Research Paper
JBER Scope: Education

Effects of Generative AI-Assisted Instruction on Creativity and Multidimensional Design Skills in Advertising Design Education: A Quasi-Experimental Study

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Received: 20 May 2026; Revised:03 June 2026; Accepted: 16 June 2026
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Abstract

Generative artificial intelligence (GAI) is increasingly being integrated into higher education and has shown considerable potential for supporting creativity and design learning. Although a growing body of research has explored the educational applications of GAI, empirical evidence regarding its effectiveness in advertising design education remains limited, particularly in relation to students' multidimensional design performance. This study investigated the effects of GAI-assisted instruction on advertising design learning through a quasi-experimental pre-test–post-test design. A total of 85 digital media students participated in the study, with intact classes assigned to either a GAI-assisted instruction group or a traditional instruction group. Students' advertising design performance was evaluated across five dimensions: theme design, creativity, audience relevance, visual effects, and copywriting. Analysis of covariance (ANCOVA) was employed to compare post-test performance while controlling for pre-test scores. The results revealed that students receiving GAI-assisted instruction significantly outperformed those receiving traditional instruction in overall advertising design performance and across all five dimensions. Specifically, significant improvements were observed in theme design, creativity, audience relevance, visual effects, and copywriting. Among these dimensions, creativity demonstrated the largest effect. These findings suggest that GAI can serve as an effective pedagogical support tool when embedded within structured instructional guidance. Rather than replacing students' creative work, GAI appears to support multidimensional advertising design performance by facilitating exploration, refinement, and iterative design development. This study contributes empirical evidence to the growing literature on AI-supported design education and offers practical implications for developing creativity-oriented learning environments that integrate technological support with human judgment.

Keywords: Generative Artificial Intelligence; Creativity; Advertising Design Education; Design Skills; Quasi-Experimental Study

1. Introduction

In design education, recent work has begun to conceptualize generative AI not merely as

an auxiliary tool but as part of an emerging design-learning infrastructure that can reshape studio-based learning processes (Zhu et al., 2025). Generative AI differs from traditional AI applications that primarily classify, predict, or recognize patterns; it is characterized by its capacity to generate new textual, visual, and multimodal content in response to prompts (Bahroun et al., 2023; Kasneci et al., 2023). Its growing use in education reflects the increasing demand for adaptive, interactive, and scalable forms of learning support. Recent reviews suggest that ChatGPT and other generative AI tools are increasingly being adopted in higher education, influencing curriculum support, personalized learning, assessment, and lifelong upskilling (Asad and Ajaz, 2024; Mittal et al., 2024; Samala et al., 2025). For educators, GAI may also support instructional preparation, feedback provision, and learning-resource development, thereby creating opportunities for more differentiated and reflective teaching practices (Ruiz-Rojas et al., 2024).

Growing integration of generative AI (GAI) technologies into educational settings has drawn considerable attention from both researchers and practitioners due to their potential to improve instructional efficiency and enrich learning experiences. Against this backdrop, the application of GAI in higher education for art and design has gradually come into focus. In art and design education, generative AI tools have been increasingly explored as supports for prompt engineering, iterative image generation, and creative ideation (Hutson and Cotroneo, 2023).

In visual and digital art education, image-generation tools have been reported to support creative ideation, visual exploration, and iterative refinement when embedded within structured pedagogical activities (Hutson and Cotroneo, 2023; Kicklighter et al., 2024).Fleischmann (2024) further argues that generative AI should be introduced into design curricula through critical engagement, enabling students to understand both the creative affordances and limitations of AI-supported design practice.Recent empirical work has also reported that integrating GAI into design and art courses can improve student achievement, motivation, and self-efficacy, while studies in art education suggest that prompt-based and iterative GAI use may support creative engagement (Chen et al., 2025; Hutson and Cotroneo, 2023).

Although reviews have documented the rapid expansion of GAI research in education, they also indicate the need for more empirical studies situated in specific disciplinary and classroom contexts (Bahroun et al., 2023). Advertising design requires students to integrate conceptual thinking, visual expression, audience awareness, and persuasive copywriting into a coherent communicative artifact. It therefore provides a meaningful context for examining whether GAI-assisted instruction can support not only creativity but also broader design competence. Accordingly, this study examines the effects of GAI-assisted instruction on students' advertising design performance using a quasi-experimental pre-test–post-test design. Students' design performance is evaluated across five dimensions: theme design, creativity, audience relevance, visual effects, and copywriting.

2. Literature Review

2. 1 Generative AI in Education

The integration of GAI into education is reshaping global pedagogical paradigms at an unprecedented pace, bringing about both profound impacts and inherent tensions. Existing literature systematically reveals the considerable potential of GAI in enhancing learning outcomes, empowering teaching practice, and advancing personalised education, while also highlighting the complex challenges triggered by GAI in terms of academic integrity, educational equity, cognitive development, and technological ethics.

Relevant studies suggest that GAI exerts a positive influence on students' learning experiences. AlGhamdi (2024), for example, found that ChatGPT-generated feedback could

support computing students' technical writing performance, suggesting the potential of GAI-based feedback in higher education.A meta-analysis of 49 studies reported positive effects of GAI on students' learning achievement and learning motivation, with effect sizes of 0.857 and 0.803, respectively (Liu et al., 2025). In a systematic review of 13 empirical studies, as many as 70% of the studies reported positive impacts of GAI on education (Wang et al., 2024). One important mechanism through which GAI may support learning is its capacity to enhance personalized feedback and intelligent tutoring systems (Reddig et al., 2025).Leveraging large language models (LLMs),ITS can dynamically generate learning content tailored to individual learners' needs, provide real-time feedback, and adapt learning pathways accordingly.

This enables scalable personalization in education, a goal that is difficult to achieve through traditional instructional approaches (Reddig et al., 2025).However, the widespread application of GAI is accompanied by risks and challenges that cannot be overlooked. First, students' over-reliance on GAI may weaken independent inquiry, critical evaluation, and higher-order thinking if AI-generated outputs are accepted uncritically (Kasneci et al., 2023).The tendency of generative models to produce plausible but factually incorrect information, commonly referred to as hallucination, poses a challenge for educational use, particularly in contexts where accuracy and evidence-based reasoning are essential (Ji et al., 2023). Academic integrity systems also face new pressures as students may use GAI to generate assignments or written work, blurring the boundary between assistance and authorship. This has led scholars and universities to call for assessment designs that emphasize process, authorship transparency, and higher-order thinking rather than only final products (Kasneci et al., 2023; Moorhouse et al., 2023).

Furthermore, unequal access to AI technologies and uneven levels of digital literacy may exacerbate existing educational inequalities, preventing the benefits of GAI from being distributed equitably across learners and institutions (UNESCO, 2023). In response to these challenges, many scholars have argued that GAI should be positioned as an augmentative tool rather than as a replacement for human instructors. Effective integration strategies therefore need to keep educators "in the loop," ensuring that AI tools are pedagogically governed rather than merely technologically adopted (Kasneci et al., 2023; UNESCO, 2023).

2.2 Generative AI in Art and Design Education

The application of GAI in art and design education has gradually shifted from tool-based experimentation toward more pedagogically structured forms of integration. Current research broadly agrees that GAI should not be regarded as a threat replacing human creativity, but positioned as a collaborative partner that enhances students' creative cognition, expands conceptual horizons, and restructures the relationship between teaching and learning (Shankar et al., 2025; Fleischmann, 2024).

Fleischmann (2024) argues that introducing GAI into design curricula should begin with critical engagement, enabling students to understand its affordances and limitations and to use it responsibly within creative processes.

A classroom-based report by Kicklighter et al. (2024) in digital art education suggested that image-generating GAI tools can improve creative efficiency and broaden conceptual exploration when embedded within structured pedagogical activities.Further research reveals GAI's potential to promote educational equity and personalized learning. Sáez-Velasco et al. (2024) further reported that art educators and students often perceive GAI as a motivating instructional strategy, particularly in contexts where visualization and prototyping resources are limited. Especially in resource constrained settings, it equips students with prototyping and visualization capabilities otherwise inaccessible, thereby democratizing the creative process. This finding aligns with broader trends in higher education, where students hold positive attitudes toward GAI and recognize its value in delivering personalized learning support and

improving learning efficiency (Chan and Hu, 2023). However, the depth of technological application is significantly influenced by teachers' belief systems.

Teachers' beliefs, digital competence, and pedagogical orientations are likely to influence how deeply GAI is integrated into classroom practice (Batista et al., 2024; Shankar et al., 2025).In the context of art and design education, students' attitudes toward GAI-image tools have also been examined through technology acceptance and self-determination perspectives, suggesting that perceived usefulness and motivational factors may shape students' willingness to use such tools (Shen et al., 2025). Studies of animation and digital media educators suggest growing interest in adopting GAI in creative disciplines, although more attention is still needed to how different AI modalities support distinct stages of design learning (Chen et al., 2024).

Recent research suggests that image-generation tools have received greater attention in art and design education than text-based large language models, although LLMs may also support conceptual framing, design brief development, and reflective critique (Chen et al., 2024).This gap is significant because the value of art and design lies not only in technical outputs but also in students' ability to critically engage with and negotiate the cultural, historical, and ethical contexts of their work (Garcia, 2025).

In this regard, the educational challenge is not merely to teach students how to generate images, but to help them critically curate, contextualize, and ethically evaluate AI-generated outputs within specific cultural and communicative contexts (Garcia, 2025; Moorhouse et al., 2023).Therefore, future research and practice must move beyond a tool-centered adoption model toward curriculum-integrated, theory-driven pedagogical models aligned with assessment systems (Moorhouse et al., 2023). This includes developing prompt engineering pedagogies tailored to art and design disciplines, designing novel evaluation criteria to assess human–AI collaborative creativity(Moorhouse et al., 2023), and exploring how GAI can strengthen students' metacognitive abilities and disciplinary literacy. In this way, GAI can be positioned not as a shortcut to visual production but as a pedagogical resource for cultivating designers who can think critically, innovate responsibly, and situate their work within broader cultural and communicative contexts.

2.3 Creativity and Design Skills in Art and Design Education

Creativity is widely recognized as a central competence in art and design education. In design contexts, creativity does not refer merely to novelty, but to the production of ideas and visual solutions that are both original and appropriate to a given communicative purpose (Runco and Jaeger, 2012). Advertising design is especially dependent on this dual requirement because students must create visually distinctive works while also communicating persuasive messages to specific audiences. Thus, creativity in advertising design should be understood as a situated and communicative capacity: it emerges through the interaction between conceptual thinking, visual expression, audience interpretation, and rhetorical intention.

Research in design education has shown that creativity can be cultivated through structured pedagogical environments rather than treated as an innate and fixed trait. Yang and Hsu (2020), for example, found that integrating design thinking into a packaging design curriculum improved students' creative self-efficacy and flow experience. Similarly, Qian et al. (2022) showed that interdisciplinary C-STEAM art and design courses enhanced students' creative interest and practical skills. These findings suggest that creativity develops through guided exploration, iterative refinement, and sustained engagement with design problems. From a philosophical perspective, design creativity is not creation from nothing; rather, it is the reconfiguration of existing signs, materials, cultural meanings, and technical possibilities into new forms of communication.This view is also consistent with the componential perspective of creativity, which regards creative performance as emerging from the interaction of domain-relevant skills, creativity-relevant processes, and task motivation (Amabile, 1996).

Creativity is also closely related to learners' psychological readiness to engage in uncertain and open-ended tasks. Bandura (1997) conceptualized self-efficacy as individuals' beliefs in their capacity to perform specific actions, and prior research has shown that creative self-efficacy is associated with creativity and design-related learning outcomes (Puozzo and Audrin, 2021; Chang et al., 2021).Although the present study does not directly measure self-efficacy, this literature is relevant because it indicates that students' creative performance is shaped not only by technical skill but also by the learning environment that supports exploration, risk-taking, and confidence in idea development.

In advertising design education, students are expected to demonstrate competence across multiple interrelated dimensions. Theme design reflects the ability to identify and communicate a central message. Creativity captures originality, conceptual innovation, and the capacity to move beyond conventional solutions. Audience relevance concerns the alignment between design expression and the expectations of target viewers. Visual effects reflect proficiency in composition, color, typography, and visual hierarchy. Copywriting evaluates the clarity, persuasiveness, and communicative effectiveness of verbal expression.

Generative AI offers new possibilities for supporting these dimensions of design learning. By providing visual references, alternative concepts, copywriting suggestions, and compositional possibilities, GAI tools may expand students' ideational resources and reduce the cost of early-stage exploration (Fleischmann, 2024; Hutson and Cotroneo, 2023; Kicklighter et al., 2024). However, the educational value of GAI depends on whether it is embedded within structured pedagogical guidance rather than used as a shortcut for final production (Moorhouse et al., 2023). It is therefore necessary to empirically examine whether GAI-assisted instruction can improve students' multidimensional advertising design performance, particularly their creative design performance.Together, these dimensions constitute a multidimensional framework for assessing advertising design performance, reflecting the fact that advertising design is simultaneously conceptual, visual, rhetorical, and audience-oriented.

2.4 Conceptual Framework

Although research on generative AI in education has grown rapidly, empirical studies focusing on its application in advertising design education remain limited. In particular, few studies have systematically examined whether GAI-assisted instruction improves students' multidimensional design performance in authentic classroom settings. To address this gap, this study adopts a quasi-experimental pre-test–post-test design to compare learning outcomes between students receiving GAI-assisted instruction and those receiving traditional classroom instruction (Shadish et al., 2002).

This study is theoretically informed by a constructivist perspective on learning, which emphasizes that knowledge and skills are developed through interaction with tools, tasks, and social guidance (Vygotsky, 1978). Within this framework, generative AI is conceptualized not as an autonomous creator but as a cognitive and semiotic mediating tool. It provides external representations—such as visual references, conceptual prompts, and textual suggestions—that students can interpret, evaluate, transform, and integrate into their own design work.From this perspective, learning with GAI is not a process of delegating creativity to a machine, but a process of reorganizing the conditions under which students perceive, compare, and transform possible design meanings.

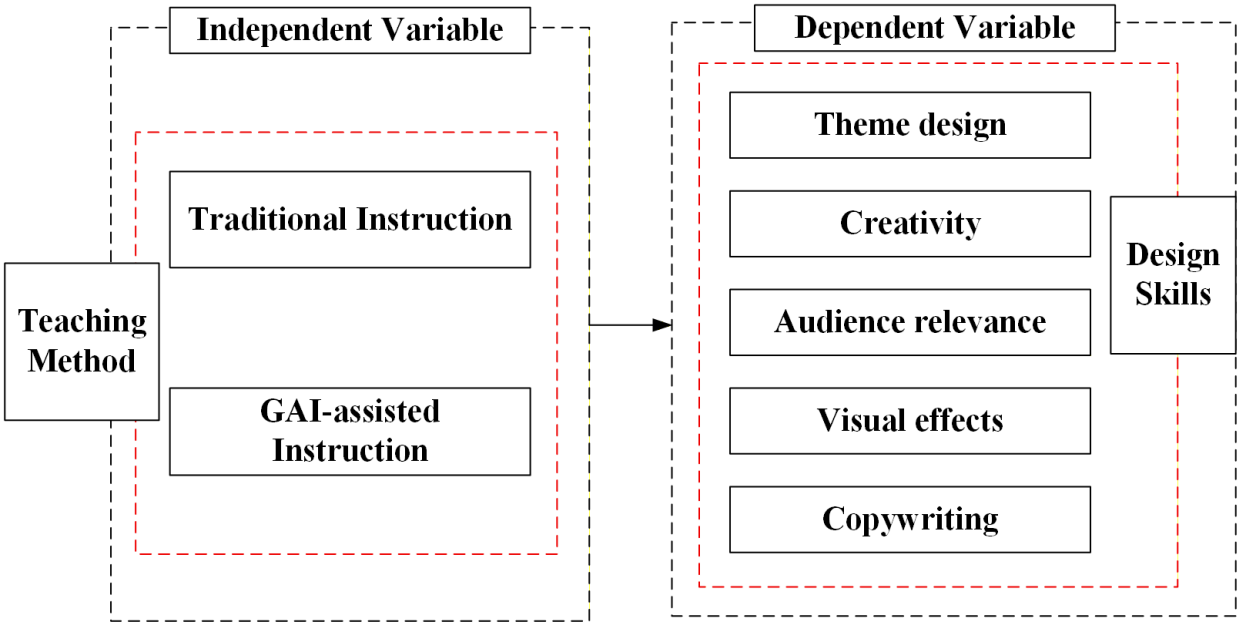


Figure 1: Conceptual framework of this study

In the conceptual framework, instructional method is treated as the independent variable, including traditional classroom instruction and GAI-assisted instruction. Students' advertising design performance is treated as the dependent variable and is measured across five dimensions: theme design, creativity, audience relevance, visual effects, and copywriting. The framework assumes that GAI-assisted instruction provides additional ideational, visual, and linguistic scaffolding during the design process, thereby improving students' performance in advertising design tasks.

Based on this framework, the following hypotheses are proposed:

H1: Students receiving GAI-assisted instruction will demonstrate significantly higher theme design performance than students receiving traditional instruction.

H2: Students receiving GAI-assisted instruction will demonstrate significantly higher creativity performance than students receiving traditional instruction.

H3: Students receiving GAI-assisted instruction will demonstrate significantly higher audience relevance performance than students receiving traditional instruction.

H4: Students receiving GAI-assisted instruction will demonstrate significantly higher visual effects performance than students receiving traditional instruction.

H5: Students receiving GAI-assisted instruction will demonstrate significantly higher copywriting performance than students receiving traditional instruction.

3. Research Methodology

3.1 Participants

This study was conducted at a college in China. The participants were 85 second-year college students majoring in Digital Media at the author's institution, aged 18 to 23. All participants had completed design theory courses in their first year and had acquired basic operational skills with relevant design software.

Due to constraints imposed by actual teaching arrangements, intact classes were used as experimental units without random assignment. Class A served as the control group, with 43 students, including 22 males and 21 females. Class B served as the experimental group, with 42 students, including 22 males and 20 females. The two groups were generally comparable in professional foundation and design skills, providing a suitable baseline for evaluating the

effects of the instructional intervention.

The study adhered to the principles of the Declaration of Helsinki (Goodyear et al., 2007). All participants volunteered to take part in the study and signed informed consent forms before the study began. They were informed that they could withdraw from the study at any stage. All research data were anonymized and stored securely.This study was approved by the Institutional Ethics Committee [Approval No. 50/2025; approval date: September 12, 2025].

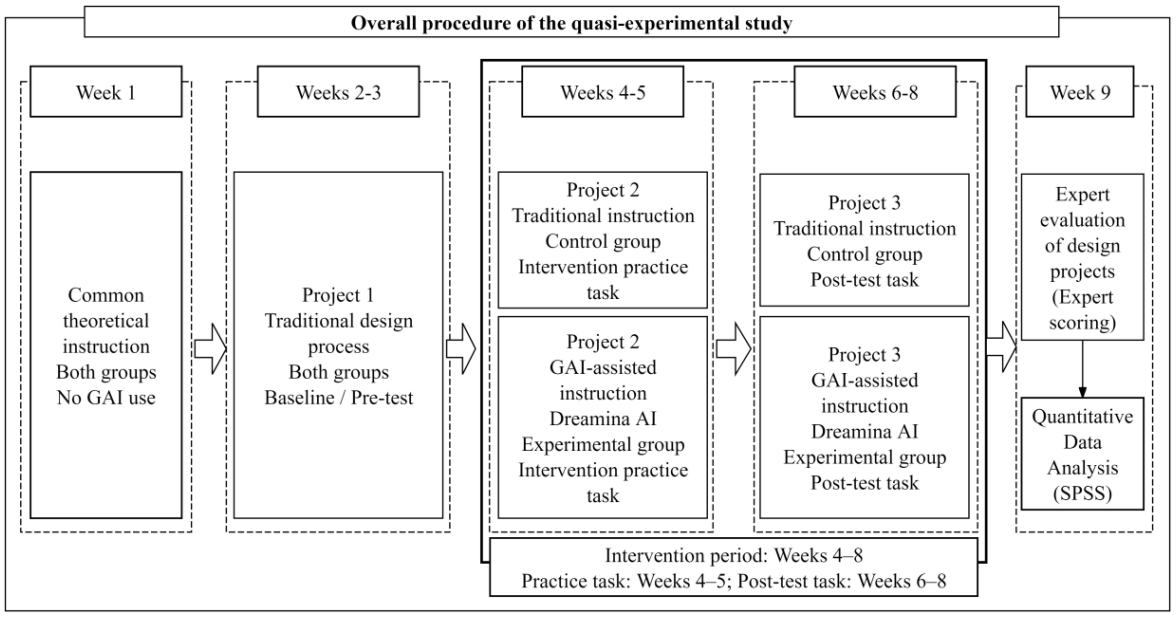


Figure 2: Overall procedure of the quasi-experimental study

3.2 Research Design

This study adopted a quantitative quasi-experimental pre-test–post-test design to examine the effects of generative AI-assisted instruction on students' advertising design skills. The instructional approach was treated as the independent variable, including two conditions: traditional classroom instruction and generative AI-assisted instruction. The dependent variable was students' advertising design performance, assessed through course-based design projects.

The control group received traditional classroom instruction, whereas the experimental group received instruction integrated with Dreamina AI, a generative AI platform that supports visual generation, concept exploration, and text-based ideation. In this study, Dreamina AI was used to support concept generation, copywriting ideation, and visual exploration during advertising design tasks. The scoring rubric was developed based on the learning objectives of the advertising design course and reflected the key competencies required in authentic advertising design tasks. Its reliability in the present study was examined through inter-rater agreement among three expert evaluators.Because individual random assignment was not feasible in the existing teaching context, the design should be interpreted as quasi-experimental rather than fully experimental.

3.3 Experimental Procedure

Before the instructional intervention, relevant background variables were collected to reduce potential confounding effects in the quasi-experimental design. These variables included gender, age, design software proficiency, and previous experience with GAI tools. Design software proficiency and previous GAI experience were treated as continuous variables and analyzed using independent-samples t-tests, whereas gender was treated as a categorical variable and analyzed using the chi-square test.

3.3. 1 Overall Instructional Framework

This study was implemented in strict accordance with the college's teaching plan for the advertising design course. The course lasted 8 weeks with a total of 64 credit hours, 8 hours per week, and each hour lasted 40 minutes. The experimental intervention was conducted from Week 4 to Week 8, lasting 5 weeks. No formal teaching was arranged in Week 9; instead, data collection and evaluation of design works were carried out, and this stage was not part of the established teaching plan.

The same instructor taught both groups in order to maintain consistency across the instructional process. Throughout the intervention, the instructor acted primarily as a learning guide and facilitator, supporting students through task instruction, demonstrations, and guided questioning. For the experimental group, the instructor demonstrated how to use GAI tools during the design ideation process to support creative exploration. The entire teaching process was implemented according to a predetermined instructional protocol. To ensure instructional fidelity, weekly teaching activities were checked against the course plan.

3.3.2 Basic Teaching

Week 1 served as the basic theoretical teaching stage, where students from both the experimental and control groups received identical lectures on advertising design theories. The core content included design principles, visual composition, layout design, typography, and colour theory. No artificial intelligence tools were introduced in this stage, and no distinctions were made in teaching methods, aiming to establish a unified theoretical foundation for all participants. Therefore, this stage did not form part of the experimental intervention.

From Week 2 to Week 3, all students completed Design Project 1 (Mid-Autumn Festival themed poster design). During this stage, neither group used any GAI tools, and both finished the task through a traditional design process. The scores of this project served as pre-test data to verify whether the design abilities of the two groups were at a statistically consistent baseline level before the experimental intervention.

3.3.3 Treatment Implementation

From Week 4 to Week 5, Design Project 2, an adolescent mental health-themed poster design task, was implemented as an intervention practice task. The results of this project were not included in the pre-test–post-test comparison or outcome measures. During this phase, Dreamina AI was introduced to the experimental group as a supportive tool for concept generation, copywriting ideation, and visual exploration. Students were instructed to critically evaluate AI-generated outputs, select appropriate design elements, and further refine their posters using professional design software. Direct submission of unmodified AI-generated images was not permitted. This requirement was intended to ensure that AI outputs functioned as design resources rather than as substitutes for students' own creative decisions.The instructor also provided guidance on prompt construction, evaluation of generated outputs, and ethical considerations related to AI-generated materials. In contrast, the control group completed the same task through a conventional design process, including instructor guidance, brainstorming, hand-drawn sketching, and digital production, without the use of GAI tools.

From Week 6 to Week 8, Design Project 3 (public welfare poster design on caring for empty-nest elderly) was implemented as the post-test task to assess changes in students' design abilities following the intervention. The experimental group continued to use Dreamina AI to support ideation and design exploration, whereas the control group completed the project using traditional design methods. Apart from the use of GAI tools, both groups received identical instructional guidance and classroom support. All other instructional conditions were kept consistent to ensure internal validity.

No formal teaching was conducted in Week 9. Instead, this stage was dedicated to the expert evaluation of students' design works and the organization of quantitative data. The

scores of the pre-test and post-test design projects were compiled for subsequent statistical analysis.

Table 1 : Overview of the Experimental Procedure

Weeks	Experimental Group (GAI-assisted learning)	Control Group (Traditional instruction)
Week 1 (Common Instructional Foundation)	Teacher provides theoretical instruction on the fundamentals of advertising design.	Same instructional content delivered by the teacher.
Weeks 2 – 3 (Project 1: Mid-Autumn Festival Poster – Pre-test)	Both groups follow the traditional design process, including brainstorming, sketching, and digital poster creation using Photoshop or Illustrator. Project 1 scores serve as the pre-test.	Same instructional activities as the experimental group.
Weeks 4 – 5 (Project 2: Teenage Mental Health Poster – Treatment Phase)	Introduction of the GAI intervention. Students use Dreamina AI to generate design concepts, slogans, and visual elements, which are later refined using traditional design software.	Traditional approach including teacher guidance, brainstorming, sketching, and digital rendering without the use of GAI tools.
Weeks 6 – 8 (Project 3: Public Welfare Poster – Caring for the Elderly – Post-test)	Students continue to use Dreamina AI to assist idea generation and visual exploration while refining the final design using digital software. Project 3 serves as the post-test assessment.	Students complete the project using traditional design methods without GAI tools.
Week 9 (Evaluation and Data Collection)	Evaluation of design projects.	Evaluation of design projects.

Note: This table presents the weekly instructional structure and task design for both the experimental and control groups, highlighting the differences in instructional approaches during the intervention period.

3.3.4 Instruments and Measures

Students' advertising design ability was evaluated through course-based design projects, an approach consistent with authentic and performance-based assessment principles (Wiggins, 1990). All design submissions were assessed using a standardized scoring rubric that has been implemented in the university's digital media design program for more than five consecutive years. The rubric assessed student performance across five dimensions: theme design, creativity, audience relevance, visual effects, and copywriting. The maximum total score was 100 points.

The five dimensions were weighted as follows: theme design, 20 points; creativity, 25 points; audience relevance, 15 points; visual effects, 20 points; and copywriting, 20 points. Theme design assessed the clarity and appropriateness of the central design concept. Creativity assessed originality, novelty, and conceptual innovation. Audience relevance assessed the degree to which the design addressed the intended audience. Visual effects assessed composition, color, typography, and overall visual presentation. Copywriting assessed the effectiveness, clarity, and persuasiveness of textual expression.

To ensure scoring objectivity and consistency, all student works were independently assessed by three professional evaluators with more than ten years of experience in design education and practice. The final score for each student was calculated as the mean of the three evaluators' ratings. Design Project 1 was used as the pre-test, while Design Project 3 was used as the post-test. Design Project 2 was used only as an intervention practice task and was not included in the pre-test–post-test comparison (Sadler, 2009; Wiggins, 1990).

Inter-rater reliability was examined using the intraclass correlation coefficient (ICC), based on a two-way random-effects model with average measures, in accordance with the guidelines proposed by Koo and Li (2016).The ICC values for the five dimensions ranged from

0.842 to 0.913, and the ICC for the total score was 0.927, indicating acceptable to excellent agreement among the three evaluators. These results suggest that the expert ratings were sufficiently consistent for subsequent statistical analysis.

3.3.5 Data Collection

Data collection was conducted over an eight-week instructional period from September 22 to November 14, 2025. During Weeks 2–3, students completed Design Project 1, a Mid-Autumn Festival-themed poster design task. The scores from this project were used as pre-test data to examine baseline equivalence between the experimental and control groups.

The instructional intervention was implemented from Week 4 to Week 8. During Weeks 6–8, students completed Design Project 3, a public welfare poster design task on caring for empty-nest elderly people. The scores from this project were used as post-test data. All design submissions were collected in Week 9 and independently assessed by three expert evaluators. The resulting scores were compiled and anonymized for statistical analysis.

3.3. 6 Statistical Analysis

SPSS 26.0 was used to analyze the quantitative data. Descriptive statistics, including means and standard deviations, were calculated for pre-test and post-test scores. Independent-samples t-tests were conducted to examine baseline equivalence between the experimental and control groups before the intervention.

The effects of GAI-assisted instruction were examined using analysis of covariance (ANCOVA), with post-test scores treated as the dependent variable, group as the fixed factor, and pre-test scores as the covariate. Separate ANCOVAs were conducted for overall design performance and for each of the five design dimensions. Assumptions of normality, homogeneity of variance, and homogeneity of regression slopes were assessed before the analysis.Effect sizes were reported using partial eta squared and interpreted according to Cohen's (1988) guidelines.

4. Results

4.1. Baseline Equivalence

Table 2 presents the results of the independent-samples t-tests conducted on the pre-test scores to assess baseline equivalence between the two groups. No significant between-group differences were found across the five design dimensions, namely theme design, creativity, audience relevance, visual effects, and copywriting (all $p > .05$). The assumption of homogeneity of variance was satisfied for all comparisons. These results suggest that the two groups were statistically comparable before the intervention and therefore suitable for subsequent comparative analyses.

The results indicated that there were no statistically significant differences between the experimental and control groups in proficiency in design software ($M = 4.01$, $SD = 0.66$ vs. $M = 4.03$, $SD = 0.64$) or previous GAI experience ($M = 3.17$, $SD = 0.92$ vs. $M = 3.19$, $SD = 0.88$), with all p-values being greater than 0.05. In addition, no significant difference was found in age between the two groups ($p > 0.05$). These findings suggested that the two groups were equivalent at baseline, thereby mitigating potential bias of pre-existing differences on the experimental results.

4.2. Overall Effect of Intervention

Analysis of covariance (ANCOVA) was performed to examine the effect of instructional approach on students' overall advertising design performance. Preliminary assumption tests were conducted before the main analysis. The Shapiro–Wilk test indicated no significant deviation from normality ($p > .05$), and Levene's test for homogeneity of variance was non-significant ($p > .05$), suggesting that the basic assumptions for ANCOVA were satisfied.

Table 2： Baseline Equivalence Test for Pre-test Scores

Dimension	Group	N	Mean	SD	t	df	p
Theme design	Control	43	14.60	0.54	0.08	83	0.93
	Experimental	42	14.60	0.50			
Creativity	Control	43	17.98	0.64	-0.38	83	0.71
	Experimental	42	18.02	0.52			
Audience Relevance	Control	43	10.86	0.56	0.64	83	0.52
	Experimental	42	10.79	0.52			
Visual Effects	Control	43	14.47	0.59	0.51	83	0.61
	Experimental	42	14.40	0.50			
Copywriting	Control	43	14.23	0.61	-0.05	83	0.96
	Experimental	42	14.24	0.48			

Note: df = degrees of freedom (df = total sample size — number of groups). No significant differences were found between groups (all $p > 0.05$), indicating baseline equivalence.

ANCOVA was then conducted with pre-test scores as the covariate and post-test scores as the dependent variable (Table 3). After controlling for baseline ability, a significant difference was found between the experimental and control groups in post-test performance ($F(1, 82) = 156.48$, $p < 0.001$, $\eta^2 = 0.66$). The adjusted mean score of the experimental group ($M = 86.85$, $SE = 0.70$) was significantly higher than that of the control group ($M = 74.62$, $SE = 0.69$). The raw means were 86.81 ($SD = 4.59$) and 74.65 ($SD = 5.07$) respectively. According to Cohen's (1988) criteria for effect size, $\eta^2 = 0.66$ represents a large effect, indicating that generative AI-assisted instruction exerted a significant and substantial positive effect on students' overall design ability.

Table 3： ANCOVA Results for Analysis of Design Skills

Group	N	Mean	SD	Adjusted mean	Std. error	F	η^2	p
Experimental group	42	86.81	4.59	86.85	0.70	156.48**	0.66	<.001
Control group	43	74.65	5.07	74.62	0.69			

Note. Adjusted means were estimated after controlling for pre-test scores. η^2 represents partial eta squared.

4.3. Differential Effects Across Dimensions

To provide a more rigorous examination of group differences, an analysis of covariance (ANCOVA) was conducted on the post-test scores across the five dimensions, with pre-test scores controlled as covariates. Assumptions required for ANCOVA, including normality, homogeneity of variance, and linear relationships between covariates and dependent variables, were examined and satisfied before the main analysis.

The results indicated that, after controlling for baseline ability, the experimental group demonstrated significantly higher adjusted mean scores than the control group across all five dimensions ($p < 0.001$). Specifically, the F-values were 118.81 for theme design ($\eta^2 = 0.59$), 191.85 for creativity ($\eta^2 = 0.70$), 101.89 for audience relevance ($\eta^2 = 0.55$), 115.97 for visual effects ($\eta^2 = 0.59$), and 130.21 for copywriting ($\eta^2 = 0.61$).

According to the effect size criteria proposed by Cohen (1988), where η^2 values greater than 0.14 are considered large, all observed effect sizes in this study exceeded 0.55, indicating substantial effects. Among these, the creativity dimension exhibited the largest effect size ($\eta^2 = 0.70$), suggesting that the instructional intervention had a particularly strong impact in this area.

These findings further indicate that, under the conditions of this study, the instructional approach integrating Dreamina AI was associated with significantly higher advertising design performance than traditional instruction across all measured dimensions.These results indicate that GAI-assisted instruction was associated with consistent improvements across all measured dimensions of advertising design performance, with the strongest effect observed in creativity.

Table 4： ANCOVA Results for Post-test Scores Across Five Design Dimensions (Controlling for Pre-test Scores)

Dimension	Group	N	Adjusted Mean	Std. Error	F	p	η^2
Theme Design	Control	43	15.18	0.15			
	Experimental	42	17.53	0.15	118.81	<0.001	0.59
Creativity	Control	43	18.54	0.15			
	Experimental	42	21.79	0.15	191.85	<0.001	0.70
Audience Relevance	Control	43	11.26	0.12			
	Experimental	42	12.98	0.12	101.89	<0.001	0.55
Visual Effects	Control	43	14.95	0.16			
	Experimental	42	17.39	0.16	115.97	<0.001	0.59
Copywriting	Control	43	14.70	0.15			
	Experimental	42	17.14	0.15	130.21	<0.001	0.61

Note: Adjusted means were estimated after controlling for pre-test scores. η^2 represents partial eta squared.

4.4. Descriptive Results

Table 5 presents the descriptive statistics for pre-test and post-test scores across the five design dimensions. Although students in both groups improved over time, the increases observed in the experimental group were considerably greater than those in the control group.

Table 5： Descriptive Statistics of Pre-test and Post-test Scores Across Five Dimensions

Dimension	Group	Pre-test Mean	SD	Post-test Mean	SD	Mean Difference
Theme Design	Control	14.60	0.54	15.19	1.05	0.59
	Experimental	14.60	0.50	17.52	0.99	2.92
Creativity	Control	17.98	0.64	18.53	1.20	0.55
	Experimental	18.02	0.52	21.81	1.09	3.79
Audience Relevance	Control	10.86	0.56	11.28	0.85	0.42
	Experimental	10.79	0.52	12.95	0.83	2.16
Visual Effects	Control	14.47	0.59	14.95	1.11	0.48
	Experimental	14.40	0.50	17.38	0.99	2.98
Copywriting	Control	14.23	0.61	14.70	1.12	0.47
	Experimental	14.24	0.48	17.14	0.93	2.90

Note: Mean Difference = Post-test Mean - Pre-test Mean. SD = Standard Deviation.

Specifically, the experimental group achieved substantial gains in theme design (+2.92), creativity (+3.79), audience relevance (+2.16), visual effects (+2.98), and copywriting (+2.90). By contrast, the control group showed only minor improvements, ranging from 0.42 to 0.59. In addition, the standard deviations of both groups increased in the post-test, suggesting that individual differences widened alongside overall improvement. These descriptive results are consistent with the ANCOVA findings and suggest greater improvement in the experimental group across all five dimensions.

4.5. Supplementary Analysis Based on Gain Scores

Additional independent-samples t-tests were conducted on gain scores (post-test minus pre-test) to further examine the stability of the findings (see Table 6). The results indicated significantly greater improvements in the experimental group than in the control group across all five design dimensions (all $p < .001$).

Table 6: Independent Samples t-Test Results for Students' Improvement Across Five Dimensions

Dimension	Group	N	Mean Gain	SD	t	df	Mean Difference	p
Theme Design	Control	43	0.58	0.98				
	Experimental	42	2.93	1.04	-10.68	83	-2.35	<0.001
Creativity	Control	43	0.56	0.98				
	Experimental	42	3.79	1.18	-13.71	83	-3.23	<0.001
Audience Relevance	Control	43	0.42	0.70				
	Experimental	42	2.17	0.91	-9.96	83	-1.75	<0.001
Visual Effects	Control	43	0.49	1.03				
	Experimental	42	2.98	1.18	-10.36	83	-2.49	<0.001
Copywriting	Control	43	0.47	0.98				
	Experimental	42	2.91	1.03	-11.16	83	-2.44	<0.001

Note. Mean Difference = gain score of the control group minus gain score of the experimental group. Negative values indicate greater improvement in the experimental group. All differences were significant at $p < 0.001$.

However, since gain score analysis fails to account for pre-test differences, these results serve mainly as supplementary evidence. The ANCOVA results (see Table 4) carry greater explanatory power and robustness in hypothesis testing. The mean difference is the mean gain score of the control group minus the mean gain score of the experimental group. Negative t-values indicate that the improvement in the experimental group was greater than that in the control group.

5. Discussion

This study examined whether generative AI-assisted instruction could improve students' advertising design performance in an authentic classroom context. After controlling for pre-test scores, the experimental group significantly outperformed the control group in overall design performance and across all five dimensions: theme design, creativity, audience relevance, visual effects, and copywriting. These findings provide quantitative evidence that GAI can function as an effective pedagogical support in advertising design education when it is embedded within structured instructional guidance rather than used as an autonomous production tool.

The strongest effect was observed in creativity. This finding is theoretically important because creativity in design is not merely the production of novelty, but the generation of ideas that are both original and appropriate to a communicative purpose (Runco and Jaeger, 2012). In advertising design, students must transform abstract themes into persuasive visual and textual forms. GAI may support this process by expanding the range of visual references, conceptual associations, and textual possibilities available during early ideation. In this sense, GAI does not create meaning on behalf of students; rather, it enlarges the field of possible meanings from which students can select, evaluate, and reconstruct design solutions. This interpretation is consistent with prior research showing that GAI can support ideation, prototyping, and creative exploration in art and design education when accompanied by pedagogical guidance (Fleischmann, 2024; Hutson and Cotroneo, 2023; Kicklighter et al., 2024).For novice designers, limited visual experience and early commitment to familiar solutions may lead to design fixation (Jansson and Smith, 1991). GAI may help reduce this fixation by exposing students to a wider range of conceptual and visual alternatives.

From a sociocultural perspective, Dreamina AI can be understood as a mediating artifact

in the design learning process. Vygotsky (1978) argued that human learning is mediated by cultural tools, and such tools reshape rather than simply transmit cognition. In the present study, AI-generated images, concepts, and slogans served as external representations that students could interpret, compare, revise, and integrate into their own work. This also aligns with distributed cognition theory, which views cognition as distributed across individuals, tools, representations, and environments (Hutchins, 1995). The design process in the experimental group therefore became a human–AI–artifact interaction, in which students' creative judgment remained central while AI outputs functioned as materials for reflection and transformation.

The significant improvements in theme design, audience relevance, visual effects, and copywriting indicate that the benefits of GAI-assisted instruction were not limited to ideation alone. Advertising design requires the integration of message, audience, image, and text into a coherent persuasive form. AI-generated prompts and visual or linguistic alternatives may have helped students organize these elements more effectively. This can be interpreted through cognitive load theory:novice designers often need to manage multiple demands simultaneously, including theme interpretation,visual composition, stylistic selection, and message construction (Sweller, 1988). By providing preliminary scaffolds, GAI may reduce unnecessary trial-and-error costs and allow students to devote more attention to higher-order design decisions.

Importantly, the effectiveness observed in this study should be attributed not only to the technological affordances of GAI but also to its pedagogical integration. Students in the experimental group used Dreamina AI for concept generation, slogan ideation, and visual exploration, but they were also required to evaluate and refine AI-generated outputs through professional design software. This structure resonates with Schön's (1983) view of design as a "reflective conversation with the situation," in which designers respond to emerging visual and conceptual possibilities. In this study, AI became part of that reflective conversation, but final design decisions remained dependent on students' interpretation,selection,and transformation.In this sense, the educational value of GAI lies not in replacing students' creative agency, but in expanding the conditions under which creative agency can be exercised.

These findings support a balanced view of GAI in design education. GAI can expand students' creative resources and improve multidimensional design performance, but its educational value depends on critical use, teacher guidance, and assessment standards that foreground human judgment.This finding shifts the focus of AI-supported design education from output generation to judgment formation: what matters pedagogically is not the mere availability of AI-generated materials, but students' capacity to interpret, question, and transform them. Previous research has warned that uncritical reliance on GAI may weaken independent inquiry, authorship transparency, and ethical awareness if students treat AI-generated outputs as finished products rather than materials for evaluation and transformation (Kasneci et al., 2023; Moorhouse et al., 2023).Therefore, the central pedagogical question is not whether AI can generate design materials, but whether students can learn to transform those materials into meaningful, audience-sensitive, and ethically responsible design outcomes.

Despite these positive findings, the educational application of GAI should be approached with caution. Excessive reliance on AI-generated suggestions may reduce opportunities for independent ideation, critical reflection, and sustained creative problem-solving. Students may become inclined to accept AI-generated outputs without sufficiently evaluating their appropriateness, originality, or communicative effectiveness. Therefore, the pedagogical value of GAI does not reside in automated content generation itself, but in its capacity to stimulate reflection, comparison, and informed decision-making.

6. Limitations & Future Research

This study has several limitations. First, participants were recruited from a single

institution and assigned through intact classes rather than random allocation. Although ANCOVA was employed to control baseline differences and the two groups demonstrated statistical equivalence before the intervention, the absence of random assignment may have introduced unobserved classroom-level influences. Consequently, the findings should be interpreted with caution when making causal claims. Future research should employ randomized controlled trials or multi-site quasi-experimental designs to strengthen internal validity and improve generalizability.

Second, the intervention lasted only five weeks within an eight-week course. The findings demonstrate short-term improvement in students' advertising design performance, but they do not show whether these gains can be sustained over time. Future longitudinal research should examine whether students continue to benefit from GAI-assisted instruction after the novelty of the tool decreases and whether repeated AI-supported practice contributes to more mature design judgment and greater independence in creative decision-making.

Third, this study assessed learning outcomes mainly through final design products. Although performance-based assessment is appropriate in design education because it captures authentic design competence (Sadler, 2009; Wiggins, 1990), it cannot fully reveal how students generate, select, revise, and negotiate meaning during the design process. Future research should incorporate process-level data, such as prompt histories, design logs, screen recordings, learning analytics, and think-aloud protocols, to better understand how students interact with GAI across different stages of design learning.

Fourth, this study did not directly measure psychological variables such as creative self-efficacy, learning motivation, design anxiety, or AI acceptance. Therefore, it cannot determine whether these variables explain or moderate the observed performance gains. Future studies should use validated quantitative instruments to examine the psychological mechanisms through which GAI-assisted instruction may influence design learning, particularly in relation to creative confidence, persistence, and motivation (Bandura, 1997; Chen et al., 2025).

Finally, this study focused on one GAI platform in one advertising design course. Different AI tools may support different aspects of design learning. Text-based models may be more useful for conceptual framing and copywriting, whereas image-generation tools may be more directly related to visual exploration and prototyping (Chen et al., 2024; Hutson and Cotroneo, 2023). Future research should compare different AI modalities and instructional models, such as teacher-guided AI use, autonomous student use, and collaborative human–AI workflows. Such work would help clarify not only whether GAI is effective, but under what conditions, for whom, and in what forms it best supports design education.

7. Conclusion

This study investigated the effects of generative AI-assisted instruction on students' advertising design skills through a quasi-experimental pre-test–post-test design. The results showed that the experimental group significantly outperformed the control group in overall design performance and across all five dimensions: theme design, creativity, audience relevance, visual effects, and copywriting. The largest effect was observed in creativity, indicating that generative AI-assisted instruction is particularly effective in supporting students' creative design performance.

These findings provide empirical evidence that generative AI can be meaningfully integrated into advertising design education to enhance students' multidimensional design competence. When embedded within structured pedagogical guidance, GAI can support idea generation, visual exploration, and advertising message development. However, its educational value depends on whether students are guided to critically evaluate, transform, and integrate AI-generated outputs rather than simply adopt them. In this sense, GAI should be understood not as a substitute for human creativity, but as a mediating tool that expands students'

opportunities for creative judgment.

Overall, this study contributes to the growing body of research on generative AI in design education and offers practical implications for educators seeking to develop AI-supported, creativity-oriented learning environments.

Ethics declarations

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Research Ethics and Integrity Office of Assumption University (Approval No. 50/2025; approval date: September 12, 2025).

Author Contributions

Yaling Zhang contributed to methodology, software, validation, formal analysis, investigation, data curation, visualization, and writing—original draft. Lu Zhu contributed to conceptualization, supervision, and writing—review and editing. All authors have read and agreed to the published version of the manuscript.All authors have read and approved the final version of the manuscript.

Informed Consent

Written informed consent was obtained from all participants involved in the study.

Conflicts of Interest

The authors declare no conflicts of interest.

Use of generative AI

Portions of the language editing in this manuscript were assisted by ChatGPT. The tool was used solely to improve clarity, grammar, and academic expression. All AI-assisted outputs were carefully reviewed, revised, and validated by the authors, who take full responsibility for the final content. The use of generative AI in this study complied with the Journal of Buddhist Education and Research's editorial policy regarding AI-assisted writing and disclosure.

Funding

This work was supported by the Digitization of Education and Lifelong Learning Research Center under Grant DELL2024YB-42 and the Sichuan Education Development Research Center under Grant CJF24044. The APC was funded by the authors.

Data Availability

The data supporting the findings of this study are not publicly available due to ethical and privacy restrictions. However, the data may be obtained from the corresponding author upon reasonable request and subject to institutional approval.

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Acknowledgments

The authors would like to express their sincere gratitude to all students who voluntarily participated in this study. Their active engagement in the instructional activities was essential to the successful completion of this research. The authors also extend their appreciation to colleagues and experts who provided constructive suggestions during the research design and manuscript preparation process. Their insights greatly improved the clarity and rigor of this study. Finally, the authors would like to thank all individuals who contributed to this work in various ways but are not listed as co-authors.

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