Vol.7 Iss.3 2026
https://doi.org/10.37420/j.adr.2026.023
Art & Design Research

Motivation and Creativity in Generative AI-Assisted Architectural Design Education: A 16-Week Mixed-Methods Study

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Abstract:
Generative artificial intelligence (GenAI) is rapidly entering architectural design studios, yet empirical evidence regarding its effects on design students' learning motivation, design experience, and creativity in authentic course settings remains limited. This paper reports a 16-week mixed-methods study of a GenAI-integrated architectural design studio. It examines how text-based and image-based generative tools were embedded in a CAAD-led design workflow and analyzes the relationships among student motivation, process experience, and expert-rated creativity. Forty-three second-year interior architecture students participated in the course; 25 provided valid pre- and post-test data and complete expert ratings. The study employed the COQ-CR, a survey of attitudes toward the design task, a questionnaire about designing, instructor-rated learning attitude, five external experts' ratings of final projects on novelty, value, and unexpectedness, and semi-structured interviews with five students. Results showed significant increases in overall COQ-CR, general beliefs, and goal beliefs, and a significant improvement in instructor-rated learning attitude. Task attitudes and process perceptions did not show uniform significant change at the cohort level, but their individual changes were positively correlated with creativity scores. Baseline motivation was positively correlated with the value dimension and composite creativity. Interviews indicated that GenAI supported learning mainly by providing direction, reducing the burden of initiation, expanding the space of possibilities, and accelerating visual externalization, while also generating tensions around reliance, authorship, and tightened process self-assessment. The paper argues that the educational value of GenAI lies not in a uniform "tool effect" but in whether it is organized as a phased, CAAD-anchored, reflective design practice with differentiated scaffolding for students with different baseline motivational profiles.

Keywords:
Generative artificial intelligence; architectural design education; design studio; motivation; creativity; human–AI collaboration; CAAD.

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1 Introduction

Generative artificial intelligence (GenAI) has become a transformative force in design practice and design education. Large language models and text-to-image generation systems, represented by ChatGPT and Midjourney, can rapidly generate text, images, and conceptual proposals, offering new exploratory space for architectural and interior design teaching. However, existing research has mostly focused on tool capabilities, conceptual generation efficiency, or creative performance in specific tasks, and has rarely systematically examined, within authentic, long-term architectural design studios, how GenAI affects students' design motivation, process experience, and creativity outcomes. The architectural design studio is the core site of architectural education. It is not only a place where knowledge from multiple courses is synthesized and applied, but also a key environment in which students' design judgment, professional identity, and creative capacity are formed (Schön, 1983; Cuff, 1992). When GenAI enters the studio, it does not simply add a tool; it alters the socio-material conditions of design cognition, representation ecology, feedback rhythm, and collaboration.

Against this background, this paper addresses three interrelated questions. First, how is GenAI integration related to changes in students' motivation and design experience? Second, how does students' baseline motivation correspond to their final design creativity? Third, how do students perceive and make sense of GenAI's role in their studio learning? Based on a 16-week authentic course, the study adopts a convergent mixed-methods design, combining longitudinal questionnaires, instructor ratings, expert creativity ratings, and interview narratives. It seeks to move beyond the binary question of whether GenAI "works" and instead analyze under what conditions, for whom, and in what ways GenAI becomes educationally meaningful.

2 Literature Review and Theoretical Framework

2.1 The Architectural Design Studio as Reflective Practice

The architectural design studio is generally regarded as the cornerstone of architectural education. Centered on open-ended design problems, it cultivates students' design judgment and professional identity through iterative making, public critique, peer exchange, and instructor guidance (Schön, 1983, 1987; Cuff, 1992). Studio learning has a clear reflective-practice character: through cycles of externalization, critique, and revision, students gradually develop their own design vocabulary. Creativity here is not only an attribute of the final product but also a processual accomplishment involving problem framing, exploration of alternatives, negotiation of constraints, and defense of decisions (Glăveanu, 2010; Rhodes, 1961). Therefore, evaluating GenAI's impact cannot rely solely on final outcomes; it must also attend to process participation, motivational maintenance, and reflective quality.

2.2 GenAI and the Design Process

Recent studies show that GenAI can support design research, concept generation, visualization, and scheme comparison. It can expand the conceptual space, reduce cognitive load, accelerate iteration, and introduce unexpected stimuli to alleviate fixation (Dai et al., 2023; Kim & Maher, 2023; Chandrasekera et al., 2024). At the same time, research warns of risks: blurred authorship, cognitive outsourcing, thematic convergence, over-reliance on AI suggestions, and responsibility allocation in team collaboration (Doshi & Hauser, 2024;

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Guo et al., 2023; Iranmanesh & Lotfabadi, 2025; Zhang et al., 2021). Agkathidis et al. (2024) found that introducing image-generation tools such as Midjourney and DALL·E into the studio can support conceptual form-finding and increase student enthusiasm, but ethical and design-authenticity issues still require pedagogical guidance. Overall, GenAI's impact is highly dependent on the pedagogical framework: how tools are embedded in tasks, assessment, and feedback determines whether they expand human agency or replace reflective labor.

2.3 Motivation and Creativity

Motivation is an important precondition for creativity. Collins and Amabile (1999) and Runco (2004, 2005) point out that without motivation, abilities and knowledge are unlikely to be transformed into creative outcomes. Design tasks are open-ended, ambiguous, and long-cycle; students need to sustain effort, tolerate uncertainty, and continue revising. Urhahne and Wijnia (2023) integrate expectancy-value, self-determination, achievement-goal, and other motivational theories, emphasizing the roles of autonomy, competence, relatedness, and task value. Vu et al. (2022) further note that motivation and achievement mutually shape each other in a cycle. GenAI may enhance motivation through personalized support, immediate feedback, and low-risk help-seeking, but it may also weaken intrinsic drive and autonomy through over-reliance. This study therefore treats motivation as a key explanatory layer for understanding the differentiated effects of GenAI.

2.4 Research Gaps and Questions

Existing research on GenAI in design education has three main gaps. First, much of it is tool-centered or short-task oriented, lacking evidence from long-cycle, authentic studio ecologies. Second, motivational change is often represented by general satisfaction or episodic self-reports rather than systematic measurement. Third, creativity assessment often relies on product indicators or idea counts, rarely combining process experience, baseline motivation, and expert judgment. Against this background, this paper proposes three research questions:

RQ1: How is GenAI integration related to motivation and design experience?

RQ2: How does baseline motivation correspond to final design creativity?

RQ3: How do students perceive and make sense of GenAI's role in their studio learning?

3 Research Methods

3.1 Research Design and Context

The study adopted a convergent mixed-methods design in a 16-week, credit-bearing second-year architectural design studio. The course was an authentic course, and GenAI tools were formally introduced into daily studio practice rather than treated as an isolated experiment. The course task was a small-scale commercial interior design project in an industrial heritage park. Students selected one of two designated sites and completed the full process from site research, conceptual design, schematic design, and design development to final review. Forty-three second-year interior architecture students participated in the course; 25 provided valid

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pre- and post-test data, instructor ratings, and complete expert ratings, forming the main quantitative analysis sample. For the qualitative component, five students were purposively selected for semi-structured interviews based on a maximum-variation logic.

3.2 GenAI–CAAD Integrated Workflow

The studio adopted a hybrid tool ecology of CAAD and GenAI. Traditional CAAD tools such as AutoCAD and SketchUp were responsible for drafting, modeling, spatial organization, and final presentation. Text-based GenAI was used for problem framing, constraint interpretation, conceptual narrative, and argumentation. Image-based GenAI was used for exploring atmosphere, style, spatial imagery, and visual alternatives. Pedagogical scaffolding emphasized that GenAI outputs should be treated as provisional leads rather than conclusions; key decisions needed to be tested, adjusted, and translated into reviewable drawings and models in CAAD; and students needed to disclose AI use and retain decision rationales. Table 1 summarizes the phased integration logic.

Table 1 Phased GenAI–CAAD integration workflow

Phase	CAAD role	GenAI role	Pedagogical scaffolding
Research and site analysis	Diagrams, baseline models, reference systems	Information synthesis, problem hypotheses, trend comparison	Traceable sources; verify facts; treat outputs as leads
Conceptual design	Sketches, exploratory models, discussable prototypes	Expand concepts and narratives; text–image translation; generate candidates	Anchor in CAAD artefacts; keep alternatives visible; document selection criteria
Schematic design	Reviewable drawings, feasibility checks, iteration	Generate alternative strategies, comparative summaries, trade-off reasoning	Feasibility substantiated in CAAD; GenAI for expansion and argumentation
Design development	Complete deliverable set, drawing–model consistency	Local alternatives, representational language, narrative coherence	Core outcomes student-authored; GenAI supports clarity and comparison
Critique and selection	Converge into submittable outcomes	Comparative synthesis, alternative arguments, textual restatement	Make criteria explicit; disclose AI use; reframe when necessary

3.3 Measurement Instruments and Data Collection

Quantitative instruments included the COQ-CR creativity-related motivation questionnaire, measuring beliefs about self, general beliefs, beliefs about norms, and beliefs about goals; the Survey of Attitudes toward the creative design problem (SA); the Questionnaire about Designing (QD); instructor-rated learning attitude (LA, A/B/C); and ratings by five external experts of final projects on novelty, value, and unexpectedness using a 1–10 scale based on Maher's (2010) framework, from which a composite creativity score was calculated (novelty × value × unexpectedness). Interviews focused on students' experiences of using GenAI, motivation-

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al effects, creative expansion, process changes, and future expectations. All questionnaires were administered in class under instructor supervision to ensure a controlled environment.

3.4 Data Analysis

Quantitative analysis included internal consistency tests, paired-sample t-tests, ICC inter-rater reliability, ANOVA, Pearson correlations, and exploratory multiple regression. Qualitative analysis used thematic analysis, organized around three a priori themes: motivation-related centrality, creativity-related centrality, and process centrality. Interview narratives were integrated with individual quantitative profiles through case-level joint displays, and evidence relationships were classified as convergent, complementary, or divergent.

4 Results

4.1 Changes in Motivation and Design Experience

Overall COQ-CR increased from 2.568 to 2.697, a significant difference ($t(24) = 2.404$, $p = .024$, $d = 0.48$). By dimension, general beliefs increased from 2.299 to 2.511 ($p = .005$, $d = 0.61$), and goal beliefs increased from 2.634 to 2.834 ($p = .015$, $d = 0.52$), whereas self beliefs and norm beliefs did not change significantly. Instructor-rated learning attitude increased by an average of 0.440 ($t(24) = 3.381$, $p = .002$, $d = 0.68$); the number of students rated A increased from 9 to 15, while those rated C decreased from 8 to 3. In contrast, SA and QD did not change significantly at the cohort level (SA: 2.943 → 2.947; QD: 3.033 → 3.093). This indicates that GenAI integration was associated with improvements in creativity-related beliefs and instructor-observed learning engagement, but task attitudes and process perceptions did not improve uniformly.

Table 2 Main quantitative results

Indicator	Pre-test/early	Post-test/late	Statistical result
Overall COQ-CR	2.568	2.697	t = 2.404, p = .024, d = .48
General beliefs	2.299	2.511	p = .005, d = .61
Goal beliefs	2.634	2.834	p = .015, d = .52
Learning attitude (LA)	—	—	mean difference = .440, p = .002, d = .68
SA	2.943	2.947	p = .959
QD	3.033	3.093	p = .366
Novelty	6.82	—	SD = 1.37
Value	7.10	—	SD = 1.44
Unexpectedness	6.79	—	SD = 1.50
Composite creativity	367.02	—	SD = 184.66

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Expert ratings had relatively high reliability: single-rater ICC(2,1) ranged from .690 to .795, and the average ICC(2,k) for five raters ranged from .918 to .951. The composite creativity scores had a wide range (60.61–736.92), indicating considerable variation in the creativity of students' final projects.

4.2 Baseline Motivation and Creativity

After dividing students into low-, medium-, and high-motivation groups based on baseline COQ-CR, each group showed an upward trend in creativity indicators, but ANOVA did not reach significance. Continuous correlation analysis showed that baseline COQ-CR was significantly positively correlated with value ($r = .402$, $p = .046$) and composite creativity ($r = .406$, $p = .044$); correlations with novelty ($r = .394$, $p = .051$) and unexpectedness ($r = .387$, $p = .056$) approached significance. The results suggest that higher baseline creativity-related motivation is associated with higher expert-rated creativity, especially in the value dimension.

4.3 Process Change and Creativity

Analysis of change scores showed that change in task attitudes (ΔSA) was significantly positively correlated with composite creativity ($r = .494$, $p = .012$), and change in process perceptions (ΔQD) was also positively correlated with creativity ($r = .425$, $p = .034$). ΔCOQ-CR and ΔLA were not significantly correlated. In exploratory multiple regression, the four change indicators jointly explained 44% of the variance in creativity ($R^2 = .44$, $p = .012$); ΔSA remained a significant positive predictor ($\beta = .576$, $p = .018$), while ΔCOQ-CR showed a negative suppression effect ($\beta = -.421$, $p = .031$), although the latter should be interpreted cautiously given the small sample. Overall, students' improvements in task attitudes and process experience were closer to creative performance than mere increases in motivational beliefs.

4.4 Student Perceptions and Case Integration

The five interview cases exhibited three types of evidence relationships. First, a convergent pattern: Jamie strongly emphasized GenAI in process and creativity themes, accompanied by substantial increases in SA and QD and a very high creativity score (composite 728.64); Yuri and Lina also showed convergence in the creativity theme. Second, a complementary pattern: Shawn and Tina showed modest quantitative changes, but interviews clearly explained how GenAI supported motivation and process by providing direction, reducing burden, and filling weak areas. Third, a divergent pattern: Lina strongly affirmed in her process narrative that GenAI saved time and unified style, but her ΔQD was negative, suggesting tightened self-evaluation standards or that the scale did not cover the process aspects she valued most.

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Table 3 Integration patterns across the five interview cases

Student	Motivation-related centrality	Creativity-related centrality	Process centrality	Main integration pattern
Yuri	High	High	High	Convergent for motivation/creativity; complementary for process
Jamie	High	High	High	Convergent for creativity/process; complementary for motivation
Lina	High	High	High	Convergent for creativity; complementary for motivation; divergent for process
Shawn	Medium	Medium	Medium	Overall complementary
Tina	Medium	Medium	Medium	Overall complementary

In the interviews, students generally described GenAI as "making complex tasks simpler," "giving direction when lost," "like playing a game," and "expanding possibilities I would not have thought of." At the same time, they emphasized selection, modification, recombination, and translation of AI outputs into CAAD outcomes. This indicates that students did not simply treat GenAI as a replacement, but positioned it within their personal design intentions and the studio's framework of responsibility.

5 Discussion

5.1 Heterogeneity Rather Than a Uniform Effect

This study shows that GenAI integration does not have homogeneous effects for all students. At the cohort level, creativity-related motivation and instructor-rated learning attitude improved significantly, but task attitudes and process perceptions did not change uniformly. This suggests that after GenAI enters the studio, students may follow different trajectories: some gain direction and process navigability, while others face translation difficulties, dependency anxiety, or shifting standards. Educators should not assume that "access to GenAI" automatically brings motivational and creative improvement; instead, they should attend to how different students appropriate it at specific stages.

5.2 Baseline Motivation and Value-Oriented Creativity

Baseline COQ-CR was positively correlated with value and composite creativity, suggesting that motivational resources may indirectly influence creativity by supporting sustained investment, constraint integration, and judgment formation. In architectural studios, creativity is not merely novelty; it also includes the defensibility, coherence, and constraint responsiveness of a proposal. The value dimension had the strongest relationship with baseline motivation, possibly because GenAI mainly helps students organize alternatives, stabilize direction, and iterate more effectively, thereby first improving the plausibility and completeness of

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proposals. This is consistent with the view that creativity is a unity of process and product (Glăveanu, 2010; Maher, 2010).

5.3 The Mechanism of Process Navigability

This paper proposes "process navigability" as an explanatory mechanism: when GenAI helps students move from uncertainty to an actionable next step—by offering alternative framings, representational variants, or rapid externalization—students are more likely to form positive task attitudes and a workable sense of process, which in turn sustains iteration and uptake of critique feedback. The positive associations of ΔSA and ΔQD with creativity support this interpretation. Notably, ΔCOQ-CR showed a negative suppression effect in the regression, which may reflect collinearity or suppression in a small sample rather than indicating that motivational improvement undermines creativity. A more cautious interpretation is that changes in task engagement and process experience are closer to creative performance than changes in general beliefs.

5.4 Differences Between Text-Based and Image-Based GenAI

Text-based and image-based GenAI play different roles in the studio. Text tools are more often used for problem framing, constraint interpretation, narrative organization, and decision support; image tools are more often used for atmosphere exploration, visual comparison, and representational variation. Interviews showed that students who emphasized text-based GenAI for framing and decision support were more likely to describe clear "next steps"; those who emphasized image-based GenAI more often described gains in visual exploration, but not necessarily improvements in process navigability. Future research should distinguish modality and purpose of use rather than treating GenAI as a single intervention.

5.5 Implications for Teaching, Assessment, and Integration Design

First, teaching should explicitly incorporate GenAI into reflective practice, so that outputs become criticizable, testable provisional leads rather than ready-made answers. Second, assessment can incorporate lightweight process documentation, such as prompt design, output selection and rejection, constraint testing, and decision rationales, to reinforce responsible use. Third, integration design should be phased: early stages for divergence and framing, middle stages for comparison and argumentation, and later stages for coherence and expression, while always anchoring to reviewable CAAD outcomes. Fourth, differentiated scaffolding should be provided for students with different baseline motivation, especially helping medium- and low-motivation students avoid dependency and maintain participation, while enabling high-motivation students to expand their creative potential.

6 Limitations and Future Research

This study is a single-course, single-cohort authentic studio study and does not attempt to provide a strict causal estimate of "GenAI versus no GenAI." The sample size is limited, the early internal consistency of QD was low, instructor-rated learning attitude is an ordinal judgment, and creativity assessment is based on final products. Future research can replicate across studios and cohorts, adopt ethically feasible quasi-comparison designs, and introduce higher-frequency measurement and process trace data (prompt histories, revision epi-

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sodes, uptake of critique feedback) to examine relationships between different human–AI interaction patterns and changes in creativity and motivation. At the same time, further research should distinguish the mechanisms of text-based and image-based GenAI, different task stages, and different learning-attitude groups.

7 Conclusion

Based on a 16-week mixed-methods study of a GenAI-integrated architectural design studio, this paper shows that GenAI can accompany improvements in creativity-related motivational beliefs and instructor-observed learning attitudes, but its effects on task attitudes, process experience, and creativity are markedly heterogeneous. Baseline motivation was positively correlated with value-oriented creativity; improvements in task attitudes and process experience were associated with higher creativity; and students treated GenAI as support for direction-finding, burden reduction, expansion of possibility space, and visual externalization, while maintaining agency in selection, modification, and CAAD translation. The key question for architectural education is not whether GenAI should exist in the studio, but how phased, CAAD-anchored, reflective, and differentiated pedagogical organization can make it serve responsible design judgment, sustained motivational investment, and meaningful creative development.

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