Cultural Erosion or Innovation? Artisans’ Attitudes Toward AI-Generated Patterns in Chinese Traditional Subcultures

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Generative Artificial Intelligence (GAI), particularly text-to-image (T2I) generation tools, presents new possibilities for preserving and innovating traditional cultural patterns. However, AI-generated images often lack cultural context, which risks cultural bias and the loss of cultural significance. This study explores the use of GAI in generating culturally meaningful patterns, focusing on Chinese intangible cultural heritage Huayao cross-stitch as a case study. By applying Low-Rank Adaptation (LoRA) fine-tuning to optimize T2I tools and using in-situ interviews and focus groups, we collected feedback from 18 Huayao artisans. The results show that while fine-tuned models improved stylistic accuracy, the cultural meaning of the patterns remained insufficient. This research highlights AI’s limited role in cultural innovation and emphasizes the necessity for dynamically maintaining cultural authenticity through the daily practices of cultural holders. It also reflects on how AI might have a long-term impact on the creative position of artisan communities.

CCS CONCEPTS • **Applied computing → Arts and humanities • Human-centered computing → Empirical studies in HCI • Computing methodologies → Artificial intelligence**

Additional Keywords and Phrases: Generative Artificial Intelligence, Cultural Authenticity, Cultural Heritage Communities, Artisans’ Attitudes toward AI, Huayao Cross-Stitch

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1 INTRODUCTION

Generative Artificial Intelligence (GAI) technologies have developed rapidly, particularly text-to-image (T2I) generation tools, which have attracted significant attention in the fields of design, art, and cultural creativity [1]. T2I tools generate high-quality images from natural language inputs, offering efficiency and accessibility for creative practices, while also providing new pathways for the digital preservation and visual reproduction of traditional cultures [2, 3, 4]. However, the application of GAI in cultural domains has also sparked a range of controversies, particularly concerning cultural bias, contextual detachment, and questions of cultural authenticity in the generated content [5, 6, 7]. Existing studies have largely focused on improving technical performance—such as pattern accuracy, stylistic consistency, and generative diversity [8, 9, 10]—while often overlooking the critical role of holders of cultural heritage. Without mechanisms for embedding cultural context, AI-generated images risk misinterpretation, cultural alienation, and the erosion of expressive agency for marginalized cultures [11, 12, 13].

At the same time, intangible cultural heritage (ICH) faces dual challenges in the context of globalization: safeguarding cultural diversity and resisting cultural homogenization [14]. Morevoer, the revitalization and protection of ICH faces widespread challenges, including the aging of cultural holders, intergenerational discontinuities in craft transmission, and the dilution of cultural identity among younger generations in the digital age—all of which contribute to the increasing fragility of traditional practice systems [15]. In terms of creative practice, traditional communities are experiencing a growing need for pattern innovation, with creators increasingly relying on external visual resources for inspiration. The rise of AI is reshaping both the approach to image generation and the mechanisms of visual dissemination, prompting traditional cultures to reconfigure their modes of expression and cognitive frameworks in response to new technological conditions [16, 17]. Therefore, a key question in contemporary cultural production is how to preserve cultural meaning and at the same time support cultural expression and innovation in the age of AI.

This paper uses Huayao cross-stitch, a traditional Chinese cultural heritage, as a case study to examine the performance and cultural adaptability of GAI in pattern generation, with a particular focus on the evaluations and attitudes of holders of traditional culture. As a traditional craft imbued with profound cultural significance, Huayao cross-stitch faces dual challenges of innovation to reflect contemporary community life and interests, and at the same time preservation in cultural transmission [18]. GAI tools that are increasingly used across design practices may offer opportunities for traditional crafts such as Huayao cross-stitch to innovate in patterns in meaningful ways whilst at the same time helping to mitigate the risks of GAI cultural homogenization [19].

We seek to explore:

RQ1. Can GenAI tools effectively generate meaningful Chinese traditional subculture patterns?

RQ2. How do artisans from cultural heritage communities perceive AI-generated patterns?

RQ3. What are the attitudes of community artisans toward the use of AI in local cultural innovation?

To address these issues, this study applies Low-Rank Adaptation (LoRA) techniques to fine-tune a pre-trained generative model [20], aiming to produce patterns that more closely align with the stylistic characteristics of Huayao cross-stitch. In addition, in-situ interviews and focus group [21] were conducted with 18 artisans to collect feedback on the AI-generated patterns, examining their levels of acceptance, evaluative criteria, and potential value-based tensions. The AI-generated materials were employed as a form of technological probe to probe holders of cultural heritage's perceptions of pattern meaning, cultural expression, and authorship [22]. This approach is intended to provide a foundation for understanding how AI technologies may be more meaningfully embedded within community-based cultural practices. In this paper we take "meaningful" generation of images to mean: i) that the generated images visually conform the traditional styles, such as the cross-shaped topology and nested composition structures characteristic of Huayao cross-stitch; and ii) that the outputs are associated by cultural holders with their cultural meaning systems—even if such symbolic semantics are not explicitly encoded by the AI.

We contribute:

1. Identification of the potential application of LoRA fine-tuning technology in generating traditional cultural patterns, though further optimization is needed in reproducing cultural authenticity.
2. Reflections on the role and potential of AI in cultural innovation, emphasizing that cultural authenticity should be dynamically maintained through the daily practices of cultural holders.
3. Reflections on how the introduction of AI technology might redefine the sources of "creativity" and potentially impact the creative role of artisan communities over the long term.

This paper is organized as follows: First, we review the applications of GAI in preserving traditional cultural heritage and examine the challenges of integrating AI into the cultural innovation of Huayao cross-stitch. Next, we construct an AI-assisted generation pipeline by adapting a LoRA-based diffusion model to produce culturally meaningful patterns, and apply in-situ research methods to collect feedback from Huayao artisans. This is followed by an analysis of artisans' perspectives and attitudes toward AI-generated patterns, with a particular focus on issues of cultural accuracy. Finally, we reflect on the potential and limitations of AI in the context of cultural pattern innovation.

2 RELATED WORK

2.1 Cultural Erosion and Bias: GAI in Image Generation

The advancement of GAI and T2I technologies has introduced new tools for cultural heritage preservation [23, 24]. While previous approaches leveraging Generative Adversarial Networks (GANs) and Transformer-based models have been explored for cultural pattern generation, the former often suffers from mode collapse resulting in a limited variety of outputs, and the latter struggles to maintain semantic coherence in complex outputs [25, 26, 27]. Diffusion models, by contrast, have demonstrated greater stability and fidelity in generating structured features such as symmetry and repetitive units, though they are typically associated with high computational costs [28, 29, 30]. In this study, we adopt a diffusion-based framework enhanced by Low-Rank Adaptation (LoRA) fine-tuning to improve generation quality while reducing resource demands. This strategy enables the model to efficiently capture culturally specific features from limited ethnic datasets, thereby mitigating the dominant aesthetic biases often introduced by large-scale general-purpose training data [31, 32].

However, technical performance alone does not adequately reflect the cultural acceptability of AI-generated patterns. In the domain of ICH, AI-generated visuals can be used as agents capable of triggering complex responses related to identity, authenticity, and cultural judgment [33, 34, 35]. To address Research Question 1—whether GAI tools can generate "culturally meaningful" Chinese subcultural patterns—this study proposes a dual-criteria framework: first, technical fidelity to traditional stylistic conventions; second, cultural meaning as interpreted by community members, such that the generated patterns are situated within rather than detached from local systems of meaning. This research does not aim to optimize model performance per se, but rather to investigate how AI-generated images are interpreted and received within the cultural context of their training data. It is worth noting, however, that the low-rank parameter space of LoRA remains limited in its capacity to encode deeper cultural semantics—a limitation that will be further addressed in Section 4.

2.2 Cultural Agency in Marginalized Communities: Voices in Social Context

The issue of cultural bias in GAI reflects the systemic oppression of technological colonialism [36]. Mainstream GAI tools are predominantly trained on publicly available internet data, within which an implicit "digital hegemony" tends to marginalize non-Western and minority cultures [37, 38]. This is directly embedded in the power structures of default technical configurations: when marginalized communities are compelled to rely on generative tools trained on dominant cultural norms, their right to cultural expression is effectively ceded to the invisible frameworks of technological platforms. This not only undermines cultural authenticity but also exacerbates the expressive disadvantages of minority groups through technological hegemony [39, 40].

Against this backdrop, social constructivism offers a critical lens for understanding the interplay between technology and culture. The theory of technological mediation challenges technological determinism by emphasizing that the role of technology is shaped by the ways in which it is socially constructed [41, 42]. In the field of cultural heritage, the same technology may yield vastly different outcomes depending on its sociocultural setting. Therefore, by empowering marginalized communities and embedding considerations of cultural equity and diversity into technological design, human-centered technological practices can significantly enhance cultural representation. Cultural constructivism further provides a critical framework: cultural authenticity is not a static attribute, but a negotiated outcome of ongoing community practices [43]. Within this framework, culture holders—those who are directly engaged in the production, transmission, and interpretation of culture, and who possess authoritative knowledge of cultural symbols—are central to any technological intervention. If technological design fails to recognize their central agency, AI-generated "innovation" risks becoming complicit in cultural detachment. Therefore, this study uses the case of Huayao cross-stitch to explore how culture holders perceive AI-generated outputs (RQ2), and whether AI intervention is recognized as a legitimate pathway for innovation (RQ3).

2.3 Cultural and Pattern Features: Huayao Cross-Stitch

Huayao cross-stitch—a nationally recognized ICH craft led by Yao women and deeply embedded with narratives of ethnic history and lived experience—is explored in this paper as a representative case for examining how technological intervention can engage with cultural transmission under conditions of endangerment and cultural sensitivity. The endangered status of Huayao cross-stitch stems from a dual scarcity of craftsmanship and semantic knowledge. First, the craft is highly intricate, with each piece requiring hundreds of thousands of hand-stitched threads over the course of one to two years. Its transmission relies heavily on an oral master-apprentice model, which significantly limits the possibility of large-scale continuation. Second, the pattern's semantic system is deeply intertwined with Yao ritual practices and ethical frameworks. However, due to traditional burial customs, many works have been interred, resulting in a severe scarcity of both surviving physical artifacts and recorded meanings [18, 44].

The Huayao people, a small subgroup of the Yao ethnic group, are primarily located in the Huxing Mountain area of Longhui County, Hunan Province, China, and boast a cultural history that spans thousands of years. The Huayao area is named after the vibrant cross-stitch patterns on the wrap-around skirts worn by its women, where 'Hua' means 'flower', refers to the flower-like intricacy and beauty of the cross-stitch, and "Yao" which refers to the Yao ethnic group in Chinese. Historically, the Huayao had their own spoken language but did not develop a written script due to geographical isolation. Consequently, Huayao women utilize intricate cross-stitch patterns as a means of visual storytelling, recording and conveying their historical narratives, daily life, and aspirations for a better life [45]. In traditional Huayao clothing, the cross-stitch patterns on the wrap-around skirts not only cover the largest area but are also the most densest and spectacular parts, possessing significant aesthetic and socio-cultural value [46, 47], as shown in Figure 1.

Figure 1: Huayao traditional clothing and cross-stitch wrap-around skirt. (a) Left: Huayao women in traditional clothing. Photograph by Yaohua Liao, 2012. Adapted from [44]. (b) Right: Wrap-around skirt with Huayao cross-stitch. Photograph via Huayao Cros s-Stitch Digital Museum [48].

Huayao cross-stitch patterns are crafted using traditional textile techniques, showcasing the ethnic and regional culture of the Huayao people while embodying the wisdom and creativity passed down through generations of Huayao women. They have always adhered to the principle of “stitching what they see” without professional art training or the need for positioning tools, directly expressing their envisioned designs on fabric using needles and thread [45]. The inspiration for Huayao cross-stitch patterns mainly comes from nature and imagination, including animals, plants, and natural landscapes. Animal themes feature tigers, dragons, and snakes, while plant themes include trees, stone flowers, honeysuckle, and others. Most of these plant patterns are abstract creations derived from natural plant prototypes, as shown on the left of Figure 2. The most iconic pattern in Huayao attire is the “Stone Flower”, inspired by the abstract representation of circular moss found on rocks. According to local elders, this plant is especially common during harvest season, leading them to incorporate this beautiful and auspicious pattern into their skirts [44]. Additionally, through the use of their imagination, creators express their longing for an ideal life and stories of auspicious meanings. For example, the dragon, as a symbol of good fortune, is widely present in folklore, even though its true form has never been seen. The right side of Figure 2 shows typical themes in Huayao cross-stitch, such as dragons and horses.

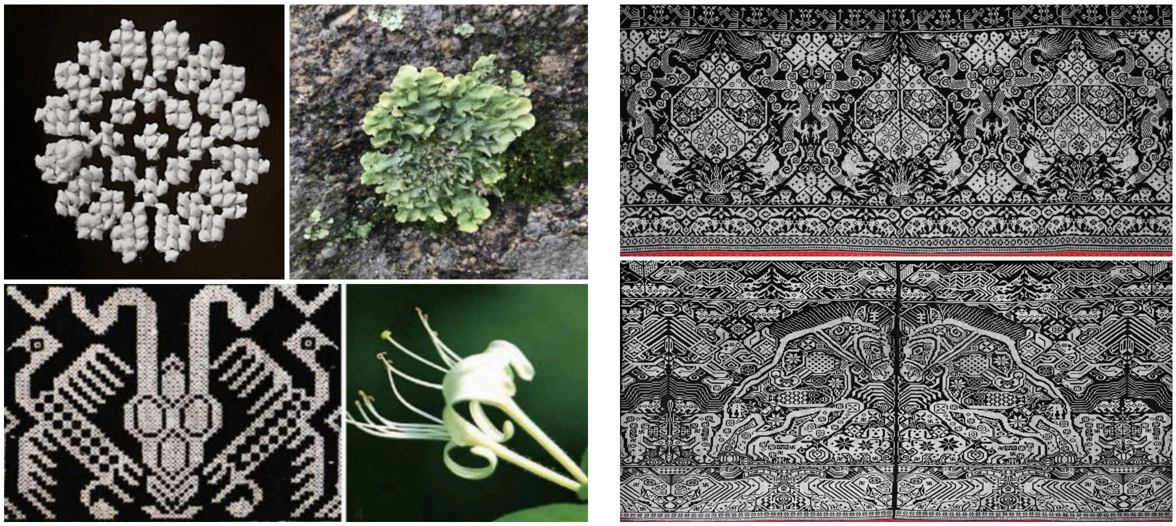

Figure 2: Representative examples of Huayao cross-stitch patterns. (a) Left: Filler patterns with botanical prototypes—stone flower (top) and honeysuckle (bottom). Photograph by Jiangjun Ruan. Reproduced from [44]. (b) Right: Complete patterns themed ar ound dragon (top) and horse (bottom). Photograph by Hou Lao. Reproduced from [45].

3 METHODS

This section takes the Chinese intangible cultural heritage of Huayao cross-stitch as a case study to explore whether deep learning GAI tools can generate culturally characteristic images. Drawing on the method of technology probes, the study treats AI-generated visuals as research triggers to examine how AI interventions in cultural creation may elicit value judgments, user attitudes, and cognitive mechanisms [22]. This methodological orientation informs the design of a mixed-methods framework. Section 3.1 constructs a dataset of 152 Huayao pattern images and explores whether culturally representative images can be generated using a diffusion model fine-tuned with LoRA, supported by a quantitative evaluation of output quality. Section 3.2 further evaluates the stylistic fidelity and cultural authenticity of the AI-generated images through qualitative fieldwork. These images served as visual stimuli in structured rating interviews (N = 10), expert in-depth interviews (N = 2), and focus group discussions (N = 6), involving a total of 18 artisans from the Huayao community.

3.1 Methods for AI-Generated Cultural Patterns

This section utilizes diffusion-based image generation techniques and debiased datasets to create patterns with visual characteristics of Huayao Cross-Stitch. Popular text-to-image models in GenAI, such as Midjourney, Stable Diffusion, and DALL·E, have been found to exhibit bias issues in their outputs, which may affect the accuracy and cultural representativeness of the generated patterns [6]. In preliminary experiments, we found that AI often misidentified Huayao patterns as belonging to other cultures, such as mistaking traditional Chinese Huayao patterns for Japanese traditional motifs.

To address this issue, we designed an AI-Generated Cultural Pattern Pipeline, as illustrated in Figure 3. This workflow incorporates LoRA (Low-Rank Adaptation) technology [31]. LoRA fine-tunes certain parameters of large pre-trained models, effectively preserving core knowledge and structure while offering an optimized approach to mitigating cultural bias. Compared to traditional full-model fine-tuning methods, LoRA performs better in generating patterns that align with specific cultural styles. To evaluate the effectiveness of this method, we designed a controlled experiment to compare the performance of the standard text-to-image generation method (M1) with the LoRA-integrated method (M2) in terms of image generation quality and stylistic expression.

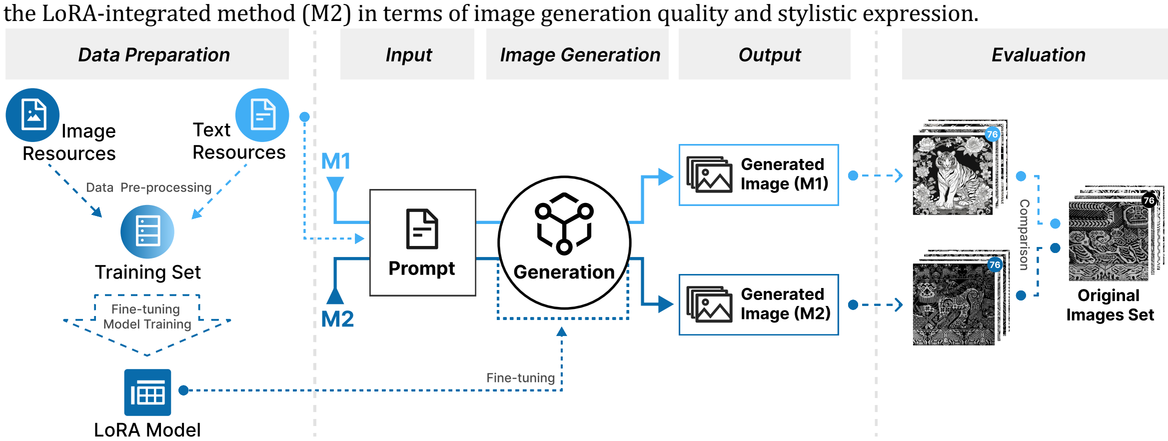

Figure 3: Overview of of the AI-generated cultural pattern pipeline. The process includes data preparation, image generation (M1: baseline; M2: LoRA-enhanced), and evaluation against original Huayao cross-stitch patterns.

3.1.1 Huayao Cross-Stitch Pattern Analysis and Data Preprocessing

Huayao patterns emphasize the concept of "fullness as beauty", with overall compositions that are symmetrical and have a well-balanced arrangement of patterns of varying sizes, with clear layers. The top of the image usually features birds and clouds, the middle section often includes figures and large animals, while the lower part is typically adorned with poultry or floral patterns. This arrangement not only directly mirrors the order of nature but also reflects the creator's artistic understanding of life and their hopes for a beautiful future [18]. Additionally, in terms of pattern layout, the main patterns usually cover larger areas and reflect the core theme of the work, while secondary and filler patterns enrich the cultural connotations and visual layers of the overall piece, as shown on the left of Figure 4.

The unique visual characteristics of Huayao cross-stitch are also reflected in its nested design, where smaller patterns are embedded within larger ones, typically including cultural symbols, plant motifs, or small animals [49], as shown on the right of Figure 4. For example, in the artistic works of some other cultures, the body of an animal is usually depicted through its fur texture or muscle lines. In contrast, in Huayao patterns, the corresponding parts are filled with auspicious motifs or have a small animal embroidered on the abdomen, symbolizing reproduction and vitality. This design approach is rich in symbolic meaning and visually enhances the work's appeal and the depth of cultural expression [50].

Figure 4: Pattern structure and visual features of Huayao cross-stitch. (a) Left: Composition and layout characteristics. (b) Right: Close-up examples illustrating nested pattern features.

The data for this study were sourced from field research photography, books and archival literature, and the Huayao Cross-Stitch Digital Museum [44, 45, 48]. During the image screening phase, complete, clear, and representative patterns were prioritized through selection to ensure that the dataset accurately reflected the cultural content and artistic value of the tradition. Based on this, we constructed a training dataset consisting of Huayao cross-stitch images and their corresponding descriptive texts, which served as the foundation for fine-tuning a stylistic concept model using Low-Rank Adaptation (LoRA) techniques.

Given the symmetrical characteristics of Huayao cross-stitch patterns, only one half of each pattern was used to improve data processing efficiency. To ensure compatibility with the pre-trained SDXL1.0 model, all images were resized to 1024×1024 pixels. During preprocessing, the images were also stretched to correct potential shape distortions and desaturated to reduce color interference introduced during the acquisition process, as shown in Figure 5. In total, 152 processed images were included in the final training set used for LoRA fine-tuning.

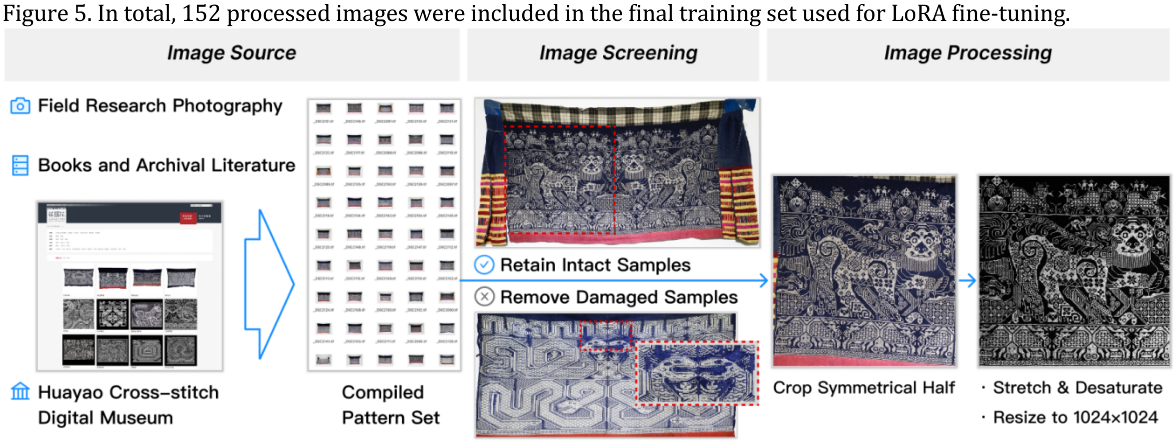

Figure 5: Image data preparation process.

3.1.2 *Text Data Labelling and Style Fine-Tuning*

During the text data collection phase, we gathered descriptive texts related to Huayao cross-stitch patterns, including information on cultural meanings, pattern elements, and production techniques, sourced from literature, academic papers, and oral records of inheritors [18, 44, 47, 50]. Through the organization and analysis of these texts, we conducted a preliminary extraction and structural interpretation of the core cultural elements embedded in Huayao patterns, providing critical reference for the semantic accuracy of AI model training and pattern generation. In the text annotation phase, a Convolutional Neural Network (CNN) [51] was used to generate detailed caption texts for each image, describing the elements, styles, and layouts to guide the model in generating culturally accurate patterns. The subsequent manual screening and annotation steps ensured the accuracy and consistency of the text data, corrected biases in machine-generated annotations, and ensured that the labels reflected the cultural content. Finally, the descriptive texts, caption texts, and manual annotations collectively formed the diffusion model prompts. The process is illustrated in Figure 6. Prompts are used to guide the diffusion model in accurately reproducing specific semantic and stylistic requirements. We maintained the consistency of the Prompts to support controlled experimental conditions in the subsequent image generation stage.

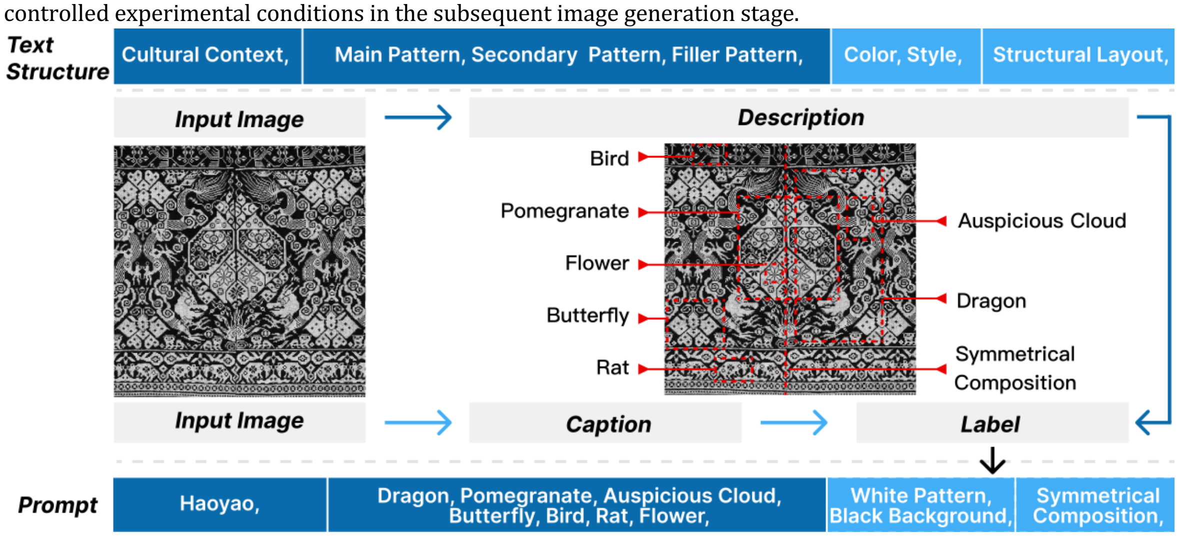

Figure 6: Example of image-based text extraction and prompt construction.

Based on the constructed training set of 152 images and the text data training set, this study selected a diffusion model, U-Net architecture, and a text encoder as the base models during the training phase for the Huayao cross-stitch feature [52]. LoRA technology was used to introduce a 64-dimensional low-rank matrix for initialization. During training, a cross-entropy loss function was used to evaluate errors, and the AdamW8bit optimizer was employed to update parameters, combined with a learning rate scheduler to optimize the training process. The data were processed through forward propagation to compute outputs, and errors were evaluated using the loss function. Backpropagation and gradient updates were used to adjust the parameters of the LoRA module. Gradient checkpointing was enabled to reduce memory consumption.

The choice of model training parameters, including maximum training epochs, batch size, and learning rate, significantly impacts the training outcomes [53, 54, 55, 56]. Sampling evaluations are conducted every two training epochs to monitor loss changes, and image generation tests are performed during the reverse diffusion process to validate model performance. When the loss values stabilize, the training is likely nearing convergence, suggesting the model has reached or is close to its optimal state. The experiments were conducted on a Windows system equipped with an NVIDIA GeForce RTX 3060 Ti GPU, an Intel i7-12700F CPU, and 32GB of RAM. Following the steps above the optimal training parameters were determined as follows: max train epoch = 20, train batch size = 3, learning rate = 1e-4, steps = 3, using a cosine learning rate scheduler.

3.1.3 *Image Generation and Quantitative Evaluation*

During the image generation phase, this study used the inclusion of the LoRA-trained model as a control variable, analyzing the differences between the standard text-to-image generation method and the method with LoRA integration, while keeping parameters such as Prompt, Steps, Sampler, and CFG Scale consistent. To test the generalization and robustness of these two methods, the study generated Huayao cross-stitch patterns with five themes: tiger, dragon, snake, rat, and fish, ensuring stable performance across different themes and avoiding performance degradation due to dataset biases. To align with the symmetrical characteristics of Huayao Cross-Stitch patterns, the generated images need to undergo horizontal flipping and merging operations to create complete AI-assisted Huayao Cross-Stitch patterns (see Figure 7).

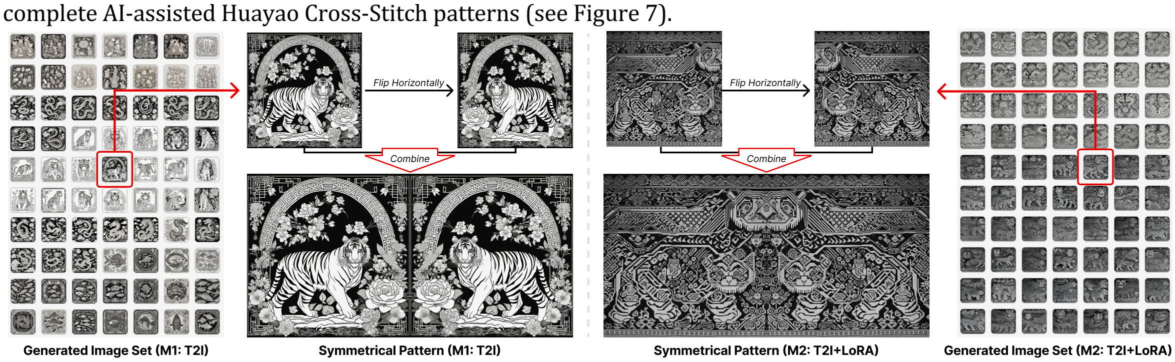

Figure 7: Example of image selection and post-processing using generated image sets from M1 and M2.

During the evaluation phase, the Fréchet Inception Distance (FID) [57] was used as a quantitative metric to assess the quality of the generated images. FID measures the statistical similarity between the original and generated images by comparing their distributions in feature space: the lower the score, the higher the quality of the generated images. Compared to other evaluation metrics such as IS (Inception Score), SSIM (Structural Similarity Index Measure), and PSNR (Peak Signal-to-Noise Ratio), FID was selected for the following reasons. IS relies on natural image classification models and would struggle to effectively capture the cultural and stylistic features of Huayao cross-stitch patterns. SSIM focuses on local structural similarity and may fail to reflect the overall complexity of the design and its cultural symbolism. PSNR emphasizes pixel-level differences, overlooking cultural context and visual details [58, 59, 60]. FID's advantage in capturing overall feature distribution makes it more suitable for this study.

The FID calculation formula is as follows:

$$\mathrm{FID} = \left\| \mu_r - \mu_g \right\|^2 + T_r\left(\sum r + \sum g - 2(\sum r \sum g)^{\frac{1}{2}}\right)$$

In the evaluation phase of this experiment, considering the variability and uniqueness of the original Huayao cross-stitch patterns, the 152 original images were evenly divided into two subsets: 76 original images (A) and 76 original images (B), which served as the control groups. The two experimental groups consisted of images generated using the standard text-to-image generation method and those generated using the text-to-image method integrated with LoRA. In the experiment, an equal number of generated images were randomly selected from each experimental group and evaluated against the original image set (A) using the FID metric, as shown in Figure 8.

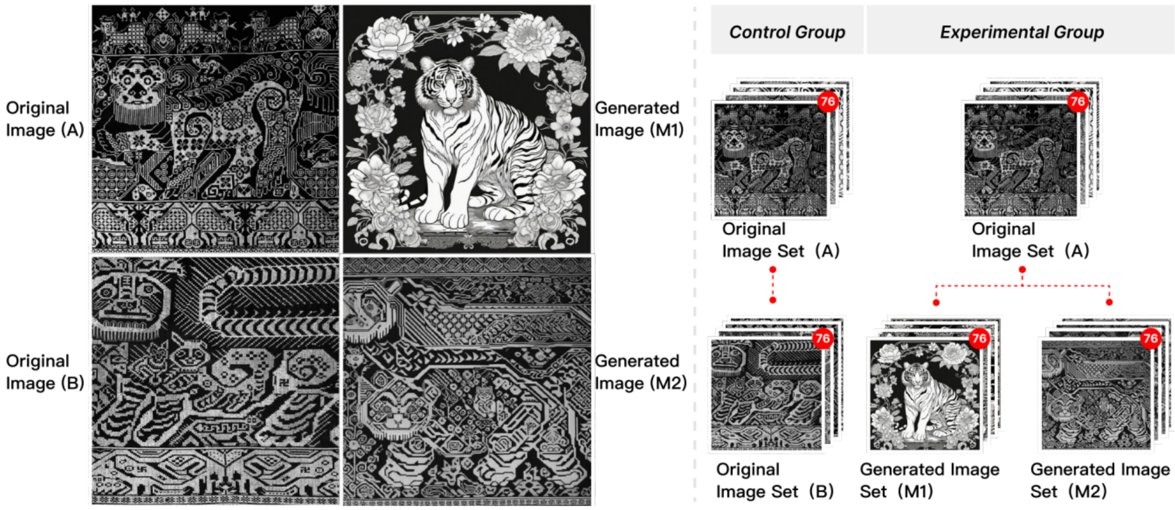

Figure 8: (a) Left: Representative samples from each set, including original images (A, B) and generated images using M1 (T2I) and M2 (T2I + LoRA); (b) Right: Structure of control and experimental groups for FID evaluation, based on comparisons between original image set (A) and generated image sets (M1, M2).

The FID evaluation results of the three image sets are shown in Table 1. The image set generated using the T2I + LoRA method (M2, 119.91) achieved a significantly lower FID than that generated by the standard T2I method (M1, 307.38), and was nearly equivalent to the original baseline group—Original Image Set B (119.36). This indicates that the model effectively captured the distributional features of the original patterns, and that the variation in the generated results falls within the natural range of variation observed in the original dataset. Therefore, the results suggest that the images generated by M2 are visually very close to the original Huayao cross-stitch patterns.

Table 1: FID evaluation results for original and generated image sets

Image Set	FID↓
Original Image Set (B)	119.36
Generated Image Set (M1: T2I)	307.38
Generated Image Set (M2: T2I + LoRA)	119.91

Typically, a Frechet Inception Distance (FID) value below 10 is considered ideal, indicating that the generated images have minimal differences in feature distribution compared to real images, reflecting high quality. However, in highly complex datasets or images with specific artistic styles, FID values tend to be higher due to the diversity and complexity of details, reflecting a broader distribution in the feature space [61]. In this study, the Huayao cross-stitch patterns, which contain rich geometric designs, symbols, colors, and cultural imagery, are distributed more broadly in the Inception model's feature space, resulting in higher FID values. The FID value of the original Huayao image dataset, used as the control group, is 119.36, indicating that relative comparisons of FID values may be more significant than absolute values when evaluating different generative models. This study found that the FID values of the image set generated with integrated LoRA technology are very close to those of the original image set, indicating that the LoRA model successfully captured the features and diversity of the original images, resulting in a high degree of consistency in feature distribution between the generated and original images. However, FID primarily relies on the similarity of statistical feature distributions, which presents significant limitations when assessing the aesthetic and cultural value of cultural patterns, as it struggles to fully reflect the cultural authenticity and design characteristics of the patterns. In other words, existing evaluation methods fail to comprehensively assess the quality of traditional cultural patterns, highlighting the importance of cultural holders' expertise in pattern evaluation.

3.2 Methods for Community Feedback and Evaluation

A two study design was taken to examine how the Huayao community respond to the AI-generated patterns. In the first study structured rating interviews were conducted with ten artisans to collect quantitative feedback assessing the effectiveness of the LoRA approach in reproducing traditional stylistic features (RQ1). This study also included the collection of verbal comments from participants, providing supplementary qualitative material for understanding their subjective judgments (RQ2). Building on this foundation, the second study focuses on community members' cultural perceptions and attitudes toward AI-generated content (RQ2 and RQ3). This study has two parts: i) individual in-depth interviews with cultural inheritors, exploring personal experiences related to cultural identity and symbolic value in AI-generated patterns; and ii) a focus group discussion with artisans, capturing collective interpretations and acceptance of AI intervention in cultural innovation within a familiar social context. These two methods—representing individual and group perspectives, respectively—are intended to reveal the diversity of attitudes, cultural judgment, and technological acceptance among community members.

3.2.1 Cultural Heritage Artisans as Participants

To ensure the cultural appropriateness and feasibility of the in-situ research a phased and context-sensitive participant recruitment strategy was adopted [62]. This approach was designed to respect the rhythms of daily life and communication norms within the Huayao community and resulted in three groups of participants as follows:

The first group (N=10) included artisans who took part in the structured rating interviews. Out of respect for the community's daily rhythm, the research team did not employ a centralized recruitment or screening process. Instead, participants were approached during field visits, typically while working on embroidery at the thresholds of their homes. After explaining the research purpose, consent to participate was obtained. No fixed sample size was predetermined; rather, the study followed a principle of gradual saturation—during the interviews, researchers observed a rapid convergence in participant evaluations of the AI-generated patterns, suggesting an emergent consensus regarding the relative merits of the two generation methods. Based on this observation, recruitment was concluded after the tenth participant (R1–R10), as sufficient quantitative feedback had been gathered to support subsequent analysis.

The second group (N=2) consisted of those officially recognized by the government as representative inheritors of the intangible cultural heritage "Huayao cross-stitch" who took part in the expert in-depth interviews. As there are currently only five formally certified inheritors in the community—many of whom hold multiple public responsibilities —for pragmatic reasons this study invited two of them (E1, E2) to participate.

The third group (N=6) consisted of artisans who participated in the focus group discussion. To remain closely aligned with the Huayao community's everyday creative and communicative practices, all focus group members (FG1–FG6) were relatives or long-term neighbors who regularly worked on embroidery together. During the discussion, participants frequently switched to Yao language for spontaneous exchanges—although this increased the effort of translation and interpretation, it significantly enriched the authenticity and depth of the cultural feedback.

Table 2 summarizes key information for all participants, including research role, age group, years of Huayao Cross-stitch experience, and cultural status. As Huayao cross-stitch is a traditional handicraft practiced by Yao women, all participants in the sample were female (N = 18). Participants ranged in age from 35 to 78 years (M = 55.6, SD = 13.9), with years of practice varying from 2 to 66 years (M = 41.2, SD = 18.9). A total of 88.8% reported having begun to learn cross-stitching between the ages of 10 and 15, reflecting extensive long-term experience. Approximately 11.2% began learning after the age of 20, often due to marrying into the Huayao community or developing a personal interest in the craft. These cases represent non-typical pathways into practice that warrant further attention.

Table 2: Information about Participants in the Huayao Cross-Stitch Study

ID	Study Phase	Research Type	Age Group	Years of Experience	Participant Role
R1	Study 1	Structured Interview—Rating Task	50+	40+	Huayao Cross-Stitch Artisan
R2	Study 1	Structured Interview—Rating Task	60+	50+	Huayao Cross-Stitch Artisan
R3	Study 1	Structured Interview—Rating Task	50+	40+	Huayao Cross-Stitch Artisan
R4	Study 1	Structured Interview—Rating Task	50+	40+	Huayao Cross-Stitch Artisan
R5	Study 1	Structured Intervie—Rating Task	50+	40+	Huayao Cross-Stitch Artisan
R6	Study 1	Structured Interview—Rating Task	60+	50+	Huayao Cross-Stitch Artisan
R7	Study 1	Structured Interview—Rating Task	70+	60+	Huayao Cross-Stitch Artisan
R8	Study 1	Structured Interview—Rating Task	70+	60+	Huayao Cross-Stitch Artisan
R9	Study 1	Structured Interview—Rating Task	50+	5+	Huayao Cross-Stitch Artisan
R10	Study 1	Structured Interview—Rating Task	30+	10+	Huayao Cross-Stitch Artisan
E1	Study 2	Expert Interview	60+	50+	Recognized ICH Inheritor
E2	Study 2	Expert Interview	40+	30+	Recognized ICH Inheritor
FG1	Study 2	Focus Group	30+	20+	Huayao Cross-Stitch Artisan
FG2	Study 2	Focus Group	50+	30+	Huayao Cross-Stitch Artisan
FG3	Study 2	Focus Group	30+	20+	Huayao Cross-Stitch Artisan
FG4	Study 2	Focus Group	70+	60+	Huayao Cross-Stitch Artisan
FG5	Study 2	Focus Group	60+	50+	Huayao Cross-Stitch Artisan
FG6	Study 2	Focus Group	30+	20+	Huayao Cross-Stitch Artisan

To ensure ethical compliance, all participants were over the age of 18 and possessed the ability to clearly articulate their perspectives and experiences. Given that some participants were elderly and primarily communicated in the Yao language, the research team invited a local community member—fluent in both Mandarin and Yao—to assist throughout the study as an interpreter and facilitator, ensuring accurate communication during the interviews. Prior to the start of the study, participants were given a brief explanation of the experimental materials, including a clear statement that the visual patterns presented were generated by computer programs rather than created by hand, in order to avoid any misunderstanding regarding their origin or mode of production. All participants provided written informed consent voluntarily, after fully understanding the purpose of the research and the nature of their involvement, and were explicitly informed of their right to withdraw from the study at any time.

Author Positionality and Reflexivity Statement. The first author primarily undertook the field work. Their statement follows in first person. As a researcher with a background in design studies, although I am not a member of the Huayao community, I have built a long-term relationship of dialogue and trust with its members through five years of participatory observation, regular interviews, and collaborative projects. Through this process, I have sought to understand the cultural and practical significance embedded in their pattern-making practices. With the emergence of generative AI, my research has increasingly turned toward examining how AI may intervene in, expand, or reshape cultural boundaries within creative processes. This interdisciplinary background give me a dual positionality: on one hand, my training in design research inclines me to explore how technology can expand creative' possibilities, on the other hand, my anthropological fieldwork has cultivated a heightened cultural sensitivity, prompting me to remain cautious about the potential of technical systems to reconfigure or destabilize established meaning structures. I have sought to make these influences transparent throughout the paper and to continuously reflect on my analytical standpoint, with the goal of contributing to a more contextually situated understanding of AI's role in cultural practice. The research team contributed to data documentation and analysis to mitigate the influence of potential individual researcher bias.

3.2.2 Study 1: Evaluation of AI-Generated Patterns

To evaluate the performance of AI-generated patterns in reproducing the stylistic features of Huayao cross-stitch, a structured rating interview task was designed for Study 1. Based on the research team's long-term ethnographic engagement with the Huayao community, prior studies on pattern culture, and relevant literature [44, 45], six preliminary evaluation dimensions for pattern quality were established: (I) Color Distribution Accuracy, (II) Structural Layout and Segment Division, (III) Recognizability and Reasonableness, (IV) Pattern Nesting Characteristics, (V) Symbolic and Iconographic Accuracy, and (VI) Texture Details (see Table 3). During the rating interviews, this rating framework was iteratively validated and refined based on participant feedback, ensuring that the definitions and scoring criteria aligned closely with the evaluative perspective of local artisans. Examples of scoring conversion are as follows: "This pattern is very similar to our Huayao style"—5 points; "Somewhat similar, but not entirely like it"—3 points; "This doesn't resemble our Huayao patterns at all"—1 point. The visual stimuli used in this study included five traditional themes: (a) fish, (b) rat, (c) tiger, (d) dragon, and (e) snake. Each participant was asked to evaluate a total of 10 images—five generated by each method (M1: Only T2I; M2: T2I + LoRA). Each image was rated sequentially across the six dimensions (see Figure 9).

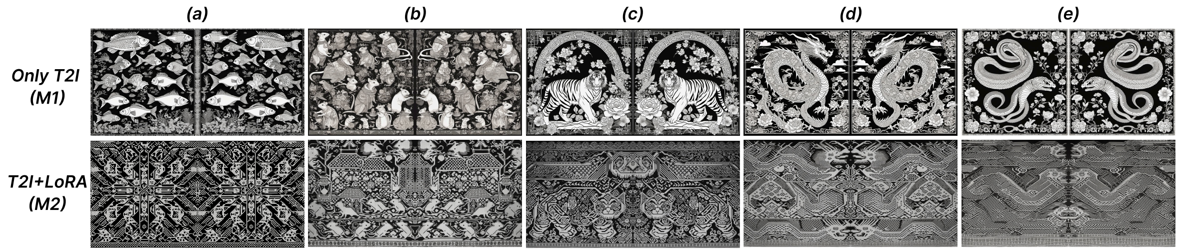

Figure 9: Evaluation image samples for five themes generated by M1 and M2.

Table 3: Huayao Cross-Stitch Pattern Evaluation Guide

Evaluation Dimension	Dimension Descriptions
I. Color Distribution Accuracy	Huayao culture emphasizes “fullness as beauty”, requiring patterns to not only exhibit black-and-white characteristics but also ensure an even distribution of white and black, avoiding local gaps to achieve visual harmony and balance.
II. Structural Layout and Segment Division	The division of the pattern’s areas should be clear, and the positions and proportions of the main and filling patterns should be reasonably distributed to enhance overall harmony and visual richness.
III. Recognizability and Reasonableness	The elements in the pattern need to be recognizable by cultural holders to accurately convey the creator’s intent within the community. For instance, animal figures must be identifiable, with their bodies and limbs fully depicted.
IV. Pattern Nesting Characteristics	Huayao pattern should exhibit the “pattern within pattern” nesting feature, where filling patterns are embedded within the main pattern to increase the depth and visual complexity of the design.
V. Symbolic and Iconographic Accuracy	Whether the symbols and imagery in the pattern maintain their cultural accuracy and depth is crucial. Accurately reproducing symbols with specific cultural meanings is essential for preserving the cultural authenticity of the patterns.
VI. Texture Details	Whether the image can appropriately represent the texture of Huayao Cross-Stitch patterns on fabric, such as the “X” details created by the stitching.

Procedure and Data Collection. A total of 10 Huayao artisans (R1—R10) participated in the structured rating interviews (see Figure 10). The process began with a dimension familiarization phase, during which researchers used visual aids—including standard reference image sets—to explain the operational definitions of the six evaluation dimensions, ensuring that participants fully understood the criteria for scoring. During the guided scoring phase, researchers posed standardized questions for each image, such as “How would you rate the similarity of this image’s color accuracy to traditional Huayao styles?” Participants were encouraged to articulate their judgments on the scale. In the data consolidation phase, researchers immediately translated the feedback into numerical scores and reviewed each item with the participant using a consensus confirmation approach to ensure alignment between the recorded score and the participant’s intended meaning [63]. Each interview lasted approximately 40 minutes, was fully audio-recorded, and documented in real time. To minimize interviewer bias, all prompts were delivered using neutral phrasing, and participants were encouraged to provide detailed explanations. This approach aimed to ensure that the final scores reflected both internal consistency and the layered subjectivity of cultural judgment, laying a solid foundation for subsequent analysis.

Figure 10: Field scenes from the structured rating interview process with Huayao cross-stitch artisans.

Data Processing and Analysis. Each participant (N=10) evaluated 10 images generated by two different methods (M1: Only T2I; M2: T2I+LoRA) across six dimensions, theoretically yielding 600 data points. However, during data collection, some artisans exhibited incomplete or inconsistent ratings during the verbal feedback phase, such as misunderstandings of certain dimensions or failure to fully respond as required. Consequently, 565 valid data points were collected, representing approximately 94.2% of the expected total.

3.2.3 Study 2: Investigating Artisans' Attitudes Toward AI in Cultural Practices

The second study employed interviews and focus group methods to explore artisans' evaluations of AI-generated patterns (RQ2) and their attitudes toward the use of AI in their cultural innovation (RQ3). The interview participants were cultural inheritors (E1, E2) of Huayao Cross-Stitch craftsmanship and the focus group participants were Huayao Cross-Stitch artisans (FG1—FG6). Through individual in-depth interviews, the cultural inheritors provided perspectives based on their rich cultural experience, while focus group discussions revealed the consensus and differences among artisans as a group.

Materials and Documentation. To obtain more granular evaluations and perspectives, the research team adjusted the LoRA weights (W = 0.8, 0.9, 1.0, 1.1, 1.2) based on the M2 method in Section 3.2.2, expanding the research sample from 5 to 25 (as shown in Figure 11), and using these as the core materials for interviews. Additionally, the study included existing Huayao cross-stitch as supplementary materials. By comparing AI-generated patterns with artisan' actual creations, the study explored the differences in how GenAI reproduces traditional cultural symbols versus drives innovation, analyzing its adaptability and potential impact in cultural practices.

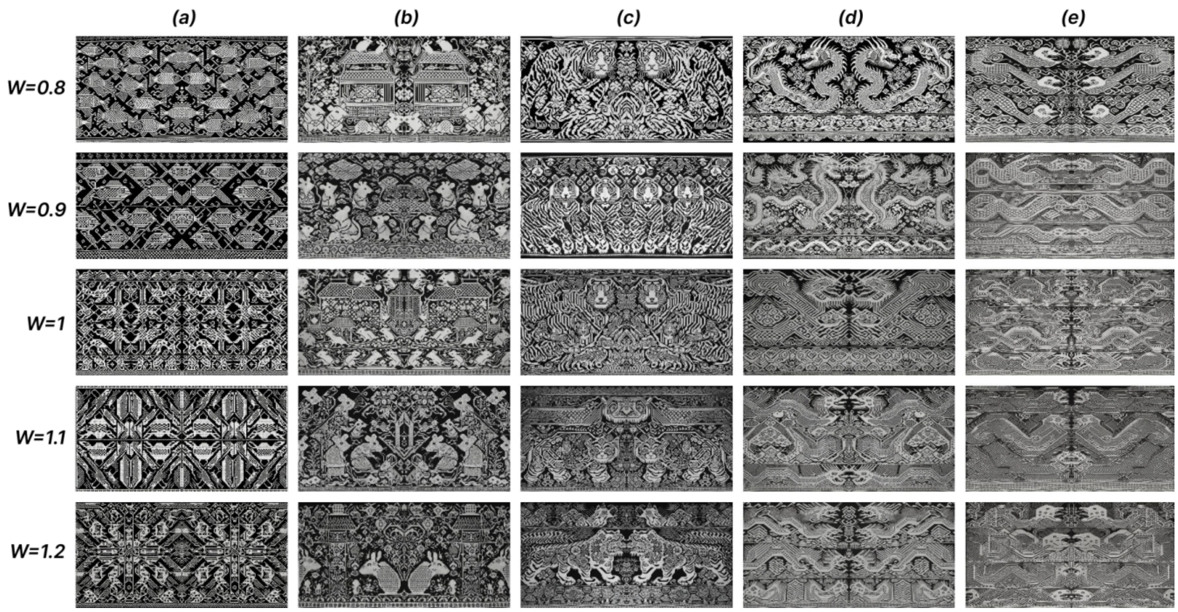

Figure 11: Evaluation image samples for five themes and five LoRA weights generated by M2.

Procedure and Data Collection. The interview and focus group questions followed the same structure and began with everyday practices, such as “How do you create new patterns in your daily cross-stitch work?” and gradually progressed to more complex topics. This progressive strategy effectively reduced participants' cognitive load, bridged the gap between researchers and participants, ensured the depth of the interviews, and facilitated participants’ active expression [64]. During the interviews, participants analyzed the cultural adaptability and innovative potential of pattern variations generated under different LoRA weight settings, focusing on the feasibility of introducing new patterns while respecting cultural traditions. Additionally, they discussed whether AI-generated patterns might lead to cultural alienation or misinterpretation, and whether these patterns could be considered part of cultural innovation.

Individual in-depth interviews lasted 90 and 120 minutes, while the focus group discussions lasted 90 minutes. When participants stopped providing new insights, the research team determined that data saturation had been reached and concluded the interviews accordingly. The interview locations were chosen by the participants. Individual interviews were conducted in familiar and comfortable settings, while the focus group discussions took place in a quiet outdoor environment, with the research team arranging a round table and surrounding chairs to facilitate participants’ observation and interaction with interview materials. To ensure data completeness, the research team used various recording tools, computers, audio recorders, video cameras, cameras, and pen-and-paper to meticulously document the entire process. The interview process is illustrated in Figure 12.

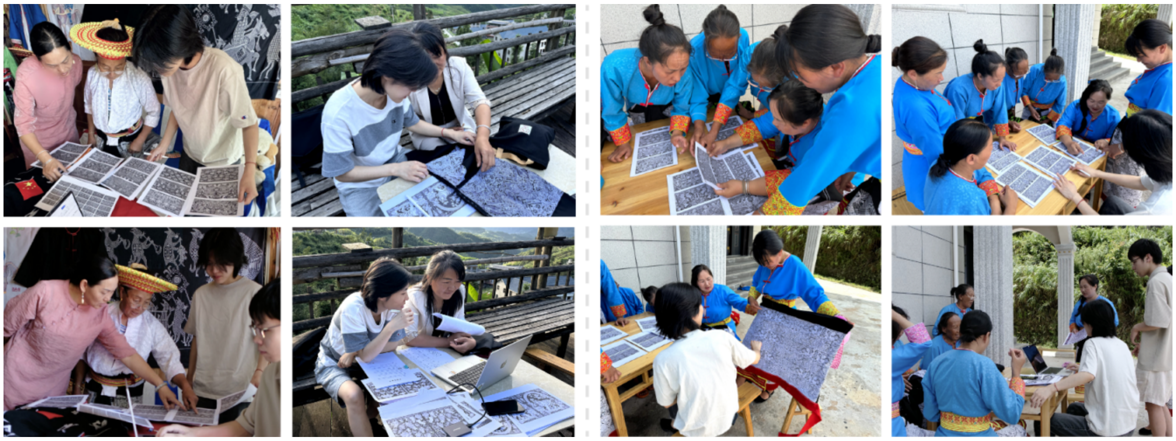

Figure 12: (a) Left: In-depth interview process with Huayao cross-stitch inheritors. (b) Right: Focus group discussion with community artisans.

Data Processing and Analysis. The data processing employed qualitative analysis methods, emphasizing thick description to deeply document and analyze interview transcripts, authentically reflecting artisans' cultural practices and their attitudes toward AI technology. This study did not adopt constructive analytical practices, such as coding data for theoretical interpretations, but instead focused on participants' experiences, using a "Naturally Accountable Accomplishment" perspective to preserve the local logic and accountability inherent in the data. This method prioritized restoring the contextual authenticity of the data by documenting participants' specific feedback on evaluating AI-generated patterns and their cultural adaptability, revealing their behaviors and underlying cultural significance while avoiding excessive theorization or abstraction of the data [65].

During the data processing stage, all interview and focus group discussion recordings were transcribed verbatim. Due to some participants speaking the Yao language, which hindered the accuracy of speech recognition technology, two researchers manually transcribed the recordings independently and cross-checked them to ensure an error rate of no more than 15%. Additionally, a local resident fluent in both the Yao language and Mandarin assisted in meticulously proofreading the transcriptions to ensure linguistic accuracy.

After preliminary organization of the transcriptions, researchers tagged statements related to the research questions: RQ2 perceptions of AI-generated patterns; and RQ3 artisans' attitudes toward AI technology, with these attitudes categorized as positive, neutral, or negative. Subsequently, the research team used the Praxeological Accounts framework [66] to explore the data from three perspectives: (1) The social significance of language: analyzing how participants described the features of AI-generated patterns through word choice, tone, and sentence structure. For example, phrases such as "very beautiful" or "I like it" reflected participants' emotional tendencies and acceptance of the technology. (2) Social interaction dynamics: in focus group discussions, some participants acted as opinion leaders, guiding the direction of the discussion or posing thought-provoking questions to deepen the dialogue. This interaction revealed the processes of consensus-building and opinion divergence within the group. (3) Contextual dynamics: researchers focused on analyzing retrospective and prospective expressions in participants' language [72]. For instance, participants might express their attitudes toward AI by recalling traditional craftsmanship experiences or envisioning the potential of AI technology in future design.

4 RESULTS AND DISCUSSION OF STUDY 1 AND STUDY 2

This section reports on the results of the community feedback in Study one (Section 3.2.2) and Study two (Section 3.2.3). In addition it offers discussion across the results of the two feedback studies and the findings of the GAI experiment in Section 3.1 in relation to the three research questions of this paper.

4.1 Comparison of Generated Images (RQ1)

As outlined in Section 3.2.2, in Study one we evaluated two sets of generated images across six dimensions—(I) Color Distribution Accuracy, (II) Structural Layout and Segment Division, (III) Recognizability and Reasonableness, (IV) Pattern Nesting Characteristics, (V) Symbolic and Iconographic Accuracy, and (VI) Texture Details through structured rating interviews. and visualized the differences in performance using box-and-whisker plots. After organizing the valid collected data in Study 1, the research team calculated the mean and standard deviation for each evaluation dimension to assess central tendency and variability. Box-and-whisker plots [70] were used to visually illustrate the performance differences between the two generation methods across dimensions, as shown in Figure 13. Results indicate that the M2 group (T2I+LoRA) outperformed the M1 group (Only T2I) across five of the six dimensions. For example, in the Color Accuracy (I) dimension, M2 achieved an average score of 4.56 with a narrow distribution range (4.2—4.8), demonstrating high precision and consistency, whereas M1 scored only 0.74 with a wide range (0.4—1.2), indicating poor and unstable performance. Similarly, in the Pattern Nesting Characteristics (IV) dimension, M1 failed to exhibit any notable nesting features (average score of 0.0), while M2 performed exceptionally well (average score of 4.42, range 3.9—4.9), showcasing its ability to handle complex visual structures. Notably, in the Recognizability and Reasonableness (III) dimension, M1 achieved a slightly higher average score (4.36) than M2 (3.86). Although its overall performance was limited, this suggests that M1 can generate recognizable and culturally reasonable patterns in certain cases. However, this advantage is negligible compared to its significant shortcomings in other critical dimensions, such as Symbolic and Iconographic Accuracy (V) and Texture Details (VI). The M1 group scored nearly zero in these dimensions, exhibiting a severe lack of detail, cultural symbols, and texture representation. These findings validate the effectiveness of LoRA fine-tuning in enhancing image quality control within generative processes.

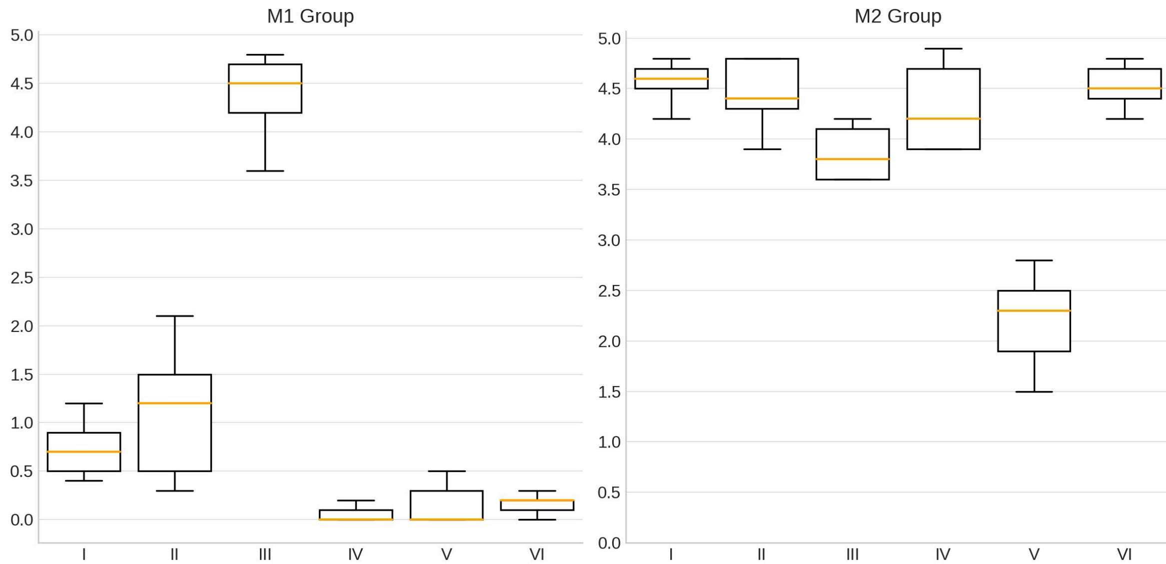

Figure 13: Comparison of M1 and M2 Methods in Six Evaluation Dimensions: I. Color Distribution Accuracy, II. Structural Layout and Segment Division, III. Recognizability and Reasonableness, IV. Pattern Nesting Characteristics, V. Symbolic and Iconographic Accuracy, VI. Texture Details.

Further analysis of the M1 group reveals that although its average score in the “Recognizability and Reasonableness” (III) dimension (4.36) was slightly higher than that of the M2 group (3.86), the images it generated exhibited a significant loss of the cultural-symbolic features characteristic of Huayao patterns. This suggests that mainstream AI models have failed to adequately learn and internalize the semantic boundaries of Huayao culture. Such cultural misinterpretation manifests in the form of visual appropriation—a tendency of AI systems to extract symbolic elements originally embedded in localized social and cultural contexts and reassemble them into a globally aestheticized, decontextualized decorative style.

In contrast, the M2 group more closely approximated the stylistic features of Huayao cross-stitch, demonstrating strong generative capabilities particularly in dimensions such as Color Distribution Accuracy (I), Pattern Nesting Characteristics (IV), and Texture Details (VI). However, in the dimension of Symbolic and Iconographic Accuracy (V), M2 scored an average of only 2.20—significantly lower than its performance in other dimensions, where scores exceeded 4.4. This result suggests that despite the strengths of LoRA in enhancing overall pattern generation, it still faces notable limitations in capturing the precision and nuance of cultural symbols and iconography. Importantly, although M2 performs well in Texture Details (VI), its underlying generative logic essentially represents a “deskilling” simulation of the artisanal process. This may diminish artisans’ sense of agency and mastery over their own craft, potentially leading to a devaluation of traditional skills.

Results of Study 1 indicate that AI-generated images using Method 2 (M2; T2I+LoRA) were able to effectively capture key stylistic features of traditional Huayao cross-stitch at the level of visual characteristics. However, these outputs also reveal risks of symbolic misreading and resultant cultural alienation, which may compromise their expression of cultural authenticity. In particular, cultural authenticity, which within the context of intangible cultural heritage (ICH) preservation, is understood as a “meaning system dynamically maintained by the community through practice [67].” Its core lies not merely in visual resemblance but in the continuity of narrative, ritual significance, and embodied experience that underpin cultural symbols.

4.2 Artisans’ Perceptions of AI-Generated Patterns (RQ2)

In the practical application of AI-generated patterns, how cultural holders interpret and utilize AI gnerated images becomes a crucial part of evaluating the cultural adaptability of AI. This section draws on the second study conducted using 25 patterns generated with varying LoRA weights (see Section 3.2.3), and explores whether and how Huayao artisans identify cultural elements within the patterns.

Use of AI-Generated Patterns: Cultural Adaptation as Inspiration Material. Interviews in Study two revealed that although participants generally felt AI-generated patterns failed to convey deep cultural meaning, they did not entirely dismiss their value. Indeed, many artisans regarded them as sources of inspiration when creating primary motifs. The main motifs in Huayao cross-stitch allow for a considerable degree of freedom, enabling artisans to interpret and construct designs based on personal experience. As E1 explained, “I don’t think there’s such a thing as a ‘Huayao-style tiger.’ The tiger patterns on old skirts probably came from what our ancestors saw in the mountains. Now I see tigers on TV, in nature documentaries, so I just stitch what I see.” This comment reflects the artisans’ open attitude toward visual resources—an openness that not only demonstrates the Huayao community’s receptiveness to cultural innovation, but also provides a practical context for the use of AI-generated materials.

In some cases, participants also demonstrated a sharp eye for pattern detail and a willingness to modify AI outputs. For instance, after examining a dragon motif generated with a LoRA weight of 0.8, FG6 remarked, “This dragon is beautiful, really beautiful. These two dragons are ‘looking back dragons’—the heads are turned to face behind, very vivid. But the body’s a bit too fat, and it’s kind of empty around the edges. I can adjust it when I stitch, add some more detail.” This feedback not only highlights the visual appeal of the pattern but also reflects the artisans’ capacity for redesign—showing a tendency to adapt composition, fill in blank spaces, and actively embed personal experience and cultural meaning into the creative process.

Boundaries of Pattern Use: Dynamic Maintenance of Cultural Symbols. In contrast to the flexible use of primary motifs, artisans exhibit a heightened sensitivity and protective stance toward traditional symbols embedded within filler patterns. These motifs are regarded as visual carriers of ethnic identity and historical memory and are largely seen as inappropriate for modification or substitution. As R9 emphasized during the interview, “The eight-pointed flower is a symbolic pattern of our Yao people. The stone pattern represents Huayao cross-stitch, and the ‘dazi’ flower is a motif we must use on the wedding skirts we stitch.” This distinction reveals that the Huayao community has established a clear internal structure for cultural content: while primary motifs may be flexibly innovated, symbolic patterns must be faithfully preserved. This internal cultural mechanism enables artisans to independently assess the usability of AI-generated content based on the function and context of each pattern, thereby maintaining community control over cultural boundaries. As Harrison (2020) notes, cultural authenticity is a dynamic process negotiated through the everyday practices of the community [68].

They further pointed out that Huayao cross-stitch has undergone multiple historical transformations. For instance, in the 1970s, influenced by Han-style line drawings, a simplified version of cross-stitch became popular in Huayao communities, altering the filler motifs and decorative details of traditional skirts. However, by the 1990s, as the visual value of traditional embroidery was reappreciated, Huayao cross-stitch returned to its earlier forms. This evolution demonstrates that Huayao culture is not static or closed, but rather continuously adjusts and repairs itself through community-led judgment and choice at different historical moments. As FG1 stated, “If a new pattern is created and a lot of people start stitching it on their skirts, then it can keep going—if everyone likes it, that's enough. But if only one person uses it, it doesn't really matter." This response reveals that while individual creativity enjoys a high degree of freedom in Huayao culture, whether a pattern is ultimately accepted as part of the cultural repertoire is not determined by the creator or by the technology itself. Instead, it depends on the pattern's acceptability and capacity for reproduction within the community.

In summary, Huayao artisans' acceptance and use of AI-generated patterns is not a matter of simple approval or rejection, but rather a culturally embedded, practice-based process of judgment. They treat primary motifs as spaces for innovation and symbolic patterns as cultural boundaries, dynamically maintaining cultural authenticity through experience, negotiation, and selective adoption. This mechanism not only illustrates how AI-generated patterns can be integrated into traditional creative workflows but also offers valuable insight for the sustainable development of AI in cultural pattern innovation.

4.3 Artisans' Attitudes Toward AI in Local Cultural Innovation (RQ3)

As AI becomes increasingly integrated into cultural creation, the attitudes of local artisans toward its role in creative practice reflect not only differences in individual skill levels and design needs, but also reveal the deeper dynamics through which technology reshapes cultural authority, innovation logics, and community structures. This section focuses on the responses of all 18 Huayao cross-stitch artisans involved in Study one and two to AI-generated patterns, categorizing their attitudes into three groups—positive, neutral, and negative—and analyzing the underlying cultural judgment mechanisms and cognitive frameworks that inform these positions.

The findings suggest that these attitudinal differences are not solely a matter of AI understanding or stages of skill acquisition, but rather reflect the artisans' complex negotiations of creative strategy, self-identity, and cultural positioning in relation to AI-generated content. Positive attitudes are often driven by the tangible benefits of inspiration and improved efficiency. Neutral attitudes combine cautious optimism—such as hopes for enhanced expressive capacity—with a critical awareness of AI's limited cultural adaptability. Negative attitudes, meanwhile, are rooted in concerns over the erosion of cultural authority and the weakening of artisanal control over the creative process. To further understand the interaction between attitude and skill level, this section draws on the Dreyfus model of skill acquisition [69] to examine how artisans at different stages of expertise engage with AI in the context of local cultural innovation.

Artisans' Positive Attitudes Toward AI. During the interviews, most artisans expressed a positive attitude toward the Huayao cross-stitch patterns generated using the LoRA method (M2 group), recognizing their stylistic coherence and cultural adaptability. For instance, participant E1 noted, "These patterns are very similar to the ones I've stitched across different decades. The generated designs for each theme show characteristics from various historical periods—some look like old patterns from the 1940s, while others resemble more recent works." This suggests that the AI-generated images possess a certain sense of historical resonance, capable of evoking artisans' awareness of stylistic diversity and pattern evolution.

Furthermore, P11 remarked, "These patterns really save me a lot of thinking time. I just need to tweak a few small parts, and I can finish a whole piece." These responses indicate that the participants see AI-generated patterns as external stimuli that can be seamlessly integrated into existing creative workflows, serving as valuable resources for enhancing both efficiency and inspiration. In the focus group discussions, we observed that participants frequently engaged in spontaneous exchanges in the Yao language to discuss specific details of the generated patterns. They collaboratively explored how to enhance cultural appropriateness by modifying structural elements or adding cultural symbols. This collective engagement indicates that AI-generated outputs were not perceived as finished or substitutive “products”, but rather as open-ended sketches introduced into the creative context. It also reflects the artisans’ practical need for improved ideation efficiency and a broader range of design materials.

It is worth noting that these positive responses primarily came from artisans with higher skill levels, typically at the “competent” or “proficient” stages of expertise. These individuals not only possess the technical ability to transform AI-generated content into completed works but also demonstrate the discernment needed to identify which patterns can be meaningfully integrated into the Huayao pattern tradition. This phenomenon suggests that the cultural effectiveness of AI-generated patterns depends not solely on the generative capacity of the technology itself, but also on whether cultural holders have the skills and interpretive competence to transform “inspiration” into culturally coherent creative outputs. In other words, the effectiveness of inspirational materials is grounded in both technical proficiency and the capacity for cultural translation.

Artisans’ Neutral Attitudes Toward AI. Artisans in the study with a neutral stance toward AI-generated patterns often view creative work as a vehicle for emotional expression and cultural storytelling, and they hope that AI can help enhance their expressive capabilities. However, unlike those with positive attitudes, these participants are typically at the novice stage of skill acquisition and have yet to develop stable pattern ideation abilities. As a result, they tend to perceive AI-generated patterns as supplemental materials that help compensate for technical limitations and improve the quality of their work. For instance, FG3 noted, “I need the image to show the pixel-level details so I can stitch it.” This type of response suggests that AI functions as a visual translator for fine-grained motifs, assisting artisans in the execution of their work more effectively.

Because the current level of AI generation does not yet fully meet their creative expectations, these artisans often remain cautiously optimistic—hoping for more precise and usable reference materials in the future. However, over the long term, access to high-quality references may lead to a growing dependency on AI tools. This dependency invites a dual perception of the issue of imitation. On one hand, existing research has pointed out that novices may become overly reliant on reference materials, particularly when lacking sufficient skill reserves, which may in turn limit their future creative capacity [19]. On the other hand, in the embodied craft of Huayao cross-stitch, imitation constitutes an essential stage of creative learning: through repeated practice, artisans accumulate muscle memory and compositional experience, eventually developing the capacity for independent creation. In this context, AI-generated patterns can function as a structured cultural input mechanism that supports this learning trajectory. Although the intervention of AI may decouple the ideation phase from embodied manual skills, such an “express first, learn later” pathway highlights AI’s potential to initially stimulate creative engagement among younger generations and subsequently motivate a return to traditional craft learning—offering valuable insights for the development of future collaborative transmission models.

In addition to its perceived value in supporting learning and creative expression, some artisans’ neutral attitudes toward AI also stem from its potential role in improving production efficiency and economic accessibility. For example, participant R5 remarked, “These patterns not only resemble traditional Huayao designs but are also very beautiful. I can’t wait for them to be used in machine weaving to directly make cross-stitch skirts, because hand-stitching is just too slow.” Currently, the production cycle for a hand-stitched Huayao skirt can take one to two years, while the cost of machine-woven versions is significantly lower (approximately 800 RMB versus 20,000 RMB for handmade garments). This positions AI-generated patterns as a potential intermediary resource that can bridge traditional craft with modern manufacturing. However, these artisans also expressed dissatisfaction with the structural coherence and cultural detailing of current AI outputs, noting that the generated patterns are not yet suitable for direct application in textile production. As such, their stance remains one of cautious observation—not focused on the inherent value of the technology itself, but on whether it can effectively align with local craft workflows and market demands. In this regard, AI is seen less as an immediate creative tool and more as a proposed industrial solution pending validation. Its usefulness hinges not on theoretical capability, but on whether it can eventually integrate meaningfully into the practical realities of regional production systems.

Artisans' Negative Attitudes Toward AI. Artisans in the study who hold negative attitudes toward AI-generated patterns are typically proficient practitioners with extensive hands-on experience and strong pattern innovation capabilities. These individuals often play a central role in cultural transmission and creative leadership within the community. Unlike novices, they tend to rely on embodied skill and intuitive judgment in their creative processes. For this reason, they expressed a clear sense of unease regarding the efficiency and "near-perfection" of AI-generated content. As E1 remarked, "These things (AI-generated patterns) are already so well made—what is there left for us to create?"

For these cultural leaders, AI-generated patterns do not expand their expressive space; rather, they raise concerns about the redefinition of authority over "cultural creativity" [70]. She further emphasized her own ability to convert visual stimuli into embroidery through imagination, "I can stitch anything I see. As long as I can see it with my eyes, I can stitch it. Even if someone tells me a story, I can imagine it and stitch it." Our analysis suggests that such responses reflect two intertwined concerns. First, AI shifts pattern generation from embodied experience to system-driven logic. Without mechanisms for collaborative construction rooted in local contexts, the technology risks evolving into a standardized output tool—ultimately weakening the expressive agency of local cultures. Second, the lowered threshold for creation brought by AI also triggers anxiety among cultural inheritors regarding the potential reconfiguration of their symbolic authority within the community.

However, it is also important to critically examine the intuitive judgment that "AI is good enough", which is often based on superficial impressions of visual realism. While current AI-generated patterns may resemble traditional motifs in form, they remain incapable of expressing the deeper cultural structures embedded in Huayao cross-stitch—such as its narrative logic, social context, symbolic systems, and embodied techniques. Overall, AI generative mechanisms have not yet been meaningfully embedded within the community's value system or everyday practices, making it difficult for them to truly support the transmission and continuity of Huayao culture.

5 LIMITATIONS AND FUTURE RESEARCH

Although this study collected in-situ feedback from artisans through field interviews and focus groups, revealing the practical role of AI-generated patterns in local cultural contexts, several limitations remain. First, the research sample is concentrated within a specific Huayao cross-stitch community, and the cultural applicability and technical generalizability of the findings require further validation across regions and ethnic groups. Second, artisans' evaluations of AI-generated patterns are largely based on short-term exposure and may be influenced by the novelty effect or the constructed nature of the research setting. As such, certain negative attitudes may have been underestimated. Third, while this study primarily focuses on the visual form of generated patterns, it does not deeply explore their transmission mechanisms or broader social impacts within the actual creative ecosystem. Future research should engage with more situated practices to further expand the analytical scope.

Based on the findings of this study, opportunities for future research are suggested to explore the long-term impacts and potential risks of generative AI in local cultural innovation from three dimensions—technological, cultural, and social.

Technological dimension: Embedding cultural context and avoiding path dependency. Future research should systematically examine the aesthetic biases and cultural exclusion mechanisms present in generative models, and explore how to achieve cultural embedding by incorporating local semantic tags, cultural metadata, and community feedback mechanisms—thereby improving AI's capacity to accurately generate non-mainstream cultural content [71, 72]. Even as the accuracy and cultural understanding of AI models continue to improve, the creative pathways shaped by AI tools also warrant critical reflection. While the "visual templates" offered by AI may lower the barriers to creation, they can also restructure the compositional thinking of cultural holders—shifting the generative process from one rooted in embodied experience to a sequence of style selection, imitation, and localized adaptation [65, 73]. Research should also examine the issue of technological accessibility–the disadvantages that local communities face in terms of computing resources and professional maintenance capacity may restrict their long-term participation in AI-driven collaborative innovation [74, 75]. Therefore, future work should explore low-threshold and sustainable strategies for technical adaptation.

Cultural dimension: Contextual adaptation and continuity of practice. Future research should expand the evaluation frameworks for generated patterns across cross-cultural contexts, going beyond visual stylistic similarity to focus on their adaptability in daily community use, symbolic meaning transmission, and cultural contextual embedding [76, 77]. There is a need to remain vigilant against the detachment of AI-generated patterns from their original cultural contexts, particularly the crisis of authenticity that may arise from the misuse of cultural symbols. At the same time, it is essential to examine whether AI can enhance expressive efficiency while preserving the practice logic of cultural creation—one rooted in craftsmanship and embodied knowledge. Particular attention should be paid to the potential tensions brought about by intergenerational differences in perception: younger inheritors may view AI tools as "shortcuts to innovation", while traditionalists emphasize the ethical value of manual skill and cultural continuity [78, 79].

Social dimension: Restructuring of power relations and the construction of governance mechanisms. The intervention of AI technologies is reshaping how intangible cultural heritage (ICH) communities exercise sovereignty over cultural expression and identity. Future research should pay close attention to the risks of AI-generated patterns being commodified without community validation—especially as they enter transregional production—consumption chains that may lead to the templating of traditional designs and the decontextualization of cultural symbols [80, 81]. If AI becomes a conduit for cultural appropriation and capital extraction, local cultures risk being reduced to replicable visual assets, stripped of their original meaning. To address this, future studies should conduct longitudinal field-based evaluations of the cultural consequences of AI-driven dissemination, and map the shifting power structures involved in the recontextualization and value translation of generative content. At the same time, there is a pressing need to establish multi-level governance mechanisms centered on community authorization, clarifying local communities' decision-making power and data sovereignty throughout the development, deployment, and dissemination of AI systems.

6 CONCLUSION

This study investigated the application of deep learning—based generative AI tools in the creation of Huayao cross-stitch patterns. By combining LoRA fine-tuning with in-situ interviews and focus groups, it evaluates the performance of AI-generated patterns in terms of cultural expression and stylistic fidelity. The findings indicate that while fine-tuned models show advantages in enhancing visual consistency, they remain limited in reproducing symbolic semantics and deeper cultural meaning. Artisans perceive AI-generated patterns as sources of inspiration rather than as autonomous vehicles of cultural expression, and their cultural adaptability largely depends on the user's capacity for redesign and cultural judgment. Differences in artisans' attitudes toward AI reveal that technology acceptance is deeply embedded in individual skill levels, cultural identity, and community structures. The study emphasizes that the cultural value of AI lies not in replicating tradition, but in serving as a creative catalyst within processes of cultural co-creation. Its effectiveness depends on the extent to which it can be embedded within local knowledge systems and co-constructed with cultural holders. Future research should focus on how to promote cultural innovation while safeguarding cultural diversity and expressive sovereignty, and on developing sustainable frameworks for technology—culture collaboration.

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