A Study on the Teaching Practice of AI-Empowered Traditional Textile Pattern Art Design: Synergistic Development of Inheritance and Modern Innovation

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ABSTRACT Traditional textile patterns, as an important component of national cultural heritage, contain rich historical information and aesthetic value. However, their design inheritance faces difficulties including strong dependence on craft experience and insufficient teaching innovation. The development of artificial intelligence provides new possibilities for revitalizing traditional patterns and reforming design teaching. This study constructs an image dataset containing multiple categories of traditional textile patterns, proposes a pattern innovation generation method based on conditional deep convolutional generative adversarial networks, and builds an AI-assisted design teaching platform. The platform is applied in course practice, and teaching effects are evaluated through quantitative assessment and questionnaire survey. Results show that AI-assisted teaching effectively improves students' understanding of traditional patterns and enhances their innovation ability. The generated patterns retain traditional elements while presenting diversified modern aesthetic characteristics. The proposed teaching model provides a feasible path for coordinating inheritance and innovation in traditional textile pattern design, and supports the digital transformation of textile art education.

INDEX TERMS artificial intelligence, traditional textile patterns, design teaching, generative adversarial networks, textile art

I. INTRODUCTION

THE textile patterns of traditional textiles are what artists crystallize formed by different ethnic groups in their long-term production and life. From the cloud and thunder patterns of the Shang and Qing dynasties, to the lotus flower patterns of the Tang dynasty, from the batik patterns of ethnic minorities to the blue printed fabrics of the Jiangnan water towns, these patterns not only have a decorative function, but cultural symbols and ethnic memories. However, with the speed of industrialization and the change of living modes, the traditional pattern designing is facing the crisis of inheritance: on the one hand, the artisans who have mastered the traditional techniques are gradually aging, and the young generation does not have enough understanding of the structural rules of complex patterns; on the other hand, the current design teaching emphasizes the imitation of classical patterns and young people lack the methods and tools of innovative design, and therefore, the application of traditional patterns in modern design is superficial and symbolized. This research is intended to discover novel models for AI-enabled teaching of the traditional textile pattern art and design, which will encourage the coordinated development of the inheritance and the modern innovation. The main contributions of this paper are reflected in the following three aspects: Firstly, a specialized and high-quality dataset of traditional textile pattern images with multiple categories was built, offering a solid foundation of the cultural resources for deep learning of AI models. Second, a pattern innovation generation method based on Conditional Deep Convolutional Generative Adversarial Network (C-DCGAN) was proposed, which can meet the diversified pattern innovation generation with the modern aesthetic characteristics and the pattern still maintain the cultural genes of traditional patterns. Finally an AI assisted design teaching platform was created and implemented. Through teaching experiments through comparative teaching of actual design courses, the positive role of AI technology in enhancing students understanding of patterns as well as stimulating innovative design capabilities has been systematically verified.

The structure of our paper is as follows: revising previous research on the application of AI technology in the field of textile design; describing the research method, which includes dataset constructing, generative model designing, teaching experiment designing; discussing the research results by analyzing the quality of generated pattern, students works and teaching feedback; summarizing the whole paper and looking for future research direction.

II. RELATED WORK

The field of textile design is undergoing a profound transformation from the penetration of sustainable concepts and the intervention of digital technology to interdisciplinary integration. Sidian et al. [1] outlined a method for textile upgrading and reconstruction, integrating the upgrading and reconstruction method into university textile courses, encouraging students to recycle textiles and adopt sustainable design practices. Khoriatin and Rahayu [2] developed "Shasiko Bags" (products combining Sasirangan waste and sashiko embroidery techniques) to provide practical teaching materials for textile experiments and decorative design courses in vocational schools. Wu and Li [3] applied generative AI tools to the knitted textile design process and compared the differences between traditional design methods and AI-assisted design methods. Tufan Tolmaç and İşmal [4] analyzed how designers use 3D printing technology to create structures, forms and textures that are difficult to achieve with traditional textile processes, and how these innovations affect the aesthetic development of fashion and textile design.

Jacquard cards are a key medium for controlling patterns in traditional jacquard weaving. Lorente et al. [5] identified and analyzed the pattern information on the jacquard cards and converted it into an editable and re-creatable digital format. Keune and Lim [6] explored the interaction between textile design and biological systems. Arikan et al. [7] explored the use of 3D printing technology to construct textile-like surfaces through different basic geometries and evaluated its application potential in the fashion industry. Basyigit et al. [8] addressed the challenges of temperature and humidity management in cotton textiles. Hameed and Mimirinis [9] analyzed the process of students using digital tools for design reflection. Nartker et al. [10] evaluated the methods and effects of integrating universal design concepts into textile design education. Existing research has failed to effectively solve the core dilemma of "inheritance relies on experience and innovation lacks tools" in traditional pattern teaching, namely, how to enable students to achieve the leap from imitation to innovation based on a deep understanding of the inherent structural laws and cultural connotations of patterns. In light of this, this study focuses on AI-enabled teaching of traditional textile pattern art and design. By constructing a specialized dataset of traditional patterns and a conditional generative adversarial network model, it aims to explore a feasible path for the coordinated development of "inheritance" and "modern innovation" of traditional patterns in the digital wave, in order to respond to the dual demands of cultural heritage revitalization and design education innovation in the era of technological intervention.

III. METHODS

A. CONSTRUCTION OF TRADITIONAL TEXTILE PATTERN DATASET

To enable AI to learn and generate traditional patterns, it is first necessary to establish a high-quality and diverse pattern image dataset. The data sources include three aspects: first, digital resources of museum collections, such as publicly available textile artifact images from the Palace Museum and Nanjing Yunjin Museum; second, published textile pattern catalogs and academic literature, which are obtained through high-resolution scanning; and third, field surveys and photography, where the research team went to areas rich in traditional textile crafts such as Jiangsu, Zhejiang, and Yunnan to collect local folk textile patterns. All images were screened to ensure that the patterns were clear and complete, and to exclude blurry or duplicate samples [11-12].

Image preprocessing includes size normalization and background removal. The original images were uniformly cropped to 256 $\times$ 256 pixels and converted to RGB mode. For the background interference in some images, the main area of the pattern was extracted by a combination of manual cutout and automatic segmentation. In order to enrich the diversity of data, data enhancement operations were performed on the images, including random rotation ($\pm 15°$), horizontal flipping, brightness adjustment ($\pm 10\%$) and contrast enhancement. The final dataset contains 10 main categories: geometric patterns, plant patterns, animal patterns, human patterns, text patterns, cloud patterns, flower patterns, bird and animal patterns, landscape patterns, and auspicious combination patterns. Each category is further subdivided into subcategories, such as plant patterns including peony, lotus, chrysanthemum, etc. The total number of images in the dataset is 5680, and the distribution of each category is shown in Table 1 [13].

TABLE 1. Statistics on the categories and quantities of traditional textile pattern datasets

Pattern categories	Number of subclasses	Number of images (pieces)	Resolution (pixels)	Main source
Geometric patterns	8	630	256×256	Museums, catalogs
Plant pattern	12	620	256×256	Museums, fields
Animal print	10	590	256×256	Museums and documents
Human figure pattern	5	540	256×256	Literature, field
Text pattern	4	510	256×256	museum
Cloud patterns	3	550	256×256	Museums, catalogs
Floral pattern	9	600	256×256	Field, Documents
Bird and animal patterns	7	560	256×256	Museums, fields
Landscape pattern	4	530	256×256	literature
Auspicious combination patterns	6	550	256×256	Museums, fields
total	68	5680	-	-

Table 1 shows that the sample size distribution of traditional textile patterns in each major category is relatively balanced, with the number of patterns ranging from 510 to 620, avoiding model training bias caused by data bias. Among them, plant and floral patterns are slightly more numerous, reflecting the prevalence of natural themes in traditional textile patterns; abstract or figurative categories such as animal patterns and geometric patterns also account for a large proportion. Although human figures and text patterns are relatively rare in

traditional textiles, the dataset still maintains a basic sample size through targeted data collection, providing effective support for the model to learn these complex categories.

B. PATTERN GENERATION MODEL BASED ON CONDITIONAL DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS

In order to achieve innovative generation while retaining traditional pattern features, a Conditional Deep Convolutional Generative Adversarial Network (C-DCGAN) is used as the basic generation model in this study. This model adds conditional variables to the dcgan, which allows the generative process to be controlled, i.e. it is possible to create corresponding images depending on the categories of patterns on demand. The generator network structure is composed of a 100-dimensional random noise vector concatenated with class labels (the class labels are mapped to 50-dimensional vectors by an embedding layer), reshaped as a $4 \times 4 \times 1024$ feature map by a fully connected layer, and upsampled by four transposed convolutions. Each layer uses batch normalization and the ReLU activation function consecutively, and, finally, a $256 \times 256 \times 3$ image is outputted. The discriminator network structure is to extract the features of the input image by four convolutional layers.

Each layer performs the downsampling operation with the help of LeakyReLU activation function and stride convolution function while at the same time, it embeds the class labels and concatenates them with

intermediate feature map. Finally, there is a fully connected layer which spits out a true/false probability. The network uses the Adam optimizer with a learning rate of 0.0002 with momentum term beta1=0.5. In the training, both the batch size is used as 64, and the number of iterations is set as 200 epochs.

The dataset used for the training was the dataset that was built in Section 3.1 and the images were normalized to the [-1, 1] interval. In order to avoid overfitting, online random flipping of was used, which is a form of data augmentation. The changes in the loss functions of the generator and discriminator were monitored, and the FID value of the generated images on the validation set and the mean cosine similarity between generated samples (used to evaluate pattern diversity) were calculated every 10 epochs. Training was stopped when the discriminator loss fluctuated between 0.4 and 0.6 and the FID value no longer decreased for 20 consecutive epochs. To avoid pattern collapse, an additional diversity regularization term was introduced, and 200 randomly generated images for each category were manually checked to confirm that there was no high degree of repetition in the generated samples. Figure 1 shows the curves of the discriminator loss, generator loss, and FID value during training (not presented in the main text due to space limitations, but submitted as supplementary material). Through the above monitoring methods, it can be ensured that the model converges to a non-collapse state.

As training progressed, the discriminator loss stabilized at around 0.48, while the generator loss decreased to 1.02, achieving a dynamic balance without pattern collapse. The FID value continuously decreased from 152.3 to 25.4, indicating a significant improvement in the quality of the generated images and a distribution that closely approximates realistic patterns. C-DCGAN successfully learned the distribution characteristics of traditional textile patterns, enabling the generation of high-quality and diverse patterns, providing a reliable generative model foundation for subsequent AI-assisted design teaching.

C. DESIGN AND EXPERIMENT OF AI-ASSISTED TEACHING PLATFORM

For the application of the models of AI-generated knowledge to real teaching it was necessary to develop a web-based “AI Pattern Innovation Design Platform”. The front end of the platform is developed using the latest version of the web technologies: html5 and css3, whereas the back end of the application is developed on python reports flask framework where a pre training version of c dggan model has been integrated. The main functional modules of the platform provide: (1) Pattern library browsing: the display of classic patterns of different categories in the dataset and their corresponding explanations of cultural background; (2) AI generation: students choose a pattern category and click the generate button, and the platform will call the model to generate 4 alternative patterns in real time, and when the random seed is adjusted, different results can be obtained; (3) Editing and adjustment: simple color editing, scaling and rotation of the generated patterns, allowing for export to vector or bitmap file; (4) Saving and sharing works: students can save and record their designs in The teaching experiment took place in the course “Innovative Design of Traditional Patterns” of a design college at a university. The course was 32 class hours and took 8 weeks. Two parallel classes were chosen as experimental group and control group, and each of them includes 30 students. Before the course started, a pre-test (including a theoretical knowledge test and a basic design skills assessment) was conducted to quantitatively compare the academic performance and design foundation of the two groups of students. The independent samples t-test results showed no significant difference between the two groups ($p > 0.05$). The courses contents were sorted into three stages: the first stage (2 weeks), which included the history and culture of traditional textile patterns and the analysis of classic patterns; The second phase (4 weeks) focuses on design practice, aiming to observe how the experimental group uses an artificial intelligence platform to assist in creating traditional textile patterns, while the

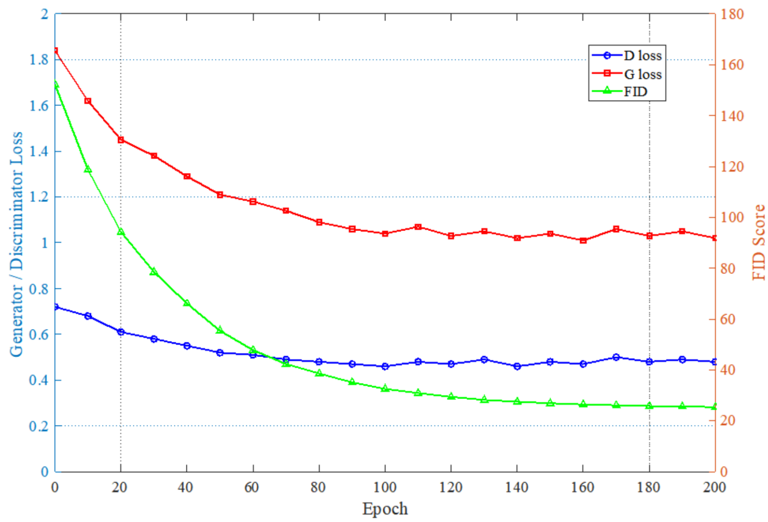

FIGURE 1. Convergence data

control group uses traditional hand-drawing and copying methods (defined here as using only paper reference books, scanners or digital cameras to collect materials, without using any Internet image search engines, online digital museums or generative AI tools).; the third stage (2 weeks), which focused on refining and showcasing the students work. Throughout the teaching process the students creative process, the numbers of work produced and the numbers of revision were recorded. Student work and questionnaire data were collected at the end of the course. Informed consent was obtained from all participants.

IV. RESULTS AND DISCUSSION

A. QUALITY ASSESSMENT OF GENERATED PATTERNS AND FEATURE ANALYSIS OF DATASET

To objectively assess the quality of patterns produced by C-DCGAN the Frerech Inception Distance (FID) was used as an evaluation metric. FID is used to measure the distributional similarity between two sets of images, i.e. obtain the distance between the real and generated images in the feature space of the Inception network, and the smaller the FID value, the better the generated images are. 2000 real images were randomly selected from the test set according to each category, and 1000 randomly generated images were paired with each corresponding category to obtain the FID value. The results come on the Table 2.

TABLE 2. FID values of generated images for each pattern category

Pattern categories	FID value	Generate image subjective feature description
Geometric patterns	24.7	The lines are clear, the structure is regular, and it conforms to geometric principles.
Plant pattern	31.2	The flower and leaf shapes are diverse, and some details are slightly blurred.
Animal print	38.5	The animal outlines are accurate, but the internal textures are occasionally distorted.
Human figure pattern	45.3	The character's pose is generally reasonable, but facial details need improvement.
Text pattern	52.1	The structure of the characters is recognizable, but the strokes lack continuity.
Cloud patterns	28.6	Strong sense of flow, natural curves
Floral pattern	33.4	The petals are richly layered, with soft color transitions.
Bird and animal patterns	40.2	The birds and animals are depicted in vivid poses, but the feather patterns are somewhat blurred.
Landscape pattern	36.8	The arrangement of rocks and trees is reasonable, and the artistic conception is well expressed.
Auspicious combination patterns	42.9	The combination of various elements is harmonious, but the integration of details is insufficient.

As shown in table 2, geometric patterns have the lowest FID value (24.7) and the best generation effect, which is related to their strong structure and clear regularity. Natural themes such as plant and floral patterns have FID values between 31 and 34 and the generated images can capture the main morphological features. Animal and bird/beast patterns have higher FID values as a result of their complicated details. Text patterns have the highest FID value (52.1) showing that it is still difficult to generate text patterns with defined semantics. The above data shows that the generated images have a relatively close similarity with the distribution of real patterns, and the model is able to learn the basic compositional rules of traditional patterns. Further observation of the generated images, we can see that although only keeping traditional elements, they also have novel combinations, such as the same flower's local features also belong to different flowers, the geometric patterns are also distorted, presentation of visual effect is familiar and unfamiliar, which demonstrates the innovative capabilities of AI.

B. EVALUATION OF STUDENT DESIGN WORKS

After the course, 30 final design works of each of experimental and control group were collected. Three experts in textile design (one university professor, one designer and one craft artist) were invited to do blind reviews of the works. The scoring dimensions included: (1) traditionality (whether or not the pattern conforms to traditional aesthetics and cultural connotations); (2) innovation (whether or not the pattern has a novel form or composition); (3) aesthetics (overall visual effect and color matching); and (4) technicality (smoothness of

lines and handling of details). The score of each dimension was put out from 10 and the average score of three experts was considered as the final score. The statistical results are given in Table 3.

TABLE 3. Comparison of scores for student design works between the experimental group and the control group (mean ± standard deviation)

Rating Dimensions	Experimental group (n=30)	Control group (n=30)	t-value	p-value
Traditional	7.8±1.2	8.1±1.1	1.02	> 0.05
Innovation	8.5±0.9	6.7±1.3	6.15	< 0.001
Aesthetics	8.2±1.0	7.5±1.2	2.44	< 0.05
technical	7.9±1.1	7.8±1.0	0.37	> 0.05

Table 3 proves that in the traditional dimension, there was no significant difference in scores between the two groups ($p > 0.05$), which means the use of AI assistance did not weaken the students' understanding of traditional elements, and the patterns generated still reflected traditional elements. In the innovative dimension, the experimental group obtained significantly higher results compared with the control group (8.5 vs 6.7, $p < 0.001$) which means that the AI tool activated the creativity of the students and the wide variation of patterns for the students became more sources of inspiration to them. The experimental group also performed better than the control group in the aesthetic dimension ($p < 0.05$), which may have been because of the harmony in color and composition of the AI-generated images. There was no significant difference between the two groups in the area of technical dimension, hence, it can be concluded that hand-drawing and AI assistance have their pros as well as cons in terms of technical expression. Overall, the use of AI technologyenabling teaching process assists in enhancing the innovative design capabilities of students without deviating from tradition.

C. ANALYSIS OF QUESTIONNAIRE SURVEY ON TEACHING EFFECTIVENESS

After the course, an anonymous questionnaire was conducted on the 30 students in the experimental group to understand their attitudes and learning experiences regarding AI-assisted teaching. Simultaneously, for comparative analysis, a questionnaire was also distributed to the 30 students in the control group, primarily investigating their subjective feelings regarding learning interest, design efficiency, and willingness to use tools under the traditional teaching model. The questionnaire used a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The experimental group questionnaire contained eight questions

covering aspects such as learning interest, tool usability, understanding of the traditional model, and design efficiency; the control group questionnaire was designed around comparable dimensions such as learning interest, design efficiency, acquisition of design inspiration, understanding of traditional patterns, and whether they wished to introduce auxiliary tools, containing five questions. Statistical analysis results are shown in Table 4.

TABLE 4. Comparison of student evaluations of teaching effectiveness between the experimental group and the control group

Question	Experimental Group (N=30)	Control Group (N=30)	t-value	p-value
1. Learning interest (EG: AI tools increased my learning interest; CG: I had high learning interest in this course)	4.6±0.5	3.8±0.9	4.12	< 0.001
2. Design efficiency (EG: AI tools helped me complete design solutions faster; CG: I could complete design solutions efficiently)	4.5±0.5	3.5±1.0	4.89	< 0.001
3. Design inspiration (EG: Generated patterns gave me inspiration; CG: I could gain design inspiration from traditional patterns)	4.8±0.4	3.9±0.8	5.23	< 0.001
4. Understanding of traditional patterns (EG: Using AI gave me a deeper understanding of structural principles of traditional patterns; CG: Through course learning, I gained a good understanding of structural principles of traditional patterns)	4.3±0.6	4.1±0.7	1.15	> 0.05
5. Willingness to continue using / hope to introduce 辅助tools (EG: I am willing to continue using AI tools in future design; CG: I hope AI-assisted tools can be introduced in future courses)	4.7±0.5	4.2±0.8	2.89	< 0.01

Table 4 shows that the experimental group students had a positive overall evaluation of AI-assisted teaching. Compared with the control group, the experimental group significantly outperformed the control group in learning interest (4.6 vs. 3.8, $p < 0.001$), design efficiency (4.5 vs. 3.5, $p < 0.001$), design inspiration (4.8 vs. 3.9, $p < 0.001$), and willingness to use assistive tools in the future (4.7 vs. 4.2, $p < 0.01$). There was no significant difference between the two groups in their understanding of traditional patterns ($p > 0.05$), indicating that AI-assisted teaching did not weaken students' understanding of traditional elements. The relatively low score on question 7 (3.9 points) indicates that some generated results require manual optimization, and there is still room for improvement in the controllability of the tool. The questionnaire results and expert scores corroborate each other, jointly demonstrating that the AI-enabled teaching model has significant advantages in stimulating innovation, improving learning interest, and enhancing design efficiency.

V. CONCLUSION

This study is aimed at the application of AI in the teaching practice traditional textile pattern art design. A dataset consisting of 5680 images in 10 categories of traditional textile patterns was built. The pattern generation method based on conditional deep convolutional generative adversarial networks was proposed, and the AI-assisted design teaching platform was constructed and used for the actual teaching of the course. The role of AI in teaching in terms of the quality of images, expert scoring of student work, and questionnaire surveys was systematically analyzed.

The results reveal that: (1) The constructed dataset contains wide-ranging categories of patterns and historical periods, which can serve as a high-quality data basis for AI model training; (2) The C-DCGAN model has the ability to create patterns that integrate traditional features and innovative forms of the pattern. Among them, geometric patterns, plant patterns have better generation effect, while complex category such as text patterns need to be improved, (3) Students have a high acceptance of AI tools and think that they can stimulate interest, encourage creativity and bring better efficiency in design.

This study opens up feasible path for digital inheritance and design education innovation of traditional textile pattern, but it also exists certain limitations, which may include the following: the generative model has certain limitations to express complex pattern, the human-computer interaction function of teaching platform needs to be raised. Future work will investigate more advanced generative models (such as the diffusion models) and to combine them with augmented reality technology to actualize real-time presentation of their patterns on virtual fabrics, further promoting the revitalization and application of traditional patterns in contemporary design. Through technological empowerment and teaching innovation, it is hoped that the textile pattern, which was being "protected," can be turned to being "created," and ancient patterns will be able to radiate new vitality in the AI era.

AUTHOR CONTRIBUTIONS

Jing Wang designed, collected and analyzed the data, and drafted the manuscript. Jing Wang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jing Wang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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