# An AIGC-Driven Teaching Model for Packaging Design Courses: Design and Experimental Study

Shengnan Wu, Jiahui Wang, Na Wang*, Weiqian Mao

Harbin Institute of Information Technology, Harbin, China

*hxciwangna@126.com

**Abstract.** With the rapid development of Artificial Intelligence Generated Content (AIGC), its application in design education has attracted increasing attention. This study proposes an AIGC-driven teaching model for packaging design courses based on a four-stage framework, including research, generation, optimization, and implementation. A controlled experiment involving 60 students was conducted to evaluate the effectiveness of the proposed model. The results show that the AIGC-based approach significantly improves creativity, visual quality, design efficiency, and learning satisfaction compared with traditional teaching methods. The findings demonstrate the potential of AIGC to enhance design education and provide a practical reference for the digital transformation of art and design curricula.

**Keywords:** AIGC; Packaging Design; Teaching Model; Design Education; Experimental Study.

## 1 Introduction

The rapid advancement of Artificial Intelligence Generated Content (AIGC) is transforming the design industry, particularly in packaging design, where creativity and visual expression are critical. However, traditional teaching approaches often rely on manual processes and iterative feedback, which may limit efficiency and hinder rapid creative exploration.

Recent studies have applied AIGC technologies to image generation and design assistance [1–4], demonstrating their potential to enhance creative workflows and visual ideation. Nevertheless, existing research primarily focuses on tool-level applications, with limited attention to their systematic integration into structured teaching models. In addition, empirical evidence based on controlled educational experiments remains insufficient.

To address these gaps, this study proposes a structured AIGC-driven teaching model based on four stages—research, generation, optimization, and implementation—and evaluates its effectiveness through a controlled experiment. The results indicate significant improvements in creativity, visual quality, efficiency, and student satisfaction, providing practical insights for integrating AIGC into design education.


R. Zur et al. (eds.), *Proceedings of the 2026 5th International Conference on Art Design and Digital Technology (ADDT 2026)*, Advances in Computer Science Research 131,
https://doi.org/10.2991/978-94-6239-737-8_27

## 2 Literature Review

### 2.1 AIGC in Design and Creative Practices

Recent AIGC research can be broadly categorized into three directions: (1) generative model development, including diffusion models and GAN-based approaches for high-quality image synthesis [1][2]; (2) multimodal models, such as CLIP, which enable semantic alignment between textual and visual representations [4]; and (3) application-oriented studies that investigate the use of AIGC in creative workflows, particularly for ideation and visual exploration.

In recent years, diffusion-based models have become the dominant paradigm due to their superior visual fidelity and controllability, and have been increasingly applied in design-related tasks to improve ideation efficiency and visual diversity [1][2]. However, most existing studies focus on the technical capabilities of AIGC or its use as a standalone design tool, with limited exploration of how these technologies can be systematically integrated into educational contexts. In addition, issues such as over-reliance on AI-generated outputs and insufficient critical evaluation skills among users have been identified as potential challenges [5]. Therefore, there remains a need for structured approaches that incorporate AIGC into design education while balancing automation and human creativity.

### 2.2 Teaching Models in Packaging Design Education

Packaging design education traditionally emphasizes manual sketching, iterative refinement, and teacher-led feedback to develop students' creative thinking and visual communication skills. Conventional teaching models typically follow a linear process, including research, concept development, and final presentation. While these approaches provide a solid foundation, prior studies have indicated that they may limit rapid ideation and iterative exploration under time constraints, resulting in reduced efficiency [6].

Although recent efforts have introduced digital tools into design education, these approaches are often fragmented and lack a coherent pedagogical framework. Moreover, the limited integration of intelligent systems across different stages of the design process has created a gap between emerging industry practices and classroom instruction. Empirical studies evaluating the effectiveness of AIGC in packaging design education, particularly through controlled experiments, remain scarce.

To address these limitations, this study proposes a structured AIGC-driven teaching model and validates its effectiveness through experimental comparison, aiming to enhance creativity, efficiency, and overall learning outcomes.

# 3 Methodology

## 3.1 Overall Framework

As illustrated in Fig. 1, this study proposes an AIGC-driven teaching framework consisting of four sequential stages: Research, Generation, Optimization, and Implementation. The framework integrates artificial intelligence tools into the conventional packaging design workflow while maintaining human-centered decision-making at each stage.
The experimental study was conducted over an 8-week course involving 60 students, who were randomly assigned to an experimental group and a control group. Both groups completed the same packaging design task based on a unified brand scenario to ensure consistency and comparability.

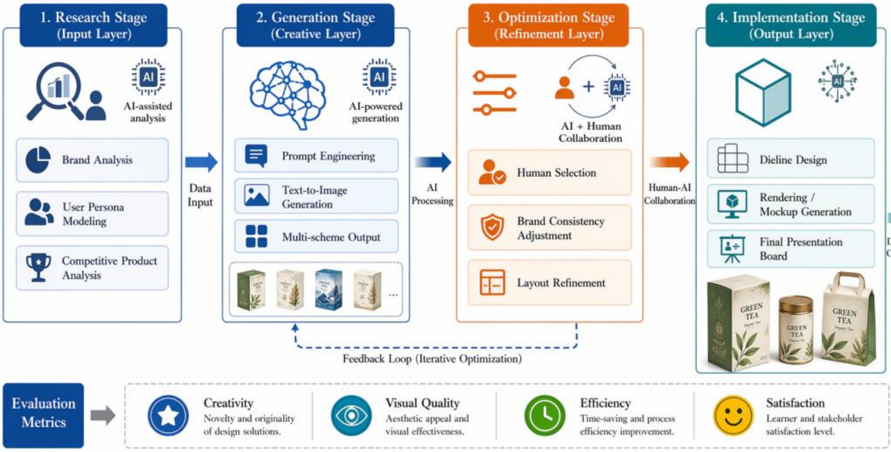


**Fig. 1.** AIGC-driven Teaching Framework for Packaging Design Courses.

As shown in Fig. 1, the experimental group followed the AIGC-supported workflow, while the control group adopted traditional design methods. The framework combines Large Language Models (LLMs) for semantic analysis and diffusion-based models for visual generation. Specifically, LLMs transform textual inputs into structured semantic features, which are then used to guide image generation through diffusion processes.

The objective of this framework is to quantitatively evaluate the impact of AIGC integration on creativity, visual quality, design efficiency, and learning satisfaction.

## 3.2 Research Stage: AI-Assisted Data Processing

In the research stage, LLM-based tools (e.g., GPT-style models) were employed to support brand analysis, user persona construction, and competitor analysis. The process begins with the input of a design brief and structured prompt templates, such as: "Generate a target user persona for a tea beverage packaging brand, including demographics, preferences, and visual expectations." Based on these inputs, the model generates structured textual outputs, including user profiles and summarized insights.

To ensure reliability, the generated content was manually reviewed and refined by students to mitigate potential hallucination issues. In addition, keyword extraction techniques were applied to competitor analysis results to identify high-frequency design features. The relevance score of each feature is calculated as:

$$R_i = \frac{f_i}{\sum_{j=1}^{n} f_j} \tag{1}$$

where $f_i$ denotes the frequency of feature i, and $R_i$ represents its normalized importance. These processed features serve as structured inputs for the subsequent generation stage, while human participants play a critical role in validating and refining the AI-generated outputs.

### 3.3 Generation and Optimization Stages

In the generation stage, diffusion-based models (e.g., Stable Diffusion) were used to produce initial design drafts. The inputs consist of structured feature keywords derived from the research stage, combined with style descriptors such as "modern packaging, eco-friendly, minimalist," which are incorporated through prompt engineering. Based on these inputs, the model generates multiple candidate design images under standardized parameters, including image resolution (512×512 or 768×768), sampling steps (20–30), and CFG scale (7–10), ensuring consistency across outputs.

Each student generated 5–10 candidate designs, which were then evaluated through a combination of subjective judgment and quantitative similarity analysis. The similarity between a generated design G and the target feature set T was calculated using cosine similarity:

$$S(G,T) = \frac{G \cdot T}{\|G\|\|T\|} \tag{2}$$

where G represents the feature vector of the generated design and T denotes the target feature vector derived from the research stage. Human participants were responsible for adjusting prompts and selecting appropriate design candidates based on both aesthetic considerations and brand alignment.

The selected designs were further refined in the optimization stage, where iterative adjustments were made to improve visual quality and coherence, resulting in optimized design solutions for final implementation.

### 3.4 Implementation and Evaluation

In the implementation stage, selected design solutions were developed into final packaging outputs, including dieline structures, mockups, and presentation boards (Fig. 1). AIGC tools were further used to generate realistic renderings by mapping 2D designs onto 3D mockup templates, improving visualization efficiency. Human participants played a key role in final decision-making and refinement to ensure design feasibility and brand consistency.

For evaluation, a multi-dimensional framework was adopted. Three expert instructors independently assessed the works using a structured rubric covering four dimensions—creativity, visual quality, brand consistency, and design completeness—each rated on a 5-point scale (1 = very poor, 5 = excellent). The final score was calculated as the average to reduce bias. Creativity evaluates originality and idea diversity; visual quality assesses aesthetics and layout; brand consistency measures alignment with brand identity; and design completeness reflects structural and presentation quality.

Efficiency was measured by total task completion time, while student satisfaction was collected using a 5-point Likert-scale questionnaire. Statistical analysis was conducted using independent sample t-tests, with the significance level set at $p<0.05$.

# 4 Experiments and Evaluation

## 4.1 Experimental Setup

The experimental data were collected from a controlled study involving 60 undergraduate students majoring in visual communication design. Participants with comparable academic backgrounds were randomly assigned to an experimental group and a control group (30 students each). Both groups completed the same packaging design task based on a unified project brief over an 8-week period, ensuring consistency in learning objectives and workload.

To ensure evaluation reliability, a multi-source assessment approach was adopted. Three experienced instructors independently evaluated the design outcomes using a standardized rubric covering creativity, visual quality, brand consistency, and design completeness, and the final score was calculated as the average. Task completion time was recorded to measure efficiency, and student satisfaction was collected using a 5-point Likert-scale questionnaire. Statistical analysis was performed using independent sample t-tests with a significance level of $p<0.05$.

## 4.2 Main Experimental Results

**Table 1.** Comparison of Experimental and Control Group Results

| Metric | Experimental Group (Mean ± SD) | Control Group (Mean ± SD) | Improvement (%) | p-value |
|---|---|---|---|---|
| Creativity | 4.32 ± 0.51 | 3.68 ± 0.57 | +17.4% | 0.003 |
| Visual Quality | 4.41 ± 0.48 | 3.74 ± 0.52 | +17.9% | 0.001 |
| Brand Consistency | 4.28 ± 0.46 | 3.85 ± 0.49 | +11.2% | 0.012 |
| Design Completeness | 4.36 ± 0.44 | 3.92 ± 0.50 | +11.2% | 0.008 |
| Completion Time (hours) | 18.5 ± 2.3 | 24.0 ± 3.1 | −22.9% | p < 0.001 |
| Satisfaction | 4.47 ± 0.42 | 3.81 ± 0.55 | +17.3% | 0.002 |

The results in Table 1 show that the experimental group outperformed the control group across all metrics. Creativity and visual quality increased by 17.4% and 17.9%, respectively, while brand consistency and design completeness also improved. The average completion time decreased by 22.9%, indicating enhanced efficiency, and student satisfaction increased by 17.3%. All differences were statistically significant ($p<0.05$), confirming the effectiveness of the proposed AIGC-driven teaching model.

### 4.3 Discussion

The results demonstrate that the proposed AIGC-driven teaching model significantly enhances packaging design education by improving idea diversity, visual quality, and efficiency. By integrating AIGC tools across multiple design stages, students can accelerate early-stage ideation and focus more on design refinement and conceptual development.

However, several limitations should be noted. Some students showed a tendency to over-rely on AI-generated outputs, which may weaken independent creativity and critical judgment. In addition, while AIGC can produce visually appealing results, ensuring brand coherence and design rationality still requires strong human intervention. Therefore, instructors play a crucial role in guiding students to critically evaluate AI outputs. Future work should explore more balanced human–AI collaboration strategies and extend the study to larger and more diverse student groups.

## 5 Conclusion

This study proposes an AIGC-driven teaching model for packaging design courses based on a four-stage framework: research, generation, optimization, and implementation. A controlled experiment demonstrates that the proposed approach significantly improves creativity, visual quality, efficiency, and student satisfaction.

The findings indicate that AIGC can effectively support multiple stages of the design process and provide a scalable solution for enhancing design education. At the same time, maintaining human guidance remains essential to ensure critical thinking and design coherence. Overall, this study offers practical insights for integrating AIGC into packaging design education and contributes to the digital transformation of design pedagogy.

## References

1. R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, “High-Resolution Image Synthesis with Latent Diffusion Models,” Proc. CVPR, 2022.
2. P. Dhariwal and A. Nichol, “Diffusion Models Beat GANs on Image Synthesis,” Advances in Neural Information Processing Systems (NeurIPS), vol. 34, 2021.

3. A. Radford, J. W. Kim, C. Hallacy, et al., “Learning Transferable Visual Models From Natural Language Supervision,” Proc. International Conference on Machine Learning (ICML), 2021.
4. H. Peng, X. Zhang, and Y. Li, “AI-Assisted Design: A Review of Generative Methods in Creative Practice,” Design Studies, 2023.
5. Z. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, “Systematic Review of Research on Artificial Intelligence Applications in Higher Education,” International Journal of Educational Technology in Higher Education, 2019.
6. J. Luckin, W. Holmes, M. Griffiths, and L. B. Forcier, Intelligence Unleashed: An Argument for AI in Education, Pearson Education, 2016.