Research on the Application of Song Dynasty Peony Patterns Based on the SD-LoRA Model

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***Abstract*— This paper responds to the growing use of AIGC in the cultural and creative industries. It targets two common issues in general-purpose foundation models for traditional pattern generation: distortion of cultural features and weak structural control. We propose an SD–LoRA modeling pathway that integrates design semiotics and cultural translation theory, and use Song-dynasty Luoyang peony motifs to explore a digital innovation route for traditional pattern design. First, we construct a high-quality peony motif dataset from authoritative museums in China. We then add semantic annotations across three translation layers: form, imagery, and context. Second, we combine LoRA fine-tuning with Stable Diffusion to train a LoRA model that can accurately capture and reproduce the aesthetic features of Song patterns. Finally, we enable controllable generation and practical application through parameter tuning. The proposed method supports the digital regeneration and creative transformation of Song peony motifs. The generated outcomes retain traditional spirit while presenting modern visual appeal. This work offers an efficient and culturally grounded paradigm for cultural product design.**

***Keywords*— Generative AI; Song-dynasty peony motifs; Digital design innovation; Extended design applications; Innovative design**

I. INTRODUCTION

Against the backdrop of the deep integration of artificial intelligence and the cultural and creative industries[1], the living transmission and innovative transformation of intangible cultural heritage (ICH) has become a key issue today[2]. With the rapid iteration of AIGC technologies, represented by general-purpose large language models (AI-Generated Content, AIGC), platforms such as Stable Diffusion and Midjourney now offer text-to-image and image-to-image functions. These tools create new possibilities for addressing long-standing problems in ICH-related cultural product design, including homogenized outcomes, high development costs, and breaks in craft inheritance[3]. However, there are still notable limitations in systematically integrating AIGC into the full workflow of ICH cultural and creative design[4].

At present, for ICH elements, the text-to-image capability of general foundation models—such as Alibaba Tongyi—still relies on insufficient data accumulation. As a result, generated images can be overly random and divergent. Fine-grained control is often lacking, and this makes it difficult to meet industry needs. In particular, key steps such as intelligent identification of cultural "genes" and the translational innovation of design semantics still require further exploration[5]. Therefore, a central challenge remains: how to ensure accurate communication of ICH-specific styles while also enabling the migration and reuse of its core elements.

However, simple element transfer can easily lead to superficial cultural imagery and the misuse of symbols. To avoid this, this study takes design semiotics and cultural translation theory as its foundation. It reframes "transfer" as "cultural translation" that is theory-guided and structured in layers. Based on this approach, we build a systematic, intelligent pathway that links traditional motifs to modern design innovation. We also explore creative routes in multiple contexts where these motifs can function as digital assets, including apparel and textiles, traditional cultural products and decorative arts, and film, animation, and digital media.

Our goal is to provide a feasible technical pathway and to map potential application scenarios for revitalizing Song-dynasty peony motifs and other traditional patterns. In addition, this work offers a useful reference for the transformation of similar cultural symbols. It aims to achieve dual empowerment for cultural heritage continuity and industrial innovation[6].

II. PRELIMINARY RESEARCH AND PREPARATION

A. Current Development of AIGC

AIGC is entering a critical phase of rapid technical iteration and deep industrial integration. Tools and platforms such as Stable Diffusion, Midjourney, and Jimeng are accelerating a fundamental shift in artistic creation. They can simulate aspects of human creative thinking and aesthetic judgment. They also generate outputs that appear both artistic and novel. As a result, the mode of art-making is being reshaped[7]. Under this new paradigm, the designer's role is gradually changing. Designers are less often the direct maker. They are increasingly responsible for guiding decisions and controlling aesthetics[8].

In design practice, rising living standards have raised public expectations for product appearance. At the same time, the social value created by design has received wider attention[9]. AIGC can offer efficient and highly generative design solutions. It can also help traditional cultural elements enter everyday life in more accessible ways[10,11]. However, mainstream foundation models often produce distorted results when generating traditional cultural patterns (Figure 1) [12]. The root cause is structural. General-purpose

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models are trained on massive internet data. They often fail to capture the rigorous and precise compositional rules that are central to many East Asian traditional patterns[13].

To address the resource burden of fine-tuning large models such as Stable Diffusion, LoRA provides a lightweight and efficient solution. Its key idea is low-rank decomposition. It adds two small low-rank matrices (A and B) in parallel with the original weights. During fine-tuning, the base model parameters remain frozen. Only these low-rank matrices are updated. This sharply reduces the number of trainable parameters. It also lowers compute and memory costs. With this approach, researchers can achieve efficient customization for specific styles or themes under limited resources. Using lightweight adapters, LoRA can inject domain knowledge into a pre-trained model without changing its original parameters. This enables more precise control over generation. After integrating LoRA, text-to-image models can follow semantic instructions more reliably. They can also produce high-quality images with consistent styles that better match domain requirements, which leads to clear improvements in generation performance.

B. *Research Status of Luoyang Peony Motifs*

As a highly representative cultural symbol in the history of Chinese decorative arts, the Luoyang peony motif embodies refined craft achievements across multiple dynasties. It has also continuously carried social ideas and aesthetic changes over time[14]. Its visual form evolved from the full and luxuriant style of the Tang dynasty, to the restrained and rational elegance of the Song dynasty, and then to the complex and diverse forms of the Ming and Qing dynasties. This trajectory clearly reflects the historical development of Chinese making concepts and cultural creativity[15].

In contemporary practice, Luoyang peony motifs have been applied in various cultural and creative product domains. This has become an important approach for revitalizing traditional patterns and supporting cultural communication[16]. However, current design approaches show strong homogenization. The workflow also relies heavily on manual labor. These issues make it difficult to meet enterprise needs for large-scale and diversified production.

In response, some studies have begun to explore the use of AIGC for generating traditional patterns[17]. Yet research on intelligent generation for Luoyang peony motifs remains at an early stage, especially for period-specific styles such as those of the Song dynasty. A key reason is that general-purpose models are trained on broad and heterogeneous data. They lack precise, high-quality learning from specific traditional pattern datasets. As a result, they often fail to achieve sufficient "cultural fidelity" when generating Song-dynasty peony motifs.

Fig. 1.Cultural products featuring Song-dynasty peony motifs generated with Alibaba Tongyi. (Source: AIGC)

C. *A Theoretical Framework of Cultural Translation and a Design Interpretation*

With the growing integration of AIGC and cultural and creative practice, general-purpose foundation models often produce traditional patterns that "look similar but feel wrong." The overall form may appear close, yet the internal order, tone, and semantics can drift. To move beyond simple "style transfer" and reach outputs that are truly usable for design, a clear design framework is needed to constrain and explain the generation process.

This paper treats the Song-dynasty peony motif as a symbolic system composed of both formal language and design semantics. Its signifier is the visible structure of the motif, such as symmetrical or balanced composition, the S-shaped vine backbone, the closed outline of roundels, and the tiling logic of continuous patterns. Its signified refers to more stable semantic orientations in Song aesthetics and making culture, such as elegance, restraint, a sense of order, and an awareness of blank space. The key task in design is not to copy the surface appearance[18]. It is to translate these structures and meanings into operable design constraints. In this way, the internal qualities of the symbol can go beyond the visual surface, become clear signals, and remain identifiable and sustainable over time[19].

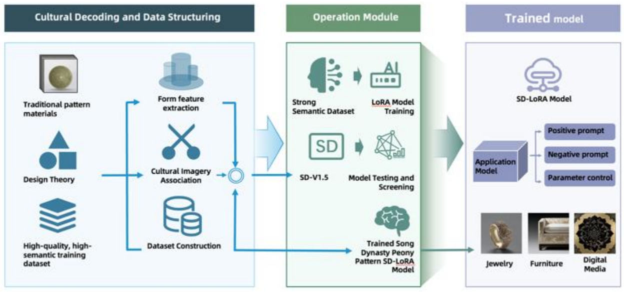


Fig. 2.AIGC cultural-translation workflow for Song-dynasty peony motifs. (Source: Author)

Based on this understanding, this paper proposes a three-layer cultural translation model for AIGC-assisted design. It establishes a reproducible research pathway:

1) *Formal translation*

Formal translation is the foundational layer. Its task is to convert the visible form of the motif into a formal grammar that is describable, taggable, and reusable. Technically, it relies on a high-quality dataset and precise labels. This enables the model to learn the structural rules of Song-dynasty peony motifs, such as the S-shaped rhythm of scrolling vines, the hierarchy and closure relations of roundels, and the docking rules of continuous patterns. This layer ensures the structural stability of the generated results.

2) *Imagery translation*

Imagery translation is the core layer. Its task is to turn key qualities of Song aesthetics into executable prompts and generation constraints. It does not aim to stack adjectives. Instead, it maps aesthetic requirements such as "elegant," "rational," and "restrained" onto perceptible visual cues. Examples include the ratio of blank space, an upper limit on detail density, line thinness, and color saturation. These constraints guide generation to remain consistent with the Song context in both style and tone.

3) *Context translation*

Context translation is the goal layer. Its task is to make the motif valid in new products and scenarios. It requires designers to consider scale, curvature, materials, and process constraints during both generation and redesign. Based on these conditions, the unit size, repeat interval, and structural direction of the motif are adjusted. In this way, the motif is not simply "applied" onto the surface. It forms a new integrated meaning together with product form and use.

This model stresses continuity across the three layers of "form–imagery–context." Formal grammar provides structural stability. Semantic constraints maintain aesthetic alignment. Carrier conditions ensure practical implementation. The data structuring, LoRA training, prompt framework, and generation screening presented later all follow this model. This ensures that the outputs are explainable and verifiable, both in cultural recognizability and in design usability.

III. Feature Analysis of Song-Dynasty Peony Motifs

In the historical development of Luoyang peony motifs, the Song dynasty stands out as a key period when the style became mature and its aesthetic features grew highly distinctive. Therefore, this study focuses on Song-dynasty peony motifs. It analyzes their core characteristics from two dimensions: compositional form and spiritual connotation. This analysis provides clear aesthetic criteria and a theoretical framework for subsequent SD–LoRA training and generation.

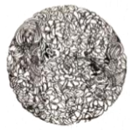
Importantly, this article does not stop at a formal summary. Instead, it adopts the perspectives of design semiotics and cultural translation. It offers a relational reading of the signifier and the signified. We examine how formal features (the signifier) carry and express the period's spiritual meanings and aesthetic ideals (the signified). For this purpose, all formal categories and descriptions in the following sections are linked to the cultural imagery behind them. We then distill these insights into translatable prompts that AIGC models can understand. In this way, this article builds an aesthetic standard and a semantic repository that are both culturally grounded and operational. They serve as the basis for later SD–LoRA training and generation.

A. Compositional Form of Song-Dynasty Peony Motifs

In composition and layout, Song-dynasty peony motifs emphasize refined shaping and the use of symmetry. They also prioritize the expression of artistic mood. Their formal structure can be summarized into three layers (Table I): the core subject, auxiliary elements, and layout patterns. The core subject is mainly expressed through broken-branch peonies, scrolling-vine peonies, and chained-branch peonies. Common auxiliary elements include arabesque (scroll) patterns, begonia motifs, and ruyi cloud-head forms. Different compositional methods produce different degrees of visual harmony and structural stability[20]. Together, these features reflect a high-level unity between rational order and natural elegance in Song pattern design.

TABLE I. Classification of compositional forms in Song-dynasty peony motifs.

Design Dimension	***Design Theme***	***Visual Representation***	***Parameter Specification***	***Cultural Imagery***
Composition	**symmetrical composition**		Centered on an axis; strict mirror symmetry, stable and formal.	Confucian "Doctrine of the Mean" and ritual order; absolute symmetry, formality, and gravitas.
	fitted (adapted-to-form) composition		Form-adapted layout; motifs follow the object's contour for functional fit.	Form-giving by the object; harmony of humans and nature, respect for the object's inherent form.
	balanced composition		Beyond strict symmetry; diagonal branching and solid–void balance create dynamic stability.	"White as black" (void–solid) aesthetics; rational restraint and dynamic balance.
	two-way continuous pattern (repeat)		Scrolling vine framework; one-directional repeat forming a continuous band rhythm.	Continuity of time and life; auspicious renewal, longevity, and cyclical flourishing.
	four-way continuous pattern (all-over repeat)		Grid-based all-over repeat; seamless extension in all directions.	Extreme rational order; abstraction of natural laws in the Song aesthetic.

Design Dimension	Design Theme	Visual Representation	Parameter Specification	Cultural Imagery
Leaf-and-branch forms	**Scrolling vine**		S-curving vines with continuous branching; peonies and curled leaves alternate in a balanced dense–sparse rhythm.	Endless vitality; elastic S-curve rhythm as a direct expression of “living resonance” (qiyun).
	Linked-branch (vertical) floral pattern		A vertical main stem with serial blossoms; staggered heights along the branch.	Hierarchical order and growth sequence; a “visual regulated verse,” strict yet varied.
	Broken-branch peony motif		Dominant upright stem; blossoms linked in sequence with varied vertical spacing.	Broken-branch poetics; selective framing of nature with lyrical observation.
Pattern	**floral medallion (roundel)**		Closed circular form; centered peony with encircling foliage; flat outer petals and inward-curled inner tips.	Wholeness and auspicious completion; full, centripetal unity.
	baoxiang flower (baoxianghua) motif		Symmetrical radial layout; geometric petals with lotus-like core; layered gilt petals and leaf-edges linked to scrollwork.	Buddhist baoxiang ideal-flower symbol; solemn purity and ornamental transcendental order
	single-bloom (flowerhead) motif		Single isolated bloom; full layered petals—outer petals open, inner petals curled.	Song “investigation of things” (gewu); focused observation and refined depiction of floral form.

B. Meaning and Aesthetic Characteristics of Song-Dynasty Peony Motifs

The Song dynasty was a crucial period when China’s traditional aesthetics of making became more mature and further refined[21]. As a material carrier of the era’s spirit and aesthetic ideals[22], Song-dynasty peony motifs were shaped by both prevailing tastes and urban citizen culture. They developed artistic features that differ clearly from those of the Tang dynasty. In terms of visual expression, Song peony motifs show a rhythmic beauty under rational rules and regulation[23]. At the same time, their meanings increasingly absorbed the poetic and painterly atmosphere of literati culture, and thus convey a strong humanistic sense of artistic mood. These aesthetic qualities not only give Song peony motifs distinctive artistic value, but also reflect the cultural integration capacity, the spirit of the time, and the social landscape of the Northern and Southern Song periods[24].

IV. SD–LoRA Model Training and Design Applications for Song-Dynasty Peony Motifs

Training a dedicated SD–LoRA model for Song-dynasty peony motifs can address the geometric distortions and structural collapse that often occur when general-purpose foundation models generate this type of traditional pattern. Guided by the rigorous compositional logic and aesthetic principles of Song motifs, the goal is to efficiently produce innovative pattern forms that meet contemporary aesthetic needs while fully inheriting the key aesthetic features of Song-dynasty design thinking.

To achieve this goal, the research workflow is organized into three main stages: a) Data Structuring; b) SD–LoRA Model Training; and c) Generation with Screening and Validation.

A. Data Structuring

The image dataset used for training in this study mainly comes from digital collections held by major museums in China, such as the Palace Museum and the National Museum of China. All images were carefully screened and curated. On the basis of accuracy and authority, we adopted a cultural translation perspective. We prioritized samples that clearly represent key Song aesthetic features, such as rationality, elegance, and a sense of order. Therefore, data structuring is not only a technical preparation for building the training set. It is also a systematic process of cultural feature annotation and a preparatory step for translation.

We did not use simple style labels. Instead, we adopted an annotation system that tightly links the form of Song peony motifs with their cultural semantics. In this study, the retrieval keywords were organized into two levels: primary keywords and refined keywords. Each image was tagged with a corresponding set of refined labels (Table II). As shown in Table II, the labeling stage aims to translate the aesthetic features identified earlier into “cultural vocabularies” that are machine-readable and machine-interpretable. For example, for a “scrolling-vine peony motif,” we do not only tag its name. We also extract its core cultural and formal genes, and assign labels such as “S-shaped rotation,” “continuous extension,” and “alternating distribution.” In essence, this process breaks down abstract aesthetic concepts—such as Song notions of “rational order” and “natural elegance”—into concrete and operable visual elements. The purpose is to help the AI model not only “see” the pattern, but also begin to “understand” the motion, vitality, and organizational logic behind its form. This provides a foundation for the later, deeper stage of imagery translation.

For image quality, we selected images at a resolution of 512 × 512 pixels. Experiments show that at this resolution, the pixel coverage of key motif feature points (e.g., petal veins and geometric nodes) reaches at least 85%. When selecting image materials, we ensured motif completeness and high overall clarity. We also tended to use images with a solid-color background.

B. SD–LoRA Model Training

During the model training stage, we used a high-resolution image dataset that covers five categories of floral motifs and seven geometric subtypes. We applied LoRA to fine-tune a pre-trained visual model. This enables multi-level recognition of motif features.

The experimental setup is as follows: CPU: 12th Gen Intel(R) Core(TM) i9-12900H at 2.50 GHz; GPU: NVIDIA GeForce RTX 3070 Laptop GPU with 8GB GDDR6 (140W full-power version); OS: Windows 11.

For training, we used the Kohya (special edition) LoRA training platform provided on Alibaba Cloud. This platform is an open-source toolkit designed for fine-tuning Stable Diffusion (SD) models. It is especially effective for LoRA-based training with low resource consumption, lightweight deployment, and efficient dataset use. The experimental procedure is described below:

1) Parameter Settings

In this training, we used SD 1.5 as the base model. After confirming that the annotation for each image was accurate, we added the images to the training set. The total steps were calculated using:

steps = NUM (number of images) × repeats (15) × epochs / batch size (default: 1).

Based on this calculation, we set epochs to 28. We selected the cosine learning-rate scheduler to reduce the risk of overfitting, which may cause the LoRA model to learn the motif in an overly rigid way. We set the Text Encoder learning rate to 0.00001 and the U-Net learning rate to 0.0001.

For Network Rank and Network Alpha, the values typically depend on whether the training target is closer to 2D or 3D visual characteristics. Given the goal of this experiment, we set Network Rank = 128 and Network Alpha = 64.

TABLE II. DATASET CAPTIONING.

Image	**Tagging**	***Description***
	Pattern display format: symbolic units Concept of pattern display format Formal symbolic units of the pattern Concept of pattern form Formal style of the pattern Dynamic formal tension of the pattern	scrolling-vine peony motif; the vines curl in an S-shaped rhythm, with branches extending continuously; peony blossoms and scrolling leaves alternate, with a well-balanced density; four-way continuous pattern; the pattern can extend infinitely in both horizontal and vertical directions; the motif is arranged in a grid, with smooth connections in all directions; a sense of order; repetitive extension;

2) Model Testing

With 28 epochs, the training produced 28 LoRA checkpoints. We saved one checkpoint every two epochs. After training, we conducted a comparative analysis and evaluation of the generated LoRA models based on their generation performance.

Experiments showed that every five adjacent checkpoints produced similar images under the same weight setting. Therefore, we selected checkpoints 10, 15, 20, 25, and 28 as variable X. We set the LoRA weight as variable Y, with values of 0.0, 0.4, 0.7, 0.8, and 1.0. We then plotted X and Y as a chart (Figure 3). Through comparison, we chose the model and corresponding weight with the most satisfactory preview results, and used them for subsequent design applications of peony motifs.

Fig. 3. X–Y plot for comparing LoRA image-generation results.

3) Generation and Screening Validation

Based on the comparative experiments above, we selected SONGD-00007 as the SD–LoRA model for subsequent generation tasks in the extended design of Song-dynasty peony motifs, due to its stable performance. During generation, we applied this LoRA model and used prompt engineering to guide the SD 1.5 base model. This approach helps control the cultural style and visual features of the outputs more effectively (Figure 4).

During the generation stage, the prompt framework developed in this study (Table III) serves as an operational guide for cultural translation. It translates the aesthetic analysis at the theoretical level into practical instructions that control the generation behavior of the SD–LoRA model. This framework systematically maps the core cultural features of Song-dynasty peony motifs to adjustable generation parameters. Through this two-way control strategy, the study achieves precise reconstruction and stable output of key design elements in Song peony motifs. As a result, the generated outcomes remain well aligned with the intended design goals (Figure 5).

Fig. 4. Comparison of outputs with and without LoRA (left: with; right: without). (Source: AIGC)

C. Design Applications

To further validate the performance of the trained SD-LoRA model across heterogeneous design scenarios, this study selected three application domains where LoRA is currently widely adopted—cultural and decorative products, textile/fabric-based products, and film & digital media. By generating concrete design outputs in each domain, we examined how effectively the model transfers and translates the Song-dynasty peony motif onto different product types, materials, and media contexts.

TABLE III. FRAMEWORK FOR POSITIVE AND DIRECTIONAL PROMPT WRITING.

Positive Prompt		***Negative Prompt***	
Trigger Terms	luxury jewelry, necklace, earrings, ring	Style Exclusions	modern style, contemporary minimalist jewelry, Western jewelry style, simple circular chain, generic chain-link design
Style	Song-dynasty aesthetics, literati painting sensibility, refined, elegant, restrained, classic "branched turning" structure" structure	Material Exclusions	plastic, synthetic materials, low-cost metals, cheap alloy, imitation gemstones
Form	single peony bloom, standalone blossom, layered petals, full petals, outer petals unfurling, inner petals curled inward, visible turns and pauses	Color Exclusions	bright yellow, neon colors, oversaturated palette, clashing gemstone colors
Cultural Symbols	Song aesthetics, peony motif, branched turning form, literati painting style, traditional Chinese silk	Form Exclusions	rigid template symmetry, overly complex composition, unnatural petal shapes, awkward geometry
Color	Matte gold tones; dark silk background; high-end contrast	Detail Exclusions	blurry, low resolution, poor lighting, visible seams, visible glue, unrealistic gemstone cuts, artificial-looking reflections
Materials	Large sapphires; fine gold filigree threads; yellow diamonds; pearls; turquoise; jadeite; diamonds; matte gold; filigree craftsmanship	/	/
Other Details	master-level product photography, 8K, ultra-high definition, hyper-detailed, centered composition, studio lighting, luxurious texture, strong volume, clear structure	/	/

1) Cultural & Decorative Products: Luxury Jewelry Concept Generation

Following the completion of the SD-LoRA training for fashion-oriented pattern generation, the research moved into a practice-oriented design phase, using the model to recognize, extract, and creatively recompose the core formal features of Song-dynasty peony motifs in response to contemporary aesthetic expectations and product requirements. In the "luxury jewelry ring" generation case (Fig. 5), the SD-LoRA model enabled a systematic enactment of a three-layer cultural translation pathway, demonstrating how a historical motif can be re-contextualized as a contemporary luxury artifact.

At the formal translation level, the ring band does not replicate the original motif. Instead, it selectively captures the signature S-shaped swirling skeleton of the scrolling peony structure and refines it through abstraction and simplification. This ensures the motif remains legible and rhythmic within the ring's fine scale and wearable constraints, while preserving the continuity characteristic of vine-like ornamentation.

Fig. 5. Luxury Jewelry Concept Generation. (Source: AIGC)

At the imagery translation level, the overall composition avoids excessive flamboyance and deliberately aligns with the Song dynasty's rational and restrained aesthetic. Rather than dense decorative stacking, the stone setting adopts a controlled, orderly arrangement, producing a sense of "disciplined luxury" that resonates with principles such as achieving richness through economy and using negative space as an active aesthetic resource.

At the context translation level, the key advancement lies in shifting a motif historically deployed on planar carriers (e.g., silk or ceramics) into a three-dimensional precious-metal domain. The model generates not only ornamental placement but also plausible volumetric structure and light–shadow behavior consistent with metallic craft logic, indicating strong cross-media adaptability. Overall, this case suggests that a domain-specific LoRA model can improve design efficiency, broaden ideation ranges, and reduce repetitive labor compared with conventional workflows.

2) Textile & Fabric-Based Products: Pattern Adaptation for Contemporary Furniture

In the application to contemporary furniture, the SD-LoRA model demonstrates a robust capacity for translating a two-dimensional motif into a three-dimensional product surface. This process can be articulated across three complementary layers—composition, morphology, and aesthetic ambience.

First, at the composition translation layer, the upholstery pattern generation follows the Song textile logic of continuous repeat structures (e.g., modular all-over repeats). This supports large-area extension with visual coherence and reduces discontinuities at seams, inheriting a practical design intelligence embedded in historical pattern systems.

Fig. 6. The Integration of Song Dynasty Peony Motifs into Modern Furniture Design. (Source: AIGC)

Second, at the morphological translation layer, the model does not "paste" a flat motif onto a curved surface. Instead, it adjusts the branching direction and layout of the scrolling peony so the ornament appears to grow along the furniture's structural lines, achieving a "pattern-following-form" fit between decoration and geometry. This aligns with an adaptive compositional principle that emphasizes responding to form rather than overriding it.

Third, at the ambience translation layer, the model can generate materially distinct outputs (e.g., soft printed textiles versus shallow carved wood effects) while maintaining a consistent Song-inspired visual ethos—open spacing, restrained elegance, and a calm rational tone. As a result, the translated motif can resonate with contemporary minimalist interiors without losing its cultural identity, enabling a cross-temporal aesthetic reconciliation between classical order and modern simplicity.

3) Film & Digital Media: A Cultural Style Filter for Visual System Building

For film and digital media production, the trained SD-LoRA model is positioned as an efficient "cultural style filter"—a tool that rapidly generates background textures and visual system elements for key visuals and concept art (Fig. 7). Crucially, the target is not a single literal peony depiction, but the motif's underlying Song-dynasty signature: structural rigor, order, repeatability, and disciplined geometry.

Fig. 7. Song Dynasty peony motif background pattern. (Source: AIGC)

Through parameter control, the outputs can intentionally reduce excessive pictorial detail and dampen high saturation/contrast, while strengthening the motif's repeatable geometric qualities. This "filtering" approach transforms a historically dense cultural pattern into a functional contemporary graphic texture—appropriate for 3D scene mapping, interface backgrounds, or motion-graphic elements—while preserving cultural depth and a restrained, recognizable Eastern visual identity. In this way, the model supports a methodological shift from evidential reconstruction toward creative, system-oriented translation in digital contexts.

V. User Satisfaction Evaluation

To accommodate diverse design scenarios, this study incorporated a user-oriented workflow into the evaluation process. A total of 20 professionals and 20 non-professionals were invited to rate the generation quality of the proposed SD-LoRA model, yielding 40 valid questionnaires in total. The results indicate that the Song-dynasty peony pattern design series generated in this research received overall positive feedback. Across four dimensions—pattern accuracy, cultural appropriateness, design innovativeness, and aesthetic appeal (see Table IV)—the mean scores for all indicators exceeded 4.0 out of 5.0, and overall satisfaction reached 97.56%. More than half of the respondents described the series as "more innovative and modern," noting that it successfully achieves a contemporary translation of traditional motifs while preserving key Song-dynasty compositional features such as intertwined scrolling branches and serial branching structures. In addition, 87.8% of participants expressed willingness to purchase or use related cultural and creative products, suggesting that the generated designs not only foster cultural identification but also demonstrate strong potential for market conversion. Although a small number of respondents commented that certain outputs appeared "mechanical and less natural," the overall evaluation confirms the effectiveness and acceptance of the SD-LoRA model in pattern regeneration and creative transformation (see Fig. 8).

TABLE IV. Scores across evaluation dimensions by two user groups.

Evaluation Dimension	**Non-professional General Audience (N=20)**	***Design/Arts Students (N=20)***	***Difference Analysis***
Overall Mean Score (weighted across all dimensions)	4.08	4.08	Comparable
Pattern Accuracy	4.05	4.16	Design/arts students rated higher
Cultural Appropriateness	4.09	4.10	Comparable
Design Innovativeness	4.04	4.03	Comparable
Aesthetic Appeal	4.16	4.05	General audience rated higher

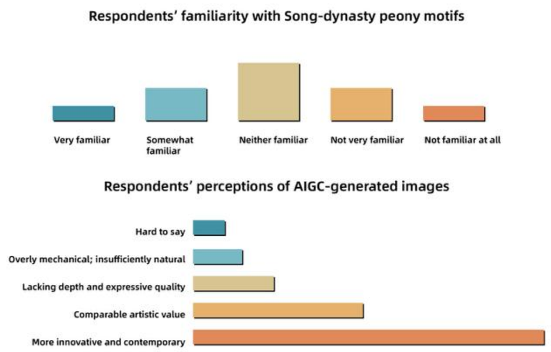


Fig. 8. User Feedback on AIGC-Assisted Design Based on Song-Dynasty Motifs.

VI. Conclusion

This study systematically developed and validated an SD-LoRA-based intelligent generation model for Song-dynasty peony motifs, enabling an end-to-end investigation spanning feature extraction, stylized control, and cross-media creative applications. The findings indicate that parameter-efficient fine-tuning of pretrained diffusion models via LoRA can effectively capture the intrinsic order and aesthetic characteristics of Song peony patterns in terms of compositional organization, line language, and spatial configuration. In doing so, it substantially mitigates key limitations commonly observed in general-purpose generative models when producing highly structured, semantically rich traditional motifs, including geometric distortion, structural collapse, and semantic drift. Overall, the proposed approach offers a technical pathway that is simultaneously high-fidelity, efficient, and controllable for the digital revitalization of intangible cultural heritage, and it advances AIGC from generic content generation toward more precise design capabilities tailored to vertical cultural domains.

Looking ahead, future work may (1) construct more authoritative and scalable multimodal datasets to strengthen the model's learning of motif genealogies and semantic nuances, and (2) integrate spatial constraint and control mechanisms—such as ControlNet—to achieve higher structural consistency and finer-grained local controllability. In parallel, establishing a comprehensive evaluation framework that combines objective metrics, expert review, and user feedback will be essential to improve interpretability and comparability of results. These directions will facilitate the extension of the proposed methodology to broader scenarios of digital innovation in intangible cultural heritage, providing sustainable technical and methodological support for the preservation-with-innovation of cultural heritage in the era of artificial intelligence.

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