The Impact of Generative AI on Architectural Conceptual Design: Performance, Creative Self-Efficacy and Cognitive Load

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Abstract

Our study examines how generative AI (GenAI) influences performance, creative self-efficacy, and cognitive load in architectural conceptual design tasks. Thirty-six student participants from Architectural Engineering and other disciplines completed a two-phase architectural design task, first independently and then with external tools (GenAI-assisted condition and control condition using an online repository of existing architectural projects). Design outcomes were evaluated by expert raters, while self-efficacy and cognitive load were self-reported after each phase. Difference-in-differences analyses revealed no overall performance advantage of GenAI across participants; however, subgroup analyses showed that GenAI significantly improved design performance for novice designers. In contrast, general creative self-efficacy declined for students using GenAI. Cognitive load did not differ significantly between conditions, though prompt usage patterns showed that iterative idea-generation and visual feedback prompts were linked to greater reduction in cognitive load. These findings suggest that GenAI's effectiveness depends on users' prior expertise and interaction strategies through prompting.

Keywords

Visual communication; Architectural design; Learning; Performance Assessment; Hybrid Intelligence; Human-AI teaming

Nomenclature

CAD	Computer-Aided Design
CLT	Cognitive load theory
DiD	Difference-in-Differences
GenAI	Generative artificial intelligent
GPT	Generative Pre-trained Transformer
SD	Standard deviation
STEM	Science, technology, engineering, and mathematics

Highlights

- GenAI boosted novice students' performance significantly.
- Creative self-efficacy showed divergent trends between GenAI and control groups.
- Cognitive load showed no overall reduction with GenAI across design phases.
- Prompts usage patterns were associated with greater reductions in cognitive load.

1. Introduction and Background

Visual communication skills are the abilities to effectively perceive and convey information using visual elements such as images and diagrams [1–3]. It plays a central role in knowledge creation and dissemination, as the capacity to process, structure, and generate visual information is essential for decision-making, problem-solving, and collaboration across STEM disciplines [4,5].

Among the many fields that rely on visual communication, architectural design stands out as particularly dependent on this skill. Designers must translate abstract programmatic goals into visual representations—sketches, diagrams, and spatial forms that can guide ideation and communicate design intentions to further development [6–8]. In this sense, architectural conceptual design can be understood as a demanding visual task that integrates creativity, technical reasoning, and communication [9]. For students, especially those without formal training in sketching or visual ideation, the difficulty could result in limited creative exploration and less effective communication [10–12].

The difficulty of visual ideation can be attributed to two interacting psychological factors: cognitive load and creative self-efficacy. First, the visual ideation process imposes a high cognitive load, which refers to the total mental effort required to hold, process, and organize unstructured details and complex spatial relationships simultaneously [13]. Second, creative self-efficacy reflects individuals' subjective beliefs about their capacity for creative performance [14,15]. Prior research has shown that such self-beliefs constitute a critical motivational factor underlying engagement in creative work [16,17]. Low self-efficacy can inhibit experimentation and lead to premature abandonment of promising design paths, further hindering the conceptual design process [18].

Recent advances in generative artificial intelligence (GenAI) offer a promising avenue for mitigating these challenges [19]. By translating natural language prompts into visually detailed design outputs, these tools provide a low-barrier, scalable complement to traditional sketching practices, potentially making visual ideation more accessible for designers in different stages and fields [20,11].

Recent research reported that GenAI can reduce cognitive load while maintaining accuracy that has the potential to outperform traditional methods [21]. While research on GenAI regarding cognitive load is still limited, the study suggests that GenAI has the potential to mitigate this cognitive burden, allowing individuals to grasp higher-order reasoning and design mechanics.

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This aligns with the cognitive load theory (CLT) [22–25] which emphasizes the design of instructional materials to optimize learning by managing the cognitive load imposed on learners. Compared to traditional methods or other AI models, GenAI offers unique capabilities to reduce cognitive load that can dynamically adapt to individual differences and preferences [26].

While GenAI tools can reduce the effort associated with manual sketching or idea generation, they introduce new demands related to prompt formulation, iterative refinement, and output evaluation [27,28]. Experimental findings are inconsistent in different groups and conditions: some report lower perceived load due to task offloading [29–31], while others using electroencephalogram (EEG) measurement found that participants experienced the same or higher cognitive load when performing high cognitive demand tasks [32], suggesting that the effect of AI's application on cognitive load varies with the content of the task. While these studies highlight GenAI's potential to influence cognitive load in decision-making and problem-solving, they do not directly address visual communication, leaving open questions about its impact in tasks that rely heavily on processing and generating visual information.

Early studies have demonstrated the potential of tools like ChatGPT to enhance the productivity of writing tasks [33,34]. For instance, Woo et al. suggest that ChatGPT may enhance the process of divergent thinking by exposing students to a wide range of potential solutions [35]. Such exposure encourages learners to explore a broader set of possibilities, enabling them to identify and select more promising prototype solutions, particularly among more experienced students [36–38]. However, Dwivedi et al. [39] and Peters et al. [40] proposed pessimistic view that ChatGPT "kills creativity" and "lacks originality" by resting on a replacement framing. At the same time, more studies elaborated when used as an augmentative tool rather than a substitute, GenAI can foster idea and task development better than sole AI or humans in creative problem-solving tasks [26,41–43]. As most GenAI tools initially focused on text generation before expanding to image generation, research on their impact on visual communication tasks is still limited.

Furthermore, novice and experienced learners engage with learning tools differently due to variations in domain-specific prior knowledge, self-efficacy, and technology acceptance [44], as well as how students frame prompts, interpret AI outputs, and decide when to iterate versus rely on their own reasoning, substantially shape both interaction patterns and academic outcomes [45]. A recent study found that experienced learner demonstrated higher quality, novelty, and creativity when engaging with AI chatbots [46]. Research has suggested greater benefits for novice users of ChatGPT in writing tasks [47,48]. Therefore, the broader impact of GenAI on different levels of group in visual design field remains largely unknown.

Evaluating learning outcomes in design education based solely on final products provides only a partial picture. Therefore, our study examines GenAI as a pedagogical intervention, investigating how it impacts visual task performance, creative self-efficacy, and cognitive load across students with varying levels of experience. Beyond simply measuring whether GenAI enhances design outputs, we aim to understand the dynamics of human–AI interaction during the ideation

process. To achieve this objective, we employed a combination of between-group comparisons, within-group analyses across design phases, difference-in-differences modeling to isolate treatment effects, and two-way ANOVA models to examine how initial student competency levels moderated GenAI's impact on learning outcomes.

2. Related Work

2.1 Image Generation with GenAI for Architectural Design

Text-to-image GenAI has become an increasingly transformative tool in architectural design, particularly during the conceptual and early ideation stages. By converting textual or verbal prompts into visually detailed outputs, these systems enable rapid conceptual exploration and visualization, accelerating the generation of high-quality design representations and facilitating more iterative, exploratory workflows [49,50]. Empirical reports from architectural practice indicate that a growing proportion of professionals and firms have adopted GenAI tools to support early-stage design ideation, improving both efficiency and throughput in concept development [51]. Recent surveys show that approximately 41% of UK architects have used AI in their projects, and 43% believe it enhances design process efficiency [52]. According to a According to a 2025 industry report by Architizer and Chaos [53], the adoption of AI is no longer theoretical but operational, with 11% of firms already integrating GenAI into their design workflows and a 20% year-over-year increase in experimental interest compared to 2024. Beyond productivity, text-to-image GenAI supports innovative and user-centered design thinking by enabling architects to rapidly experiment with alternative styles, forms, and spatial configurations during the sketching phase. When integrated with traditional or parametric design methods, these tools expand the designer's creative capacity, fostering aesthetic innovation and more responsive design outcomes [50,54].

There are differences in the performance capabilities of different generative models. Recent advances in text-to-image generation have been led by models such as Midjourney, DALL-E 3, Stable Diffusion. Midjourney demonstrates superior image quality and artistic expressiveness, offering highly stylized results that appeal to creative professionals. Its cloud-based accessibility and active community-driven ecosystem foster iterative exploration, though its outputs are less controllable compared to open-source models such as Stable Diffusion [55,56]. DALL-E remains strong in text–image alignment and visual reasoning, benefiting from GPT-integrated prompt interpretation; however, studies note moderate image quality and persistent representational biases that limit its reliability for domain-specific design tasks [57–59]. Stable Diffusion, as an open-source and modular framework, excels in customizability and controllability, particularly when augmented with tools like ControlNet or LoRA, yet it generally yields lower visual fidelity and less stylistic consistency compared with Midjourney [60,61]. Collectively, these findings indicate a trade-off between openness and controllability on one end and aesthetic quality and semantic precision on the other.

Despite GenAI's demonstrated ability to accelerate visual ideation and broaden formal exploration, its educational impact cannot be inferred from output quality alone. The next section therefore reviews evidence on GenAI's effects on creative self-efficacy and cognitive load as key mechanisms shaping learner outcomes.

2.2 GenAI's Effects on Creative Self-Efficacy and Cognitive Load

Prior research shows that supportive creative environments can directly enhance students' creative self-efficacy and creative thinking [62]. GenAI contributes to this process by rapidly iterating and visualizing designers' ideas without demanding extensive time or technical skill, thereby facilitating early-stage ideation for students and novice designers. Self-efficacy plays a crucial moderating role in this interaction, with higher levels of confidence linked to more exploratory engagement and more effective use of AI tools [48,63]. Survey data from Guo et al. further indicate that creative self-efficacy significantly moderates creativity gains in everyday and professional uses of GenAI [64]. In early computational design education, establishing students' confidence has been shown to have a stronger impact on creativity than merely increasing motivation. Complementing this, a recent meta-analysis of university-wide experiments found that while ChatGPT improves academic performance, affective-motivational states, and higher-order thinking, it reduces mental effort and does not significantly change self-efficacy [31].

Although fewer studies have examined these mechanisms in architectural design, emerging evidence suggests that GenAI-supported design instruction can meaningfully enhance students' creative self-efficacy. For example, Huang et al. integrated multimodal AI into architectural design workflows and found that AI-assisted strategies significantly outperformed traditional instruction in boosting self-efficacy, with more advanced students reporting higher confidence than novices [44]. In elementary visual arts education, students using AI-generated imagery exhibited significantly higher self-efficacy than those under traditional teaching, as the visual appeal and specificity of AI outputs strengthened students' perceived competence in understanding and applying new material [65].

At the same time, GenAI introduces a distinctive cognitive profile in creative tasks. It can reduce cognitive load by offloading routine visual-ideational processes, yet it can also increase cognitive load when users must interpret ambiguous outputs, formulate effective prompts, or manage iterative refinements. Unlike traditional tools, GenAI redistributes cognitive effort from low-level manual production toward higher-level evaluation, judgment, and decision-making [66]. Consequently, the impact of AI on workload in creative design is not uniformly beneficial; it depends on learners' prior knowledge, prompting literacy, and the alignment between AI outputs and task goals.

High-quality prompting also appears to be a learned cognitive skill. In a study of non-routine problem solving, providing ChatGPT with explicit evaluation criteria, detailed contextual

background, and iterative feedback substantially improved the originality and specificity of generated solutions. Higher-performing participants used more frequent and more detailed prompts, suggesting that effective prompting itself contributes to better design outcomes [45]. Empirical findings in visual education further indicate that GenAI does not necessarily increase overall workload. In an elementary art study, students using GenAI showed no significant differences in cognitive load relative to traditional teaching, implying that AI-generated images did not add learning burden while helping maintain conceptual complexity through intuitive visual scaffolding [65]. In higher education design contexts, Chandrasekera et al. found that students working on urban furniture concepts experienced significantly lower cognitive load when using AI compared with traditional sketching, and GenAI substantially enhanced lateral and abstract thinking [29]. Similarly, in an ideation and concept-development experiment with trained designers, AI-assisted brainstorming significantly reduced perceived mental demand. Eye-tracking analyses showed shorter visual search paths and more distributed attention under AI assistance, indicating reduced extraneous cognitive load [67]. Chen et al. [68] compared a structured, choice-based interface (Choices2I) with the traditional text-based prompting used in GPT-4's official web version. They found that users from creative industries (e.g., designers, artists, film directors) consistently preferred Choices2I because it offered greater flexibility and control, regardless of their expertise level. In contrast, users from non-creative fields, who favored text-based prompting, which imposed lower cognitive load and avoided the pressure of making multiple design choices.

3. Methodology

We conducted an experiment in Spring 2024 to examine the impact of GenAI on visual communication in architectural concept design. This study was approved by the Institutional Review Board (IRB) at Worcester Polytechnic Institute (WPI) (IRB-20–0001).

3.1 Participants

We first recruited 41 participants through flyers and snowball sampling. We then randomly assigned them to the Control group and GenAI group. However, 5 participants did not complete the study. Thirty-six students were formally considered and randomly assigned to either the Control group or the GenAI group. The Control group consisted of 19 participants (8 females), while the GenAI group had 17 participants (9 females). The participants represented a range of academic disciplines and years of study since the goal of this study is to understand the effectiveness of GenAI across general disciplines beyond architecture for external validity. Table S1 in the Appendix describes the study major of each participant. Participants were compensated with a total payment of $50 (Amazon gift card) for their participation in this experiment. Additionally, the top three participants received an extra $100 bonus based on expert evaluation of their design work.

3.2 Experimental Design

As a key step in conceptual design, participants in the Control group used a popular online repository (ArchDaily.com) of existing design projects for their precedent study, while participants in the GenAI group used DALL-E3 in ChatGPT 4 to inspire their conceptual design.

The experiment consisted of two visits: a group tutorial session and an individual design session. During the individual session, participants completed a design task in two phases: 1) an initial design without tools and 2) a revised design using ArchDaily in the Control group or DALL-E3 in the GenAI group. Both initial and revised designs were submitted and evaluated by a panel of experts. In addition, survey data were collected to assess self-efficacy in creativity and cognitive workload. Further details are provided in the sections below.

3.3 Architectural Conceptual Design Task

Participants were asked to develop an architectural concept design for a research laboratory building located at Gateway Park of WPI (Fig. 1). Gateway Park is a mixed-use facility housing a range of academic, research, and commercial enterprises. The site is located in the ASHRAE climate zone 5A.

The task focused on conceptual design of building massing and geometries. Given the diversity of participants' backgrounds, we gave a mini crash course on how to develop architectural design concepts in a separate visit before the formal experiment. The formal design experiment consisted of two phases including free design phase without consulting any design project repositories for precedent studies or applying any AI tools. The deliverable of each phase of the design task is a sketch using a 15.6" digital drawing tablet (Artist 15.6 Pro, XP-PEN) with a stylus. Fig. 1b displays sketches of the two phases from two participants in control and GenAI groups, respectively.
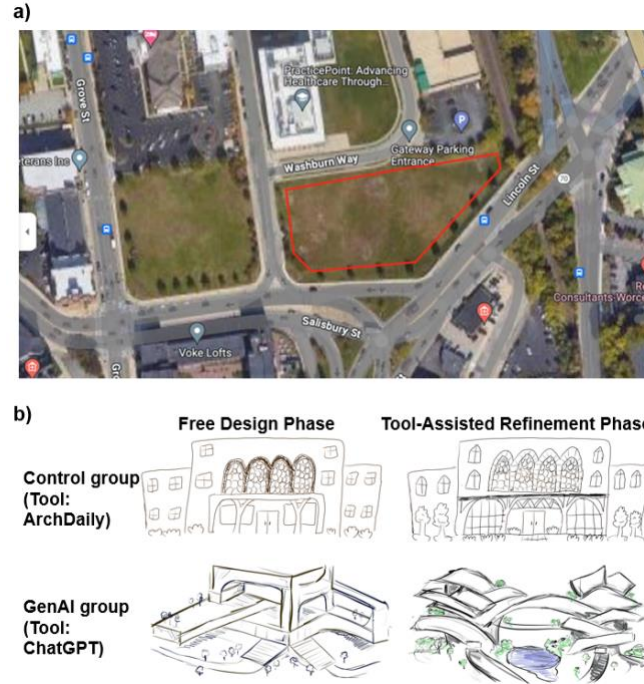
Fig. 1. *Site and sample conceptual design; a) Design site and neighborhood of the research laboratory building; b) Design samples of two participants in Control and GenAI groups respectively.*

3.4 Procedure

To accommodate participants' schedules and enhance their experience, the experiment was conducted in four batches. The experimental procedure consisted of two visits: a group tutorial session (Visit 1) and an individual design session (Visit 2). Participants were assigned to one of the four batches based on their availability, with each batch attending a separate tutorial session during the first visit.

Fig. 2. *Experimental protocol across two visits. Visit 1: Group tutorial; Visit 2: Individual design.*

3.4.1 Group Tutorial Session (Visit 1)

The first visit lasted approximately one hour. During this session, a professional provided a detailed explanation of the experiment, including an overview of the *design* task for the second visit. A brief lecture on fundamental design principles was also *provided*. To help participants familiarize themselves with the design process, *p*articipants *were instructed to* use these woodblocks to explore architectural concepts and practice design strategies *(Fig. 3)*.

Fig. 3. *Students in the group tutorial used woodblock to learn conceptual design. The image was converted from a photo taken from a session.*

3.4.2 Individual Design Session (Visit 2)

The second visit lasted approximately 1.5 hours (**Fig. 2**). Each participant scheduled a time slot and was randomly assigned to either the control group or the treatment group. After Visit 2, each of the 36 participants will submit both an initial design drawing and a revised design drawing for their design concepts. The session was structured into three phases:

1) ***Setup Phase (approximately 30 min):*** A researcher assisted each participant with donning the neurophysiological sensors and configuring the software used for data collection. Details of the neurophysiological measures will be reported in future publications. After the setup was completed, the researcher left the lab, and the participant completed the remainder of the session independently. Step-by-step guidance was provided through an online platform that displayed dynamic countdowns indicating the remaining time for each task.

2) ***Initial Design Phase (35 min):*** Participants created their initial design on the drawing tablet using only wood blocks. When they either finished their design or the allotted time elapsed, they completed a survey assessing creativity self-efficacy and workload, as described in Section 3.6.

3) ***Revision Design Phase (35 min):*** After a 5 min break, participants refined their initial design by searching for precedent projects on ArchDaily for inspiration in the Control group or

using DALL-E3 in the GenAI group. To ensure sufficient data collection, participants were asked to consult at least five architectural concepts to improve their design using ArchDaily or DALL-E3. After submitting their revised design, they completed the same survey assessing creativity self-efficacy and workload.

3.5 Design Performance Assessment

Participants' drawings of conceptual design were assessed by a panel of eight judges including four architectural professionals and four senior architectural students. Each judge independently assessed all the drawings randomly displayed on a developed website using modified rubrics based on previous studies [69–71] as described in Table 1. The rubric includes three core dimensions, clarity and legibility, complexity and detail, and overall visual communication. Each criterion was assessed using a 5-point Likert scale ranging from "1=Poor" to "5=Excellent." The design task performance was rated with the average of the three criteria. The final score was calculated by averaging eight judges' ratings.

Table 1. *Design performance evaluation rubrics*

Dimension	1 - Poor	2 - Fair	3 - Good	4 -Very Good	5 - Excellent
Clarity and Legibility	Sketches are unclear, with indistinct features or lines.	Sketches are somewhat clear but with inconsistent line quality.	Sketches are mostly clear, with minor readability issues.	Sketches are clear, legible, and understandable with minor issues.	Sketches are exceptionally clear, with all elements easily distinguishable.
Complexity and Detail	Minimal detail is included, with simplistic forms.	Some detail is present, but much of the design is too simple.	Adequate details are present but could be more comprehensive.	Design includes significant detail and demonstrates complexity.	Design is richly detailed, with all aspects clearly and intricately represented.
Overall Visual Communication	Design is poorly communicated visually, and it is difficult to understand the intent.	Visual communication is fair, but the design is hard to understand without further clarification.	Design is communicated well visually, with most aspects easy to understand.	Visual communication is very effective, with minor gaps.	Visual communication is highly effective, and the design is fully understandable with minimal effort.

3.6 Self-efficacy in Creativity and Workload

After each design phase, participants took the questionnaires of self-efficacy in creativity [72] and NASA Task Load Index (NASA-TLX) [73]. The average of the six subscales was used to represent the workload experienced by participants as suggested by previous studies [73–75]. Self-efficacy in creativity (Table 2) consists of task-specific creative self-efficacy by averaging responses to Q1 and Q2, and general creative self-efficacy calculated by averaging responses to Q3-Q5.

Table 2. *Questions on self-efficacy in creativity*

	Questions	Scale (1-5)
Task-specific creative self-efficacy	(Q1) My responses to the task were creative.	1 = Strongly Disagree, 5 = Strongly Agree
	(Q2) My responses were more creative than the average person at my age.	1 = Strongly Disagree, 5 = Strongly Agree
	(Q3) I am good at coming up with new ideas.	1 = Strongly Disagree, 5 = Strongly Agree
General creative self-efficacy	(Q4) I have a lot of good ideas.	1 = Strongly Disagree, 5 = Strongly Agree
	(Q5) I have a good imagination.	1 = Strongly Disagree, 5 = Strongly Agree

3.7 Prompt analysis procedure

To relate prompt behavior to changes in cognitive load, we conducted a prompt-mining analysis using prompts extracted from screen recordings of participants' GenAI interactions during the design task. All prompts produced during the design task were coded using a nine-category scheme adapted from a prior study on AI-supported creative problem solving [45]. The first two authors and a senior undergraduate student in Architectural Engineering at WPI as experts established labeling principles by jointly reviewing two sample cases; disagreements were resolved through discussion. We deleted "providing additional context" based on our task after reviewing. The expert raters then independently coded the remaining prompts in randomized order, yielding acceptable to strong inter-rater reliability (weighted $\kappa = 0.73$–0.78) [76]. The final coded dataset was used to quantify prompt-use patterns for each participant.

For each prompt category, we computed descriptive statistics including the minimum, maximum, and mean frequency of use per participant, along with standard deviations. To examine associations between prompt use and changes in cognitive load, we calculated delta cognitive load as the mean difference across six NASA-TLX items (revision design phase – initial design phase). Normality of distributions was assessed with the Shapiro–Wilk test. Depending on normality, correlations between each prompt category and delta Cognitive Load were computed using *Pearson's r* when variables showed approximately normal distributions and linear relationships or *Spearman's ρ* when these assumptions were violated.

3.8 Statistical analysis

All analyses were conducted in Python using *scipy* and *statsmodels* [77,78]. Collected survey results are reported for overall between-group comparisons (GenAI vs. Control), we applied Shapiro–Wilk and Levene's tests to evaluate normality and homogeneity of variance, respectively. Depending on the results of these assumptions, Welch's independent-samples t-tests or Mann–Whitney U tests were applied for parametric dataset and non-parametric dataset, respectively. To compare the difference within groups, outcomes were analyzed using a difference-in-differences (DiD) regression,

$$Y_{it} = \beta_0 + \beta_1 \text{Tool}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Tool}_i \times \text{Post}_t) + \varepsilon_{it} \tag{1}$$

where β_3 captures the two phase change in the GenAI group relative to the control group. The outcome variable Y_{it} represents the score of participant i at time t. The intercept β_0 corresponds to the mean outcome of the control group during the initial design phase. The coefficient β_1 captures the baseline difference between the GenAI and control groups prior to the intervention. The coefficient β_2 represents the average change from the initial design phase to the revision design phase for the control group. The error term ε_{it} represents unexplained individual-level variation. Standard errors were clustered by participant level to account for repeated measures.

DiD estimates and their 95% confidence intervals were standardized by dividing them by the pooled standard deviation of the initial design phase scores. To examine whether the effectiveness of GenAI varied by participants' initial competency level, initial design performance scores were dichotomized at the median value into Novice and Experienced subgroups Four two-way ANOVA models were then conducted to test the interaction between Tool (GenAI vs. Control) and Initial Competency Level across four outcome measures: design performance, task-specific creative self-efficacy, general creative self-efficacy, cognitive load. Effect sizes were reported using partial eta-squared (η^2_p). All tests were two-tailed with $p = 0.05$ to determine statistical significance.

4. Results

4.1 Between-Group Comparisons across Different Design Phases

Table 3 presents the comparison of design performance, cognitive load, and creative self-efficacy between the Control group and the GenAI group across the Initial Design Phase and the Revision Design Phase. In the Initial Design Phase, participants in both groups developed their conceptual designs without the use of any external tool. No statistically significant differences were observed between the two groups for design performance, cognitive load, or either measure of creative self-efficacy (all p values > 0.32). The similarity in group means indicates that the random assignment procedure successfully produced comparable baseline conditions. Design performance ratings were approximately 2.8 to 2.9 on a five-point scale for both groups, and cognitive load remained lower than 3, suggesting a moderate level of perceived mental demand.

In the Revision Design Phase, the GenAI group demonstrated marginally higher design performance relative to the Control group (*Control: M = 2.785, SD = 0.361; GenAI: M = 2.903, SD = 0.433; p = 0.381*), although this difference did not reach statistical significance. Cognitive load followed a similar pattern. Participants in the GenAI group reported a slightly lower level of cognitive demand than those in the Control group, but the difference was not significant. In

contrast, both task-specific creative self-efficacy and general creative self-efficacy were modestly but not significantly lower in the GenAI group compared to the Control group.

Table 3. *Comparison of design performance, cognitive load, and self-efficacy between Control Group and GenAI Group across two design phases.*

Design Phase	Tool Used	Parameter	Control (mean ± SD)	GenAI (mean ± SD)	P value	Cohen's *d*
Initial Design Phase	None	Design performance	2.921 ± 0.369	2.819 ± 0.388	0.426	-0.269
		Cognitive load	2.787 ± 0.322	2.778 ± 0.478	0.946	-0.023
		Task-specific creative self-efficacy	3.472 ± 0.866	3.556 ± 0.765	0.761	0.102
		General creative self-efficacy	3.537 ± 0.76	3.796± 0.81	0.329	0.33
Revision Design Phase	Control: ArchDaily GenAI: DALL-E3	Design performance	2.785 ± 0.361	2.903 ± 0.433	0.381	0.296
		Cognitive load	2.880 ± 0.442	2.843 ± 0.604	0.835	-0.07
		Task-specific creative self-efficacy	3.861 ± 0.854	3.556 ± 0.82	0.281	-0.365
		General creative self-efficacy	3.741 ± 0.805	3.574 ± 0.899	0.562	-0.195

4.2 Difference in Difference Analysis across Design Phases

A difference-in-differences (DiD) analysis was conducted to estimate the treatment effects of GenAI use across the initial and revision design phases (Table 4, Fig. 4). The results indicate a positive treatment effect for design performance (DiD = 0.583 SDs, 95% CI = [−0.476, 1.643]), suggesting that participants using GenAI exhibited greater improvement than the control group, although the confidence interval included zero. No significant treatment effect was observed for cognitive load (DiD = −0.069, 95% CI = [−0.742, 0.604]). In the control group, both task-specific creative self-efficacy (p = 0.054) and general creative self-efficacy (p = 0.023) exhibited similar upward trends from the initial to the revision design phase, indicating increased confidence following iterative design practice. In contrast, while the GenAI group showed a comparable pattern for task-specific creative self-efficacy, general creative self-efficacy declined during the revision design phase, resulting in a significant negative DiD effect (DiD = −0.543, 95% CI = [−1.068, −0.017]). As a result, the observed treatment effect appears to be driven primarily by the decrease in general creative self-efficacy in the GenAI group rather than by gains in the control group, suggesting a potential divergence between task-focused confidence and broader creative self-beliefs when GenAI support is introduced during design revision.

Table 4. *DiD Estimates of Treatment Effects for GenAI Group*

Covariate	Initial Design Phase	Revision Design Phase	Initial Design Phase	Revision Design Phase	DID (SDs)	95%CI
	Control		*GenAI*			
Design performance	2.921 ± 0.369	2.785 ± 0.361	2.819 ± 0.388	2.903 ± 0.433	0.583	[-0.476, 1.643]
Cognitive load	2.787 ± 0.322	2.880 ± 0.442	2.778 ± 0.478	2.843 ± 0.604	-0.07	[-0.742, 0.604]
Task-specific creative self-efficacy	3.472 ± 0.866	3.861 ± 0.854	3.556 ± 0.765	3.556 ± 0.82	-0.48	[-1.233, 0.269]
General creative self-efficacy	3.537 ± 0.76	3.741 ± 0.805	3.796± 0.81	3.574 ± 0.899	-0.54	[-1.068, -0.017]

DiD estimates and their 95% confidence intervals were standardized by dividing them by the pooled standard deviation of the initial design phase scores.
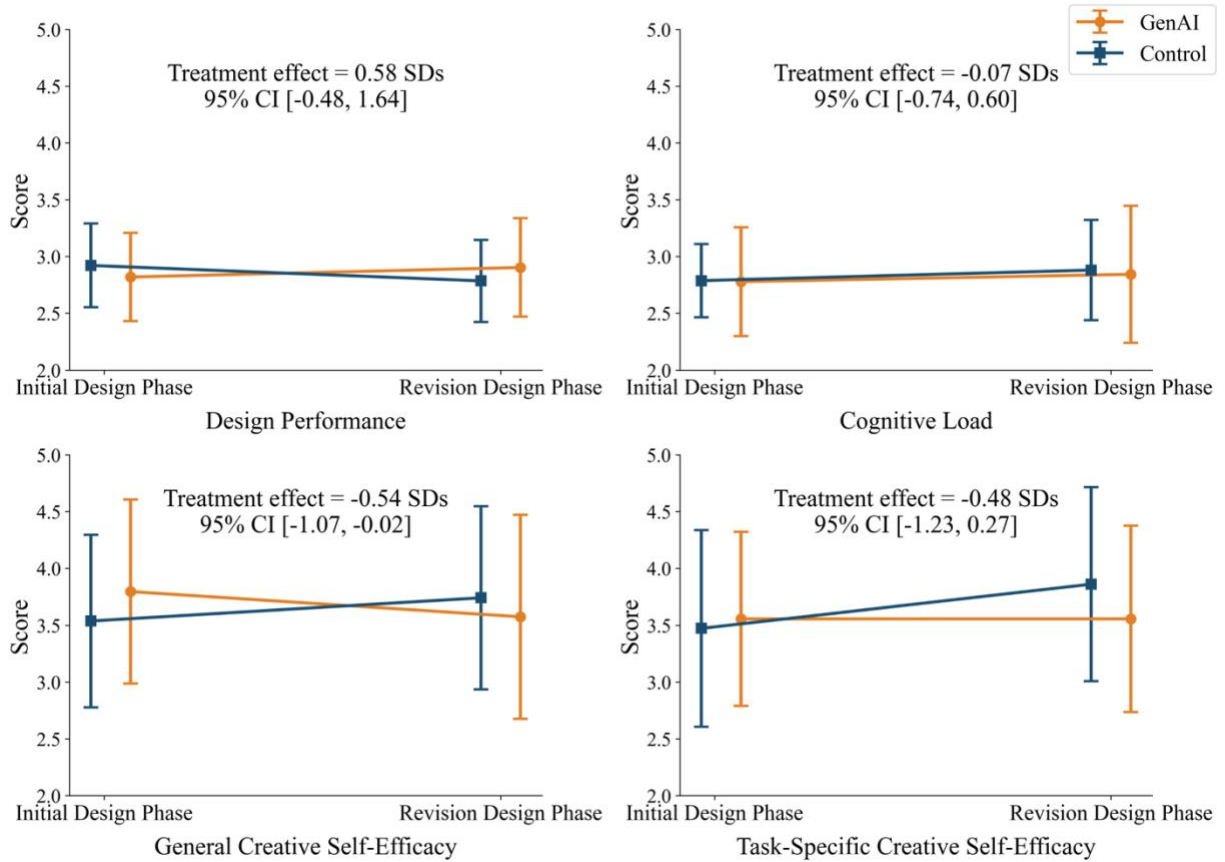
Fig. 4. *Within-Group Changes in Design Performance from the Initial Phase to the Revision Phase for the GenAI and Control Groups. Displayed are the treatment effect coefficients and their corresponding 95% confidence intervals, rescaled in units of the outcome variable's standard deviation from the initial design phase.*

4.3 Examining the Impact of Initial Competency Level on Outcomes in Revision Design Phase

A two-way ANOVA revealed a significant interaction effect between tool condition and initial competency level on design performance during the Revision Phase *(F (1, 32) = 4.303, p = 0.046, partial η² = 0.118)* (Table 5). As illustrated in Fig. 5, novice participants using GenAI achieved significantly higher revision-phase design performance than those in the Control condition (*p = 0.023*), indicating that GenAI support was particularly beneficial for participants with lower initial competency. In contrast, no significant difference was observed between GenAI and Control conditions among Experienced participants (*p = 0.449*). In addition, no significant main effects of Tool or Initial competency level, nor their interaction, were found in the remaining two-way ANOVA models (Table S2).

Table 5. *Two-way ANOVA results for the effects of initial competency level on design performance during the revision phase*

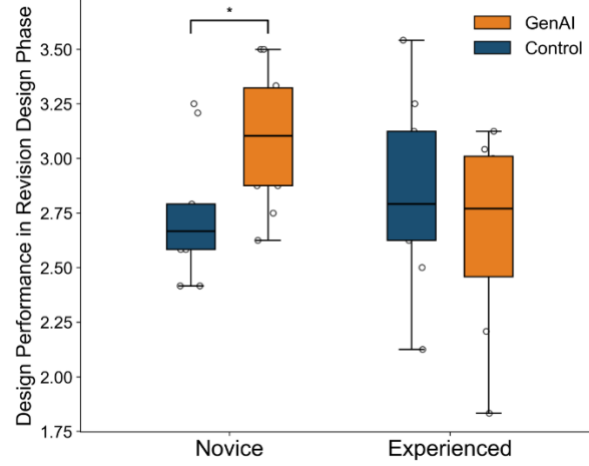| Variable	SS	df	F	Sig.	Partial η²
Tool	0.106	1	0.745	0.394	0.022
Initial Competency Level	0.263	1	1.857	0.182	0.055
Tool* Initial Competency Level	0.61	1	4.303	**0.046**	0.118

Fig. 5. The effects of initial competency level on design performance during the revision phase. *: p < 0.05.

4.4 Associations between GenAI prompt use and cognitive load change

We identified eight prompt categories in our coding scheme. Sixteen participants who used GenAI were included in the analysis, with two excluded due to missing screen-recording data. Across the 16 participants who used GenAI prompts, prompt usage varied widely in both quantity and type. Participants produced between 3 and 26 prompts (M = 9.38 ± 6.02) with word counts ranging from 20 to 295 words (M = 110 ± 74.73). Neither prompt count nor word count were significantly associated with changes in cognitive load (both *ps > .05*) as described in Table 6.

Among the eight prompt categories, CD2 (Idea generation, specifically for visual communication) was used most frequently (M = 4.38 ± 4.33), followed by CD3 (Idea generation, based on previous answer). Correlation analyses revealed two significant negative relationships: greater use of CD3 prompts (*r = –0.566, p = 0.022*) and CD6 prompts (*r = –0.518, p = 0.039*) were associated with larger decreases in cognitive load. We observed that CD3 and CD6 (Feedback, improve visual communication) prompts focused on improving visual communication specifically, such as clarifying design intent, composition, or presentation. All other prompt types showed insignificant correlations.

The associations observed for CD3 and CD6 suggest that prompts supporting iterative refinement and visual communication may be linked to reduced cognitive load during design

revision. These prompt types emphasize clarification and improvement of existing ideas rather than initial idea generation. This pattern may help explain why overall cognitive load did not uniformly decrease for GenAI users in earlier analyses, as cognitive outcomes appear to vary depending on how GenAI is incorporated into the design workflow.

Table 6. *Descriptive statistics and intercorrelations between prompts and changes of cognitive load, qualitative description, and examples of individual prompts.*

Code	Variable	Min	Max	M ± SD	Correlation coefficient[†] *(p value)*	Description	Example
	Prompt count	3	26	9.38 ± 6.02	-0.261 (>0.05)	Range of prompt counts	
	Word count	20	295	110 ± 74.73	-0.003 (>0.05)	Range of word counts	
CD1	Generation (based on task instruction)	0	4	1.06 ± 1.34	0.075 (>0.05)	The initial prompt rephrasing information from a task instruction.	*"Draw a building."* *"Give me 10 images of modern laboratory buildings."*
CD2	Idea generation (specifically for visual communication)	0	14	4.38 ± 4.33	-0.312 (>0.05)	Specific instruction for specific idea generation evaluation criteria (effective communication and understandable).	*"Can you please generate me two more buildings in the shape of the letter O and another in the shape of S, both buildings should have a brick exterior."* *"Add a courtyard."*
CD3	Idea generation (based on previous answer)	0	5	1.06 ± 1.39	-0.566 (0.022)	Participants selected one idea from previous answers and asked GenAI to generate more ideas based on their selection.	*"Now make the building shorter, while maintaining the gabled roof."* *"Make 5 more."*
CD4	Information gathering	0	8	0.75 ± 2.02	0.021 (>0.05)	Using GenAI as an information resource by creating image	*"Head of snake building."* *"Show me a modern laboratory."*
CD5	Feedback (general)	0	1	0.19 ± 0.40	0.035 (>0.05)	Feedback without any specific details.	*"Good job."*
CD6	Feedback (improve visual communication)	0	12	1.63 ± 73.12	-0.518 (0.039)	Feedback specifically asking GenAI to improve communication and understand understandability	*"Too spiky, try again."* *"This picture also has grass on the roof, you failed. Try again."*
CD7	Asking for feedback	0	1	0.13 ± 70.34	0.041 (>0.05)	Asking GenAI to provide feedback on ideas that were created.	*"What might such a building look like?"*

CD8	Regenerate	0	2	0.19 ± 0.54	0.391 (>0.05)	Pressing the "regenerate" button in the chat console.	↻

Min represents the minimal value obtained by an individual participant. Max represents the maximal value obtained by an individual participant.
M and SD represent the mean and standard deviation values obtained by an individual participant, respectively.
[†]: Spearman's r coefficient is reported for association between prompt features and delta cognitive load. This table follows the framework proposed by Urban et al. [45].

5. Discussion

This study investigates the influence of GenAI on conceptual design performance in architecture, revealing distinct differences between novice and experienced learners and demonstrating that varying prompt strategies produce divergent cognitive-load outcomes.

5.1 GenAI scaffolds early-stage ideation for novice architecture students

In the traditional architectural conceptual design workflow, designers typically begin with broad brainstorming followed by in-depth site analysis to produce preliminary concept sketches. During this process, it is often challenging for designers, especially novice ones, to translate design concepts into visual expressions that are aligned with clients' expectation. The time-consuming nature of the work significantly constrains creativity and exploration [79]. Our findings indicate that DALL-E3's text-to-image capability functioned as an effective scaffold for novice learners, providing pronounced benefits particularly for students with lower creative self-efficacy and enhancing their design performance. These results align with observations reported in prior studies [42,80]. Unlike experienced designers who can fluently generate, iterate, and evaluate spatial ideas through sketching and analog reasoning [81], novices often struggle in early-phase architectural ideation due to a lack of design precedents, internalized schemas, or visual thinking strategies [82,83]. Therefore, novices benefit from external scaffolds that help trigger ideation and structure their thought processes. Thus, GenAI served as an idea generator supplementing underdeveloped internal processes with linguistic and visual stimuli [79,84].

However, this benefit did not necessarily extend to experienced students in this study, which is consistent with prior studies in other creative tasks [85,85]. Furthermore, some demonstrated performance declines with the help of GenAI. Experienced designers often have refined mental models and workflows, and more accustomed to traditional design processes [80]; For these individuals, the generic or context-insensitive outputs produced by GenAI may have been more distracting than beneficial. Instead of enhancing their design performance, GenAI's interventions may have disrupted their design flow or imposed ideational friction. Highly proficient learners may be more sensitive to perceived inadequacies in feedback when engaging with complex tasks, making such limitations more salient to them [86]. Recent meta-analytic evidence indicates that the effects of ChatGPT are significantly moderated by both subject area and intervention setting, with laboratory-based interventions yielding non-significant effects compared to traditional classroom implementations [31]. This helps explain the absence of broad design performance gains observed in our study. Our results further indicate that students' initial competency level serves as a significant moderating factor.

5.2 Creative Self-Evaluation Affects Human–AI Visual Collaboration

Unlike findings in writing-based tasks [34], our visual communication task yielded insignificant changes in creative self-efficacy, which was consistent with recent meta-analyses. On a technical

level, this stagnation may be attributable to the limitations of early GenAI models in producing specific architectural concepts or accurately interpreting prompts; such friction can directly undermine a student's perceived competence during the task.

However, technical limitations alone do not explain the disconnect observed in novice students. This divergence suggests that although GenAI can temporarily compensate for psychological barriers by enhancing task outcomes, it does not automatically translate into corresponding shifts in students' self-beliefs [87]. This phenomenon may reflect how GenAI reshapes the evaluative frame through which learners assess their own creativity. When working alongside a highly capable generative system, learners' internal standards for originality and creativity may shift upward, resulting in more conservative self-assessments even when design outcomes are comparable [88].

From a design cognition perspective, creative self-efficacy is closely tied to perceptions of authorship and creative agency [89], and GenAI can blur the boundary between self- and system-generated contributions by redistributing cognitive effort toward evaluating and integrating AI-generated alternatives rather than generating ideas. Consequently, the lack of gains in general creative self-efficacy likely reflects a shift toward perceiving creativity as a distributed property of the human–AI system rather than an individual attribute [90]. These findings underscore the critical need for pedagogical framing that positions GenAI as a subordinate tool requiring human curation, thereby reinforcing the learner's agency and preserving confidence in their distinct creative role.

5.3 Prompt Strategy Influences Cognitive Burden

Despite improvements in design performance, participants did not report a significant reduction in perceived workload when using GenAI, a finding consistent with recent research on AI integration in conceptual design workflows [67]. The reason might be partially explained through the prompt analysis. Prior studies indicate that simplified or imprecise prompts often fail to elicit high-quality AI responses, particularly in creative domains [28,45,91,92]. Building on this literature, our prompt-mining analysis shows that students who were more adept at crafting task-specific prompts and iteratively refining GenAI outputs experienced greater reductions in cognitive burden. These findings align with a growing body of work emphasizing prompt construction as a critical component of effective AI-supported creativity [93,94].

Rather than simplifying the design process, GenAI appeared to redistribute cognitive effort from ideation toward interaction management, such as, prompt formulation, interpretation of AI-generated outputs, and iterative refinement. This prompt–generate–evaluate cycle required substantial cognitive resources, echoing prior research that characterizes prompt engineering as a cognitively demanding activity in design contexts where semantics, style, and spatial logic are tightly coupled [68,93,95,96]. Moreover, students varied in how they engaged with GenAI: some used AI outputs as stimuli to extend their design thinking, while others became overly reliant, deferring critical decisions to the system and engaging less actively in reflective reasoning

[67,97–99]. Under hybrid human–AI regulation theory [100,101], students must continuously monitor whether AI-generated elements align with the broader design context. Such overreliance can weaken self-regulation, critical reflection, and ownership of creative outcomes, which increase cognitive load [26].

To summarize, these findings contribute to ongoing discussions of the productivity paradox of emerging technologies: while we did not find cognitive load reduction for the GenAI group in general, the improper prompting can even increase the cognitive load due to learning curves, interface friction, and limited domain alignment [28]. In architectural design education, GenAI's potential benefits therefore remain inseparable from the need for structured guidance and pedagogical support.

5.4 Limitations and Future Work

This study has several limitations. Although the sample size was sufficient for exploratory analyses, it limits the generalizability of subgroup effects related to prior competency. The short, task-bounded study design captures participants' initial exposure to GenAI rather than its sustained use and integration within extended design studio workflows. In addition, the study examined only a single GenAI system (DALL-E3), and different patterns may emerge with multimodal or architecture-specific AI tools that offer stronger support for visual communication and spatial reasoning. Finally, the absence of post-task qualitative interviews restricted insight into participants' subjective experiences, sensemaking processes, and adaptation strategies. Future work should adopt longitudinal and mixed-methods approaches to examine how human–AI collaboration, prompt strategies, and design competencies evolve over time, and to inform responsible and pedagogically grounded integration of GenAI in architectural education.

6. Conclusion

This study investigated the effects of GenAI on conceptual design performance, creative self-efficacy, and cognitive load in an architectural conceptual design task. Overall, GenAI use did not lead to statistically significant differences in design performance, cognitive load, or creative self-efficacy relative to a traditional reference tool, nor did it produce robust within group gains in a short-term experiment. Of note, analyses that accounted for individual differences revealed a more differentiated pattern of effects. Students with lower initial design performance benefited more from GenAI during the revision phase than their counterparts in the control condition, whereas students with higher baseline performance showed no comparable advantage. In contrast, general creative self-efficacy declined during the revision phase for students in the GenAI condition, suggesting that AI-generated content may reduce learners' perceived authorship or creative agency, even when performance gains are observed. Finally, prompt analyses indicated that how GenAI was used mattered: engagement with iterative refinement and visual communication focused prompts was associated with reduction in cognitive load during design revision.

These findings suggest that the educational value of GenAI in visual-spatial and conceptual design tasks lies not in uniformly enhancing outcomes, but in its capacity to function as a conditional scaffold. For less-prepared learners, GenAI may support idea generation, clarify design intent, and alleviate cognitive demands during iterative refinement. By contrast, for more experienced students, GenAI does not appear to confer performance benefits and may require additional cognitive or reflective effort to integrate AI generated suggestions with established design strategies and mental models. Together, these results underscore the importance of ability sensitive approaches to AI integration in design education approaches that leverage GenAI to support novices without diminishing the autonomy, confidence, or creative agency of more advanced learners. The findings also highlight the central role of human–AI interaction strategies in shaping cognitive outcomes. Effective use of GenAI depends less on the volume of interaction and more on the nature of engagement, particularly prompts that support iterative development and visual communication rather than information retrieval alone. This points to the need for explicit pedagogical frameworks that teach students how to collaborate productively with AI systems, including prompt formulation, critical interpretation of AI outputs, and the integration of AI-generated representations into coherent design workflows.

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Author contributions

Han Jiang: Writing – original draft, Visualization, Methodology, Investigation, Preliminary analysis, Conceptualization. Yao Xiao: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. Rachel Hurley: Data acquisition. Shichao Liu: Writing - review & editing, Supervision, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Gemini and ChatGPT in order to improve grammar, spelling and clarity. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data supporting the findings of this study will be made available on the Open Science Framework (OSF).

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