten days, allowing for iterative experimentation, reflection, and refinement.

Participants worked independently and were required to implement a think-aloud protocol, screen-recording their sessions, preserving prompt logs, and exporting all artefacts for analysis. The overseeing co-lead researcher conducted periodic check-ins to ensure methodological consistency and adherence to the protocol. Generative AI was treated as the mandatory first point of creative engagement: participants were expected to attempt all components using AI tools before undertaking any manual refinement. Any moment in which participants deviated from AI-driven generation—whether due to breakdowns, limitations, or quality concerns—was explicitly documented and treated as a key site of analytic interest.

The study employed a reflexive thematic analysis informed by Braun and Clarke (2006, 2013), drawing on three interconnected data sources: process recordings and transcripts, prompt and iteration logs, and a post-production group discussion. Together, these materials enabled the analysis to connect participants' lived visual design experiences with their evaluative judgements about creativity, quality, and system performance. Following completion of the design tasks, an artefact-led collective focus group was conducted in which participants reviewed their outputs against the creative brief, discussed moments of friction and success, and reflected on the shifting relationship between human expertise and generative systems. The analytical process was also shaped by a collaborative autoethnographic orientation (Chang, 2021), allowing the researchers to interpret the data through their shared participation in the creative process.

Collaborative autoethnography is a qualitative research method that brings together personal narrative and cultural analysis. It involves researchers examining their own lived experiences while also situating those experiences within the broader sociocultural contexts they inhabit (Chang, et al., 2013; Hernandez, 2021; Lapadat, 2017). Rather than working alone, collaborators engage in ongoing dialogue with one another, collectively analysing and interpreting their autobiographical accounts. As outlined by Chang et al. (2013), the approach includes careful consideration of each stage of the research process—from forming the research team and identifying a shared focus, to gathering and analysing personal narratives, writing, and considering the study's applications. Like individual autoethnography, it provides rich first-person insight and allows participants to retain agency over how their voices and experiences are represented, but it extends this work through collaborative reflection and co-interpretation (Lapadat, 2017).

As part of the thematic analysis, the co-leads first became familiar with the data through watching and listening to the recordings of each participant. Initial coding was conducted independently before being brought together for comparison and discussion. Through an iterative process of negotiation and refinement, overlapping and divergent codes were consolidated, progressively narrowing an initial set of approximately 10 codes into three overarching analytical dimensions. Guided by reflective questioning around thematic coherence, boundaries, and evidentiary sufficiency (Byrne, 2022), these final themes—*inform, challenge,* and *extend*—structure the analysis presented in this article. Throughout the process, the team engaged in ongoing reflexive practice (Braun et al, 2023), critically examining their assumptions and interpretive positions, with consistency and analytical rigour maintained through repeated discussion and reconciliation of coding decisions.

Data Analysis

Inform: Human Decision-Making as the Anchor of Intent in Generative Practice

Informing the engine emerges as a recurring theme and refers to the role of human intent as the primary organising force in AI-assisted visual design. Creative expertise keeps generative systems focused and aligned with the creative brief, rather than allowing outputs to drift toward default or generic forms. Existing research shows that while generative AI can accelerate and extend creative production, it lacks intrinsic intentionality, relying instead on pattern reproduction rather than contextual or cultural judgment (Desmar, et al, 2025)

Video 1: The 15-30 second adverts - https://youtu.be/KwtpscJiaZ0

In our research, this limitation was particularly evident when GenAI models repeatedly collapsed distinct aesthetic traditions, producing a genericised Nordic–Scandinavian visual shorthand that conflicted with established cultural meanings (see video 1). This tendency aligns with Atkinson and Barker's (2023) observations on algorithmic narrowing in digital ideation environments. Similarly, the system confused visual symbols, generating "ancient Greek" imagery in response to prompts intended to evoke Scandinavian visual styles. As Matthews et al. (2023) argue, such systems function primarily as engines of speed rather than engines of meaning. They provide scale but not direction, placing responsibility on the expert to identify and correct inconsistencies or culturally problematic interpretations. In one instance, a participant receiving Greek imagery was required to redirect the system toward a Midsommar-inflected pastel aesthetic to maintain brand coherence. This intervention reflects what Desmar et al. (2025) describe as the necessity of human-led cultural interpretation, given AI's lack of experiential grounding to distinguish between nuanced cultural forms.

Comparable patterns emerged in relation to regulatory interpretation. When a GenAI system misread "Nord Grain Zero" as a zero-calorie food product, it generated copy that breached national health regulations in New Zealand. The participant was required to intervene and re-prompt the system, echoing concerns raised by scholars regarding AI's inability to reliably navigate legal and ethical constraints without human oversight because of the data it is trained on (Ungureanu & Amironesei, 2023). In this case, human judgment functioned as a protective mechanism against institutional and commercial risk. Across both cultural and regulatory misunderstandings, participants' roles shifted from originators to what might be understood as a gatekeeper. Human expertise operated as a stabilising force, ensuring outputs did not drift into inaccurate or undesirable outcomes (Serra-Simón, et al, 2025).

Beyond cultural and regulatory issues, disciplinary knowledge also countered what participants described as the model's gravitational pull toward the generic. One participant reported that the system repeatedly generated colourful cereal loops despite explicit instructions to render them as zeroes: "There's a very biased sort of sense of what cereal is. It's always Fruit Loops". This behaviour is consistent with Runco's (2024) view that GenAI is not authentically creative because it does not produce original content, but is instead reliant on training data which it recombines or defers to in the development of creative outputs. It also helps explain participants' shared frustration with what they described as "generic AI slop", where outputs appeared "really pedestrian" or like "stock stuff". Participants characterised these results as "absolute garbage" and noted that they were "not happy with anything". These responses reflect the iterative friction where GenAI models can follow stylistic prompts but fail to deliver particularly original content (Runco 2023, 2024).

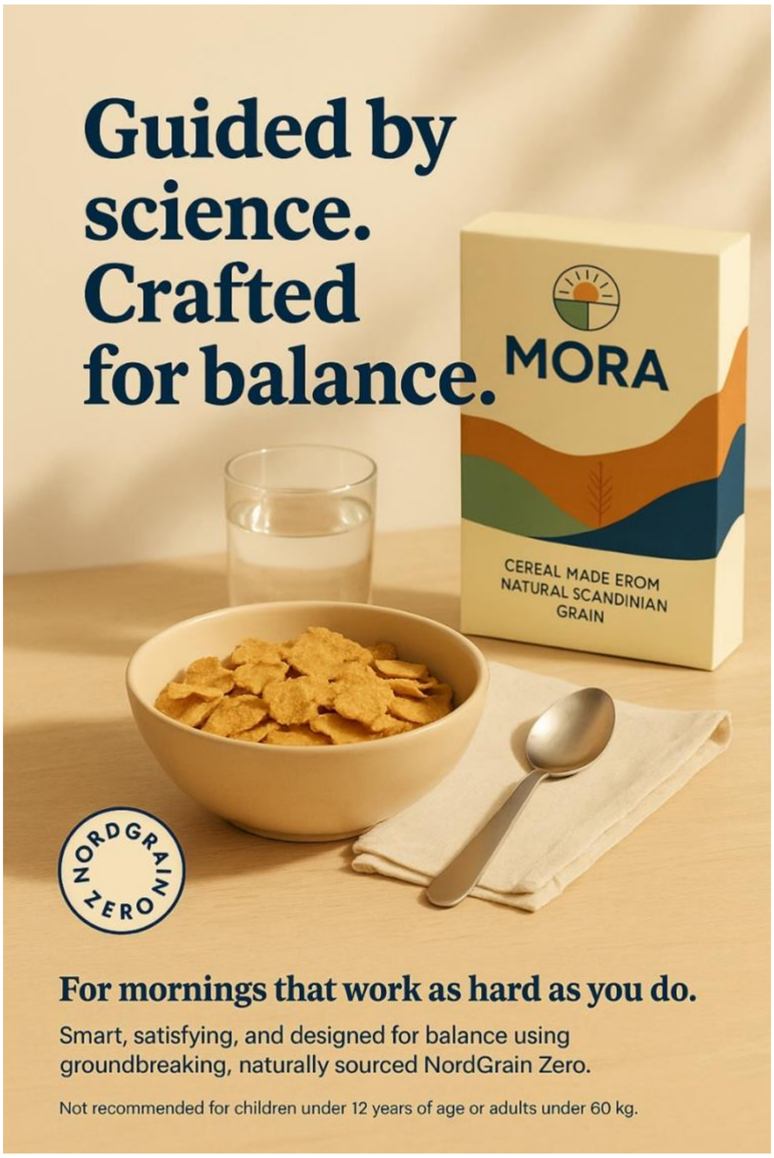

Figure 2: Mora bus shelter poster with text misspelled on box

Technical limitations further underscored the need for human mediation. Observations such as "the copy on the box says scanned man. This should be Scandinavian" (see figure 2) or that "Gemini just does not have that purity of text that ChatGPT does" point both to the constraints of current systems and to the importance of expertise in identifying errors as they emerge. Difficulties in maintaining compositional logic or integrating text and imagery without artefacting align with Matthews et al.'s (2023) critique of systems such as DALL-E, particularly in relation to proportion, sharpness, and compositional control. In video production, participants similarly noted that Sora struggled "with relatively simple actions like someone picking up a package and pouring cereal into a bowl" (see video 1). This inability to model physical causality reflects the broader limitation of generative systems operating without embodied cognition, which restricts their capacity to reason about motion, physics, and real-world constraints as they mimic the world around them. As

Wilmink (2025) puts it: “GenAI does not create representations based on inputs from the world (i.e., light capture or spatial dimensions). Rather, it bases representations on pattern analysis of two-dimensional images and their accompanying descriptions” p. (5927), which can lack nuance and realism.

These limitations appeared repeatedly across the project, with additional examples discussed in later sections. At this stage, it is sufficient to note that participants consistently intervened not only to correct cultural, aesthetic, and semantic drift, but also to impose strategic coherence. Rather than rehearsing each instance in detail, the key patterns can be summarised as follows:

- *Strategic steering*: Practitioners used disciplinary judgment to frame conceptual territory, set design directions, and filter out generic system defaults.
- *Cultural and linguistic interpretation*: Humans supplied cultural specificity and semantic nuance the model could not sustain.
- *Technical judgement*: Practitioners enforced typographic hierarchy, compositional logic, and fidelity standards the system could not reliably produce.
- *Regulatory and ethical oversight*: Humans made decisions requiring accountability, contextual awareness, and compliance knowledge.
- *Recognition of value*: Participants identified moments of conceptual potential within stochastic output, translating accidental artefacts into intentional design choices.

Together, these patterns clarify the structural role of the human practitioner, while subsequent sections (Challenge and Extend) provide deeper analysis of these dynamics. Collectively, these moments point to a shared conclusion in the literature: while generative AI broadens creative possibilities, human expertise remains essential for coherence, meaning, and quality (Cui et al, 2025). Guiding the model is not a passive add-on but an active, ongoing process of restating intent when the system drifts, oversimplifies, or misinterprets the brief. Without sustained human input, outputs increasingly diverge from professional visual design standards and move toward undirected generative results.

Challenge: The Friction of Negotiation and the Erosion of Craft in Generative Workflows

The integration of generative AI into creative workflows has produced a marked shift in visual design practice, transforming processes of active direction into what participants repeatedly described as “passive negotiation.” Because of the challenges they encountered using GenAI systems, all of the participants remarked that they became complacent, opting for content that was “passable” or “adequate”. One participant noted that in two hours, they had something that “passes and ticks all the boxes," implying a lowering of professional standards to meet the time constraint and the tool's limitations. Furthermore, the passive negotiation emerged in response to lacking control of the GenAI, as they were not able "to dial in exactly what you're looking for". Such passive negotiation forms the basis on the theme, *challenge*.

Passive negotiation was not unexpected. As prior studies note, while such systems automate and accelerate production, they remain constrained by training data biases, limiting their capacity for nuance, specificity, and originality (Matthews et al, 2023; Schetinger, et al, 2023). This decoupling of intent from execution frequently positioned practitioners as 'curators of accidents,' echoing Lyu et al.'s (2022) account of artists who experience GenAI outputs as simultaneously generative and destabilising. While some of Lyu's artists were "surprised by accidents", others "felt a little out of control" (p. 15), which aligns with our findings. For the participants, the infrequency of positive accidents, coupled with the prolonged iterative process and repeated issues in the content produced, also led to emotional and cognitive implications that facilitated the feelings of passive negotiation.

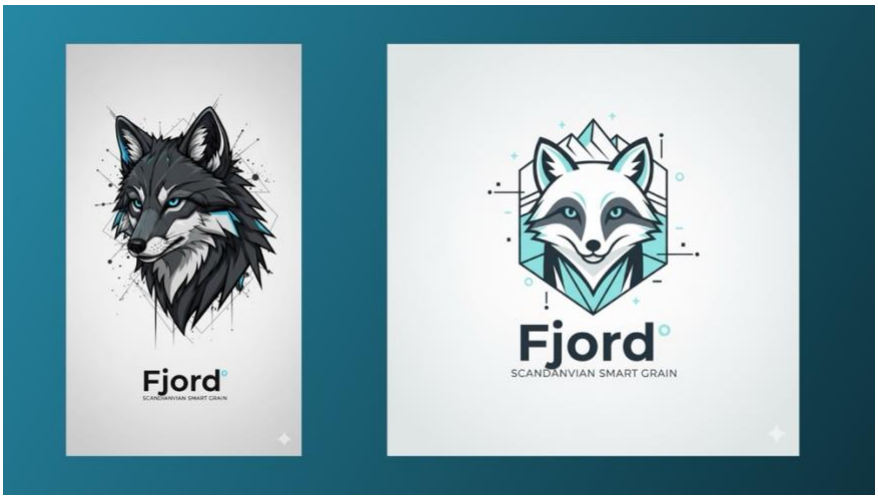

Figure 3: Hyper-detailed fox vs. preferred logo design

The challenges of ongoing, and oftentimes unsuccessful iteration are noted when one participant repeatedly attempted to generate cereal loops that were "grain coloured" to support a natural brand positioning. Despite providing Froot Loops as a negative reference and explicitly stating "I do not want it to be coloured," the system consistently returned rainbow-coloured loops. Although the model apologised and claimed to have corrected the issue, subsequent iterations reverted to the same visual trope. Comparable breakdowns occurred when another participant generated a logo for a cereal named after the Norse goddess "Sif," which the system rendered in a generic, "very Greek" aesthetic, and when another participant produced an Arctic fox mascot whose hyper-detailed fur made it unusable as a clean brand mark (see figure 3). Even when visual fidelity was high, text integrity frequently failed, with logo elements dropped or complex terms such as "Scandinavian" repeatedly misspelled.

These problems were not experienced as isolated errors but as structural limitations. Participants described a recurring pattern of "gaslighting," in which the system acknowledged an instruction, apologised for failing to follow it, and claimed to have resolved the issue, only to reproduce the same error. One participant recounted repeatedly asking the model to adjust the "J" in a Fjord logo so it no longer covered the tagline; each iteration confirmed the textual change while returning an image that continued to obscure the line. A common occurrence experienced by the participants was addressing one variable only to find it caused previously stable elements to fail, producing what participants described as a "whiplash" effect. Participants also reported that extended prompting, file uploads, and detailed PDF briefs could "break the context window," resulting in the model abruptly losing access to mandatory warning text or other core constraints established earlier in the interaction. Such emotional and cognitive frustrations, dampened creative motivations, turning what was designed as an opportunity to be creative in responding to a brief, into a tick box exercise because participant energy and engagement were sapped. The thoughts of one participant encapsulated the loss of motivation when she said:

> *It was like cool you've listened to me you get it and then a few couple steps later back to square one and then you're like fine, we'll leave that carry on, and then that would come back, but then the thing we just worked on would go away, and I'm like, whatever let's move because then you're just like in this loop of going back to the same thing. It's like you take one step forward and like three back*

This difficulty in working against the model's defaults aligns with broader critiques of algorithmic gatekeeping in creative systems, where exposure to dominant patterns constrains originality and reinforces derivative forms (Barker, 2019; Matthews, et al, 2023), as well as with documented limitations in instruction following that remain unresolved in generative modelling (Betker et al, 2023).

Figure 4: Odd shadowing on the table around the Frisk cereal box

Failures in spatial reasoning further compounded these challenges. Participants found that simple adjustments—such as rotating a poster, changing the direction of a light beam, or repositioning a tagline—often resulted in distorted compositions or hallucinated elements (see figure 4). Attempts to refine a logo with a "simple halo" required more than fifteen minutes of prompting before the participant abandoned the effort and accepted a suboptimal result. In response to "whiplash" and long generation times, participants adopted what they described as a "Frankenstein" approach: generating individual assets—logos, textures, backgrounds, mascots—and manually compositing them in Photoshop or Illustrator to impose coherence the model could not maintain. Several participants explicitly broke the experimental protocol and "jumped back" into traditional tools simply to flip a poster or merge partial results, reinforcing industry analyses that position AI as effective for ideation but unreliable for the final stages of craft refinement (Matthews, et al, 2023).

As suggested above, GenAI latency introduced an additional layer of friction by disrupting the 'flow' that Nakamura and Csikszentmihalyi (2002) consider key to the creative process. Being in flow entails "intense and focused concentration on what one is doing in the present moment" sometimes to the "distortion of temporal experience" (p. 90). Yet participants were jarred out of the possibly of experiencing a flow state as the GenAI prompting and iterating could be time extensive and unstimulating. As one participant stated, the experience was akin to "waiting for a cake to bake," describing long pauses characterised by little activity beyond watching a progress indicator. Rather than supporting creative flow, this delay reframed visual design labour as a form of administrative supervision, running counter to basic usability principles, and diluting the intrinsic motivation that propels individuals to pursue creative activity (Nakamura & Csikszentmihalyi, 2002). These disruptions were particularly pronounced in video workflows. Both Gemini (Veo3) and third-party tools such as Kling.AI imposed strict output limits, typically allowing only two or three eight-second clips per day. Participants described attempting to assemble commercial-length material from these fragments before abandoning the AI workflow altogether. Such constraints align with research showing that AI reconfigures the temporality of creative labour, accelerating some stages while impeding others (Matthews et al, 2023; Campbell et al, 2022a). As the effort required for refinement increased, many participants settled into a "good enough" plateau, accepting outputs that they perceived would not normally pass internal review but were tolerated because pushing the system the final ten percent was perceived as too costly in time and effort.

Semantic misalignment and cultural flattening further intensified these frictions. Requests for "Nordic" imagery routinely produced exclusively white actors, reproducing demographic biases well documented in training data systems (Atkinson & Barker, 2023; Schetinger, et al, 2023). Efforts to evoke distinctions between regional aesthetics—such as Nordic ruggedness versus Scandinavian minimalism—were repeatedly collapsed into a single, generic visual shorthand. The misinterpretation of "Sif" as a vaguely classical rather than Norse figure, alongside the cereal brief's repeated regression to rainbow loops, illustrates how culturally specific markers were reduced to familiar tropes. Participants resisted this pull toward the statistical mean by rejecting outputs described as "boring, boring crappy stuff" or "vanilla," and by introducing external reference materials, such as Pinterest boards, to force the system away from default patterns. In moments of frustration, participants reported telling the system to "try fucking harder," signalling a perception that the model was not only biased but insufficiently exploratory. These dynamics reflect broader industry concerns that generative systems risk producing a homogenised aesthetic (Tsao, et al, 2025), while positioning practitioners as cultural filters tasked with screening out the most pedestrian outputs (DiStefano, et al, 2025; Matthews et al, 2023).

Taken together, these frictions point to a reconfiguration of professional identity. Rather than simply extending creative capacity, generative AI required practitioners to expend significant cognitive and emotional effort navigating system limitations and negotiating compromise. Participants described a shift away from mastery of a single tool—such as Photoshop—toward managing workflows across multiple subsystems, using ChatGPT for scripts, Gemini for imagery, 11Labs for voice, and traditional software for final assembly. Expertise increasingly involved knowing how to work around the system's blind spots rather than directly shaping materials. Where traditional tools extend the hand, generative AI often operates as an intermediary whose outputs must be negotiated rather than directed. Without sustained human intervention, creative work risks fragmenting into disconnected outcomes, detached from the intentionality and craft that underpin professional visual design practice.

Extend: The Shift from Linear Authorship to Multiverse Navigation

As the previous themes have discussed, the integration of high-velocity generative tools is reshaping how creative work unfolds, aligning with research showing that generative AI streamlines creative processes, accelerates ideation, and reduces production costs (Amankwah-Amoah et al, 2024; Campbell et al, 2022a). Of note, rather than progressing step by step through a single idea, participants could explore multiple directions simultaneously. To this end, our final theme is *extend*, where all the opportunities afforded by GenAI in the creative process are documented.

GenAI can expand the creative space by lowering the cost of comparison, allowing creatives to assess options side by side without the labour typically required to produce each draft. Such practices are consistent with research on text-to-image systems that support rapid iteration and exploratory divergence (Oppenlaender, 2022). The speed of models such as Gemini enabled practitioners to bypass the traditional "cost overhead" of iteration and engage instead in what can be described as simultaneous pathing. In this configuration, the creative process is no longer constrained by the sequential development of a single idea; instead, it opens into a space where divergent territories—copywriting, art design, research —are generated and evaluated in parallel. This was evident when one participant used Gemini to explore all three territories at once, describing the experience as "boom, boom, boom" and noting that seeing fully realised options simultaneously fundamentally "changed the territory" of creation.

Equally, participants described being able to move rapidly from a single design concept to a broader product ecosystem, including flavour variants, colour palettes, and shelf presence. In one instance, a participant instructed the system to generate five cereal box variants with distinct palettes, immediately visualising the brand's shelf presence as a coherent system. This capability echoes claims that AI supports scalable content variation and system-level visualisation (Campbell et al, 2022a; Chen et al, 2019). Tasks that previously required mood boards, competitor scans, and persona development were compressed into minutes. One participant produced an entire research package—comprising mood boards, competitor analysis, and audience personas—in approximately fifteen minutes, remarking that the same work would normally take "an intern a day." This compression allowed practitioners to shift their attention earlier toward strategic judgment rather than the mechanics of production.

Alongside speed, generative systems also introduced unanticipated variations that redirected creative outcomes, paralleling research on AI-generated "happy accidents" that stimulate new conceptual directions (Epstein, et al, 2022; Matthews et al, 2023). For example, the system unexpectedly rendered small “zeros” as visual motifs, directly referencing the product name. Although unplanned, the participant immediately recognised the potential of this approach and incorporated it into the final concept. Similarly, when creating the videos, 11Labs voice generation produced subtle breaths and micro-pauses that one participant described as capturing “individual breaths between phrases,” noting that without being told the audio was synthetic, they “wouldn’t have believed it” (see video 1). Participants described this fidelity as “next level crazy.” In video workflows, systems occasionally combined assets into coherent animated frames without explicit instruction. One participant reported that three separate image prompts were unexpectedly composited into a unified animated end-frame, describing the result as a “happy accident” that improved the output beyond their original intent. Together, these moments illustrate how generative tools can function as unplanned collaborators, introducing ideas that prompt visual designers to reconsider or refine their approach, consistent with co-creativity models that frame AI as an agentic contributor rather than a passive instrument (Cui et al, 2025).

Working with these systems also introduced a new layer of practice centred on coordinating interactions between multiple GenAI models. This form of orchestration reflects the emergence of hybrid human–machine workflows in which creative labour can involve integrating distinct AI subsystems (Oppenlaender, 2022). Participants frequently combined tools, for example using text-based models to generate prompts for video systems. One practitioner instructed Gemini to act as an art director by producing scene-by-scene guidance for a fifteen-second advertisement, effectively delegating narrative structuring before passing the output to a video generator. This approach echoes centaur and cyborg creative models in which humans coordinate AI subsystems rather than directly executing each task (Dell’Acqua et al, 2023). In more advanced workflows, participants treated AI as both translator and technical intermediary. One practitioner uploaded Kling’s technical documentation and instructed the model to rewrite creative concepts into the precise syntactic format required by the video system. In this configuration, the practitioner assumed a directing role, steering how tools interacted and managing the composite system they formed when combined. This shift aligns with research suggesting that creative roles are increasingly moving from direct production toward the management of algorithmic processes (Osadchaya et al, 2024). Inter-model orchestration, therefore, marks a broader transition in creative identity, from author to navigator.

Within these AI-supported workflows, the human role increasingly centres on guidance, selection, and refinement. Creative labour becomes less about producing a single crafted artefact and more about evaluating and shaping a range of generated possibilities. Practitioners maintain alignment with intent by stabilising generative processes and ensuring coherence across the multiple systems involved. Additionally, the potential of GenAI to extend the talent of creative people demonstrated that, despite the myriad of issues and challenges that accompany such systems, they still have value to the overall creative process.

Discussion

This study examined how experienced creative practitioners who are also academics teaching core visual design principles work with generative AI systems under realistic professional constraints. Using collaborative auto-ethnography (Chang, 2021; Hernandez et al., 2017), the research drew on shared reflective accounts to examine how generative AI functions in practice, not as an abstract technology but as a system that can both support and disrupt creative work. Reflective thematic analysis of session and focus group recordings (Braun and Clarke, 2013, 2023) identified three interrelated themes, inform, challenge, and extend. Together, these themes describe how disciplinary expertise shapes engagement with GenAI, where points of friction arise when these systems are used in creative development, and how expert practitioners adjust their workflows in response.

The study contributes to existing research by focusing on expert friction rather than the novelty often associated with novice use of generative systems. Much of the current literature emphasises GenAI's capacity to increase ideation volume, speed, or perceived output quality Campbell, et al, 2022a; Cui, et al, 2025; Hartmann et al, 2025). Less attention has been given to how experienced practitioners, particularly those involved in visual design education, work with these systems in professional and pedagogical contexts (Chandrasekera et al, 2025; Xiao, 2025; Zailuddin et al, 2024; Zhang, et al, 2026). This distinction matters in the context of the rapid democratisation of generative tools (Ahmed & Ali, 2024; Chamakiotis & Panteli, 2024), which has coincided with the widespread circulation of derivative and culturally flattened outputs, often described as AI slop (Matthews et al, 2023; Smith & Southern, 2025). These outputs increasingly shape the broader media environment and may contribute to future training datasets.

Participants, then, demonstrated the value of expertise through their ability to identify issues that would likely go unnoticed by less experienced users. These included legal and regulatory breaches, problems with fidelity or appropriateness, and misalignments between outputs and creative intent. Participants also adapted their prompting strategies and, in some cases, combined multiple GenAI platforms to better meet the requirements of the creative brief. These findings indicate that GenAI does not reliably produce meaningful outputs without sustained human intervention. This observation aligns with scholarship suggesting that generative AI systems lack experiential grounding and intentionality, relying on pattern recognition rather than context-sensitive judgment (Runco, 2023; Grassini and Koivisto, 2025).

Rather than reducing the importance of expertise, the findings suggest that generative systems increase the demands placed on expert users. Responsibility for legal, ethical, and reputational risk remains with human practitioners, even as control over execution is partially delegated to automated systems. In institutional and commercial settings where errors carry consequences, expertise becomes more, not less, important. The ongoing requirement to recognise, diagnose, and repair breakdowns highlights that effective use of GenAI depends on disciplinary knowledge rather than access to technology alone. In this context, the growing availability of generative tools points to a need for expanded AI literacy, particularly within creative and visual design-focused education (Ding, et al, 2025; Tadimalla & Maher, 2025; Teo & Chew, 2025).

A key theoretical contribution of this study is the identification of stabilisation as an emergent mode of creative labour when working with generative AI. Established models of creativity typically describe a process that moves between divergent idea generation and convergent evaluation (Cropley, 2006; Puccio and Cabra, 2011; Ward et al., 1999). While both modes were present in participants' workflows, they were not where most effort was concentrated. Instead, participants devoted sustained labour to stabilising meaning against stochastic systems: repeatedly reasserting intent, reinstating constraints, correcting cultural and meaning shifts, and repairing or restoring coherence after each iteration. This work was not episodic or corrective in the traditional evaluative sense. It was continuous, anticipatory, and structurally necessary. Because generative systems are designed to produce probabilistic variation rather than deterministic outputs, creative practice becomes oriented toward holding meaning steady in the face of constant fluctuation. This reveals stabilisation not as a subtask of evaluation, but as a distinct mode of creative labour that emerges specifically under conditions of generative automation. In this context, expertise is exercised less through selecting the best idea from a set, and more through the ongoing anchoring of intent, coherence, and cultural validity across unstable outputs. By making this labour visible, the study extends creativity theory beyond divergent and convergent thinking, demonstrating that GenAI introduces stabilisation as a genuinely new and necessary form of creative work.

Stabilisation here refers to the ongoing labour of maintaining continuity of intent, constraints, and meaning across iterative interactions with probabilistic generative systems. In our data, participants repeatedly described a pattern in which each new generation introduced drift, regression, or partial failure—where fixing one element destabilised another ("whiplash"), or where the model acknowledged an instruction yet reproduced the same error ("gaslighting"). Stabilisation names the expert work required to keep a creative trajectory coherent under these conditions: reasserting brief requirements after context breaks, reinstating previously agreed constraints (e.g., mandatory copy or visual rules), correcting cultural and semantic misalignments, and repairing fidelity losses (especially in text, logos, and layout).

Importantly, stabilisation is not simply evaluative judgement. Evaluation can determine that an output is off-brief, generic, or technically broken; stabilisation begins once a direction has been selected and the practitioner must prevent that chosen intent from being eroded by subsequent generations. The need for stabilisation becomes visible when "solved" problems return across iterations (e.g., recurring typographic errors, layout collapse, or loss of previously correct design elements), requiring repeated re-anchoring rather than a one-off critique.

Conceptually, stabilisation sits between classic divergent/convergent creativity models and the realities of generative automation. Traditional models often frame creative work as oscillating between idea production and subsequent evaluation/selection (e.g., generation followed by evaluation) (Cropley, 2006; Puccio and Cabra, 2011; Ward et al., 1999). In our study, however, the dominant effort was not selecting among ideas after generation, but preventing the erosion of selected intent while iterating. This is because GenAI systems are designed to produce variation rather than preserve invariants: even when outputs are "good", subsequent refinements commonly reintroduce errors (misspellings, layout collapse, unintended stylistic shifts), requiring experts to continuously re-anchor the work.

Stabilisation is, therefore, not merely a quality check at the end of a pipeline. It is a structurally necessary mode of creative labour that emerges when authorship becomes a negotiation with a non-deterministic generator—particularly under conditions of context loss and system defaults that pull outputs toward generic tropes.

Table 1. Distinguishing stabilisation from adjacent concepts in human–AI creative work

Concept	Focus	Key question	Typical moves	Not stabilisation because…
Stabilisation	Maintaining continuity across iterations (intent, constraints, meaning)	"How do we stop drift/regression while iterating?"	Re-anchor constraints; repair regressions; lock invariants; patch/composite	—
Evaluation	Judging outputs	"Is this on-brief / good enough?"	Critique; accept/reject; diagnose issues	It identifies problems; stabilisation keeps a chosen direction from unravelling.
Calibration	Tuning inputs to improve alignment	"What prompt/constraint tweak gets us closer?"	Rewrite prompts; add constraints; references/negatives	It aims to improve the next output; stabilisation prevents backsliding across outputs.

Curation	Selecting/assembling outputs	"Which bits do we keep, and how do we combine them?"	Shortlist; compare variants; assemble composites	It chooses what to keep; stabilisation preserves those choices through further iteration.
Orchestration	Managing workflow across tools/models	"Which tool does which step?"	Tool chaining; hand-offs; pipeline planning	It's workflow logistics; stabilisation is continuity-of-meaning under iteration.

Although designers have always engaged in refinement and quality control, stabilisation is conceptually distinct because it addresses a specific property of generative systems: iteration does not reliably preserve prior decisions. In conventional tool-based workflows, changes are largely deterministic—adjustments typically modify what the practitioner targets without systematically destabilising unrelated elements. In contrast, our participants experienced a recurring pattern where small revisions triggered broader regressions (e.g., text errors returning, layout drift, or previously correct elements disappearing), and where the model's confirmation of compliance did not predict actual compliance. Under these conditions, creative labour shifts from primarily "making" or "selecting" to maintaining coherence against drift.

We are not claiming the underlying human activity of "keeping work on track" is unprecedented. Rather, we argue that GenAI makes this maintenance labour structurally central and unusually visible: what was previously a background competence becomes a dominant, repeated mode of work required to counter probabilistic variation, context loss, and regression. Stabilisation therefore extends creativity and labour frameworks by naming a distinct category of expert effort—maintenance-of-invariants under stochastic iteration—that becomes pivotal when creative production is mediated by generative systems.

These findings also complicate more optimistic accounts of human–AI co-creativity. Existing frameworks describe productive cycles of co-inspiration, co-generation, and co-calibration (Cui et al., 2025), as well as centaur and cyborg models that distribute labour between human and machine (Dell'Acqua et al., 2023). While these configurations were visible at a structural level, participants' accounts point to a more uneven and demanding experience in practice. Creativity research consistently highlights intrinsic motivation as central to sustained creative engagement (Nakamura and Csikszentmihalyi, 2014). However, participants described GenAI-mediated workflows as involving extended periods of waiting, repeated correction, and supervisory oversight rather than active making. These conditions constrained creative agency, with participants responding to system defaults and failures rather than directing the process. Importantly, participants did not reject creative labour itself or the value of craft. Rather, they expressed frustration with workflows that emphasised orchestration over creation. This reflects industry observations that creative practitioners are reluctant to adopt roles limited to directing automated systems without meaningful involvement in the making process (Matthews et al., 2023). When the flow state described by Nakamura and Csikszentmihalyi (2014) was repeatedly interrupted by system latency, regression, or cascading failures, motivation declined. As a result, participants were more likely to accept adequate outputs rather than continue refining work that no longer sustained creative engagement.

This study documents the experiences of a small group of creative-academic professionals with visual design backgrounds. As such, the findings are not intended to be generalisable to all creative practitioners, nor can they predict how creative work with GenAI may evolve as the technology continues to change. Future research should therefore examine how other creative professionals engage with generative systems, particularly those with limited affinity for emerging technologies. Further work is also needed to explore how different GenAI platforms are used in practice and what forms of education and training are required to ensure that creative graduates are equipped to work critically and productively with these tools.

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