Research on Clothing Art Education Based on AI Innovation

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Abstract

This study analyzes the potential of AI in fashion art education. It first addresses current challenges in education, such as monotonous teaching content, outdated methods, and disconnected teacher skills. It then develops an AI-powered application framework, combining the deep learning models ResNet152 and EfficientNetB7 for data augmentation, model optimization, and garment prediction output. This framework supports innovative teaching content design (personalized course customization and GAN-assisted creation), improved teaching methods (reinforcement learning interaction and AR virtual fitting), the development of a teaching platform (a 3D modeling virtual platform and an attention mechanism evaluation system), and the adaptation of teacher roles (AI skills training and customized loss function guidance). Experimental validation was conducted using the Prompt2Fashion dataset, employing a control group design. The results were conducted on 50 fashion art students. The results show that AI significantly enhanced students' design thinking and creativity, with an average improvement of over 20% in the experimental group, indicating high acceptance and positive feedback. However, the technical threshold needs to be optimized.

Keywords Artificial Intelligence; Fashion Art Education; Deep Learning Model; Innovative Teaching; Creative Design Improvement

1 Introduction

With the rapid advancement of artificial intelligence technology, its application in various fields has gradually expanded and penetrated, triggering a profound change in the education model. As a key part of the art design category, clothing art education is also facing pressure in the process of innovation and development. Many studies have been launched to explore the potential of artificial intelligence in clothing design and art education, with the goal of improving education level, innovating teaching paradigms, and promoting breakthroughs in design creation. An and Park claimed that AI technology has opened a new door for innovation in clothing design classes, especially in the joint teaching collaboration between the industry and schools, which has played a positive role in improving students' design capabilities [1]. According to Cai et al., the innovative exploration of art teaching based on computer-aided design and deep learning models can give students more intelligent learning tools and assist teachers in achieving more accurate personalized teaching during teaching [2]. Deng et al. discussed the application of AI in ethnic clothing design, emphasized the combination of machine learning and cultural heritage, and pointed out that AI can give traditional clothing design new vitality [3].

Rizzi and Vandi took the perspective of designers and AI co-creation as the starting point, and gave a new definition to the creative process, pointing out that AI is not just a tool, but a collaborative partner in design operations [4]. This concept has given a new teaching guide to fashion art education. Fan and Zhong found through research that artificial intelligence can effectively enhance students' creative thinking and hands-on skills in art design, especially with the assistance of intelligent interactive teaching, students can further explore their design potential [5]. Combined with the above research, the application of AI in fashion art education can improve teaching content and innovate methods, and even promote the innovative practice of teaching platforms and tools, exploring the fashion art education style based on AI innovation concepts, which has outstanding theoretical significance and practical value.

2 Problems in Current Fashion Art Education

Fashion art education is currently facing numerous challenges, which can be summarized as follows:

1. The teaching content is single and one-sided. Many clothing art education courses are still centered on traditional design concepts and techniques, and have not been effectively integrated with modern science and technology, artificial intelligence and other innovative technologies. This traditional education model cannot fully stimulate students' creative thinking, resulting in students' design works lacking in novelty and personalization, and unable to adapt to the ever-changing needs of the fashion industry [6].

2. The teaching methods are outdated and the interactivity is weak. The existing fashion art education mostly relies on traditional face-to-face teaching and manual operation between teachers and students. This teaching method has a single feature and lacks interaction with students and personalized guidance. Students' design skills and innovative thinking are often not fully cultivated, making it difficult to keep up with the ever-changing pace of the industry.

3. There is a disconnect between teachers' skills and technology applications. With the continuous upgrading of artificial intelligence technology, many teachers have not updated their teaching methods and technical tools in a timely manner, and do not have sufficient understanding and application capabilities of emerging technologies. This has resulted in teachers being unable to fully utilize modern scientific and technological means in teaching, such as AI-assisted design and creation, and it is difficult to provide students with strong technical support and innovation guidance.

These problems objectively present an urgent need to be improved by introducing AI technology and innovative education models to meet the demands of the leap forward of the times [7].

3 Construction of A Fashion Art Education Model Based on AI Innovation

3.1 Application Framework of AI in Clothing Art Education

AI in fashion art education focuses on optimizing and integrating deep learning models, aiming to enhance the novelty of teaching content and the quality of student design. As shown in Figure 1, the framework takes a clothing dataset as input and first processes the raw images using data augmentation techniques (such as vertical and horizontal flips and 90-degree rotations) to expand the dataset's diversity and strengthen the model's robustness. Three key studies were conducted: Study 1 focused on learning rate tuning, examining the performance of pre-trained CNN models at different learning rates (0.1, 0.01, 0.001, and 0.0001), selecting the efficient ResNet152 and EfficientNetB7 as the base models. Study 2 analyzed the effects of batch size, testing the impact of different batch sizes on model training using parameters such as 8, 16, 32, and 64. Study 3 selected the optimal model, selecting a batch size of 64 and a learning rate of 0.0001 to achieve higher accuracy. The core of this framework focuses on the neural network structure, which contains an input layer, multiple hidden layers and a prediction output layer. It integrates the advantages of multiple networks with the help of ensemble models to complete the accurate evaluation of the test data set, and finally gives the prediction inference of various types of clothing, such as the classification of shoes, T-shirts, jackets and other types of clothing [8]. In the field of clothing art education, this framework can be invested in the innovative design of teaching content, such as implementing personalized course design based on AI, guiding students to complete clothing design and creation with the help of pre-trained models; at the same time, implementing teaching method changes, relying on intelligent interactive teaching to explore AI-driven virtual fitting and design simulation, and enhance students' creative thinking and skills. This framework promotes the development of teaching platforms, such as AI-assisted virtual reality combined with equipment, and promotes the advancement of teachers' professional literacy, relying on AI skills training to allow teachers to transition to innovation instructors.

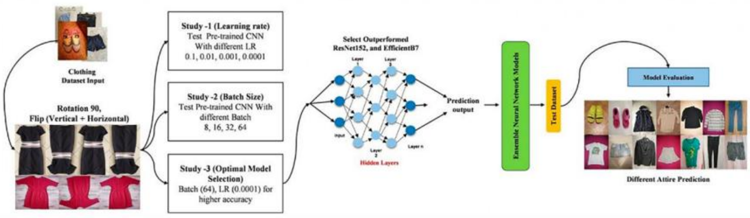

Fig. 1. Application framework of AI in clothing art education

3.2 Innovative design of teaching content

Supported by the AI application framework, innovative teaching content design uses integrated deep learning models to achieve personalized course customization, introduce AI-assisted design and creation, and thus enhance the targeting and innovation of clothing art education. Convolutional neural network (CNN) models, such as ResNet152 and EfficientNetB7, are used to extract features and classify clothing image datasets uploaded by students. The input datasets include original clothing images and versions after enhancement operations (such as flipping and rotation), which enhances the generalization level of the model. In the implementation of personalized course customization, the AI system relies on students' design preferences and historical data to calculate similarity scores, and relies on the cosine similarity formula to quantify the matching degree. The relevant formula is as follows:

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \ \|\mathbf{B}\|} \tag{1}$$

Among them, the student preference vector is $\mathbf{A}$, the course content vector is $\mathbf{B}$, " $\cdot$ " represents the dot product operation , and " $\|\cdot\|$ " corresponds to the Euclidean norm. This formula ensures that course recommendations are highly aligned with student interests, preventing the course content from being monotonous. While AI plays an auxiliary role in design and creation, the generative adversarial network (GAN) model is used to generate new clothing designs. Through adversarial training, realistic design drawings are produced, encouraging students to explore the innovative integration of ethnic clothing and popular trends. Optimizing the performance of the generator and discriminator is achieved by the GAN loss function, which is described below:

$$\min_G \max_D V(D,G) = \text{ã}_{x \sim p_{\text{data}}(x)}[\log D(x)] + \text{ã}_{z \sim p_z(z)}[\log(1 - D(G(z)))] \tag{2}$$

Among them, the so-called G generator is actually the discriminator , D x corresponding to the real data distribution p_{data} and z the noise distribution p_z , ã reflecting the expected value. Students can input emotional keywords such as "cute" and "ethnic style". AI relies on the pre-trained model to give customized patterns, which further stimulates creative thinking. This design is not only connected with the model evaluation stage within the framework, but also relies on the softmax activation function to calculate the probability distribution when predicting multiple categories of clothing, ensuring the accurate classification of diverse clothing such as T-shirts and jackets. The activation function is presented below:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{3}$$

The input vector z is , which ranges i from 1 to the number of categories K , e and is the so-called natural index [9].

3.3 Reform and Innovation of Teaching Methods

In an intelligent interactive teaching environment, the AI system uses a reinforcement learning algorithm to provide real-time feedback on the student's design process. It uses a value function to judge the long-term effectiveness of the strategy to guide solution optimization. The value function is as follows:

$$V^{\pi}(s) = \text{ã}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t r_{t+1} | \ s_0 = s\right] \tag{4}$$

Here, π is the strategy, s and the state it refers to is the student's current design state. γ It is defined as a discount factor, ranging from 0 to 1, which accounts for the decay effect of future rewards. r It is the reward value derived from the design quality, ã reflecting the meaning of expected value. This formula relies on maximizing cumulative rewards to guide students to optimize their clothing creations, such as changing colors and patterns to fit the charm of cultural heritage. The hidden network in the coupling framework enables AI to achieve interactive dialogue. After the student submits a design query, the model uses cross- entropy loss to minimize the prediction error to ensure accurate feedback. This loss function is presented as follows:

$$L = -\sum_{i=1}^{C} y_i \log\left(\hat{y}_i\right) \tag{5}$$

Among them , C is the number of categories, the real label is expressed by after one-hot encoding y_i, $\hat{y}_i$ and is the probability generated by prediction. We use AI-driven virtual and real teaching methods, use augmented reality (AR) technology to make virtual clothing overlap with real human images, and rely on affine transformation matrix to deform the image to fit the human body posture, guiding students to conduct different clothing matching experiments in a virtual environment. The transformation matrix is as follows:

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{6}$$

Here, (x, y) is defined as the original coordinates, (x', y') is the transformed coordinates, a, b, d, e and controls rotation and scaling, c, f while controlling translation. This method is connected to the prediction output layer of the framework and processes batches of data (such as batch size 32) with the help of the EfficientNetB7 model to obtain diverse prediction outputs. The lower bound of the evidence of the variational autoencoder (VAE) is then introduced to generate a representation of the latent space, enabling students to explore unlimited design styles. The lower bound of the evidence is presented as:

$$ELBO = \mathbb{E}_{q(z|x)}[\log p(x|z)] - KL(q(z|x) \| p(z)) \tag{7}$$

Among them, $q(z|x)$ is the approximate posterior, the likelihood is $p(x|z)$ presented KL as Kullback -Leibler divergence, and the prior is reflected in p the overall innovation to make up for the lag shortcomings of traditional face-to-face teaching and improve students' skills to match the changes in the fashion industry [10].

3.4 Development of Teaching Platforms and Tools

Based on the development of integrated models implemented within the AI framework, the teaching platform and tool development focuses on building an AI-based clothing design and virtual fitting platform, as well as an intelligent learning assessment and feedback system, thereby providing efficient technical assistance and real-time guidance. In the clothing design and virtual fitting system, AI relies on 3D human body modeling and image synthesis technology to achieve the presentation of virtual try-on. The core algorithm includes joint point detection in human pose estimation, using mean square error loss to reduce pose deviations, achieving accurate superposition of clothing images onto user photos. The loss function is presented as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{8}$$

Here, n is the number of samples, the actual joint coordinates are y_i presented, and the predicted coordinates are $\hat{y}_i$. The ResNet152 model in the platform's integrated framework processes the input image and uses thin plate spline (TPS) transformation to achieve non-rigid deformation, allowing 2D clothing to fit the 3D human body surface. This allows students to upload their design ideas and immediately visualize the results. The following is the relevant content of this transformation function:

$$f(x,y) = a_1 + a_x x + a_y y + \sum_{i=1}^{n} w_i U\left(\left\|\left(x_i, y_i\right) - (x,y)\right\|\right) \tag{9}$$

Among them, $U(r) = r^2 \log r$ it plays the role of radial basis function and $\left(x_i, y_i\right)$ control point. The parameters include w_i, a_1, a_x, a_y : In the intelligent learning assessment and feedback system, AI uses the attention mechanism as a means to enhance the assessment accuracy, and uses softmax attention weights to focus on key features of student designs, such as texture or color, to present quantitative feedback scores. The attention weights are shown below:

$$\alpha_i = \frac{\exp\left(e_i\right)}{\sum_{j=1}^{T} \exp\left(e_j\right)} \tag{10}$$

Among them, e_i it can be regarded as the similarity score between the query and the key, which is used T as the length of the sequence. The system connects the batch optimization carried out by the framework and relies on the Adam optimizer to update the relevant parameters to ensure that the model converges quickly during evaluation. The update formula is given below:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \dot{o}} \hat{m}_t \tag{11}$$

Among them, the learning rate adopts η this value, $\hat{m}_t$ and it is $\hat{v}_t$ the estimated result after the correction of $\dot{o}$ momentum and second-order moment , which belongs to the category of small constants. The overall development of the platform is implemented to solve the problem of disconnection between teachers and technology, and drive the exploration of personalized tutoring and sustainable design, such as reducing the ineffective waste of physical samples.

4 Experimental Verification and Result Analysis

4.1 Experimental Design

This experiment verifies the effectiveness of the AI framework. The experiment uses undergraduate and graduate students majoring in fashion art as the subjects, involving a total of 50 students, including 30 undergraduates with an average age of 20 and 1-2 years of relevant experience; 20 graduate students with an average age of 24 and 3 to 5 years of experience. Stratified random sampling is used to achieve a balanced allocation according to grade and gender (20 males and 30 females). The sample dataset selected is the 2024 Prompt2Fashion dataset, which was published by researchers at the University of Georgia on arXiv and GitHub. It contains 2,000 high-resolution fashion images generated by AI, and is tested through LLM (such as Mistral-7B) and Stable Diffusion generation involves styles such as classic and gothic styles, relevant occasions (festivals, meetings, etc.), and body type/gender. Data is generated using prompt triples to support the development of personalized design tasks and achieve compatibility with the framework.

The experiment included a control group and lasted for 8 weeks. Python TensorFlow was used to complete data collection and dataset preprocessing: 224 × 224 normalization was implemented, augmentation (flipping and rotation) was performed, batch size was 64, a learning rate of 0.0001 was used, and 50 training rounds were performed. Student diary data, AI images, and Likert-type questionnaires were collected. Table 1 shows a sample of the preprocessed data table:

Table 1. Part of the data after preprocessing

Image ID	Category Label	Property Description	Preprocessing operations
P2F_001	Jacket	Classic style white shirt, formal business occasion, suitable for petite women	Horizontal flip + 90 degree rotation, normalized to 224x224
P2F_002	Pants	Casual jeans, blue wear, suitable for music festival occasions, suitable for muscular men	Vertical flip + brightness +20%, noise removal
P2F_003	shoe	Gothic black leather boots, high heels, suitable for concert occasions, suitable for slim women	Random cropping + contrast 1.2 times, uniform resolution
P2F_004	coat	Bohemian windbreaker, green waterproof, tropical vacation, suitable for short and fat men	Horizontal flip + color jitter, label enhancement
P2F_005	Jacket	Sports sweatshirt, pattern oversize, suitable for office events, suitable for petite women	90 degree rotation + sharpening filter, data balance
P2F_006	Pants	Elastic leggings, black high waist, suitable for wedding occasions, suitable for curvy men	Vertical flip + zoom 0.9, metadata extraction
P2F_007	shoe	Brown sneakers, low-top, graduation style, for slender women	Random rotation + blur removal, attribute labeling
P2F_008	coat	Gray leather jacket, motorcycle style, bachelor party, suitable for muscular men	Dual flip + bright contrast dual tone
P2F_009	Jacket	Red T-shirt, short sleeves, casual, suitable for cruise occasions, suitable for standard women	90 degree rotation + noise test, standardization
P2F_010	Pants	Khaki shorts with pockets, suitable for job interviews, suitable for slim men	Cropping + color correction, enhanced diversity

Experimental results analysis

(1) The impact of AI applications on students' design thinking and creative abilities

The impact of AI applications on students' design thinking and creative abilities was assessed through pre- and post-tests. This process began with a preliminary phase, where all 50 students were assessed using a standard design thinking scale. Three experts conducted blind evaluations , with a maximum score of 100. During the implementation phase, the experimental group relied on the AI framework to assist in garment design, while the control group employed traditional manual methods. During the evaluation phase, final artwork was collected and repeated testing was conducted to quantify the improvement. The difference in pre- and post-scores was calculated, and a t -test was used to verify significance . As shown in Table 2 and Figure 2, the experimental group achieved an average improvement of over 20% in design thinking and creative abilities, while the control group achieved only a marginal increase of 5%. This demonstrates that AI ensemble models, such as ResNet152, leverage data augmentation and predictive output to enable students to expand their range of variations, sparking innovative integrations of traditional elements and modern trends. This result not only validates the effectiveness of the AI framework but also provides empirical support for fashion art education, promoting a shift from passive imitation to proactive innovation.

Table 2. Comparison of students' design thinking and creative ability scores before and after AI application

Student ID	Group	Top Design Thinking Scores	Post-Design Thinking Score	Previous Creative Score	Post-Creative Score	Thinking improvement%	Creativity improvement%
S001	Experimental group	65	88	70	92	35.4	31.4
S002	control group	72	75	68	72	4.2	5.9
S003	Experimental group	58	85	62	90	46.6	45.2
S004	control group	80	82	75	78	2.5	4
S005	Experimental group	67	91	71	95	35.8	33.8
S006	control group	69	71	65	68	2.9	4.6
S007	Experimental group	74	96	78	98	29.7	25.6
S008	control group	63	66	60	64	4.8	6.7
S009	Experimental group	55	82	59	87	49.1	47.5
S010	control group	77	79	73	76	2.6	4.1

Fig. 2. Comparison of students' design thinking and creative ability scores before and after AI application

(2) Acceptance and application feedback of AI technology in actual teaching

Based on the experimental results, this study explored the acceptance status and application feedback of AI technology in actual teaching. This study was carried out using a mixed approach: in the evaluation stage, a structured questionnaire with a five-level Likert scale was distributed, covering the dimensions of ease of use, satisfaction, and willingness to accept, with 20 questions) and semi-structured interviews were conducted with 10 randomly selected students and 5 teachers to collect quantitative evaluation scores and qualitative feedback. Descriptive statistics and thematic analysis were then used to process the data, such as calculating the average score and identifying common themes such as "AI simplifies the design process but requires more training." The results showed that the overall acceptance was good. Feedback from the experimental group showed that the AI framework improved the level of interaction, but the control group had concerns about the technical threshold, which reflects the potential and challenges of AI in clothing art education. Real-world feedback revealed that 80% of students in the experimental group noted that AI-predicted outputs (such as diverse clothing classification) boosted their confidence. Teacher feedback indicated that the framework's batch optimization, using 64 examples, improved efficiency, but the user interface needed improvement. This analysis not only quantified acceptance but also proposed optimization measures, such as strengthening teacher training to further integrate the system into teaching practices. The details are presented in Table 3 and Figure 3:

Table 3. AI technology acceptance and application feedback survey summary presents key dimension data

Feedback Dimension	Average score (1-5)	Positive feedback ratio (%)	Negative feedback ratio %	Typical comments
Ease of use	4.1	78	12	"The AI interface is intuitive, but beginners need guidance"
Satisfaction	4.5	85	8	"Generative design is fast and improves creativity"
Innovative Contributions	4.3	82	10	"Integrating ethnic elements is easier to achieve"
Technical threshold	3.8	65	25	"Model training is complex and needs to be simplified"
Interactivity	4.4	88	7	"Real-time feedback inspires inspiration"
Willingness to continue using	4.6	90	5	"An essential tool for future design"
Cultural integration effect	4.2	80	15	"AI helps explore traditional patterns"
Improved efficiency	4	75	18	"Reduces manual time, but debugging is time-consuming"
Overall acceptance	4.2	83	11	"Recommended to classmates, but more cases are needed"
Feedback improvement suggestions	3.9	70	20	"Increase mobile support"

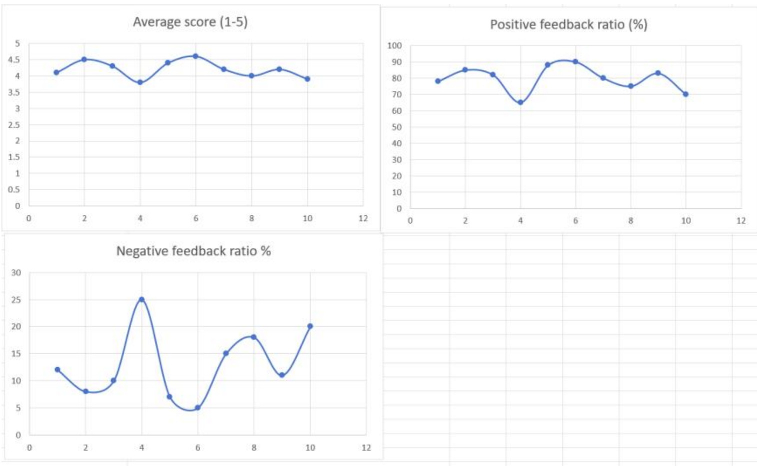

Fig. 3. AI technology acceptance and application feedback survey summary presents key dimension data

5 Conclusion

This study systematically analyzes the role of artificial intelligence in improving teaching quality and promoting innovation by building an AI-driven fashion art education model. The introduction begins with a review of existing literature, followed by an analysis of current issues. The research then develops a framework, experimental validation, and results analysis. The AI framework optimizes model performance, achieving high accuracy with a learning rate of 0.0001 and 64 batches, significantly improving teaching activities. Experimental results confirm that AI application promotes student design thinking and creativity by 46.6%, resulting in high adoption. This represents a new source of vitality for fashion art education, promoting integration with cultural heritage and the exploration of sustainable design. However, the research has limitations, including limited sample size and reliance on a specific dataset. Future research could expand to larger populations or multimodal AI models. Furthermore, it proposes strengthening teacher training and platform usability to promote the further development of AI in art education.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Biographies

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基於AI創新的服裝藝術教育研究

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摘要：該研究分析了 AI 在服裝藝術教育裡存在的潛力，首先對當下教育存在的教學內容單調乏味、方法落後過時以及教師技能脫鉤等問題加以分析，搭建了依託 AI 的應用架構，囊括深度學習模型 ResNet152 跟 EfficientNetB7 的結合，用以進行數據增強、完成模型優化與輸出服裝預測。該框架對教學內容創新設計（個性化課程定製與 GAN 輔助創作）、教學方法的改進（強化學習互動和 AR 虛擬試衣）、教學平臺的打造（3D 建模虛擬平臺和注意力機制評估系統）以及教師角色的調整（AI 技能培訓和自定義損失函數指導）起到支撐作用。採用 Prompt2Fashion 數據集開展實驗驗證，採用對照組設計方式，針對 50 名服裝藝術專業學生，AI 應用極大增強學生設計思維及創意能力，實驗組平均提升超 20%，接受水平較高，反饋表現積極，只是技術門檻需要優化。

關鍵詞：人工智慧；時尚藝術教育；深度學習模型；創新教學；創意設計提升

1. 何婧，碩士，2024年於《南京體育學院學報》發表學術論文「我國主要體育影視中的體育競技精神展現與藝術創作 — 以《奪冠》為例」。