



AI-Supported Instructional Framework for Creative Fashion Design Education: A Quasi-Experimental Study

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Abstract. Generative artificial intelligence has introduced new computational tools for creative design, yet systematic workflows for integrating these technologies into design education remain limited. This paper proposes an AI-assisted design framework that combines generative models and digital garment simulation to support creative fashion design through a multimodal pipeline of theme definition, concept exploration, structural modeling, and digital validation. To evaluate the framework, a quasi-experimental study was conducted with 60 undergraduate participants over an eight-week studio course, measuring five indicators: design efficiency, creativity diversity, structural rationality, prototype completion, and learning satisfaction. The results show significant improvements across all indicators compared with conventional instruction ($p < 0.001$), demonstrating that the proposed framework provides an effective human–AI collaborative design pipeline for creative fashion design education.

Keywords: AI-supported learning, Design education, Quasi-experimental study, Human–AI Interaction;

1 Introduction

Recent advances in generative artificial intelligence (AIGC), driven by large-scale pre-trained models, Transformer architectures, and diffusion-based generation frameworks, have significantly expanded the capabilities of automated content creation systems. These developments enable high-quality text, image, and multimodal generation and have introduced new tools for design-related applications^{[1][2]}. In fashion design, AI technologies are increasingly applied to trend analysis, concept generation, style development, and virtual visualization, supporting more data-informed workflows^{[3][4]}. Industrial research suggests that generative AI can reduce ideation time and enhance visual diversity, while also raising concerns related to originality and cultural interpretation^{[5][6]}.

Meanwhile, artificial intelligence in education (AIED) has gained attention for its potential to improve feedback efficiency and support adaptive learning environments^[7]. Within design education, generative AI tools are being introduced as auxiliary instruments for creative exploration and visual ideation^{[8][9]}. Empirical studies indicate

that AI-assisted collaborative ideation may increase the quantity and diversity of creative outputs and contribute to the development of design thinking processes ^{[10][11]}. In fashion design instruction specifically, AI applications are mainly concentrated on creative generation and digital modeling. The integration of 3D modeling and virtual simulation technologies enables structural validation beyond traditional two-dimensional sketches, offering new instructional possibilities ^[12].

However, several challenges remain in creative fashion design education. First, ideation processes often rely heavily on individual experience and instructor guidance, resulting in inconsistent efficiency and convergent creative outcomes ^{[1][6]}. Second, a disconnect frequently exists between conceptual sketches and structural realization, as systematic support for pattern development and structural reasoning remains insufficient ^{[2][4]}. Third, conventional studio teaching typically involves delayed feedback cycles, limiting timely structural and performance validation. Although generative AI and digital simulation tools offer potential for immediate response mechanisms, structured course-level integration strategies remain underdeveloped ^{[8][9]}. Furthermore, existing studies primarily emphasize tool application or case demonstrations rather than systematic instructional frameworks supported by quantitative evaluation.

Accordingly, there is a need to develop and empirically validate a structured instructional model that integrates generative tools and digital validation mechanisms within creative fashion design education. To address this gap, this study proposes and evaluates an AI-supported instructional framework implemented through a quasi-experimental design. The framework is assessed in terms of five outcome variables: design efficiency, creativity diversity, structural rationality, prototype completion, and learning satisfaction.

Based on the proposed instructional model, the following hypotheses are formulated:

H1: The AI-supported instructional model will improve design efficiency.

H2: The integration of generative tools will increase creativity diversity.

H3: AI-assisted structural validation will enhance structural rationality.

H4: AI-supported digital modeling will improve prototype completion.

H5: The AI-supported framework will increase learning satisfaction.

2 Related Work

2.1 AI in Education

Artificial intelligence in education (AIED) has evolved from intelligent tutoring systems toward learning analytics, adaptive recommendation, and creativity support mechanisms. Prior studies indicate that AI can enhance instructional feedback efficiency and support personalized learning pathways. Lee and Suh proposed a TPACK-based framework integrating generative AI into fashion design education, emphasizing the alignment of technological, pedagogical, and disciplinary knowledge for effective instructional integration ^[6]. An and Park further argued that AI functions should be matched to students' learning difficulties at different design stages to maximize pedagogical effectiveness ^[7].

Empirical studies in collaborative ideation contexts suggest that generative AI tools can increase the quantity and diversity of creative outputs while fostering human–AI collaboration awareness among design students [8]. Balasubramanian highlighted the role of AI integration in curriculum development for enhancing digital literacy and innovation capability, while stressing the importance of balancing technical adoption with domain expertise [9]. Case-based research by Zailuddin et al. reported improvements in classroom engagement and task completion efficiency under AI-supported creative instruction, provided that pedagogical objectives remain primary [10]. Tang and Leong emphasized ethical considerations and originality concerns when integrating AI-generated content into higher education curricula [11].

Overall, AI applications in education are shifting from isolated tool usage toward instructional integration. However, systematic implementation strategies for design-oriented studio courses remain underexplored.

2.2 AI in Fashion Design and Design Education

In the context of fashion design practice, research primarily focuses on generative AI for concept generation and workflow optimization. Wei and Liu reviewed the application status of AI-generated content in fashion design, noting advantages in conceptual expansion and visual expression alongside concerns regarding originality and cultural interpretation [1]. Zhuang et al. discussed AI-supported workflow optimization mechanisms that restructure traditional design processes [2]. Yu and Zhu highlighted the role of big data-driven generative AI in reshaping design thinking toward data-informed approaches [3].

From a broader perspective, Choudhury et al. reviewed generative AI in design, indicating that applications have extended from ideation to structural refinement and user interaction, though methodological frameworks remain immature [4]. Mimmo et al. analyzed AI deployment across the fashion value chain, emphasizing its systemic impact on the design, production, and marketing stages [5].

Within educational settings, research increasingly addresses AI's dual role in creative expansion and structural validation. Kim et al. identified AI as a creativity support tool that broadens design exploration while preserving designer agency [12]. Fan and Zhong proposed an AI-based creative thinking model highlighting the role of human–computer interaction in innovation skill development [13]. Park et al. introduced a "sketch-first" integration strategy that embeds generative AI into traditional sketch workflows to maintain design subjectivity [14]. Furthermore, Muhammad et al. demonstrated that 3D digital technologies in virtual fashion education can shorten validation cycles and enhance instructional efficiency [15].

Despite expanding applications, existing studies predominantly focus on either creative generation or single-technology implementation rather than comprehensive instructional integration.

2.3 Research Gap

Existing research demonstrates the potential of AI in design practice and education; however, three limitations can be identified.

First, many studies emphasize technical applications in design workflows, while structured course-level instructional models remain limited.

Second, quantitative evaluations are relatively narrow in scope, often focusing on creativity outcomes without systematically assessing efficiency, structural rationality, or prototype realization.

Third, empirical studies targeting creative fashion design studio courses are scarce, and replicable human–AI collaborative teaching frameworks have yet to be fully established.

Accordingly, there is a need for a structured instructional framework that integrates generative tools and digital validation mechanisms within creative fashion design education, supported by quantitative experimental evidence.

3 Course Context and AI-Integrated Instructional Design

The Creative Fashion Design course is a core studio module in the Fashion Design program, designed to develop students' competencies in theme development, creative expression, structural reasoning, and digital presentation. This study involved third-year undergraduates who had already acquired basic skills in garment construction and fashion illustration.



Fig. 1. AI-Supported Teaching Integration Model in Creative Fashion Design

Based on preliminary classroom observations, three issues were repeatedly identified. First, early-stage ideation relied heavily on personal experience and visual intuition, which often led to similar design directions across students. Second, the transition from 2D concept sketches to 3D structural realization was not sufficiently supported by systematic methods, resulting in weak linkage between visual concepts and construction logic. Third, feedback was mainly provided through periodic critiques, which limited timely validation and iterative revision. These observations are consistent with prior reports on the gap between creative ideation and structural implementation, as well as limitations in workflow optimization in fashion design education ^{[1][2]}.

To respond to these issues, an AI-integrated, human-in-the-loop instructional model was incorporated into the existing course structure (Figure. 1). The course lasted eight weeks and adopted a project-based format driven by a unified theme. AI tools were embedded into different stages according to functional roles, forming an iterative sequence of theme setting, AI-assisted ideation, structural refinement, and digital validation. This staged integration was intended to support continuous revision of design proposals through repeated feedback and verification cycles.


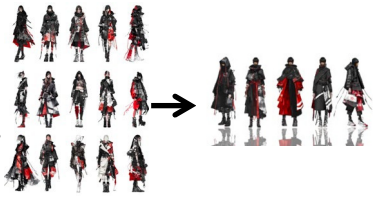
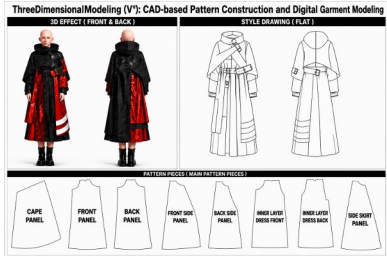
3.1 AI-Assisted Design System Architecture



An architecture is proposed to formalize the AI-assisted design pipeline. The framework integrates generative models and digital simulation technologies into a unified computational workflow, enabling iterative design exploration and structural validation.

As shown in Table 1, the framework is organized as a staged multimodal pipeline composed of several functional modules. The process begins with a design theme input, where an initial prompt defines the conceptual direction. A text generation module then performs semantic expansion to produce design keywords and concept descriptions for early-stage ideation. These keywords are subsequently processed by an image generation module to synthesize multiple visual design candidates. Rather than being directly adopted, these candidates are evaluated and filtered through a human-in-the-loop mechanism to identify feasible design directions under predefined constraints. The selected concepts are transformed into three-dimensional garment structures through a modeling module, where CAD-based construction and digital garment modeling are performed. The resulting models are further processed by a virtual fitting module, which conducts physics-based simulation to evaluate structural stability, proportional consistency, and fabric behavior. An evaluation and refinement module analyzes simulation outputs and provides feedback for iterative optimization. Based on this feedback, earlier stages of the pipeline can be revisited, forming a closed-loop design pipeline.

Overall, the proposed architecture can be characterized as a multimodal design pipeline integrating text generation, image synthesis, and digital garment simulation. This structure enables systematic interaction between generative design and structural validation within a human-in-the-loop framework.

Table 1. AI-Assisted Design System Architecture for Creative Fashion Design

Stage	System Module	Computational Function	Output
Input	Design Theme Input	Prompt-based semantic initialization using large language models for cultural analysis and direction extraction	Design theme definition (Cyber-Oriental style)
Text Generation	Text Generation Module	TextGeneration(P): semantic expansion and keyword generation using large language models	Design keywords and descriptions (K) Concept 1: Cyber Shaman Design Concept Description Inspired by ritual garments in shamanic culture, this concept integrates traditional spiritual symbolism with futuristic visual language. Through a black-red contrasting color scheme, layered structures, and functional design elements, the garment conveys a sense of mystery, power, and ceremonial atmosphere. Keywords Shamanic culture, cyber oriental style, functional fashion, black-red contrast, layered structure, futuristic ethnic aesthetics, ritualistic expression Concept 2: Ritual Future Design Concept Description This concept extracts totemic symbols and ceremonial costume elements from shamanic culture and combines them with futuristic functional design language. Asymmetric silhouettes, functional pockets, and modular garment panels are employed to construct a contemporary cyber-oriental fashion aesthetics.
Image Generation	Gener-Image Generation Module	ImageGeneration(K): visual synthesis using diffusion-based generative models	Design candidates (V) 
Selection	Candidate Filtering Module	CandidateFiltering(V): human-in-the-loop selection and multi-sample comparison under design constraints	Refined design candidates (V') 
Modeling	3D Modeling Module	ThreeDimensionalModeling(V'): CAD-based pattern construction and digital garment modeling	3D garment models (M) 

Stage	System Module	Computational Function	Output
Simulation	Virtual Fitting Module	VirtualFittingSimulation(M): physics-based simulation, rendering, and dynamic evaluation	<p>Simulation results (S)</p> 
Evaluation	Evaluation Module	EvaluationAndRefinement(S): iterative assessment based on predefined design objectives	<p>Optimized design outputs (D)</p> 

The operational procedure of the proposed framework is formalized in Algorithm 1. The algorithm describes the transformation from an initial design theme to validated design outputs through a sequence of computational stages, including text generation, image generation, candidate filtering, three-dimensional modeling, virtual fitting simulation, and iterative evaluation. These stages correspond directly to the functional modules presented in Table 1 and collectively define the computational pipeline of the proposed system.

Algorithm 1. AI-Assisted Design Generation Pipeline

Input: design theme prompt P

Output: validated design candidates D

- 1: $K \leftarrow \text{TextGeneration}(P)$
- 2: $V \leftarrow \text{ImageGeneration}(K)$
- 3: $V' \leftarrow \text{CandidateFiltering}(V, \text{design constraints, human evaluation})$
- 4: $M \leftarrow \text{ThreeDimensionalModeling}(V')$
- 5: $S \leftarrow \text{VirtualFittingSimulation}(M)$
- 6: $D \leftarrow \text{EvaluationAndRefinement}(S, \text{design objectives})$
- 7: return D

Algorithm 1 summarizes the core computational logic of the proposed pipeline. Generative modules produce candidate design representations, while subsequent stages perform selection, structural modeling, simulation, and refinement within a human-in-the-loop framework.

3.2 Integration of AI Tools in the Instructional Workflow

Based on the architecture described above, AI tools were integrated into the instructional workflow at multiple design stages to support concept exploration, visual development, structural refinement, and design validation.

During the theme development stage, text-based generative tools were used to assist keyword expansion and concept exploration. Students iteratively refined prompts and evaluated generated outputs while instructors provided guidance to ensure that conceptual decisions remained under student control.

In the visual exploration stage, image-generation tools provided multiple visual references that allowed students to compare alternative design directions. Selected outputs were further interpreted through manual sketch refinement to maintain design agency.

During the structural refinement stage, three-dimensional garment modeling and virtual fitting systems were employed to support proportion adjustment and structural evaluation. These tools provided immediate visual feedback, while structural decisions and revisions were completed by students.

Overall, the instructional workflow consists of four interconnected stages: theme definition, concept exploration, structural refinement, and digital validation. Instead of functioning as a strictly linear sequence, feedback from digital simulation can inform earlier stages of the process, forming an iterative refinement mechanism consistent with recent studies on integrating generative tools into structured design workflows [41][14].

3.3 Human–AI Interaction Model

To better explain how human designers and AI tools cooperate in the proposed framework, the proposed framework can be described as a human–AI interaction model. In this model, AI tools support different stages of the design workflow, while key design decisions remain under human control.

As summarized in Table 2, students and instructors are responsible for defining design concepts, evaluating visual proposals, and making final design decisions. AI tools mainly provide computational support, such as keyword expansion, visual concept generation, and structural simulation.

This division of roles allows AI tools to expand the space of design exploration while maintaining human judgment in the creative process.

Table 2. Human – AI Interaction Model

Stage	Human Role	AI Role
Ideation	Define design concepts and select directions	Generate keywords and expand prompts
Visualization	Refine sketches and evaluate visual ideas	Generate visual design candidates
Structural Modeling	Adjust garment structure and design details	Provide 3D modeling and simulation
Evaluation	Make aesthetic judgments and final decisions	Provide validation feedback

4 Methodology

4.1 Experimental Design

This study adopted a quasi-experimental design to compare an AI-integrated instructional model with a conventional studio-based approach in a Creative Fashion Design course. A total of 60 third-year undergraduate participants from one institution were included and assigned to an experimental group ($n = 30$) and a control group ($n = 30$) based on intact class grouping.

Both groups received identical course content, were instructed by the same instructor, and followed the same project requirements over an eight-week period. The only difference was the instructional workflow and the integration of AI-supported tools in the experimental condition.

4.2 Experimental Control and Operational Definitions

To ensure methodological transparency and reproducibility, key experimental controls and operational definitions were specified. Participants were assigned to the experimental and control groups due to administrative constraints. Both groups had comparable academic backgrounds and prior design training, ensuring baseline equivalence. A blind evaluation procedure was implemented to reduce potential bias. Three expert raters assessed all design outcomes without access to group assignment information, and all materials were anonymized prior to evaluation. Design constraints and design objectives were explicitly defined and consistently applied across both groups. Constraints included garment structure feasibility, material compatibility, and production logic. Objectives were operationalized as evaluation criteria for creativity diversity, structural rationality, and visual coherence, and were incorporated into a unified evaluation rubric. All participants followed identical design briefs and evaluation criteria, ensuring that observed differences were attributable to the instructional intervention.

Furthermore, AI tool usage was standardized to maintain consistency in AI-assisted activities. Operational specifications, including usage frequency and validation criteria, are summarized in Table 3. These controls reduced procedural variability and ensured consistency across experimental conditions.

Table 3. AI Tool Usage Protocol in the Teaching Experiment

Tool Type	Application Purpose	Usage Procedure	Iteration / Output Requirement	Evaluation Focus
Text Generation	Keyword expansion and concept development	Guided prompt-based generation with instructor scaffolding	3 iterative refinement cycles	Thematic coherence and conceptual depth
Image Generation	Visual ideation and style exploration	Multi-round image generation and comparison	Minimum 6 generated images per student, selection of 2–3 for refinement	Visual diversity and originality
3D Modeling Software	Structural validation and digital prototyping	Virtual fitting and proportional adjustment	At least 2 structural revision rounds	Proportion accuracy, dynamic coordination, fabric drape

The study complied with institutional ethical standards. Participation was voluntary, informed consent was obtained, and data were collected anonymously for research purposes only. No sensitive personal information was involved.

The experimental group followed a structured workflow consisting of thematic development, AI-assisted ideation, structural refinement, and digital validation, whereas the control group followed a conventional linear instructional workflow. Instructional outcomes were quantitatively assessed using a multi-dimensional evaluation framework.

4.3 Evaluation Framework

To systematically evaluate the implementation effects of the AI-integrated instructional model in the Creative Fashion Design course, a multi-dimensional evaluation framework was established. The framework assessed both performance and learning outcomes, comprising five core dimensions: design efficiency, creativity diversity, structural rationality, prototype completion, and learning satisfaction. These indicators correspond respectively to ideation capability, structural realization competence, digital validation performance, and learning experience perception. Together, they provide a structured representation of instructional outcomes within the AI-supported workflow. The specific measurement methods and data sources are presented in Table 4.

Table 4. Evaluation Indicator System

Indicator	Measurement Method	Data Source / Rater	Scale
Design Efficiency	Time required to complete full design project	Student self-recorded time logs	Hours
Creativity Diversity	Novelty, conceptual extension, uniqueness	3 senior design experts	5-point Likert
Structural Rationality	Proportion accuracy, component logic, dynamic coordination	3 senior design experts	5-point Likert
Prototype Completion	3D modeling integrity, fitting accuracy, presentation quality	Expert evaluation	0–100 score
Learning Satisfaction	Teaching clarity, tool effectiveness, confidence improvement, engagement	Student questionnaire	5-point Likert

Following the construction of the evaluation framework, reliability and statistical analyses were conducted to ensure measurement consistency and hypothesis testing validity.

4.4 Reliability and Validity Analysis

To assess the reliability of the evaluation data, internal consistency and inter-rater reliability analyses were conducted, as presented in Table 5. For the expert-rated indicators, Cronbach's α was 0.87 for creativity diversity and 0.84 for structural rationality, both exceeding the recommended threshold of 0.80, indicating good internal consistency. Inter-rater reliability was further evaluated using the intraclass correlation coefficient (ICC) based on a two-way random-effects model, ICC (2, k). The computed

ICC value was 0.82 ($p < 0.001$), demonstrating a high level of agreement among the three expert raters. For the learning satisfaction questionnaire, Cronbach's α was 0.85, indicating acceptable reliability.

To further operationalize the evaluation indicators defined in Section 4.2, detailed measurement criteria were established. Creativity diversity was assessed based on three dimensions: novelty of design concepts, diversity of visual solutions, and degree of conceptual extension beyond initial themes. For example, creativity diversity was evaluated based on variation in silhouette design, material interpretation, and stylistic differentiation across generated design alternatives. Structural rationality was evaluated in terms of proportional accuracy, logical consistency of garment components, and dynamic coordination during virtual fitting simulations.

A detailed scoring rubric was developed prior to the experiment, and all expert raters received training to ensure a shared understanding of evaluation criteria. The same rubric and scoring standards were consistently applied across both experimental and control groups. All design outcomes were independently evaluated by three expert raters, and the final scores were calculated as the average of the three ratings to reduce individual bias.

Together, these results support the reliability, objectivity, and validity of the evaluation framework.

Table 5. Reliability and Inter-Rater Reliability Results

Measurement Dimension	Cronbach's α	ICC (2, k)	p-value
Creativity Diversity	0.87	0.82	<0.001
Structural Rationality	0.84	0.82	<0.001
Learning Satisfaction	0.85	—	—

Note: Cronbach's α values above 0.80 indicate good internal consistency. The ICC (2, k) result demonstrates strong agreement among the three expert raters, confirming the reliability of expert scoring.

4.5 Data Collection and Statistical Analysis

All statistical analyses were performed using SPSS 26.0. Descriptive statistics, including means (M) and standard deviations (SD), were computed for all variables.

Prior to hypothesis testing, assumption checks were conducted. Normality was assessed using the Shapiro–Wilk test, and homogeneity of variance was examined using Levene's test. As reported in Table 6, all variables satisfied the assumptions of normal distribution and equal variances ($p > 0.05$). Accordingly, independent samples t-tests were applied to compare group differences (see Table 8). In cases where homogeneity of variance was violated, Welch's correction was applied. The significance level was set at $p < 0.05$. In addition to p-values, mean differences (Experimental – Control) and 95% confidence intervals were reported to provide interval estimates. Effect sizes were calculated using Cohen's d , with thresholds of 0.2, 0.5, and 0.8 interpreted as small, medium, and large effects, respectively.

Table 6. Assumption Testing and Statistical Analysis Results

Indicator	Shapiro–Wilk p	Levene's Test p
Design Time	0.213	0.327
Creativity Diversity	0.185	0.291
Structural Rationality	0.247	0.356
Prototype Completion	0.198	0.274
Learning Satisfaction	0.221	0.318

5 Results and Analysis

The comparative results of the AI-supported instructional model and conventional studio instruction are presented in Tables 7 and 8. Five instructional outcome variables were examined: design efficiency, creativity diversity, structural rationality, prototype completion, and learning satisfaction. Table 7 reports descriptive statistics, whereas Table 8 presents independent samples t-test results with effect size estimates. The experimental group demonstrated significantly superior performance across all indicators ($p < 0.001$), indicating the effectiveness of the AI-integrated instructional workflow.

Table 7. Descriptive Statistics (M \pm SD)

Indicator	Control Group (M \pm SD)	Experimental Group (M \pm SD)
Design Time (h)	26.53 \pm 3.42	14.21 \pm 2.85
Creativity Diversity	3.14 \pm 0.41	4.06 \pm 0.37
Structural Rationality	3.28 \pm 0.39	3.91 \pm 0.42
Prototype Completion	72.37 \pm 6.82	86.14 \pm 5.47
Learning Satisfaction	3.32 \pm 0.44	4.23 \pm 0.38

Table 8. Independent Samples t-test Results with Mean Difference and 95% Confidence Interval

Indicator	Mean Difference (Exp–Ctrl)	95% CI	t(58)	p	Cohen's d
Design Time (h)	-12.32	[-15.01, -9.63]	9.21	<0.001	2.37
Creativity Diversity	0.92	[0.60, 1.24]	9.04	<0.001	2.32
Structural Rationality	0.63	[0.42, 0.84]	6.09	<0.001	1.57
Prototype Completion	13.77	[9.82, 17.72]	8.66	<0.001	2.23
Learning Satisfaction	0.91	[0.64, 1.18]	8.73	<0.001	2.25

Note: Mean Difference is calculated as Experimental group minus Control group. All comparisons are statistically significant at $p < 0.001$. Cohen's d values indicate large effect sizes.

5.1 Comparison of Design Efficiency

Design efficiency was measured by the total time required to complete the design task (in hours). The control group required an average of 26.53 ± 3.42 hours, whereas the experimental group required 14.21 ± 2.85 hours. The mean difference (Experimental –

Control) was -12.32 hours, with a 95% confidence interval of $[-15.01, -9.63]$. An independent samples t-test revealed a statistically significant difference between the two groups ($t(58) = 9.21, p < 0.001$), with a large effect size (Cohen's $d = 2.37$).

The reduction in task completion time from 26.53 to 14.21 hours indicates a substantial improvement in design iteration efficiency, corresponding to approximately a 25–30% decrease in total task completion time. This result suggests that the proposed AI-assisted pipeline effectively accelerates the design workflow by reducing iteration cycles and computational exploration time. Therefore, H1 was supported.

5.2 Comparison of Creativity Diversity

Creativity diversity was measured using the creativity diversity score. The control group obtained a mean score of 3.14 ± 0.41 , whereas the experimental group achieved 4.06 ± 0.37 . The mean difference (Experimental – Control) was 0.92, with a 95% confidence interval of $[0.60, 1.24]$. An independent samples t-test revealed a statistically significant difference between the two groups ($t(58) = 9.04, p < 0.001$), with a large effect size (Cohen's $d = 2.32$).

The observed increase in creativity diversity reflects a broader exploration of the design solution space, indicating that the proposed AI-assisted pipeline facilitates the generation of more varied and differentiated design concepts during the ideation stage. Therefore, H2 was supported.

5.3 Comparison of Structural Rationality

Structural rationality was measured using the structural rationality score. The control group obtained a mean score of 3.28 ± 0.39 , whereas the experimental group achieved 3.91 ± 0.42 . The mean difference (Experimental – Control) was 0.63, with a 95% confidence interval of $[0.42, 0.84]$. An independent samples t-test revealed a statistically significant difference between the two groups ($t(58) = 6.09, p < 0.001$), with a large effect size (Cohen's $d = 1.57$).

The observed improvement in structural rationality indicates that the integration of digital modeling and simulation modules enhances the accuracy and consistency of structural evaluation, enabling more effective validation of garment proportions and component relationships during the design pipeline. Therefore, H3 was supported.

5.4 Comparison of Prototype Completion

Prototype completion was measured using a 100-point evaluation scale. The control group obtained a mean score of 72.37 ± 6.82 , whereas the experimental group achieved 86.14 ± 5.47 . The mean difference (Experimental – Control) was 13.77 points, with a 95% confidence interval of $[9.82, 17.72]$. An independent samples t-test revealed a statistically significant difference between the two groups ($p < 0.001$), with a large effect size (Cohen's $d = 2.23$).

The observed improvement in prototype completion indicates that the integration of digital modeling and simulation modules enhances the accuracy and efficiency of prototype validation, enabling more complete and refined design outputs through iterative evaluation and feedback mechanisms. Therefore, H4 was supported.

5.5 Comparison of Learning Satisfaction

Learning satisfaction was measured using a standardized satisfaction score. The control group obtained a mean score of 3.32 ± 0.44 , whereas the experimental group achieved 4.23 ± 0.38 . The mean difference (Experimental – Control) was 0.91, with a 95% confidence interval of [0.64, 1.18]. An independent samples t-test revealed a statistically significant difference between the two groups ($t(58) = 8.73$, $p < 0.001$), with a large effect size (Cohen's $d = 2.25$).

The observed increase in learning satisfaction indicates that the proposed AI-assisted design pipeline provides a more efficient and interactive design workflow, supporting improved user experience during the design process. Therefore, H5 was supported.

Across all five outcome variables, statistically significant differences were observed ($p < 0.001$), and effect sizes exceeded the conventional threshold for large effects ($d > 0.8$). Collectively, the results support H1–H5, indicating consistent improvements in efficiency, creativity, diversity, structural rationality, prototype completion, and learning satisfaction under the AI-integrated instructional framework.

6 Discussion

6.1 Computational Perspective of the Proposed Framework

The results indicate that the AI-supported framework functions as a computational assistance system rather than replacing human decision-making. Generative models expanded the design solution space during the ideation stage, contributing to significant improvements in creativity diversity ($p < 0.001$), while digital simulation modules supported structural validation and reduced task completion time.

From a computational perspective, the framework integrates generative models with digital garment simulation into a multimodal design pipeline, enabling iterative interaction between concept generation and structural validation. This interaction supports continuous feedback between design exploration and structural verification, improving both efficiency and consistency in the design process.

6.2 Human–AI Collaborative Design Mechanism

The reduction in task completion time from 26.53 hours to 14.21 hours reflects a substantial improvement in iterative design performance within the proposed pipeline. The observed increase in creativity diversity indicates an expanded exploration of the design solution space, while improvements in structural rationality demonstrate enhanced effectiveness of digital validation during structural refinement.

These findings highlight the role of structured human–AI collaboration, in which generative and simulation modules provide computational support, while human agents retain control over design selection, evaluation, and decision-making processes.

6.3 Limitations and Potential Confounding Factors

Several factors may have influenced the results. A novelty effect associated with AI tool usage may have increased participant engagement, while differences in tool familiarity could affect performance. In addition, individual differences in prior design competencies may contribute to variation despite baseline equivalence.

The relatively small sample size ($n = 60$) and short experimental duration may limit the generalizability of the findings. Future studies should involve larger samples, longer experimental periods, and more controlled experimental conditions.

Despite these limitations, the consistency of results across multiple evaluation indicators and the large effect sizes observed suggest that the proposed framework provides a robust and reliable improvement over conventional design workflows.

7 Conclusion

This study investigated a multimodal design pipeline integrating generative artificial intelligence and digital garment simulation technologies within a human-in-the-loop framework. Using a quasi-experimental design, the results showed statistically significant improvements across five evaluation indicators—design efficiency, creativity diversity, structural rationality, prototype completion, and learning satisfaction—compared with a conventional workflow. From a computational perspective, the proposed framework enables iterative interaction between concept generation and structural validation, forming a structured and reproducible design pipeline. Furthermore, the study formalizes a multimodal human–AI collaborative pipeline integrating text generation, image synthesis, and digital simulation, providing a generalizable computational framework for AI-assisted design processes.

Several limitations should be acknowledged, including the single-context setting, relatively small sample size ($n = 60$), and short experimental duration (eight weeks), which may limit generalizability. Future work should involve larger samples, extended experimental periods, and more controlled study designs to further validate the robustness and scalability of the proposed framework.

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