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Generative AI as a Design Collaborator: Redefining Authorship, Creativity, and Pedagogy in Contemporary Design Practice

Pooya Lotfabadi [1]*

[1] Faculty of Architecture and Fine Arts, Final International University, Beşparmaklar Avenue, No: 6, Çatalköy, Girne, Turkey.

* Correspondence: pooya.lotfabadi@gmail.com

What happens to design authorship when the machine can generate a hundred variations of a facade before the architect has finished their first sketch? This question, which might have seemed hypothetical even five years ago, is now routine in architectural and graphic design studios worldwide. This paper examines how generative AI is unsettling three interlocking foundations of design practice: the attribution of creative authorship, the cognitive basis of design creativity, and the pedagogical conditions under which design judgment is formed. Rather than treating these as separate problems, the discussion tries to show how they reinforce each other, and why responding to any one of them in isolation is likely to produce incomplete and potentially counterproductive solutions. The paper draws on a range of recent empirical and theoretical work, including jury-based studio research and computational performance studies, and situates current debates within the longer history of design's relationship with disruptive technologies. The argument is not that generative AI is simply good or bad for design. It is that the profession is, at this moment, making choices whose consequences will be difficult to reverse, and that making them thoughtfully requires a clearer sense of what design has always been for, not just what it currently does.

Keywords: Generative AI, Design authorship, Design pedagogy, Creativity, Artificial intelligence, Human-centered design, Design ethics, AI tools, Design education, Co-authorship.

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1. Introduction

Design has always been entangled with its tools. But there is something qualitatively different about what is happening now, and it is worth trying to be precise about what that difference is. Previous computational tools such as; CAD, parametric modelling, and BIM extended the designer's capacity to execute and test ideas. They were faster and more precise than hand-drawing or physical modelling, but the ideas still had to originate somewhere in a human mind. Generative AI systems such as Midjourney, DALL-E 3, Stable Diffusion, and an expanding array of spatial and product design tools do something structurally different: they participate in the generative phase itself [1]. They propose. They iterate. They produce outputs that look, in many cases, like the products of a creative imagination, even when the person who prompted them had no clear image in mind when they began [2].

This has happened very quickly. Between 2022 and 2025, tools that were experimental curiosities became embedded features of professional design software. Students at architecture schools are now regularly submitting AI-generated imagery in studio crits. Graphic designers are using text-to-image systems to produce client mood boards in minutes rather than hours. Spatial planning consultancies are running AI-assisted massing studies before a brief has been properly written. Whether one regards this as exciting or alarming, and reasonable people differ, it is undeniably real, and it is not going to reverse.

What follows is an attempt to think carefully about what this means, particularly for three dimensions of design practice that tend to be discussed separately but are, the argument here suggests, deeply connected: how design authorship is understood and attributed, how creativity functions when a machine contributes to ideation, and how design judgment is developed in educational settings. Figure 1 presents the conceptual framework that structures this discussion. None of these questions is simple, and this paper does not pretend to resolve them. What it tries to do is map the terrain honestly enough to make better conversations possible.

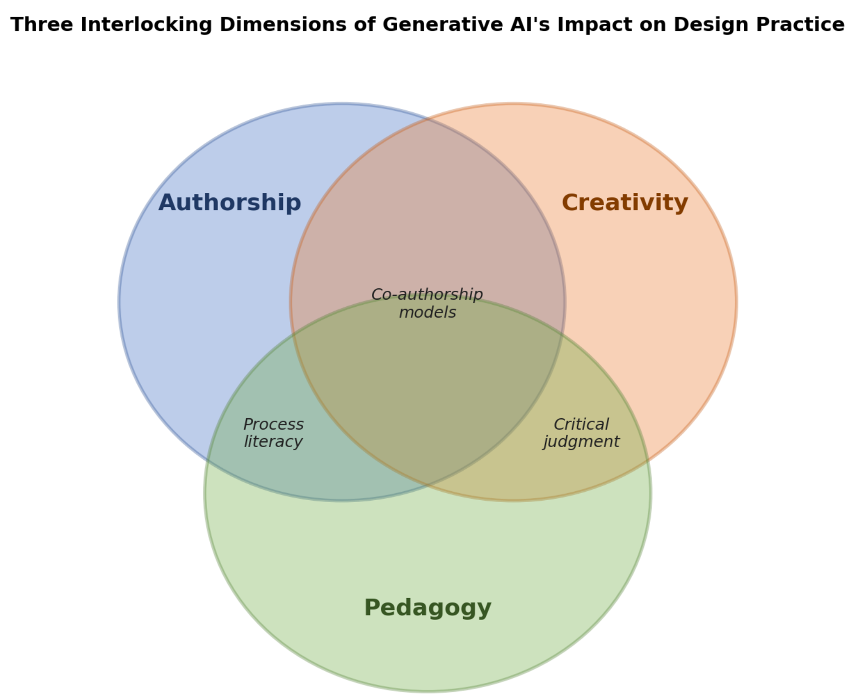

Figure 1. Conceptual Framework: Three Interlocking Dimensions of Generative AI's Impact on Design Practice. The zones of overlap, co-authorship models, process literacy, and critical judgment, represent the sites of most pressing practical and theoretical difficulty.

2. Historical Context: Design and Technological Disruption

The anxiety provoked by generative AI in design circles is not unprecedented, though it is perhaps more intense than previous disruptions warranted. When the personal computer arrived in design studios in the 1980s, there were genuine fears about deskilling, that designers would lose their ability to think spatially and typographically if they outsourced these tasks to software [3]. Similar arguments were made about CAD, about desktop publishing, about parametric modelling. In each case, the profession eventually absorbed the new technology without dissolving, though not without real losses and real reorganisations of practice.

The parametric design movement of the early 2000s is perhaps the most instructive precedent. Architects like Zaha Hadid, Patrik Schumacher, and Greg Lynn used algorithmic tools to generate forms that no hand-drawing process could have produced, and this raised early versions of the authorship questions that generative AI raises more acutely today [4]. But in that context, a crucial transparency remained: the designer authored the rules, even when the machine generated the outcomes. The logic of the system was available for inspection. You could follow the reasoning, even if you could not reproduce the output by hand.

Contemporary deep learning systems do not offer this transparency. A diffusion model trained on billions of images operates through patterns latent in its training data that are, in an important sense, inaccessible even to the model's developers [5]. This epistemic opacity is qualitatively new. When a designer prompts a generative system and selects among its outputs, they are navigating a latent space whose topology they did not design and whose biases they cannot fully identify. The question of what, exactly, the designer is responsible for in that process is not a philosophical abstraction, it has immediate professional and legal implications.

None of this means that the current situation is unmanageable, or that the design disciplines lack the resources to respond. The historical record suggests they do not dissolve under technological pressure. But the speed of the current shift, and the depth of its penetration into what had previously been considered the irreducibly human core of design work, makes complacency risky.

3. Authorship Under Pressure

Design authorship was already a contested concept well before generative AI arrived. The modernist mythology of the solitary creative genius, Le Corbusier at his drawing board, Eames in his studio, had been challenged from multiple directions by the late twentieth century. Collaborative, participatory, and process-based models of practice redistributed creative agency across teams, clients, users, and communities [6]. Postcolonial and feminist scholarship made visible the labour of the many unnamed contributors, fabricators, consultants, local craftspeople, whose knowledge shaped the work attributed to single celebrated practitioners. By the time generative AI appeared, design theory had already complicated the idea that authorship resided in any single human mind.

What generative AI introduces is something different again. When a designer generates a hundred spatial configurations using a diffusion model and selects the most promising three, the creative act has migrated almost entirely to the curatorial. The designer is choosing among possibilities they did not conceive, and in some cases could not have conceived, because the outputs lie in regions of formal possibility that no individual practitioner could have reached through unaided imagination. This is not simply a question of attribution; it has legal dimensions that are now being contested in courts across multiple jurisdictions, as existing intellectual property frameworks strain to accommodate outputs generated by systems trained on existing works without the consent of their creators [7].

Some writers argue that prompt engineering constitutes a genuine form of authorship in its own right, that the skill required to direct a generative system toward a desired outcome is itself a creative act, analogous to writing a brief or a programme [8]. There is something to this. The difference between an expert and a naive prompt is visible in the outputs. But the analogy is not quite right, because a brief shapes a process whose outputs remain fundamentally authored by the people who carry it out. A prompt shapes the sampling of a latent space whose contents were formed by the labour of millions of people who had no say in the matter and receive no credit for it. These are not equivalent situations.

What seems needed is a more differentiated vocabulary for how designers relate to AI-generated work, something that can distinguish between the designer as initiator, as curator, as critical evaluator, and as the person who integrates generated elements into a coherent and responsible whole. None of these roles is trivial, but they are not the same as authorship in the traditional sense, and pretending they are is likely to obscure more than it clarifies.

4. The Restructuring of Creativity

There is a persistent assumption in public discourse about AI, and, in some academic discourse too, that if machines can generate creative outputs, human creativity must be diminishing in importance. This seems wrong, but the reasons why it is wrong are worth spelling out. Design creativity, as it is understood in the research literature, is not primarily a matter of generating novel images or forms [9]. It involves reframing problems, recognising what a situation actually requires rather than what the brief says it requires, reasoning analogically across domains, and exercising judgment in conditions of genuine uncertainty. These are capacities that generative AI systems conspicuously lack. They can produce plausible-looking outputs at extraordinary speed and scale, but they cannot tell you whether the problem you have asked them to solve is the right problem.

What AI does is restructure where in the design process human effort is most needed. Figure 2 illustrates this schematically: the phases in which human cognitive effort was historically concentrated, divergent ideation and formal exploration, are precisely the phases in which AI is now most capable. The phases that require contextual judgment, ethical reasoning, and communicative intelligence are not. This is not necessarily bad news for designers; it may free up time and cognitive bandwidth for the higher-order work. But it does mean that the nature of what a skilled designer needs to be good at is shifting, and design education needs to register this shift explicitly rather than assuming the old curriculum still applies.

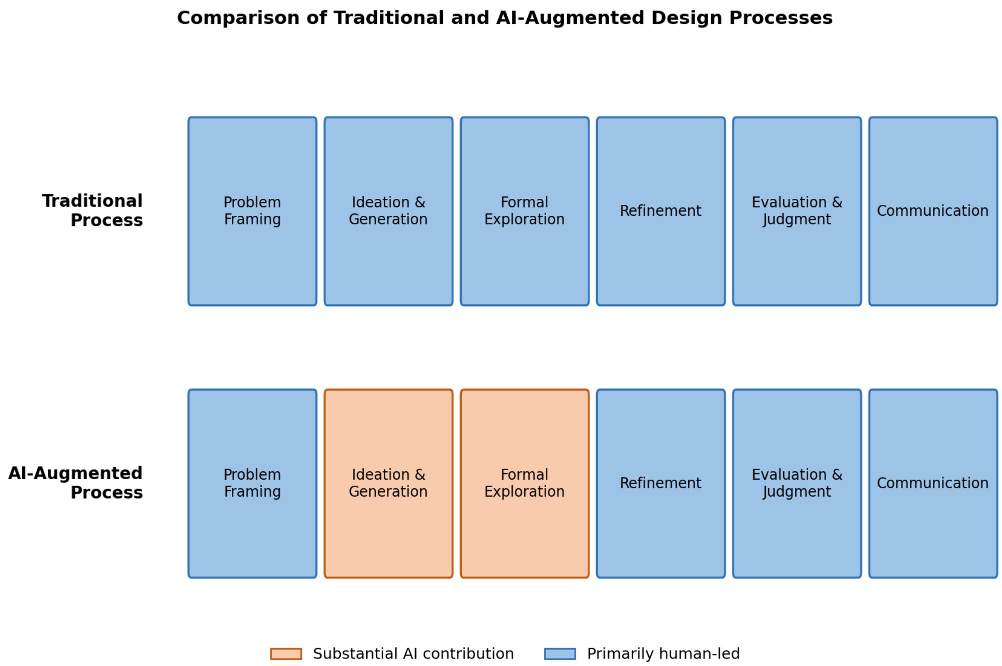

Figure 2. Comparison of Traditional and AI-Augmented Design Processes. Phases in orange involve substantial AI contribution; blue phases remain primarily human-led.

Figure 3 offers a more granular picture of how creative labour is redistributed across specific design activities. The figures are indicative rather than empirically derived, they reflect patterns reported in practitioner accounts and recent survey literature [2, 10], but the overall pattern is consistent: AI contribution is highest in visual generation and early-stage prototyping, and lowest in problem framing and communication. The inversion in the generation phase is particularly striking.

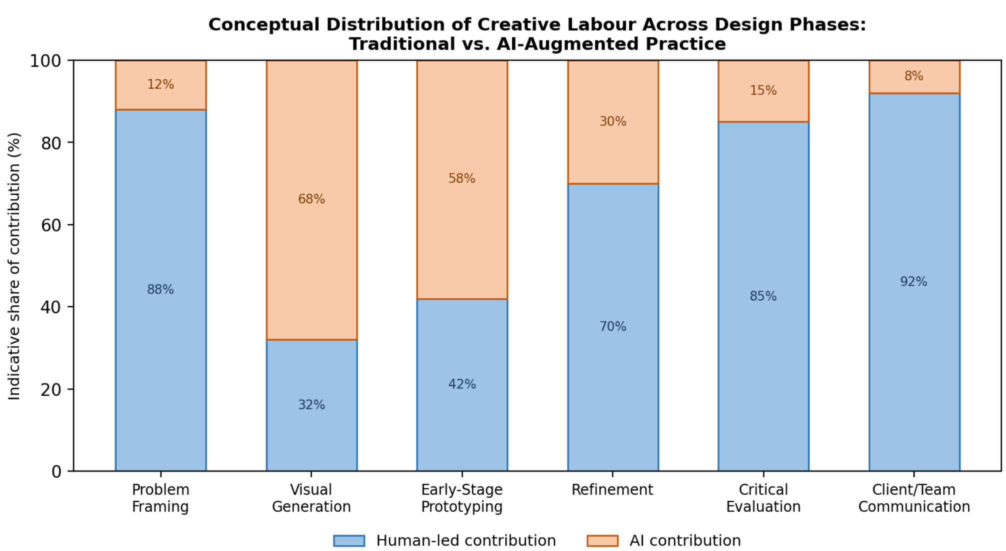

Figure 3. Conceptual Distribution of Creative Labour Across Design Phases: Traditional vs. AI-Augmented Practice.

A further concern involves what is sometimes lost when the generative act is delegated to a machine. Schön's work on reflective practice identifies something important here: much of what designers learn, they learn by doing, by the resistance of materials, the surprises of sketching, the way a spatial idea transforms under the pressure of making it concrete [12]. If this process is short-circuited by systems that produce polished results before the designer has properly wrestled with the problem, the learning loop that makes practice sustainable over time may be broken. This is not a trivial concern. It is one of the reasons why pedagogical questions cannot be separated from questions about creativity.

Empirical evidence for these dynamics comes from structured studio research. Iranmanesh and Lotfabadi [19], observing five architectural design studios over two consecutive semesters and drawing on self-reported AI usage across 221 public jury assessments, found that text-to-image tools genuinely expanded students' design versatility and encouraged more ambitious formal exploration, but at a cost. Students who relied heavily on generated imagery showed reduced attentiveness to questions of human scale, material logic, and what the authors describe as the 'reality of architectonics'. The tool lowered the barrier to impressive-looking outputs while raising, in some respects, the barrier to architecturally grounded ones. That is a trade-off worth naming clearly.

There is also a homogenisation risk that deserves more attention than it typically receives. Large-scale generative models are trained on datasets that over-represent certain aesthetic traditions, historical periods, and geographic contexts [5]. They have a gravitational pull toward what already exists and is already well documented. A designer who relies on them heavily may produce work that is visually fluent but aesthetically conventional in ways they do not fully recognize, because the frame of reference they are using has been invisibly shaped by the model's training distribution.

5. Current AI Tools in Design Practice: A Survey

It is worth being specific about what tools are actually being used, because the landscape is more varied than the term 'generative AI' implies, and different tools raise different questions. The most widely discussed and most rapidly adopted are visual generation tools: Midjourney, DALL-E 3, Stable Diffusion, Adobe Firefly, and their successors [2]. These tools have become standard features of concept design workflows in architecture, branding, graphic design, and product development. Their speed is genuinely transformative; a designer can now explore a far wider range of visual possibilities at the early stages of a project than was previously feasible. The limitations are real, though. Spatial relationships remain unreliable, typographic accuracy is poor, and the tools have no understanding of materiality or structural logic [13]. For architecture and industrial design especially, this means that AI-generated imagery needs substantial critical filtering before it can inform actual design decisions.

The performance limitations of AI-generated spatial outputs have been examined empirically by Çelik [20] in a study evaluating housing plans produced by diffusion models against climate-based daylight simulation. The findings were unambiguous: none of the models tested produced plans that consistently integrated solar orientation or seasonal lighting considerations. The generated plans looked plausible, rooms in recognisable configurations, reasonable proportions, but they failed basic environmental performance criteria at a rate that would make them unusable as actual design proposals without substantial human reworking. This is useful empirical grounding for what might otherwise remain an abstract concern about AI limitations in spatial design.

A different category of tools operates at the level of spatial performance optimisation. Autodesk Forma, Spacemaker, and AI-assisted features in Rhino and Grasshopper allow designers to evaluate large numbers of spatial configurations against defined criteria, daylight, wind exposure, structural efficiency, with a speed and comprehensiveness that no human analyst could match [4]. Here the relationship between the designer and the AI is cleaner: the human sets the performance targets and interprets the results; the AI does the computational heavy lifting. This division feels more clearly like a tool in the traditional sense, the designer remains firmly in command of the problem definition and the interpretation of results, though the apparent cleanliness of the relationship should not be overstated. Questions about which performance criteria are selected, how they are weighted against each other, and whose priorities they ultimately reflect are not settled by the technology; they remain human judgments, and ones that carry real design consequences.

Perhaps the most consequential category, precisely because it is the least visible, is AI embedded in standard professional software. Generative fill in Adobe Photoshop, AI-assisted layout suggestions in Figma, smart selection and auto-complete features in AutoCAD, these are used by millions of designers every day, often without explicit reflection on the fact that they involve AI assistance at all [2]. The normalisation of these tools is probably inevitable and not obviously problematic. But it does mean that developing critical AI literacy, an understanding of what these tools are doing, where their biases lie, and when to override them, is now a baseline professional competence rather than a specialist interest.

6. The Industry-Education Gap

One of the more uncomfortable realities of the current moment is that professional design practice and design education are operating on markedly different timescales. Firms and studios have adopted generative AI tools rapidly, driven by competitive pressure and the genuine efficiency gains on offer. Design schools, for the most part, have not kept pace, not necessarily because of inertia, but because developing coherent curricula for a technology that is changing this quickly is genuinely difficult [14].

The consequences of this gap are worth thinking through carefully. At the most immediate level, graduates arrive in practice without having encountered the tools that are already standard in the studios that hire them. That is a practical problem with practical solutions. More troubling is the possibility that students are using these tools informally and unreflectively in their coursework, in contexts where educators have not yet developed frameworks for assessing AI-assisted work, and that this is happening before students have built the foundational competencies that would allow them to use the tools critically rather than dependently [14].

There is also a financial dimension that rarely gets enough attention. Access to the most capable generative AI tools is currently mediated by subscription costs and, in some cases, hardware requirements. Design schools in the Global South, and individual students in under-resourced programmes anywhere, may simply not have access to the same tools as their better-resourced counterparts [15]. If AI-augmented design competence becomes a marker of institutional privilege, the integration of AI into the profession will deepen existing inequalities rather than distributing creative capacity more widely, which is what its proponents tend to promise.

Some schools have started responding in genuinely interesting ways. Requiring students to document every prompt, every iteration, and every decision point, making the human intelligence in an AI-assisted process visible and examinable, is one approach. Structured comparative exercises, in which students solve the same brief with and without AI tools, are another [14]. These are reasonable starting points. But they remain local and ad hoc. The field needs accrediting bodies and professional organisations to develop shared frameworks, and it needs them before the gap widens further.

7. Implications for Design Education

Studio pedagogy is built on a particular theory of learning, one in which knowledge is not transmitted but constructed through repeated cycles of making, failing, receiving critical feedback, and making again [12]. The design crit, the jury, the peer review, the iterative model: these are not just delivery mechanisms for content. They are the conditions under which design judgment is formed. And judgment, the capacity to recognise what a good solution looks like in a specific context, and to explain why, is ultimately what a design education is trying to produce.

Generative AI puts pressure on this pedagogy in a specific way. It is not that students can now cheat more easily, though that is also true. It is that the tool allows students to arrive at polished-looking outcomes without having gone through the formative struggle that is supposed to produce judgment. A student who generates a sophisticated-looking section drawing before they understand section drawing may produce technically impressive work while learning surprisingly little. The output and the learning are decoupled in ways that are not immediately visible to either the student or the assessor.

Evidence for the formative importance of the specific social and evaluative structures of studio learning comes from Lotfabadi and Iranmanesh [21], who used an analytic hierarchy process to assess the relative weight of four learning modalities in the architecture studio, critique, jury, peer learning, and self-directed study, as perceived by both students and educators. Their findings suggest that the structured interpersonal encounter of the jury and the crit carries formative weight that cannot be reduced to the transmission of technical knowledge. These are, in part, the settings in which students learn to give accounts of themselves and their decisions, to explain why they made the choices they made. That capacity is precisely what risks atrophy when AI takes over the generative phase, because there is less to explain and less pressure to develop the vocabulary for explaining it.

This is not an argument against using AI in design education. It is an argument for sequencing and intentionality. There are good reasons to think that AI tools can be genuinely pedagogically valuable once students have developed a baseline of spatial, material, and typographic intuition, once they have something to evaluate the AI's outputs against. The problem is premature integration, before those intuitions are in place. Getting the sequencing right is one of the more important curricular challenges the field faces, and it cannot be addressed without research on how AI use actually affects design learning over time.

Professional accrediting bodies, RIBA, NASAD, the Design Council and their counterparts in other regions, have an obvious role to play here. The current situation, in which individual institutions are improvising their own policies without shared reference points, creates inequities and inconsistencies that ultimately harm students. Guidelines do not need to be prescriptive or technology-specific to be useful; what is needed is a framework that helps educators think through the pedagogical purpose of specific exercises before deciding whether AI assistance is appropriate to that purpose.

8. Toward an Ethical Framework for AI in Design

Ethical frameworks for new technologies tend to age badly when they are written too close to the moment of disruption, because the technology keeps changing and the frameworks do not. With that caveat, there are some principles that seem robust enough to be worth stating. The first is transparency about process. Designers who use generative AI in their work should say so, in client proposals, in published work, in academic submissions [16]. This is not because AI-assisted work is inherently lesser, but because the people evaluating that work need to know how it was made in order to assess it properly. A rendering that emerged from an hour of prompt-refinement is a different kind of thing from a rendering that emerged from three weeks of spatial thinking, even if they look similar on a screen. Professional codes of conduct and academic submission requirements are slowly updating to reflect this; they should do so faster.

Second, intentionality in how AI is deployed. The strongest uses of generative AI in design practice share a common feature: the designer has a clear idea of what they are trying to do and is using the AI to do it more efficiently or more comprehensively, rather than using the AI to decide what to do. This sounds obvious, but it is consistently violated when designers turn to generative tools precisely because they are uncertain about direction. The tool then sets the direction by default, through its training biases, and the designer curates without having established the critical framework needed to curate well [11]. Cultivating intentionality is partly an individual professional responsibility and partly a pedagogical one.

Third, and this cannot be said too plainly, human designers remain accountable for everything that bears their name, regardless of what role a machine played in producing it. The existence of an AI in the design chain does not transfer responsibility to the machine. A building that fails structurally because an AI-generated proposal was not properly scrutinised is the failure of the architect who signed off on it. A brand identity that reproduces stereotypes absorbed from training data is the responsibility of the designer who chose to use it. This principle is uncontroversial in theory; sustaining it in practice as AI systems become more capable, and the temptation to defer judgment grows stronger, will require ongoing institutional reinforcement.

A fourth principle, equity in access, is less often discussed in design ethics frameworks but deserves to be. If the most capable AI tools are available only to well-resourced practitioners and institutions, the technology will concentrate competitive advantage rather than distributing creative capacity [15, 17]. Design organisations and technology companies should actively address this, not because it serves their interests in any obvious short-term way, but because a design profession that is more globally diverse and less resource-stratified is, in the long run, more capable of addressing the actual range of human design problems.

Finally, and this connects back to the training data issues raised earlier, designers have a responsibility to interrogate the representational politics of the tools they use. Generative AI systems trained predominantly on Western, Anglophone, and historically dominant design traditions will produce outputs that implicitly marginalise other visual and spatial cultures, even in the hands of practitioners who have no intention of doing so [5, 15]. Critical engagement with this tendency is not an optional extra for the culturally minded designer. It is a basic requirement of responsible professional practice.

9. Future Directions

The research agenda that generative AI opens for design studies is substantial, and a full survey is beyond the scope of this discussion. A few priorities stand out. Longitudinal empirical studies of AI-assisted design learning are urgently needed. Most of what has been written on this topic, including this paper, is based on relatively short-term observations or theoretical inference. There is not yet good evidence about whether and how AI use affects the development of design judgment over the course of a degree programme, or how the skills of AI-trained graduates compare to those of graduates who learned without these tools [9]. Without that evidence, curricular decisions are being made on the basis of intuition and ideology, which is a poor foundation for either pedagogy or policy.

Legal and regulatory frameworks for AI-generated design work are in serious disarray. Intellectual property law was not written for a world in which a single system trained on the work of millions of people can produce outputs that are stylistically indistinguishable from those people's work [7]. Design professional organisations should be actively engaged in the policy processes that will shape how these frameworks develop, rather than waiting for frameworks developed in other sectors to be applied to design by default. The window for shaping those decisions is not indefinitely open.

There is also an underexplored opportunity in developing AI tools specifically designed for design education rather than professional practice. Tools that scaffold rather than substitute, that offer suggestions at appropriate moments, require students to articulate their reasoning before generating alternatives, or make the generative process legible and analysable, could potentially combine the benefits of AI assistance with the formative demands of studio pedagogy [18]. This is a direction that requires collaboration between design researchers and AI developers, and it is not currently receiving the attention it merits.

Finally, the question of training data diversity is not going away. If current AI tools produce outputs biased toward certain aesthetic and cultural traditions, the most direct remedy over time is more representative training data. Building such datasets requires concerted effort from design historians, cultural institutions, and design communities in contexts that are currently under-represented in the datasets driving the tools that are reshaping the field.

10. Conclusion

There is a certain version of the generative AI story that design professionals are probably tired of hearing: the tool is either going to liberate creativity or destroy it, and whichever side one takes, the stakes are existential. The reality is more mundane and, in a way, more demanding. Generative AI is a genuinely disruptive technology, not merely a faster version of what came before, but the design disciplines have navigated disruptions before and have the intellectual resources to navigate this one. What is required is not panic, and not complacency, but the kind of sustained, careful thinking that the best design scholarship has always tried to do.

The specific arguments advanced here are these. The restructuring of creative labour that generative AI is producing is real, and it shifts the most important design skills toward judgment and critical evaluation rather than eliminating them. The destabilisation of authorship is real, and the vocabulary needed to discuss it, that distinguishes initiator, curator, evaluator, and integrator, has not yet been adequately developed. The pedagogical risks are real, particularly for students who encounter AI tools before they have established the foundational competencies that would allow them to engage those tools critically. And the ethical obligations of transparency, intentionality, accountability, equity, and cultural criticality are real, regardless of how the technology develops.

What connects all of these is a prior question: what is design for? If the answer is efficient delivery of configured artefacts, then AI is straightforwardly useful and the concerns raised here are merely managerial. If the answer involves something about situated judgment, cultural responsiveness, and the formation of practitioners who can exercise authority over the built and visual environment responsibly, which is the answer that most serious design education has tried to embody, then the challenges are deeper and more worth the effort of thinking through carefully.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author used Claude (Anthropic) to assist with language editing, structural organization, and to explore the research process from AI-assisted perspectives. After using this tool, the author carefully reviewed and edited the content as necessary.

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