

AI-ENABLED DESIGN PIPELINES AND THEIR IMPACT ON TEACHING PRACTICE

Xiaozhu Lin, & Matteo Oreste Ingaramo
Department of Design, Politecnico di Milano (Italy)

Abstract

Artificial intelligence is restructuring design workflows by automating tasks that traditionally required substantial human expertise. These changes are accelerating the need for existing design training systems to adapt to new methods since they were developed on the premise of linear processes and manual skill acquisition. This paper presents a review of the current state of AI-assisted design and its impact on teaching practice. A design case is selected to demonstrate in detail how text-based prompts are transformed into visual patterns, digital fabrics, and ultimately digital garments, featuring virtual fittings, still images, and even video outputs, all ready for direct market release. Each part of the process exemplifies a mode of computational delegation that shortens the production time and alters the notion of authorship. While such workflows expand creative reach, they also raise critical questions for educators regarding control, evaluation, and the preservation of human creativity. The review recommends that educators should not be averse to technological changes, but instead, they should integrate programmed reflections on the pros and cons of AI to empower students to use these systems effectively without compromising their creative agency. The paper aims to provide ways for curriculum updating, adaptive expertise development, and designers' preparedness for a rapid professional environment change through analyzing new AI workflows and their impacts on teaching.

Keywords: *AI-enabled design, digital workflow, design education, teaching practice, creative agency.*

1. Introduction

Artificial intelligence has progressed from being a supportive computational resource to an active collaborator in the creative process. In the field of design, the role of AI has expanded from mere optimization and automation in isolated phases to full engagement throughout the production pipeline, hence changing the order of things in idea generation, development, visualization, and delivery to the market (Boden, 2016; McCormack et al., 2019). This transition has far-reaching effects on design education, which has so far been based on the linearity of the workflow and the gradual acquisition of technical skills. Most existing design curricula are structured around the idea of students progressing through levels, from concept creation to production and final presentation. Even if the models depict past production situations, they are becoming increasingly out of tune with the professional world, where AI-assisted systems often shrink or skip several stages of production. Thus, students may be trained to have technically proficient but poorly adapted skills to the current workflow, which in turn increases the distance between education and industry practice.

This paper aims to fill the gap created by the above scenario by analyzing the potential impact of AI-assisted design pipelines on teaching practices. The paper not only highlights the positive aspects of AI usage but also outlines the implications of this case study regarding the evaluation of past and traditional fashion design workflows that can be transformed into AI-native workflows. Through a detailed case study, the paper examines how. The goal is not to recommend a particular software platform but rather to consider this case study as a practical viewpoint through which one's broader educational and knowledge implications can be discussed.

2. From AI tools to AI agents

To understand the transformation of design workflows, it is essential to distinguish between AI tools and AI agents. Many AI applications used in design processes today work as reactive tools. They

perform specific tasks, such as image processing or color control, in response to direct user input. The designer is always responsible for combining results and organizing the process.

In contrast, AI agents are more proactive and goal-driven systems that operate autonomously within a specific environment. Instead of merely performing one task, an agent may engage in diverse tasks to accomplish a broader goal, while flexibly making decisions that are unknown to the agent to reach that goal. This duality has been a topic of great importance in AI research, where an agent is characterized as a setup in an environment that perceives and acts (Russell & Norvig, 2021).

According to a human-centered orientation, this change, of course, invites important questions regarding control and responsibility. Shneiderman (2022) has further explained that mechanisms that require human control are critical, particularly in creative and cultural domains. In design education, this implies that students must learn not only how to operate AI agents, but how to direct, evaluate, and constrain them.

3. Traditional design workflows and educational assumptions

The traditional fashion design process has always been a linear one, with a series of steps to be followed. From research and conceptualization, the designer would then proceed to pattern making, followed by visualization after completing the fabric design, garment construction, and fitting. Each process stage has its own set of skills, and transitioning from one stage to another typically requires a significant investment of time and resources.

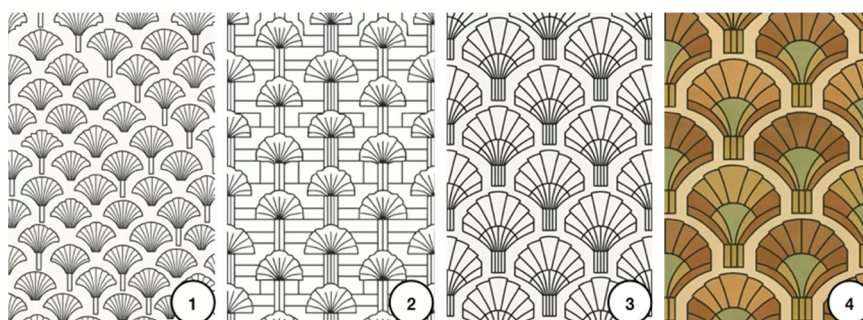
Educational models draw inspiration from this layout. Courses are typically organized by skill type, such as illustration, textiles, pattern making, photography, and video production. Such an organization facilitates the gaining of in-depth knowledge, but at the same time promotes a fragmented view of the overall workflow. Research in design education has found that such compartmentalization can undermine students' ability to integrate knowledge across stages (Kolko, 2010).

On the other hand, the advent of computational design systems is slowly but surely changing these assumptions. According to Oxman (2017), design with computers opens up non-linear movements that are feedback-driven and require different design thinking. When AI systems can carry out tasks such as generating patterns, simulating materials, and producing lifelike visualizations within a few minutes, educators need to reassess the importance of protracted manual execution.

4. Case study: An AI-Native workflow using Style3D AI functions

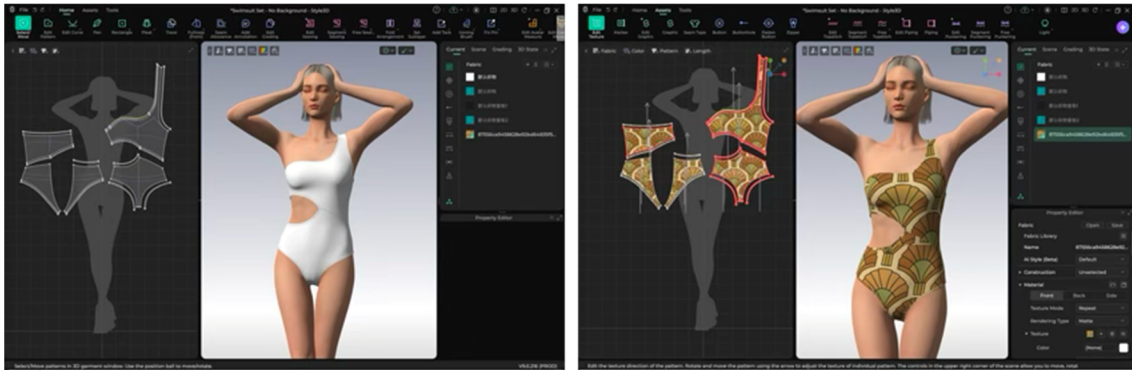
The case examined in this paper demonstrates an AI-native workflow implemented through the Style3D AI+3D ecosystem. The process begins with text-based prompts authored by the designer, describing aesthetic intentions, references, color palettes, and material characteristics: "Geometric abstract mushroom pattern, symmetrical fan-shaped caps with stepped edges, vertical linear stems, radiating line details, clean black and white linework, structured repetition, grid and band-based layout, seamless and orderly, minimal and elegant." These prompts are processed by the Style3D Moda - Graphic Design Agent, which generates corresponding graphic patterns (Fig. 1-1). In most cases, the initially generated output does not fully align with the designer's vision (Fig. 1-2). Therefore, the text prompt needs to be carefully refined and iteratively adjusted through multiple attempts until the ideal result is obtained (Fig. 1-3). After several attempts, the designer arrived at the ideal black-and-white pattern and then asked the AI to "color this pattern using tones inspired by mushrooms found in nature" (Fig. 1-4). Unlike traditional digital textile design, where designers manually construct repeats and colorways, the AI agent rapidly produces multiple variations. The designer's role shifts toward prompt refinement, selection, and conceptual evaluation. This stage exemplifies computational delegation, where technical execution is largely automated while creative direction remains human-led.

Figure 1. The designer iteratively refined the initial text prompt to achieve a satisfactory final pattern.



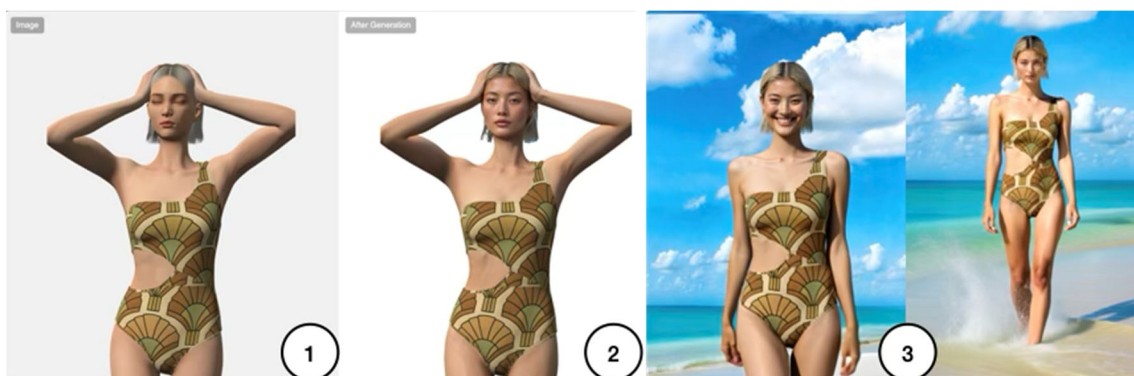
The generated colored pattern file is then imported into Style3D Studio and applied directly to digital garment designs. In this case, the designer selected a women's swimsuit from the Style3D cloud database and applied the previously generated pattern (Fig. 1-4) to the existing 2D pattern, replacing the original white fabric (Fig. 2). Garment silhouettes and fabric behaviors are adjusted within the same environment, allowing immediate assessment of fit and drape in 3D window, avoiding the repetitive physical sampling process commonly required in traditional workflows.

Figure 2. In Style3D Studio, the generated pattern is applied to the chosen garment.



After finalizing the 3D design and making refinements, the designer leveraged a new AI-assisted image generation feature, AI Snap. Instead of traditional rendering processes, which are often time-consuming and yield limited realism (Fig. 3-1), AI Snap generates marketing-ready images featuring highly realistic human models (Fig. 3-2). These images can be produced with minimal setup and are suitable for immediate commercial use. In the final stage, still images are used as inputs for the Style3D Moda - Style to Video function. Through additional text prompts that describe motion and atmosphere: “I want the model to walk out of the sea on a beach in the Maldives, showcase the outfit, then turn around once and walk back into the water, the overall mood should be enjoying the beautiful seaside scenery,” a short marketing video is automatically generated in a fraction of the time required by traditional workflows, fundamentally altering the temporal and cognitive structure of design practice.

Figure 3. Marketing-ready images and videos generated using AI Snap and Style3D Moda - Style to Video functions.



5. Authorship, creativity, and computational delegation

AI systems have begun to play an ever-greater part in carrying out generative tasks, and thus, authorship conceptions start to wobble more than ever before. When patterns, materials, images, and videos are produced through coordinated AI agents, creative ownership becomes distributed across both human and machine actors, rather than residing in a single, identifiable author. Manovich (2019) sees this as a sign of contemporary software-driven culture, which not only combines but also obscures the intent of individuals and the structures, defaults, and affordances embedded in computational systems that influence outcome creatively.

The shift toward AI-enabled workflows is best illustrated by the notion of computational delegation. Delegation is not a matter of replacement, and human creativity still plays a significant role, but now it is shared among the team, with each member assigned a different part to work on. AI is taking over

technical execution, variation generation, and even visualization, but humans still are the ones who determine the problems, set the constraints, and judge the outcomes. This split of responsibilities is challenging the educational models that are based on the assumption that authorship is equivalent to manual production or technical skill. In such cases, the designer's role is not so much to manufacture artifacts as to direct the processes and make well-informed decisions.

The ethical and educational dimensions present in this redistribution of roles create a scenario where issues of originality, accountability, and assessment arise. Floridi and Sanders (2004) contend that artificial agents become involved in moral and creative processes through which they demand new evaluative frameworks, especially when the sharing of agency is involved rather than the clear assignment of it. In design education, this means that traditional assessment methods, which favor visible labor and craftsmanship, are no longer adequate.

Instead, the teaching practice needs to be changed to evaluate decision-making processes, articulate intent, and engage in critical reflection on AI-generated outputs. Students should be evaluated on their ability to provide reasons for their prompt choices, identify limitations or biases in AI systems, and take action if the results produced conflict with their concepts or ethical intentions. If such a change doesn't happen, there is a possibility that the AI-assisted work will be considered either as unearned automation or as unquestioned authorship, both of which will eventually degrade educational rigor.

In terms of reframing authorship as a conceptual rather than a manual task, the design education can take advantage of human creativity and, at the same time, recognize the reality of computational delegation. Reframing does not mean that the designer's role gets diminished, but rather that it positions creativity on a higher level of abstraction where critical judgment, responsibility, and intentionality are still very much human competencies.

6. Implications for teaching practice

AI-native workflows are questioning the current pedagogical models in different fundamental aspects. The most critical effect of this is that they shatter the main assumption of linear skill progression, which is the foundation of much design education. The traditional curriculum expects students to progress gradually from basic exercises to complex projects, building on the technical proficiency they have gained. However, in the context of AI-native, students can create complex, ready-for-market outputs even at the very beginning of their training. This does not necessarily mean that the person has mastered the skill in the traditional sense; however, it does create a problem regarding the long-standing classifications of beginner and advanced work and causes educators to take a new look at how learning progress is formulated and measured.

Another issue relates to the evaluation of learning outcomes. The use of AI tools in the design process necessitates the creation of criteria for evaluation that take into account not only the quality of the output but also the quality of the process. Studies on reflective practice have shown that learning outcomes are strongly related to a person's ability to articulate reasoning, justify decisions, and evaluate alternatives (Schön, 1983). When AI systems contribute significantly to visible work, these cognitive and reflective capacities become even more crucial. Hence, assessment must focus on how students define their problems, how they create prompts, how they choose among the generated options, and how they adjust their paths based on the results.

The speed of AI-enabled production introduces a third pedagogical challenge by altering reflective cycles. Rapid iteration can significantly enhance experimentation and exploratory learning, allowing students to test ideas that would previously have been constrained by time or technical barriers. At the same time, such speed carries the risk of superficial engagement, where students accept generated outputs without sufficient critical scrutiny. To mitigate this risk, educators must intentionally incorporate structured reflection into their coursework. This includes requiring students to document prompt iterations, explain why certain results were accepted or rejected, and identify limitations or biases present in AI-generated outputs.

Most importantly, the adoption of AI-native workflows in design training does not mean relinquishing basic knowledge. The practitioner's understanding of the materials, form, proportion, and visual language remains crucial for a thorough evaluation of the AI systems and their effective guidance. Those fundamentals have to be reframed, though, in today's production environments, where execution is no longer the primary learning site. Thus, foundational knowledge is increasingly being perceived as a characteristic of the critical judgment process rather than a goal in itself.

AI-native workflows demand a shift in educational priorities from training specific tools to developing adaptable expertise. The educational system must prioritize important skills that will remain relevant as software continues to evolve, rather than just teaching students to handle fixed software interfaces. Students should be placed in positions of system ownership rather than merely being users of

tools. In design education, this means that prompt literacy, system-level thinking, and evaluative judgment will be regarded as the core competencies. Therefore, students will be able to navigate and influence the rapidly evolving AI-powered design environments with confidence and responsibility.

7. Conclusion

The pipeline for AI-enabled design suggests a significant shift in the creative process, rather than just a technological improvement. The example of Style3D demonstrates how AI-enabled processes break down the usual separation of design, visualization, and marketing, resulting in the modern market receiving output with exceptional speed. This upheaval in teaching practice necessitates the transition from tool-centered instruction to workflow-centered education. Design educators must not resist or automatically adopt AI systems but rather integrate them into curricula through reflective and structured pedagogical strategies. By keeping control sharp and emphasizing human creativity as a conceptual leadership over manual execution, education will not only remain relevant but also equip students with the tools necessary to navigate and even shape the rapidly changing professional environments.

References

- Boden, M. A. (2016). *AI: Its nature and future*. Oxford University Press.
- Floridi, L., & Sanders, J. W. (2004). On the morality of artificial agents. *Minds and Machines*, 14(3), 349–379.
- Kolko, J. (2010). Abductive thinking and sensemaking: The drivers of design synthesis. *Design Issues*, 26(1), 15–28.
- Manovich, L. (2019). *Cultural analytics*. MIT Press.
- McCormack, J., Gifford, T., Hutchings, P., Llano Rodriguez, M. T., Yee-King, M., & d’Inverno, M. (2019). In a silent way: Communication between AI and improvising musicians beyond sound. *ACM Transactions on Computer-Human Interaction*, 26(1).
- Oxman, R. (2017). Thinking difference: Theories and models of parametric design thinking. *Design Studies*, 52, 4–39.
- Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
- Schön, D. A. (1983). *The reflective practitioner: How professionals think in action*. Basic Books.
- Shneiderman, B. (2022). *Human-centered AI*. Oxford University Press.