4 From Digital Craft to Automation

Exploring the Trade-Off Between Traditional Digital Skills and Automation in the Creative Arts

Antonio Daniele

4.1 Introduction

A radical transformation has been reshaping the creative industries since around 2020. With the emergence of transformer-based models and generative artificial intelligence (AI) such as DALL·E, MidJourney, and Stable Diffusion, professionals and amateurs can now generate complex visuals through simple prompts (McCormack et al., 2024). Image-making is separating from what we knew consisted of technical skills applied to hours of digital manipulation. Some argue this represents a democratization of creativity (Park, 2024; Tigre Moura, 2023). For others, it signals a deeper shift of techniques and cognition, authorship, and the very essence of creative labour (Jiang et al., 2023). To understand this moment, it helps to look backwards at the early 2000s, when the creative industries experienced a major digital revolution (Balbi & Magaudda, 2018). The transition from analogue to digital formats reduced media production costs and complexity, thanks to software for non-linear editing and image manipulation (e.g., FinalCut, Photoshop), DSLRs and DV cameras. However, creating compelling digital videos and images still required knowledge, practice, and a hands-on approach to digital tools, as a form of "digital craft".

Digital craft, as used in this chapter, refers to the set of expert practices involving hands-on interaction with professional digital tools, in this text also named "traditional" digital tools. These include software like Adobe Suite, 3D modelling applications such as Blender or Maya, and video editing platforms like Premiere among others. These tools require control, iteration, and mostly, time to master. Rarely formalized in academic discourse, digital craft is recognized across media practice (McCullough, 1998). It can be considered a digital form of artisanry where, instead of chisels or brushes, images are shaped through layers, masks, rotoscoping, and rendering pipelines. This hands-on relationship with software can be traced to Schneiderman's (1983) concept of direct manipulation: an embodied interaction mode where designers' actions immediately affect on-screen objects. Over time, this principle has evolved to include 3D and virtual environments (Whyte, 2007), and now interfaces with large language models (LLMs) via prompts and natural

DOI: 10.4324/9781003606802-5

language instructions (Masson et al., 2024). This evolution from *hand-to-mouse-to-mind* traces a path towards abstraction, calling into question the very nature of "making" in digital culture. If cinematic images or motion design can be generated with a few words and clicks, what happens to the learned expertise that once defined professional creative work? If crafting becomes effortless, what becomes of the exploratory value of iteration and mistakes? Is this just another phase in media evolution (Manovich & Arielli, 2024), or an epistemic redefinition of creativity?

The cognitive implications of this transition are only beginning to be understood. While some argue that AI integration has the potential to boost critical thinking (Ruiz-Rojas et al., 2024), studies in education and HCI suggest that excessive reliance on automated systems can induce forms of cognitive offloading (Gerlich, 2025). This might reduce active involvement in decision-making and problem-solving, especially problematic in youth still developing divergent thinking (Habib et al., 2024). Delegating creative tasks to generative models, may lead to unlearning or forgetting (Hislop et al., 2014) valuable procedural knowledge and cognitive skills that were once integral to craft. In this context, the adoption of generative AI tools is not a neutral boost in efficiency, rather a shift in cognitive responsibility where decision-making is distributed between human intention and machine prediction. Daniele and Song (2019a) describe AI-generated artworks as output of shared human-machinic agency distributed along a spectrum from full control to near autonomy. Drawing from Hayles's (2017) concept of "cognitive actors", these tools influence decisions in material and creative ways, adding artificial layers that may further distance creators from the audience. AI tools are shaping both process and product in ways that require scrutiny, especially when they are exploited for capitalist aims. Moruzzi (2022) extends this argument, describing AI as "social agent" and demonstrating how perception of agency positively correlates to creativity, which is key to understanding the dynamics of intersubjectivity between humans and AI. This dynamic lies at the heart of the trade-off examined in this study, leading to the main research question: what is gained and what is lost when digital craft is displaced by automation?

This transformation intersects with issues of bias, inequality, and contradictory perspectives on labour practices (Caramiaux et al., 2025). Generative models training data are often web-scraped without creators' consent or compensation (Warburton, 2023), re-elaborating their styles and content, raising questions about ownership, authorship, and intellectual property (Chesterman, 2025). These same datasets embed socioeconomic, gender and racial biases that frequently manifest in AI outputs (Gebru, 2020) and narratives (Cave & Dihal, 2020). Studies have shown that generative models tend to reproduce stereotypical and racialized representations, for instance depicting CEOs predominantly as white men or criminals as people of colour (Ferrara, 2023). The more generative systems assume decision-making roles, the more the balance of agency shifts, redefining how creative weight and responsibility are distributed across human-machine assemblages (Daniele & Song, 2019b).

This chapter interrogates the shifting relationship between creators and their tools through a mixed-method approach (Fetters et al., 2013) of semi-structured interviews and survey data. It explores how digital craft is being redefined or traded with automation, asking how AI reshapes workflows, politics of making, cognitive habits, and creative identity, in a time when speed, scalability, and control are gradually abstracted from designers' hands.

4.2 Methodology

The aim of this study is to understand how professional designers perceive and respond to the increasing integration of generative AI in creative practice. It used a mixed-method approach, combining a quantitative survey with three elite interviews to triangulate insights. It targeted international designers working in digital media, communication design, and visual arts. The study was structured around four conceptual areas: (1) technological change and AI advancement; (2) human-machine agency; (3) AI's influence on creative workflows; (4) trade-offs between traditional tools and generative AI. Together, these areas build towards the central focus of this study: the trade-off between digital craft and automation. They address questions of AI agency (Moruzzi, 2022), authorship and automation (Daniele & Song, 2019a), ethical risk and bias (Cave & Dihal, 2020; Gebru, 2020), and transformations in creative workflows (Park et al., 2024). The four areas informed both the development of survey questions and the interview guide, ensuring conceptual continuity across data collection methods.

The 62-item survey was administered via Qualtrics. It included 5-point Likert scales assessing agreement or frequency (e.g., from "Strongly disagree" to "Strongly agree", or from "Never" to "Always") of subjective perceptions of technological change, creative control, authorship, skill transformation, agency, and bias. Matrix questions allowed comparison of attitudes across human-AI interaction modes (e.g., manual control, collaborative AI, and full automation). Multiple-choice questions collected demographic and contextual data on professional roles, software use, and AI familiarity. Participants (N = 150) were recruited internationally: 126 via the Prolific platform (screened and compensated) and 24 through professional networks and social media (voluntary). To encourage participation, one Euro donation per completed response was pledged to the Aladina Foundation, a Spanish children's cancer charity. The study received ethical approval from IE University's Research Committee (ref. IERC-27/2024-2025).

4.2.1 Survey Participants

Most respondents were aged 30–44 (51.3%), followed by 18–29 (26.7%), 45–64 (21.3%), and 65+ (0.7%). Gender was nearly balanced: 51.3% women, 46.7% men, and 2% non-binary or not identifying with a gender. The majority were professional designers (83.3%), 5.3% were educators,

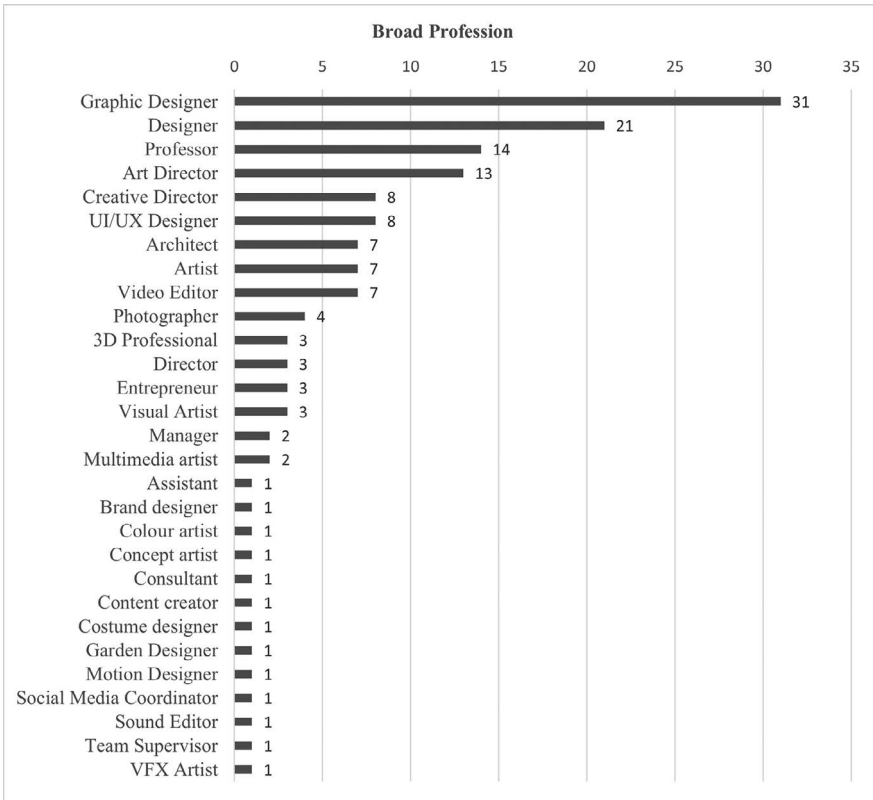

Figure 4.1 The chart displays the distribution of broad professions among participants involved with professional design practices.

and 10% both. Among 150 participants, 115 distinct roles were grouped into 29 categories (Figure 4.1). Design experience: 36.7% had over 10 years, 34% had 1–5 years, and 22.7% had 6–10 years. A detailed breakdown of participants' self-reported knowledge of generative AI models is presented in Table 4.1.

4.2.2 *Exploratory Factor Analysis (EFA) Procedure*

An EFA (Mulaik, 2009) was conducted to identify the latent structure of the survey, focusing on constructs related to perceptions of generative AI and its trade-offs with traditional digital tools in creative practice. The analysis included Likert-scale and matrix-format items aligned with the four conceptual areas described in the previous section. Categorical variables (e.g., multiple-choice items) were excluded in line with factor analysis assumptions

Table 4.1 The table displays participants' knowledge of AI models for image or video generation

Knowledge of AI models (%)			
AI Model	*No Experience*	*Basic-Moderate*	*Advanced-Expert*
DALL-E	24.48	60.14	15.38
MidJourney	20.95	62.84	16.22
Stable Diffusion	58.33	27.78	13.89
FireFly	54.48	36.55	8.97
Sora	66.43	31.47	2.10
Veo2	83.80	15.49	0.70
Runway	65.75	28.77	5.48
Other	55.81	30.23	13.95

(Watkins, 2018). The Kaiser-Meyer-Olkin measure (0.675) and Bartlett's test of sphericity ($p < 0.001$) assessed suitability (Henson & Roberts, 2006; Hutcheson & Sofroniou, 1999). Principal axis factoring (PAF) was used to identify latent constructs by capturing shared variance among variables (Henson & Roberts, 2006). Parallel analysis (PA), used to reduce risk of over-extraction (Horn, 1965; Watkins, 2018), initially suggested eight factors. However, Factor 8 showed weak loadings and lacked conceptual clarity, while Factor 7 had unacceptable internal consistency (Cronbach's alpha < 0) so both were excluded for statistical and theoretical coherence (Henson & Roberts, 2006; Watkins, 2018). The final model retained six EFA-derived constructs. Additionally, three independent constructs (A, B, C) were extracted outside EFA to further explore perceptions of generative AI: one theory-driven ("Agency and Human Involvement Expectations") and two data-driven ("AI Integration and Pedagogical Innovation" and "Encountered Bias in AI Outputs"). All constructs were validated using Cronbach's alpha, ranging from 0.601 (exploratory according Gliem & Gliem, 2003) to 0.913 (Nunnally & Bernstein, 1994) (Table 4.2).

Composite scores were averaged for each construct and used in subsequent analyses, including nonparametric correlations and post-hoc item comparisons. Survey data analysis proceeded in stages. Spearman's rank correlations were run on the six EFA-derived constructs, then on three additional constructs. Post-hoc item-level Spearman's correlations were conducted for the strongest construct pairs to clarify key associations. Standalone items and multiple-choice questions were analysed separately. Multiple-response categorical questions were examined using descriptive statistics and chi-square tests (Agresti, 2007). Items on general perceptions of AI's future role in the creative industry were analysed as standalone indicators. This multi-level approach ensured statistical rigour and conceptual alignment, supporting identification of latent structures and interpretation of key perceptual indicators (de Winter et al., 2009; Watkins, 2018).

Table 4.2 The table summarizes the constructs extracted from EFA (1-6) and outside EFA (A-C), a brief theoretical description, and Cronbach's alpha value for internal consistency and reliability

ID	*Construct Name (EFA)*	*Description*	*Cronbach's Alpha*
1	AI Integration and Creative Empowerment	Gains in workflow efficiency, originality, skill growth, flexibility, authorship.	0.913
2	Technological Disruption and Adaptability Challenges	Challenges adapting to technological change and AI integration.	0.782
3	Ethical Concerns and Accountability	Concerns about bias, IP rights, plagiarism, transparency, and creativity loss.	0.824
4	Perceived Control and Shifts in Creative Process	Perceptions of control and evolving workflows with AI tools.	0.74
5	Perceived AI Agency	Beliefs about AI autonomy and creative decision-making.	0.718
6	Awareness of Bias in AI Outputs	Awareness of social/cultural biases in AI-generated content.	0.898
A	Agency and Human Involvement Expectations *(theoretical)*	Expectations of human agency and involvement in AI-assisted creativity.	0.601
B	AI Integration and Pedagogical Innovation *(data-driven)*	Role of AI in educational settings, including support and critical thinking.	0.828
C	Encountered Bias in AI Outputs *(data-driven)*	Reported experiences of bias in AI-generated outputs.	0.689

4.2.3 Reflexive Thematic Analysis (RTA)

To complement quantitative insights derived from EFA, a RTA (Braun & Clarke, 2006, 2021) explored experiences and perceptions with generative AI of professionals in the digital design and arts sector. Three elite professionals provided in-depth perspectives of the creative industry. Alan Warburton (AW): a creative technologist working with CGI/AI/XR, bridging art, industry, and academia; Estela Oliva (EO): director, producer, and artist working within arts, film, and immersive media; Lorenzo Levrero (LL): award-winning creative director with extensive collaborations with blue chip companies. These elite interviewees offered context-specific insights that might not be obtained through a larger sample of non-specialists (Harvey, 2011; Welch et al., 2002).

Semi-structured interviews (70–90 minutes via Microsoft Teams) mirrored the survey's structure for coherence. Transcripts were auto-generated and

manually verified for accuracy, ensuring integration between quantitative and qualitative data (Creswell & Plano Clark, 2011).

The RTA followed Braun and Clarke's (2006) six-phase framework: from immersive familiarization and coding to theme development, refinement, and integration into a coherent narrative. The analysis was facilitated using the open-source software QualCoder. Reflexivity and positioning were integral to the analysis as a resource for enhancing analytical depth and authenticity in qualitative research (Braun & Clarke, 2021; Finlay, 2002). Drawing on two decades of experience in digital art and design, I engaged in ongoing self-reflection to critically examine potential biases and their impact on interpretation. Reflexivity subthemes were refined through multiple iterations to improve thematic coherence and clarity. Six themes were identified and described in the following section.

4.2.4 Extracted Theme Description

Theme 1: *AI contradictions: the double-edged sword of creative automation*. This theme condenses the ambivalence designers experience with AI. While it enhances productivity and expands creative possibilities, it simultaneously imposes constraints on expression, often leading to compromises in artistic control and authorship.

Theme 2: *A new paradigm of creation: rethinking process, cognition, and workflow*. Generative AI is reshaping creative processes, shifting from hands-on craft to a more abstract, curatorial role. This transition demands new skills in data management and manipulation as well as high adaptability which is radically redefining the creator's engagement with their work.

Theme 3: *Craft vs. Automation: what gets lost, what gains value?* The rise of generative AI models challenges traditional notions of digital craft, where manual intervention and iterative processes risk being lost in favour of fast, soulless mass production. This may also erase a type of learning and creative thinking tied to embodied interaction with machines and software. As a result, a niche of designers may return to traditional digital craft, with renewed appreciation and growing cultural and economic value.

Theme 4: *The illusion of AI: a ghost in the shell or a mirror of our minds?* This theme explores the tendency to attribute human-like creativity and agency to AI due to its complex outputs. Interviewees highlight the risk of confusing algorithmic pattern-matching with intentionality, unmasking the illusion of AI's capabilities.

Theme 5: *The problem of labour: efficiency at the expense of ethics*. AI's integration into creative industries raises ethical concerns regarding labour exploitation and the devaluation of creative processes. While facilitating workflow efficiency, generative AI often obfuscates the human labour it is built on. Interviewees call for more ethical and transparent prompting and use of generative models, supported by companies and institutional bodies.

Theme 6: *Trust and Bias: hyper realities and ethical loopholes*. The hyper realistic outputs of generative AI blur the lines between authenticity and fabrication, raising issues of trust within the creative industry and the audience. Strong concerns are expressed over generative models perpetuating stereotypes and creating unrealistic standards, calling for a critical engagement with AI-generated content.

4.3 Results

4.3.1 EFA

Primary analyses examined correlational relationships across the full sample (N = 1 50) to explore shared perceptions of AI in creative practice. Spearman's rank correlations assessed associations between constructs: EFA-derived (1–6) and data/theory-driven (A and C) (Tables 4.2 and 4.3). Construct B, related to teaching, was excluded due to data heterogeneity. The strongest correlation occurred between Construct 1 and 4, $\rho = 0.745$, $p < 0.001$, linking AI empowerment with creative control. Further strong correlation included Construct 1 and C; $\rho = 0.575$, $p < 0.001$, revealing connections between empowerment and awareness of bias (Table 4.3).

Post-hoc Spearman's rank correlations were calculated between all items within construct pairs showing large effects (Construct 1 and 4; Construct 1 and C). In the first pair, strong item-level correlations ($\rho \geq 0.5$) included "Frequency of AI use" with "Creative process shift" ($\rho = 0.612$, $p < 0.001$) and "Control during AI creation" ($\rho = 0.599$, $p < 0.001$). "AI for idea generation" was also strongly linked to "Creative process shift" ($\rho = 0.563$, $p < 0.001$), highlighting the overlap between perceived empowerment and changes in creative workflow. For the second pair, the largest effect was between "AI strengthens emotional connection" and "Satisfaction with outcome" ($\rho = 0.507$, $p < 0.001$), indicating that emotional resonance with AI-generated works correlates with higher satisfaction in producing them. Additional item-level correlations ($\rho \geq 0.4$) are reported in Table 4.4.

Table 4.3 The table presents correlations between constructs with large (>0.5) and medium (≥0.3 and <0.5) effect sizes and significance levels

Constructs	*ρ*	*p-value*	*Interpretation*
1 ↔ 4	0.745	< 0.001	Empowerment ↔ Control Shifts
1 ↔ 10	0.575	< 0.001	Empowerment ↔ Bias Encountered
1 ↔ 5	0.469	< 0.001	Empowerment ↔ AI Agency
4 ↔ 10	0.468	< 0.001	Control Shifts ↔ Bias Encountered
3 ↔ 6	0.388	< 0.001	Ethical Concerns ↔ Bias Awareness
4 ↔ 5	0.383	< 0.001	Control Shifts ↔ AI Agency
5 ↔ 10	0.32	< 0.001	AI Agency ↔ Bias Encountered

Table 4.4 The table presents the post-hoc item-level effect sizes (Spearman's ρ) for the two construct pairs that exhibited the highest correlations in the preceding analysis

Construct 1	*Construct 4*	*ρ (Spearman)*	*p-value*
Frequency of AI use	Creative process shift	0.612	< 0.001
Frequency of AI use	Control during AI creation	0.599	< 0.001
Frequency of AI use for idea generation	Creative process shift	0.563	< 0.001
Efficiency of workflow	Creative process shift	0.483	< 0.001
Frequency of AI use	Control with AI collaboration	0.476	< 0.001
Reliance on AI	Creative process shift	0.471	< 0.001
AI aids technical skill	Control during AI creation	0.455	< 0.001
AI improves accuracy	Control during AI creation	0.448	< 0.001
AI enhances authorship	Control with prompt-based AI	0.446	< 0.001
Frequency of AI use for idea generation	Control during AI creation	0.445	< 0.001
AI enhances authorship	Control during AI creation	0.422	< 0.001
Frequency of AI use	Control with prompt-based AI	0.422	< 0.001
AI and skill development	Creative process shift	0.421	< 0.001
AI enhances speed	Creative process shift	0.417	< 0.001
Frequency of AI use for idea generation	Control with AI collaboration	0.413	< 0.001
AI improves accuracy	Creative process shift	0.41	< 0.001

Construct 1	*Construct C*	*ρ (Spearman)*	*p-value*
AI enhances authorship	Satisfaction with outcome	0.516	< 0.001
AI strengthens emotional connection	Satisfaction with outcome	0.485	< 0.001
AI strengthens emotional connection	Spontaneity in design	0.426	< 0.001
AI enhances authorship	Spontaneity in design	0.425	< 0.001
AI enhances authorship	Hands-on engagement	0.406	< 0.001

4.3.2 Independent Items Outside EFA

Most participants associated agency with "the ability to act independently and make decisions" (65%), with few (9%) linking it to rule execution. When using AI, 62% saw themselves as "directors", reflecting a sense of oversight. The main perceived AI limitation was its lack of "emotional depth" (81%), emphasizing beliefs in human uniqueness and a supervisory approach to AI tools. Generative AI is expected to play a significant role in the future of the creative industry for 58.7% of participants, with 56.7% preferring a "selective AI assistance", limited to technical tasks rather than creative decisions. Concerns about AI's impact on the creative industry were high (73.3% very or extremely concerned). Only 9.3% believed

Table 4.5 Summary of participants' general attitudes towards AI (most selected responses and associated chi-square significance levels; N = 150)

Topic	*Most Selected/ Deviating Response*	*n*	%	χ^2	*df*	*p*
Future Role of AI	Significant role	88	58.7	160.33	4	< 0.001
Ideal AI Integration	Selective AI assistance	85	56.7	99.49	3	< 0.001
Concern About AI	Very or extremely concerned	110	73.30	73.60	4	< 0.001
Future of Traditional Craft	Replaced by generative AI	31	20.7	27.97	3	< 0.001
Benefit of AI	Extremely beneficial	11	7.3	19.93	4	< 0.001

traditional digital craft skills would remain essential, while 20.7% believe generative AI would replace them. Only 7.3% rated AI as extremely beneficial (Table 4.5).

Most participants (63.3%) perceived technological change as slower prior to AI. Adaptation to updates in traditional software was reported as "occasional" (52.7%), in contrast with "often" for generative AI models (35.3%) (Table 4.6).

Participants were split between some believing technological acceleration makes it hard maintaining necessary skills (48%), and others feeling somewhat confident in adapting (48.4%). Perceptions of AI impact on workflow were mixed, with 39.3% strongly agreeing that AI advancements create uncertainty about long-term skill relevance; 38.7% somewhat agreeing that frequent updates disrupt consolidated workflows yet making it more efficient (36%) (Table 4.7).

Table 4.6 Summary of participants' perceived disruption of technological (most selected responses and associated chi-square significance levels; N = 150)

Topic	*Most Deviating Response*	*n*	%	χ^2	*df*	*p*
Perceived pace of change since AI	Slower before AI	95	63.3	64.36	2	< 0.001
Non-generative software updates	Occasionally impactful	79	52.7	120.80	4	< 0.001
Generative AI model updates	Often impactful	53	35.3	57.13	4	< 0.001

Table 4.7 Summary of participants' attitude towards generative AI (most selected responses and associated chi-square significance levels; N = 150)

Item	*Most Selected Response*	*n*	*%*	χ^2	*df*	*p*
Speed of change makes it hard to keep up	Somewhat agree	72	48.0	82.47	4	< 0.001
Confidence in adapting to tech change	Somewhat agree	75	48.4	98.77	4	< 0.001
Workflow efficiency from rapid updates	Somewhat agree	54	36.0	44.47	4	< 0.001
Uncertainty from speed of AI	Strongly agree	59	39.3	80.20	4	< 0.001
Workflow disruption from frequent updates	Somewhat agree	58	38.7	52.33	4	< 0.001

4.4 Discussion

The integration of AI into creative workflows is producing both transformation and tension. This study reveals no clear split between traditional and automated practices, rather a dynamic negotiation. Participants in the survey described AI tools as empowering, however refused giving up control, especially in creative tasks. Many described themselves as directors rather than collaborators. This duality suggests that empowerment through AI does not necessarily involve a transfer of authorship, rather, it may reflect a persistent anthropocentric view of creativity, where machines are tools and only humans possess true creative agency. This view remains dominant in public discourse, despite scholarly challenges from Boden (2004) to Guckelsberger et al. (2017), Daniele and Song (2019b), and Moruzzi (2021), a framework opening towards a human-machine entanglement in creative practice. EFA results reveal a strong correlation between perceived empowerment, control, and agency. The more participants used AI, the more they perceived its influence while retaining control over its creative outputs. This distributed agency allows designers to feel both empowered and in charge, even when tools become more autonomous.

As AI becomes part of creative work, participants reported feeling overwhelmed by the rapid pace of technological change and expressed concern that traditional digital craft might be lost. Insights from RTA indicated that these concerns were not simply nostalgia, rather a desire to preserve embodied knowledge embedded in digital craft. Watching footage repeatedly, adjusting layers by hand, revisiting iterations are more than routines, they are modes of understanding. EO commented: "*if your job is an editor […] deleting spots from my film, once you've done it, you have learnt a lot. But if*

you never do it, you don't really think about it". Similarly, AW noted: "*…3D modelling, for example, or texturing or animation, still required us to engage in a direct kind of perceptual relationship with the world*". These quotes highlight the level of conscious participation and physical involvement in "craft" as described in McCullough (1998).

Designers are undergoing a radical shift in creative practice where AI feels increasingly necessary (AW: *"I don't think that we can go put the genie back in the bottle")*. Interviewees framed this shift as both "liberating" and "limiting". AI was consistently described as enhancing speed and scale, especially under time pressure, budget constraints, or in early exploration. LL: "*Sometimes it's useful for brainstorming […] instead of Pinterest"; AW: "It feels like you're getting your own team of designers"; EO: "…without AI we would have spent so many hours doing that job"*. This practical use aligns with findings by Park et al. (2024), who found designers primarily using generative AI tools during early-stage brainstorming and idea development. In these cases, AI is not perceived as replacing creativity, rather as accelerating workflow. However, interviewees expressed frustration with its lack of predictability and control, LL: *"It's a rebel agency!"*; AW: *"It always says something that you don't want it to say"*. Prompting was often described as trial-and-error reflecting a "structured randomness" of generative models, where complete control is elusive even for expert users (Manovich & Arielli, 2024).

Ethical concerns were widespread, especially in relation to style mimicry, authorship, labour exploitation, race and gender bias embedded in datasets and visual outputs (EO: *"I even look for aliens and they are still genderised"; AW: "their labour is at risk of being stolen and automated."*). Some were less concerned by uncredited training data, viewing imitation as part of creative culture. However, the same criticized how this feeds a capitalist mode of mass-production overcoming quality design and enriching the few.

Trust emerged as a deeper theme. Interviewees noted how AI-generated visuals, especially in pitching, can set unrealistic expectations in clients. Furthermore, they questioned how audiences interpret AI-generated media. Lorenzo stressed how not perceiving human intervention in advertising could ultimately harm brands (LL: *"It will create distrust in brands. Everything I see, I don't know if it's true.*") possibly leading to a form of collective apathy (LL: *"It becomes apathy, it becomes… 'oh well, who cares!' It means not trusting. It means not being represented. Because it makes me doubt, it doesn't give me certainty.")*. Lack of trust expands further with Estela reflecting on emotional responses to AI-generated images: "*Are these eyes taken from pictures of real kids? So it's not about the AI, it's about the database or the large model that they use that involves real people. Therefore, I'm having that connection*". The issue goes beyond technical, or ethical. It becomes existential. Ultimately, all interviewees stressed how collective effort and collaboration among people involved in the making of creative work represent a value that is often overlooked.

4.5 Conclusion

This study explored the trade-off between digital craft and automation, focusing on the integration of generative AI into creative practice. Designers gain speed in workflows, and new ways to explore visual ideas, particularly during early-stage development. AI expands possibilities, especially under time and resources constraints. However, this comes at a cost of a compromised expression. As AI takes over parts of the process, key aspects of learning, reflection, and authorship risk being bypassed. Craft goes beyond technique: it is a way of thinking and learning. When speed replaces iteration, and outputs precede process, something is lost. The tension is not between old and new, rather between automation and care. As AI becomes embedded in creative practice, it is crucial to reflect on what is being displaced. This trade-off is a continuum, and tracking its changes is essential to foster innovation and meaning in a healthy creative industry. As Garvin et al. (2023) point out, the value of craft lies in unalienated labour focused on quality and meaning over profit, prioritizing community over corporate policies. This principle should guide AI design and deployment in a way that cultivates a more equitable and sustainable future.

4.6 Future Research Agenda

This study is part of a broader research programme investigating how creative industries and education are adapting to generative AI. Next steps aim to triangulate perspectives from designers, students, educators, and policy makers to build a comprehensive understanding of this transformation. The goal is to support educators, empower younger generations, and shape a healthier, more meaningful creative industry. The following four questions will guide future investigations:

RQ1: *How are young designers experiencing the integration of generative AI in established design practices?*

This question focuses on early-career designers who are learning to use generative AI before fully mastering traditional tools. It examines how they adapt to established workflows, approach creative problem-solving, and perceive this technological shift, whether as an opportunity, a disruption, or a seamless part of their design education and practice.

RQ2: *How are educators responding to the rapid shift in design tools and educational practices?*

This investigation will mirror the current study, using mixed-methods to examine how educators are teaching, learning, and adapting to the integration of generative AI. It explores how educational approaches are evolving in response to institutional pressures, ethical concerns, the opportunities and challenges introduced by these technological changes.

RQ3: *How are students learning and comparing generative AI tools and traditional design software?*

This study will use mixed-methods to investigate how students learn, use, and apply both generative and traditional design tools. It will measure learning curves, usage patterns, and preferences, while also identifying potential biases in creative education. A series of workshops and group discussions will be combined with surveys to capture how students acquire, apply, and reflect on these tools within their creative practice and learning.

RQ4: *How can we build a collective, open-minded response to the impact of generative AI on creative practice and education?*

This final phase of the research programme will engage students, educators, designers, and policy makers through interviews, roundtables, and public dialogue (e.g., podcasts). The research will be informed by insights from the studies mentioned above. The aim is to develop a comprehensive, multi-faceted perspective of current needs and concerns in the creative industry, supporting ethical and inclusive approaches to creative education and design practices.

AI Disclaimer Statement

In this chapter, generative AI tools (i.e., OpenAI ChatGPT-4o and Google Gemini 2.5) were used to support quality assurance and language improvement. Tasks included refining the questionnaire and chapter structure, checking methodology and potential biases in the survey and interview design, improving clarity, reducing redundancy, and clarifying concepts from literature. All ideas, analysis, results, and interpretations are original. Every AI-assisted suggestion was independently verified, edited, or discarded by the author, following multiple review iterations, truth and hallucination checks to ensure accuracy and prevent misinformation.

References

Agresti, A. (2007). *An introduction to categorical data analysis* (2nd ed.). Wiley.

Balbi, G., & Magaudda, P. (2018). *A history of digital media: An intermedia and global perspective*. Routledge.

Boden, M. A. (2004). *The creative mind: Myths and mechanisms*. Routledge.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101.

Braun, V., & Clarke, V. (2021). *Thematic analysis: A practical guide*. Sage.

Caramiaux, B., Crawford, K., Liao, Q. V., Ramos, G., & Williams, J. (2025). *Generative AI and creative work: Narratives, values, and impacts*. arXiv preprint arXiv:2502.03940.

Cave, S., & Dihal, K. (2020). The whiteness of AI. *Philosophy & Technology*, *33*(4), 685–703.

Chesterman, S. (2025). Good models borrow, great models steal: Intellectual property rights and generative AI. *Policy and Society*, *44*(1), 23–37.

Creswell, J. W., & Plano Clark, V. L. (2011). *Designing and conducting mixed methods research* (2nd ed.). Sage.
Daniele, A., & Song, Y. (2019b). Artistic assemblage. In *Proceedings of the Seventh Conference on Computation, Communication, Aesthetics and X* (pp. 240–255).
Daniele, A., & Song, Y. Z. (2019a). AI+ art= human. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 155–161).
de Winter, J. C. F., Dodou, D., & Wieringa, P. A. (2009). Exploratory factor analysis with small sample sizes. *Multivariate Behavioral Research*, *44*(2), 147–181.
Ferrara, E. (2023). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci*, *6*(1), 3.
Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs – Principles and practices. *Health Services Research*, *48*(6pt2), 2134–2156.
Finlay, L. (2002). Negotiating the swamp: The opportunity and challenge of reflexivity in research practice. *Qualitative Research*, *2*(2), 209–230.
Garvin, M., Eglash, R., Robinson, K. P., Robert, L., Guzdial, M., & Bennett, A. (2023). Counter-hegemonic AI: The role of artisanal identity in the design of automation for a liberated economy. In *AI and the future of creative work* (pp. 71–88). Routledge.
Gebru, T. (2020). Race and gender. In M. D. Dubber, F. Pasquale, & S. Das (Eds.), The Oxford handbook of ethics of AI (Vol. 4, p. 253). Oxford University Press.
Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. *Societies*, *15*(1), 6.
Gliem, J. A., & Gliem, R. R. (2003). Calculating, interpreting, and reporting Cronbach's alpha reliability coefficient for Likert-type scales. In *Midwest Research-to-Practice Conference in Adult, Continuing, and Community Education*.
Guckelsberger, C., Salge, C., & Colton, S. (2017). Addressing the "why?" in computational creativity: A non-anthropocentric, minimal model of intentional creative agency. In *International Conference on Computational Creativity 2017*. Association for Computational Creativity (ACC).
Habib, S., Vogel, T., Anli, X., & Thorne, E. (2024). How does generative artificial intelligence impact student creativity? *Journal of Creativity*, *34*(1), 100072.
Harvey, W. S. (2011). Strategies for conducting elite interviews. *Qualitative Research*, *11*(4), 431–441.
Hayles, N. K. (2017). *Unthought: The power of the cognitive nonconscious*. University of Chicago Press.
Henson, R. K., & Roberts, J. K. (2006). Use of exploratory factor analysis in published research: Common errors and some comment on improved practice. *Educational and Psychological Measurement*, *66*(3), 393–416.
Hislop, D., Bosley, S., Coombs, C. R., & Holland, J. (2014). The process of individual unlearning: A neglected topic in an under-researched field. *Management Learning*, *45*(5), 540–560.
Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179–185.
Hutcheson, G., & Sofroniou, N. (1999). *The multivariate social scientist: Introductory statistics using generalized linear models*. Sage.
Jiang, H. H., Brown, L., Cheng, J., Khan, M., Gupta, A., Workman, D., & Gebru, T. (2023, August). AI art and its impact on artists. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 363–374).
Manovich, L., & Arielli, E. (2024). Artificial aesthetics. *Generative AI, Art and Visual Media*. https://manovich. net/index. php/projects/artificial-aesthetics
Masson, D., Malacria, S., Casiez, G., & Vogel, D. (2024, May). Directgpt: A direct manipulation interface to interact with large language models. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (pp. 1–16).

McCormack, J., Llano, M. T., Krol, S. J., & Rajcic, N. (2024, March). No longer trending on artstation: Prompt analysis of generative ai art. In International Conference on Computational Intelligence in Music, Sound, art and Design (Part of EvoStar) (pp. 279–295). Springer Nature Switzerland.
McCullough, M. (1998). *Abstracting craft: The practiced digital hand*. MIT press.
Moruzzi, C. (2021). Measuring creativity: an account of natural and artificial creativity. *European Journal for Philosophy of Science*, *11*(1), 1.
Moruzzi, C. (2022). Creative agents: rethinking agency and creativity in human and artificial systems. *Journal of Aesthetics and Phenomenology*, *9*(2), 245–268.
Mulaik, S. A. (2009). *Foundations of factor analysis*. CRC press.
Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory*. McGraw-Hill, Inc.
Park, H., Eirich, J., Luckow, A., & Sedlmair, M. (2024, October). "We are visual thinkers, not verbal thinkers!": A thematic analysis of how professional designers use generative AI image generation tools. In *Proceedings of the 13th Nordic Conference on Human-Computer Interaction* (pp. 1–14).
Park, S. (2024). The work of art in the age of generative AI: aura, liberation, and democratization. *AI & Society*, *40*(3), 1807–1816.
Ruiz-Rojas, L. I., Salvador-Ullauri, L., & Acosta-Vargas, P. (2024). Collaborative working and critical thinking: Adoption of generative artificial intelligence tools in higher education. *Sustainability*, *16*(13), 5367.
Tigre Moura, F. (2023). Artificial intelligence, creativity, and intentionality: The need for a paradigm shift. *The Journal of Creative Behavior*, *57*(3), 336–338.
Warburton, A. (2023). *The wizard of AI* [AI-generated film]. Data as culture, Open Data Institute.
Watkins, M. W. (2018). Exploratory factor analysis: A guide to best practice. *Journal of Black Psychology*, *44*(3), 219–246.
Welch, C., Marschan-Piekkari, R., Penttinen, H., & Tahvanainen, M. (2002). Corporate elites as informants in qualitative international business research. *International Business Review*, *11*(5), 611–628.
Whyte, J. (2007). *Virtual reality and the built environment*. Routledge.