AI as Pedagogy in Design Education: Can GenAI-Integrated Teaching Achieve Course Learning Goals in the Short Term?

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Abstract

Generative Artificial Intelligence (GenAI) is increasingly embedded in design courses, not only as a production aid but also as a pedagogical approach that can reshape how students work through creative tasks. However, it remains unclear whether GenAI-integrated teaching can help students meet core learning requirements typically associated with studio-based design education within a compressed instructional period, and which difficulties may persist. This study investigates a four-week, 32-contact-hour undergraduate design course that integrated GenAI into creative assignments, using pre- and post-course surveys supplemented by written student reflections. The surveys captured student-reported indicators of perceived efficiency and task progression, perceived improvement in creative output quality, self-efficacy and controllability when using GenAI, as well as process indicators such as iteration behaviors and actions taken after initial AI outputs; they also documented commonly encountered difficulties and coping strategies. Descriptive and comparative analyses were used to summarize changes from pre to post, and reflections were thematically reviewed to contextualize and explain observed patterns. The findings suggest partial alignment with course learning requirements over the short period: students commonly reported faster progress and more deliberate prompting and iteration practices, while persistent challenges remained in controllability, output consistency, and integrating AI results into coherent design solutions. These patterns indicate that GenAI may reduce difficulty in generating options but foreground new demands in steering, refining, and synthesizing outputs into design decisions. The study discusses implications for GenAI-integrated pedagogy, including explicitly teaching control and integration strategies and evaluating learning processes alongside final artifacts.

Keywords: Generative AI (GenAI), design education, GenAI-integrated pedagogy, pre-post survey, student reflections, iterative prompting

Introduction

Generative Artificial Intelligence (GenAI) has rapidly entered higher education as both a practical tool and a force that reshapes teaching and learning expectations (Cotton et al., 2024; Kasneci et al., 2023; UNESCO, 2023). This shift is especially consequential in design education, where learning develops through cycles of making, critique, revision, and reflection rather than one-shot correctness (Schön, 1983). In this setting, GenAI does more than accelerate production. It can change the sequence of design decisions and the kinds of difficulty students encounter while learning.

Its educational value therefore cannot be inferred from output quantity alone. GenAI may support ideation while also introducing new constraints, including fixation and weaker originality under some conditions (Wadinambiarachchi et al., 2024). The pedagogical question is not simply whether students can produce more with AI, but what kinds of learning AI-supported teaching actually enables.

Current literature has identified both opportunities and tensions surrounding GenAI in education, including support for idea development and concerns about overreliance, integrity, and assessment redesign (Kasneci et al., 2023; UNESCO, 2023; Xia et al., 2024). However, these discussions often remain broad and do not always clarify what GenAI integration means for the learning requirements of a specific design course.

This gap is especially important in short-cycle courses. Students may report faster progress or stronger support, yet these benefits do not automatically mean that they have achieved core studio-based learning goals. A short-term GenAI-integrated course may help students generate more options while leaving unresolved the more demanding work of steering outputs, maintaining consistency, and synthesizing fragments into coherent design decisions.

Accordingly, this study asks whether GenAI-integrated teaching can help students approach course learning goals within a four-week undergraduate design course, while also identifying which difficulties remain visible from students' perspectives.

This study investigates a four-week, 32-contact-hour undergraduate design course in which GenAI was integrated into creative assignments as part of the pedagogy. Using pre- and post-course surveys supplemented by written student reflections, it examines whether students' reported experiences suggest partial alignment with core course learning requirements over a short period. The study contributes by reframing the issue from GenAI as a production aid to GenAI as pedagogy, and by combining perception-based indicators with reflections to interpret how support and difficulty were experienced in practice.

To guide the analysis, the study addresses three research questions: RQ1. In what ways do students report changes in perceived efficiency, task progression, creative quality, and self-efficacy/controllability after a short-term GenAI-integrated design course? RQ2. What process changes emerge in students' use of GenAI, particularly in prompting, iteration, and actions taken after initial AI outputs? RQ3. What persistent difficulties remain, and what do these difficulties suggest about the extent to which GenAI-integrated teaching aligns with course learning goals in the short term?

Literature Review

Studio-Based Design Learning and Course Learning Goals

In studio-based design learning, students develop through cycles of making, critique, revision, and reflection (Schön, 1983). For the purposes of this study, course learning goals are understood through five dimensions relevant to both the course design and the available data: progressing through tasks, generating creative options, controlling outputs, iterating and refining work, and integrating outputs into coherent design solutions. These dimensions do not function as direct performance criteria; they provide an interpretive framework for reading student-reported experiences of alignment and difficulty.

GenAI in Design Education: Support and Tension

GenAI may support design learning by lowering the barrier to ideation, accelerating alternatives, and helping students externalize rough concepts. At the same time, meaningful use depends on judgment, oversight, and pedagogical design (UNESCO, 2023). In higher education, concerns include superficial completion and the underassessment of process (Cotton et al., 2024; Xia et al., 2024). In design-related work, GenAI may also increase fixation and reduce variety under some conditions (Wadinambiarachchi et al., 2024). These tensions are especially relevant in short-term design teaching, where faster generation does not automatically imply stronger learning.

From Production Aid to Pedagogy

When GenAI is treated as part of pedagogy rather than only as a production aid, the focus shifts from efficiency to what students are learning through their interaction with the tool, how the tool reorganizes design work, and what kinds of instructional support become necessary (Ioannou, 2018). This study therefore approaches GenAI as a mediating element within the course's learning environment and examines how it appears to reshape students' progress, practices, and bottlenecks during a short cycle of design learning.

Analytical Lens: Partial Alignment With Course Learning Goals

The study uses partial alignment with course learning goals as its central analytical lens. The term acknowledges that the available evidence is based primarily on student-reported perceptions and process descriptions rather than artifact-based evaluation. Survey data provide proximal indicators of support and difficulty, while reflections clarify how gains and bottlenecks were experienced. The aim is to determine whether GenAI-integrated teaching appeared to support some core design course requirements over a short period and where the remaining difficulty concentrated.

Methodology

Course Context

This study was conducted in a four-week required undergraduate course, *Artificial Intelligence and Visual Communication*, totaling 32 contact hours. Students moved from identifying a communication topic and framing a concept to developing visual proposals, extending them into related design outputs, and producing a final short video. Deliverables included a logo, IP character, static and animated stickers, static and motion posters, a short script, and an approximately 40-second video. GenAI was integrated across ideation, visual exploration, refinement, and production support rather than being used as an optional supplement.

Participants and Data Sources

Three sources of data were used: a pre-course survey, a post-course survey, and written student reflections collected at the end of the course. The pre-survey yielded 43 valid responses, the post-survey yielded 39 valid responses, and matched pre-post responses were obtained for 36 students using the last four digits of student IDs. In addition, 25 written reflections were available for qualitative analysis. The surveys tracked changes in student-reported perceptions, while the reflections provided context for how support and difficulty were experienced.

Survey Measures

The pre-course survey captured baseline experience and expectations regarding AIGC, including prior use, frequency, attitudes, expected areas of support, and concerns related to operation and controllability. The post-course survey focused on course-related experiences, including frequency of use, preferred stages of use, responses to problems, first-response behavior after initial AI outputs, number of attempts, success in realizing intended ideas, improvement in guiding AIGC, workflow formation, perceived effectiveness, and reported difficulties. These measures were mapped onto the course learning goal framework used in this paper, especially task progression, creative development, controllability, refinement, and integration.

Reflection Data

The reflection data consisted of structured written responses about frustrating or unsuccessful AIGC experiences, adjustment processes, emerging personal routines, preferred stages of use, and the perceived role of AIGC in the course. Students often described prompt revision, repeated generation, switching tools, borrowing references, or coping with unstable outputs. These reflections were thematically reviewed to contextualize the survey-based patterns.

Data Analysis

The quantitative analysis combined descriptive and comparative approaches. Paired comparisons were used for comparable pre- and post-course items, and descriptive statistics were used to summarize post-course process indicators and persistent problems. The qualitative analysis used thematic review of the written reflections, with attention to prompt adjustment, repeated generation, use of references or external help, perceived control, consistency, and integration. Overall, the study follows an explanatory mixed-methods logic in which survey data establish broad patterns and reflections clarify how those patterns were experienced in practice.

Ethical Considerations

The project was approved by the School of Design of The Hong Kong Polytechnic University (Reference Number: HSEARS20250217010). Student data were handled in anonymized form for analysis and reporting. Survey matching used only the last four digits of student IDs, and reflection materials were treated as course-related research data for interpretive analysis rather than public personal statements. Any direct quotations used in later versions of the paper should be selected and presented in ways that protect student identity.

Results

Table 1 summarizes the quantitative pattern across the main result domains discussed in this paper: perceived progress toward course learning goals, post-course process changes, and persistent bottlenecks. Rather than reproducing every statistical detail, the table organizes findings in relation to course learning goals and short-term pedagogical alignment.

Table 1

Summary of Quantitative Findings on Short-Term Alignment With Course Learning Goals

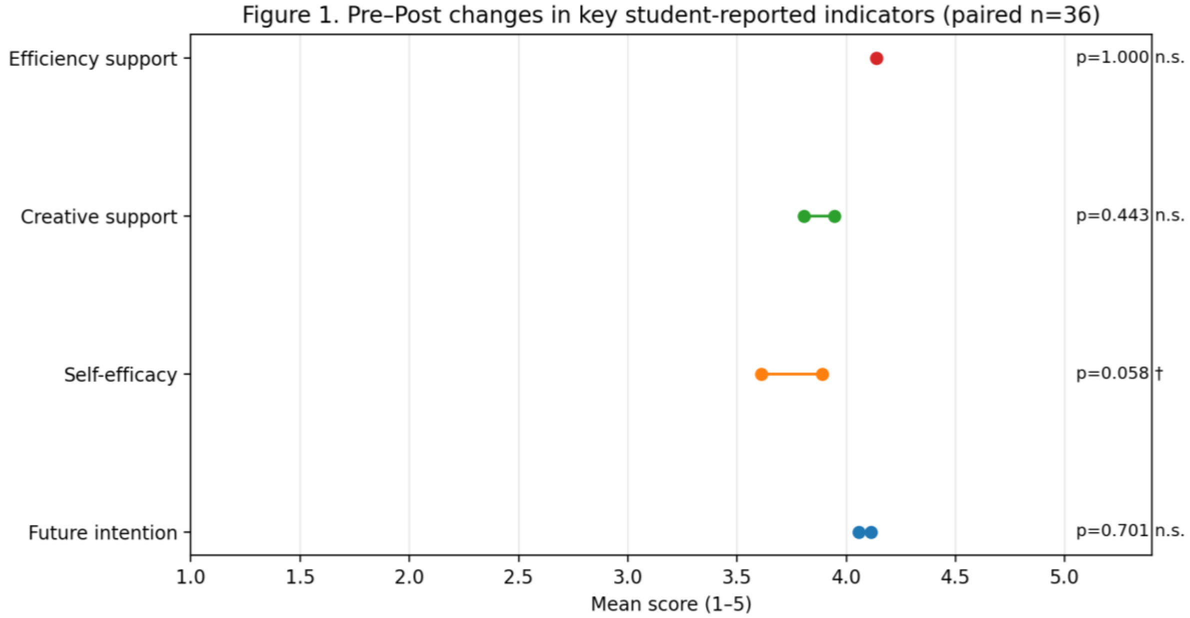
Dimension	Indicator	Key result	Interpretation
Panel A. Conceptually aligned pre-post indicators (paired n = 36)			
Task progression	Efficiency support	4.14 ± 0.59 -> 4.14 ± 0.87; n.s.	High and unchanged
Creative development	Creative support	3.81 ± 0.86 -> 3.94 ± 0.95; n.s.	Slight increase
Controllability / self-efficacy	Effective AI use	3.61 ± 0.77 -> 3.89 ± 0.82; p = 0.058	Clearest short-term gain
Future orientation	Future intention	4.11 ± 0.62 -> 4.06 ± 0.92; stable	Positive but unchanged
Panel B. Post-course process patterns (post n = 39)			
First-response behavior	First output	Revise prompt 14/39; accept with mismatch 24/39; use directly 1/39	First outputs were provisional
Iteration	Number of attempts	1 time 2/39; 2-3 times 14/39; 4-5 times 20/39; >5 times 3/39	Iteration was common
Guidance ability	Guiding AIGC	Clear improvement 12/39; some improvement 25/39; little/no change 2/39	Growth in directing AIGC
Workflow formation	Personal method	Clear 7/39; broad 24/39; early preference 7/39; none 1/39	Emerging personal routines
Task realization	Realizing intended ideas	Complete 1/39; basic 21/39; partial 15/39; difficult 2/39	Approximation was more common than full realization
Panel C. Persistent bottlenecks (post n = 39)			
Consistency	Unstable / hard to reproduce	24/39 (61.5%)	Most common bottleneck
Controllability	Mismatch with intention	21/39 (53.8%)	Steering remained difficult
Refinement	Aesthetic qualities hard to adjust	21/39 (53.8%)	Detail refinement remained difficult
Integration	Hard to edit or integrate outputs	16/39 (41.0%)	Integration remained difficult

Note. Pre-survey n = 43; post-survey n = 39; matched paired sample n = 36. Panel A uses conceptually aligned pre-post indicators rather than identical repeated items. Panels B and C summarize post-course process indicators and persistent bottlenecks.

The figure shows pre- and post-course mean scores for efficiency support, creative support, self-efficacy, and future intention to use GenAI. The pattern indicates modest overall change, with the clearest movement in self-efficacy.

Figure 1

Pre-Post Changes in Key Student-Reported Indicators (paired n = 36)



Perceived Progress Toward Course Learning Goals

The pre-post survey results suggest that students perceived meaningful, though limited, progress toward several course learning demands over the four-week period. As shown in Figure 1, perceived efficiency support remained high from pre to post (Pre 4.14 ± 0.59; Post 4.14 ± 0.87), creative support increased slightly but not significantly (Pre 3.81 ± 0.86; Post 3.94 ± 0.95), and self-efficacy showed the clearest positive movement (Pre 3.61 ± 0.77; Post 3.89 ± 0.82), reaching marginal significance. Future intention to use GenAI remained high and stable. These patterns indicate that students did not report a dramatic transformation in all aspects of AI-supported learning, but they did report a noticeable gain in their confidence to use AI more effectively.

The post-course distributions help clarify what this modest pre-post pattern means in practice. In the post-survey, 71.8% of students rated AIGC as contributing strongly to design efficiency, 66.7% reported strong improvement in creative quality, and 64.1% rated their self-efficacy at 4 or above on a 5-point scale. For the item asking whether AIGC improved design efficiency, 16 students selected 5 and 12 selected 4; for creative quality, 13 students selected 5 and 13 selected 4. On the item measuring overall ability to use AI effectively for design tasks, most students clustered in the upper-middle range (16 selected 4, 13 selected 3, and 9 selected 5), suggesting that perceived competence improved but did not become uniformly high.

The reflections support this interpretation of progress as real but bounded. Students often described AIGC as helping them externalize ideas, accelerate exploration, and sustain movement when they lacked direction. One student described AIGC as helping to “make the things in my mind concrete”, while another wrote that, at the ideation stage, AI could provide cases and inspiration “when I have no inspiration” and thereby increase efficiency. A third student described AIGC as an “efficient creative collaboration assistant” because it could quickly convert design thinking into visible draft forms. These descriptions align with the quantitative pattern: students did not necessarily report full command over AI-supported design, but many did perceive that AIGC helped them move from vague concepts toward visible and workable outputs.

These findings support a cautious interpretation of short-term alignment with course learning goals. On the one hand, the data suggest that students felt more able to maintain task momentum, explore design alternatives, and make use of GenAI in producing course deliverables. On the other hand, the relatively modest size of the pre-post shifts suggests that such support should not be mistaken for full mastery. In other words, students appeared to feel more supported in progressing through course tasks, but this does not by itself indicate that the more demanding learning requirements of control, refinement, and synthesis were fully achieved.

Emerging Process Changes in Prompting, Iteration, and Post-output Action

The clearest evidence of learning-related change appears in students' reported process behaviors. First outputs were rarely accepted without revision. Only one student reported directly using the first generated result, while 14 of 39 said they would revise the prompt immediately and 24 accepted the output only with differences or partial mismatch. Iteration was also common: 20 students reported trying four to five times, 14 reported trying two to three times, and only two said the first attempt was basically enough.

The same pattern appears in reported growth in guidance and workflow formation. In the post-survey, 37 of 39 students reported at least some improvement in their ability to guide AIGC, and 31 of 39 reported having formed at least a mostly identifiable way of using it. Reflections point in the same direction. One student wrote, “I kept giving AIGC more specific generation conditions and kept generating again”, while another described “looking at the results given by AI, adjusting them step by step, and regenerating”. These responses indicate more deliberate prompting and iteration by the end of the course.

Persistent Barriers in Controllability, Consistency, and Integration

Despite these gains, several difficulties remained concentrated in areas central to studio-based design learning. The most common bottlenecks were unstable or hard-to-reproduce outputs (61.5%, 24/39), mismatch with intended goals (53.8%, 21/39), difficulty refining aesthetic qualities (53.8%, 21/39), and difficulty editing or integrating outputs into later work (41.0%, 16/39).

The reflections make these barriers visible. One student wrote that AI “could not understand what I wanted”, and another found that a unified emoji set became “different in style”. Integration problems also appeared in comments about relying on “local modifications” because outputs could not be used directly. These responses show that controllability, consistency, and integration remained unresolved for many students.

Discussion

What GenAI Supported in the Short Term

The results suggest that GenAI supported short-term design learning mainly at the level of initiation, option generation, and task momentum. Students commonly perceived that AIGC helped them move forward more efficiently, provided support when they lacked ideas, and made it easier to produce early visual or conceptual material that could be worked on further. This is broadly consistent with the wider GenAI-in-education literature on access, productivity, and new forms of learning assistance (Kasneci et al., 2023; UNESCO, 2023). In this course context, the most immediate value of GenAI was that it helped students sustain movement across multiple tasks within limited time.

The findings also suggest that GenAI supported process engagement rather than only output volume. Many students reported repeated prompt adjustment, multiple attempts, and emerging personal workflows, and this iterative engagement aligns with studio-based design learning, where progress depends on cycles of making, feedback, and revision (Milovanovic & Gero, 2020; Schön, 1983). In this sense, the short-term pedagogical contribution of GenAI may be understood as support for divergence more readily than convergence: it lowered the threshold for early exploration, but not the need for judgment, direction, and synthesis.

Why Alignment Remained Partial

Partial alignment is central to interpreting the findings responsibly. Improvements in speed, idea generation, and iterative prompting did not automatically translate into strong controllability or reliable integration. Students often felt better able to proceed, but not fully able to steer the process toward what they intended. In this paper, partial alignment can be understood in three senses: alignment at the level of momentum, emerging alignment at the level of process practice, and incomplete alignment at the level of higher-order control.

The unresolved demands also shifted upward in complexity. Students were less often stuck at the point of starting work and more often challenged by the need to steer outputs, refine details, maintain consistency across artifacts, and synthesize AI-generated materials into coherent solutions. This pattern resonates with broader educational concerns that GenAI can encourage superficial completion unless teaching and assessment foreground higher-order judgment and process evidence (UNESCO, 2023; Xia et al., 2024). It also speaks to design-specific concerns raised by Wadinambiarachchi et al. (2024): once students entered AI-supported exploration, many found it difficult to maintain authorship over direction and coherence. The findings therefore suggest that GenAI redistributes effort, lowering some thresholds while exposing students more sharply to the demands of specification, evaluation, and synthesis.

Rethinking AI as Pedagogy in Design Education

The title of this paper proposes AI as pedagogy rather than AI as tool, and the discussion supports that framing. When GenAI is embedded in a design course, it reorganizes what students must learn in order to work effectively. The central pedagogical issue becomes less about access to generation and more about how students learn to guide, evaluate, revise, and integrate what is generated. The tool changes the shape of the learning bottleneck, and pedagogy must respond accordingly.

This has direct implications for how design education understands process. Studio-based learning has long been described as a mentored form of reflective practice in which critique, feedback, and iterative reworking are central to how students learn to design (Milovanovic & Gero, 2020; Schön, 1983). Work on studio critique likewise emphasizes that design learning depends on making tacit design knowledge more explicit through dialogue, reflection, and feedback (Fleischmann, 2025). From this perspective, GenAI integration does not bypass reflective practice; it changes the material through which reflection must occur. Students still need to articulate intentions, inspect mismatches, diagnose failures, and justify revisions, but now partly through interaction with AI-generated outputs.

This is why AI as pedagogy is analytically useful here. If AI is treated only as a faster means of production, the main question becomes whether it saves time. If it is treated as part of pedagogy, the more important question becomes what kinds of reflective and evaluative practices the course enables students to develop around it. The present study suggests that GenAI can support exploratory activity, but it also makes tacit aspects of design learning newly visible: students must decide how much specificity is needed, how to preserve style across iterations, how to judge which output is worth developing, and how to convert generated fragments into a coherent visual system.

This also differentiates design education from more general GenAI-in-education discussions. In broader higher education, GenAI is often discussed in relation to integrity, authorship, assessment redesign, and AI literacy (Cotton et al., 2024; Kasneci et al., 2023; Xia et al., 2024). Those concerns remain relevant here, but the design context adds another layer: the problem is whether students can turn AI-supported production into meaningful design development. That requires iterative visual judgment, stylistic control, and integration across linked deliverables. The educational value of GenAI in design should therefore be judged less by output volume than by whether it helps students participate more effectively in reflective, iterative, and evaluative design processes.

Implications for GenAI-Integrated Pedagogy

Teaching Controllability Explicitly

Teach controllability directly. Courses should show students how to specify intent, state constraints, preserve key features, and refine prompts across iterations. Reference anchoring, style constraints, and negative instructions should be treated as part of design articulation.

Teaching Integration, Not Just Generation

Teach integration, not only generation. Students could often produce usable fragments, but had more difficulty turning them into coherent design systems. Assignments should require editing, combining, sequencing, and justifying AI-generated outputs across linked deliverables.

Evaluating Learning Processes Alongside Final Artifacts

Evaluate process alongside artifacts. If GenAI makes plausible outputs easier to produce, assessment should capture how students arrived at them, revised them, and exercised judgment throughout the process (UNESCO, 2023; Xia et al., 2024). Useful evidence includes prompt iterations, comparison sets, revision pathways, and short rationales for selection and modification.

Limitations and Future Research

This study has several limitations that should be acknowledged. First, the findings rely primarily on perception-based measures and structured reflections. These data are valuable for understanding how students experienced support, difficulty, and process change during the course, but they do not provide direct evidence that course learning outcomes were fully achieved. Students may feel more efficient, more confident, or more capable of guiding AI without demonstrating the same degree of improvement in artifact quality or design judgment under formal evaluation.

Second, the course lasted only four weeks and totaled 32 contact hours. This compressed duration is central to the study's contribution, but it also constrains what kinds of learning could reasonably be expected to emerge. Some of the observed process gains may represent early adaptation rather than stable competence, and some of the unresolved difficulties may reflect the time needed for more mature design judgment to develop. The findings should therefore be interpreted as evidence about short-term alignment, not long-term mastery.

Third, the study is based on a single undergraduate course in a specific instructional context. While this context is useful for examining GenAI-integrated pedagogy in a realistic design setting, the findings are not intended to be universally generalizable across all design disciplines, institutional conditions, or student populations. Relatedly, the reflection materials varied in depth and completeness. Some students offered detailed accounts of their prompting strategies and frustrations, while others responded more briefly. Although these reflections were sufficient to identify recurring themes, they cannot fully substitute for richer qualitative methods such as interviews, observations, or longitudinal design diaries.

These limitations point directly toward future research. A next step would be to triangulate perception-based findings with artifact-based assessment, rubric-aligned evaluation of integration quality, and instructor judgment of process development across stages of work. Future studies could also incorporate interviews, observations, or collected prompt logs to examine how design decisions unfold in more detail over time. In addition, comparative studies across longer courses or across different types of design tasks could clarify whether the shift from generation difficulty to orchestration difficulty persists, weakens, or intensifies under different pedagogical conditions. Such research would help move the field from early descriptive accounts of GenAI use toward more robust models of how GenAI integration shapes design learning.

Conclusion

This study examined whether GenAI-integrated teaching in a four-week undergraduate design course could support core course learning goals associated with studio-based design education. Drawing on pre- and post-course surveys and written student reflections, the findings suggest partial alignment rather than full achievement. Students commonly reported that AIGC helped them progress more quickly, generate options, and engage in more deliberate prompting and iteration practices. At the same time, persistent challenges remained in controllability, output consistency, and the integration of AI-generated materials into coherent design solutions.

Taken together, the findings suggest that GenAI redistributes difficulty in short-term design learning. It appears to reduce barriers to starting, visualizing, and generating alternatives, while foregrounding new demands in steering, refining, evaluating, and synthesizing outputs into meaningful design decisions. This shift is pedagogically significant because it suggests that the central challenge of GenAI-integrated design education lies less in access to generation than in teaching students how to work critically and reflectively with what is generated.

For that reason, GenAI in design education is best understood not only as a tool of production but as a pedagogical condition that reshapes where learning effort is required. If design educators want GenAI-integrated teaching to remain aligned with course learning goals, they will need to teach control and integration strategies explicitly and evaluate learning processes alongside final artifacts. In the short term, then, GenAI may help students move faster and explore more; but whether that support becomes meaningful design learning depends on how well pedagogy addresses the higher-order work of direction, judgment, and synthesis.

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

The authors used ChatGPT during the preparation of this work to refine language and check formatting; after utilizing the tool, the authors thoroughly reviewed and edited the content as necessary and assumed full responsibility for the publication's content.

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