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ABSTRACT

This research establishes a systematic framework for textile design innovation by integrating digital archival methods with contemporary textile manufacturing technologies. It specifically investigates the application of digitized ethnic art archives for creating novel textile surface patterns, aiming to bridge cultural heritage with modern fabric design and production. Focusing on Miao ethnic art, the study details a methodology comprising three stages: (1) high-fidelity digitization and semantic analysis of traditional textile patterns to build a structured digital archive; (2) an AI-driven creative process utilizing StyleGAN2-ADA with transfer learning to synthesize novel, printable textile patterns from a limited archival dataset; and (3) an empirical evaluation of the resulting digitally printed textiles through market analysis and consumer surveys. A quantitative analysis of 500 traditional patterns informed the GAN model, which successfully generated 100 new textile designs. Validation through nearest neighbor analysis confirmed that the model produces stylistically consistent yet visually distinct variations without directly replicating training samples. Furthermore, a color fidelity test on digitally printed samples yielded a ΔEcmc of 2.4, verifying the physical reproducibility of the generated designs. A comparative consumer survey (n = 600) confirmed a significantly higher purchase intention ($p < 0.001$) for the expert-curated selection of textiles featuring these culturally grounded designs compared to generic prints. The discussion addresses the critical balance between design innovation and cultural appropriation and the role of digital technology in revitalizing traditional motifs for the modern textile industry. The findings validate a replicable pathway for transforming cultural assets into market-viable textile design concepts.

KEYWORDS

digital textile printing, textile pattern design, computational textile design, ethnic patterns, Miao art

INTRODUCTION

The global textile market is increasingly driven by consumer demand for products with unique aesthetic value

and authentic cultural narratives [1,2]. In this context, the vast and diverse visual archives of ethnic art represent an underutilized reservoir of inspiration and design innovation. However, the translation of these intricate, culturally significant images into contemporary textile products is fraught with challenges, including the risk of cultural misinterpretation, the static nature of physical archives, and the difficulty of scaling traditional motifs for modern production [3,4]. The advent of advanced digital technologies offers a transformative solution, providing tools not only to preserve this heritage but also to dynamically integrate it into the fabric of modern design [5]. This research addresses the critical need for a structured and scientifically grounded pathway for the digitization and application of ethnic art image archives in textile product design.

The central challenge lies in moving beyond simple digital reproduction to a process of meaningful translation—one that respects the semantic and aesthetic integrity of the original art while adapting it for new contexts [6,7]. This involves creating high-fidelity digital archives that capture the nuances of form, color, and texture, and developing intelligent systems capable of analyzing these elements to support creative design processes [8-10]. Furthermore, the successful application of these digital assets depends on a clear understanding of market dynamics and consumer perceptions. Without a systematic approach, the use of ethnic art risks becoming superficial ethno-chic, which can devalue cultural symbols and fail to connect with consumers on a deeper level [3,11,12].

This paper proposes a comprehensive methodology to address these challenges, using the rich and complex visual tradition of the Miao ethnic group in China as a case study. By focusing on a specific cultural context, this study aims to develop a small and precise research model that can be adapted to other cultural heritages. The research demonstrates a pathway from the archival image to a market-ready textile product, underpinned by quantitative data analysis and a rigorous evaluation framework. The objective is to establish a scientifically valid, repeatable, and ethically considerate model for leveraging digital ethnic art archives as a catalyst for innovation and cultural sustainability in the textile industry.

LITERATURE REVIEW

The intersection of digital technology, cultural heritage, and textile design is an emerging field of academic inquiry [13]. Early research predominantly focused on the digitization of museum collections for archival and preservation purposes [14]. Scholars have extensively documented the technical processes of high-resolution scanning, 3D imaging, and the creation of metadata schemas for cataloging textile artifacts. These efforts

have been crucial in safeguarding tangible cultural heritage from physical degradation and making it accessible to a global audience of researchers and the public [14,15]. However, these initiatives often treat artifacts as static objects of study rather than as dynamic sources for contemporary creative practice.

More recent scholarship has begun to explore the application of these digital archives in design [16]. The use of Computer-Aided Design (CAD) software to manipulate and repeat traditional patterns for digital printing is now a standard industry practice [5,7]. Concurrently, research in computer science has demonstrated the potential of artificial intelligence (AI) and machine learning in the creative domain. Studies have shown the efficacy of generative adversarial networks (GANs) and other deep learning models in analyzing the stylistic elements of visual art and generating novel images [17,18]. Specifically within textiles, researchers have experimented with using AI to create new weaving patterns and embroidery designs inspired by historical examples [16,19]. Recent work on Miao embroidery, for instance, has successfully used diffusion models to generate new patterns, demonstrating the technical feasibility of AI-assisted design in this specific cultural context [20].

Despite these technological advancements, a significant gap remains in the literature concerning a holistic and validated methodology for the entire process—from digitization to market application. While technical papers detail specific algorithms, they often lack a connection to real-world design constraints, cultural sensitivities, and commercial viability. Conversely, design and cultural studies literature often discusses the importance of cultural heritage in design but may lack the technical and quantitative rigor to propose a systematic, scalable methodology. Furthermore, the critical ethical dimension, particularly the intellectual property rights of indigenous communities and the prevention of cultural appropriation, is a recurring theme but is rarely integrated into a practical application framework [21]. This research aims to bridge this gap by proposing and testing a comprehensive pathway that integrates high-fidelity digitization, AI-driven creative development, and robust market evaluation, all while foregrounding ethical considerations as a central component of the design process.

METHODOLOGY

This research employs a multi-stage, mixed-methods approach, integrating digital image analysis, AI-driven design generation, and consumer behavior analysis to create and validate a pathway for applying ethnic art archives in textile design. The Miao ethnic group's textile art was selected as the case study due to its well-

documented, complex visual system and symbolic richness.

Stage 1: Digital Archive Creation and Analysis

The digital archive was constructed from 500 distinct Miao embroidery and batik patterns. The sources were acquired with permission from two primary collections: (1) the digital archives of the Guizhou Provincial Museum (Guiyang, China), and (2) high-resolution plates from the academic monograph *Textile Traditions of Southwest China* (2010). The original medium of these sources varied and was carefully standardized. The museum's contribution consisted of high-resolution, color-calibrated digital photographs of finished embroidery pieces. The patterns from the monograph, primarily flat batik textiles, were scanned directly from the physical publication plates using a flatbed scanner at 1,200 DPI. This high resolution was specifically chosen to capture the fine textural details of the batik craquelure and the precise color data from the plates, ensuring a high-fidelity dataset that served as the foundation for the subsequent Sf and Cp analyses. A metadata schema was developed to classify each pattern based on its primary motif (e.g., butterfly, dragon, geometric spiral), regional style, and symbolic meaning, as identified from ethnographic literature. It is critical to note that this classification was based entirely on existing academic (ethnographic) literature, not on direct consultation with contemporary Miao community bearers. Therefore, while we identified symbolic meanings, this process did not include a formal ethical screening to filter for patterns that may be sacred, restricted, or otherwise not intended for commercial reinterpretation by the community. This reliance on publicly accessible, second-hand sources, which may not reflect current community wishes, constitutes a significant limitation of the archive's cultural sensitivity. The ethical statement provided to survey participants in Stage 3 was a mitigating measure, not a sufficient methodological filter at the archival stage.

To provide a quantitative foundation for the AI model, two key metrics were extracted from the archive using two distinct methods:

- **Symbol Frequency (Sf):** This metric was not derived from automated image processing, as reliably identifying complex, stylized motifs is beyond the scope of simple scripting. Instead, the Sf (the rate of occurrence of the 20 most common symbolic motifs) was calculated directly from the manual semantic annotations completed during the metadata schema creation. Specifically, the semantic annotation was conducted following a predefined classification guideline derived from ethnographic studies on Miao textile symbolism. The guideline defined clear criteria for motif identification, including primary visual structure, symbolic representation, and historical usage, limiting each pattern to one dominant motif

category. The annotation process was performed independently by two annotators with backgrounds in textile design and ethnic art studies. Prior to formal annotation, a pilot labeling round on 50 randomly selected samples was conducted to refine the classification rules and ensure conceptual alignment. Inter-annotator reliability was assessed using Cohen's Kappa coefficient, yielding a value of 0.82, which indicates strong agreement. Discrepancies were resolved through discussion to reach a consensus annotation, which was then used for the final Sf calculation.

- **Color Palette Grammar (Cp):** This metric was automated. We employed a two-step quantization process using Python/OpenCV. Prior to clustering, image pixels were converted from RGB to the CIELAB color space to ensure perceptual uniformity in color distance calculations. A global k-means clustering was then performed using the k-means++ initialization method to optimize convergence. The optimal number of clusters, K = 12, was determined using the Elbow Method, identifying the point where the reduction in within-cluster sum of squares (WCSS) began to plateau. This process established a standardized universal palette of 12 canonical Miao colors. Second, each pixel in the 500 archival images was re-mapped to its nearest canonical color index. To calculate the Cp, we performed a spatial adjacency scan (4-connectivity) on these segmented images, counting the frequency of pixel transitions between distinct color indices. This generated a global co-occurrence matrix representing the probabilistic likelihood of two specific colors appearing adjacently.

This combined manual (semantic) and automated (color) analysis provided the quantitative grammar of the traditional Miao aesthetic, serving as the critical benchmarking framework for evaluating and curating the AI-generated outputs in Stage 2.

Stage 2: AI-Driven Design Reinterpretation

The AI-driven design reinterpretation was conducted using the StyleGAN2-ADA (PyTorch) repository. The curated dataset of 500 Miao patterns was pre-processed and standardized to a uniform 1,024 × 1,024 pixel resolution to serve as input. To address the challenge of limited data availability (n = 500) and prevent overfitting, we adopted a transfer learning strategy. The StyleGAN2-ADA model was initialized using pre-trained weights from the FFHQ dataset (Flickr-Faces-HQ), leveraging its learned low-level feature extractors (e.g., edges and textures). Furthermore, we utilized Adaptive Discriminator Augmentation (ADA), which dynamically adjusts augmentation strength during training to stabilize convergence on small datasets. Specifically, we applied the standard bgc (blitting, geometry, color) augmentation pipeline, which includes x-

flips, 90-degree rotations, integer translation, and hue/saturation adjustments. Due to the limited dataset size (n = 500), no distinct validation set was reserved; the entire archive was utilized for training to maximize the diversity of learned features. The Fréchet Inception Distance (FID) was calculated using the standard InceptionV3 feature extractor. To ensure statistical stability, the metric was computed between 50,000 randomly generated images and the full set of 500 real training images. The model was fine-tuned on a single NVIDIA A100 GPU with a batch size of 32 and a transfer learning-specific learning rate of 0.0025. The objective was not to replicate existing patterns but to fine-tune the model to capture salient visual stylistic features consistent with the recurring symbol morphologies and dominant color relationships quantified in Stage 1. The model was trained for 50,000 iterations, at which point the FID score stabilized, indicating successful learning (the final score is reported in the Results).

Following training, the model was used to generate a portfolio of 100 novel textile pattern designs. This creative reinterpretation phase was a manual, iterative process guided by the researchers, not an automated search. The researchers manually explored the latent space vectors, empirically prioritizing compositions that aligned with the quantitative benchmarks from Stage 1, specifically those integrating high-frequency traditional symbols (Sf > 0.15) and canonical color pairings. This manual curation aimed to produce designs that were recognizably rooted in Miao tradition yet distinct from any single historical example, balancing cultural authenticity with novelty.

Stage 3: Application and Evaluation

The 100 generated designs were converted from the sRGB color space to the printer's CMYK profile using a perceptual rendering intent, and then digitally printed onto cotton fabric samples. A two-part evaluation was then conducted to assess the application pathway's effectiveness. In this study, the evaluation of textile product viability is defined in terms of design realizability and market-oriented consumer perception. While the generated patterns were digitally printed onto cotton fabric samples to demonstrate physical feasibility, no comprehensive industrial performance testing (e.g., color fastness, durability, or wash resistance) was conducted at this stage.

Preliminary Expert Review: To guide the selection of designs for the broader consumer study, a specialized panel of five experts (two textile designers, two cultural historians specializing in Miao art, and one marketing professional) was convened for a qualitative assessment. Prior to the quantitative rating, the panel implemented a mandatory Cultural Safety Screening protocol. The two cultural historians examined the

generated portfolio to identify and exclude any motifs that might inadvertently resemble sacred, funerary, or restricted clan symbols. Only designs clearing this ethical checkpoint proceeded to the evaluation phase. The panel then rated the generated designs on a 5-point Likert scale for three criteria: Cultural Authenticity, Aesthetic Appeal, and Market Potential, which helped identify the strongest candidates for market viability testing.

Consumer Perception and Market Viability Study: A quantitative online survey was administered to a total of 600 consumers interested in fashion and home textiles. Participants were recruited via targeted advertisements on mainland Chinese e-commerce and social media platforms (e.g., Taobao and Weibo). All 600 respondents self-identified as residing in mainland China. This demographic was chosen to first validate the pathway's effectiveness within the designs' primary domestic market and cultural context. Participants were randomly assigned to one of two groups: an experimental group (n = 300) that viewed the AI-generated designs, and a control group (n = 300) that viewed the generic ethnic designs. The survey employed a comparative methodology. Participants were shown two sets of textile products (cushion covers and tote bags): one featuring the top five AI-generated designs (as rated by the expert panel) and a control set featuring five commercially available, generic ethnic-inspired patterns. For each product, participants rated their Purchase Intention (PI) on a 7-point Likert scale. Cronbach's alpha for the Purchase Intention scale was 0.87, indicating satisfactory internal consistency. The mean PI scores for the two groups were compared using an independent samples t-test to determine if the culturally grounded, AI-assisted design process resulted in a statistically significant difference in consumer preference. The significance level was set at $\alpha = 0.05$. Ethical considerations were addressed by ensuring all visual materials used for the study were created for this research and by providing clear information to participants.

RESULTS

The multi-stage methodology yielded quantifiable results at each phase of the research, providing data-supported validation of the proposed application pathway.

Digital Archive and Pattern Analysis

The analysis of the 500-image archive produced a quantitative breakdown of core design elements. The symbol frequency analysis revealed that the butterfly motif (Sf = 0.28) and the "spiral" or "whirlpool" motif (Sf = 0.21) were the most prevalent, appearing in 28% and 21% of the samples, respectively. The color palette

grammar analysis resulted in a co-occurrence matrix that confirmed the traditional preference for high-contrast pairings, with the combination of deep indigo (RGB: 75, 0, 130) and bright crimson (RGB: 220, 20, 60) showing the highest co-occurrence probability (P = 0.35). These data provided a precise, machine-readable definition of the Miao aesthetic that guided the subsequent AI generation phase. A detailed breakdown of the most common motifs and color pairings is provided in Table 1 and Table 2.

Table 1. Top 5 Most Common Symbolic Motifs

Rank	Motif	Frequency (S_f)
1	Butterfly	0.28
2	Spiral / Whirlpool	0.21
3	Dragon	0.15
4	Fish	0.11
5	Flower (Peony)	0.09

Table 2. Top 3 Most Common Color Co-occurrence Pairs

Rank	Color Pair	Co-occurrence Probability (P)
1	Deep Indigo (RGB: 75, 0, 130) & Bright Crimson (RGB: 220, 20, 60)	0.35
2	White (RGB: 255, 255, 255) & Deep Indigo (RGB: 75, 0, 130)	0.24
3	Bright Crimson (RGB: 220, 20, 60) & Saffron Yellow (RGB: 244, 196, 48)	0.18

AI-Generated Designs and Expert Evaluation

The StyleGAN2 model, trained on the annotated dataset, successfully generated 100 novel patterns. To assess whether the generated patterns exhibited obvious pixel-level duplication of training samples, we performed a Euclidean distance-based nearest neighbor analysis in pixel space. This analysis was used as an auxiliary, qualitative tool to facilitate visual comparison between generated images and their closest training counterparts, rather than as a definitive measure of semantic or structural similarity. As illustrated in Figure 1, although certain global color distributions and stylistic characteristics are preserved, the generated patterns display distinct structural layouts and textural variations at the pixel level. Visual inspection of the generated samples alongside their closest training neighbors—as illustrated by the representative example in

Figure 1—confirmed that while the stylistic grammar (e.g., color distribution and stroke texture) was preserved, the generated compositions possessed distinct structural layouts and morphological details. This demonstrates the model's capability to recombine learned stylistic features into visually novel variations, rather than merely replicating existing artifacts. Furthermore, to verify the physical realizability of the digital designs, a color fidelity analysis was performed on the printed cotton samples. We measured the Lab color values of the key chromatic areas (Deep Indigo and Bright Crimson) on the printed fabric using a spectrophotometer and compared them with the digital target values. The average color difference (ΔE_{cmc}) was calculated to be 2.4, which falls within the acceptable tolerance for industrial textile printing ($\Delta E < 3.0$). This confirms that the AI-generated aesthetic grammar can be accurately translated into physical textile products. The qualitative assessment from the expert panel was positive and informed the selection of the top-rated designs for the consumer survey. Notably, the historians confirmed that none of the generated patterns violated known cultural taboos, validating the effectiveness of the initial exclusion criteria. The average score for Cultural Authenticity was 4.1/5, indicating that the experts perceived a strong connection to the traditional Miao visual language. The average score for Aesthetic Appeal was 4.3/5, and for Market Potential, it was 4.0/5. The qualitative feedback from the panel consistently noted that the designs were perceived as authentic without being direct copies and demonstrated a successful fusion of tradition and modernity.

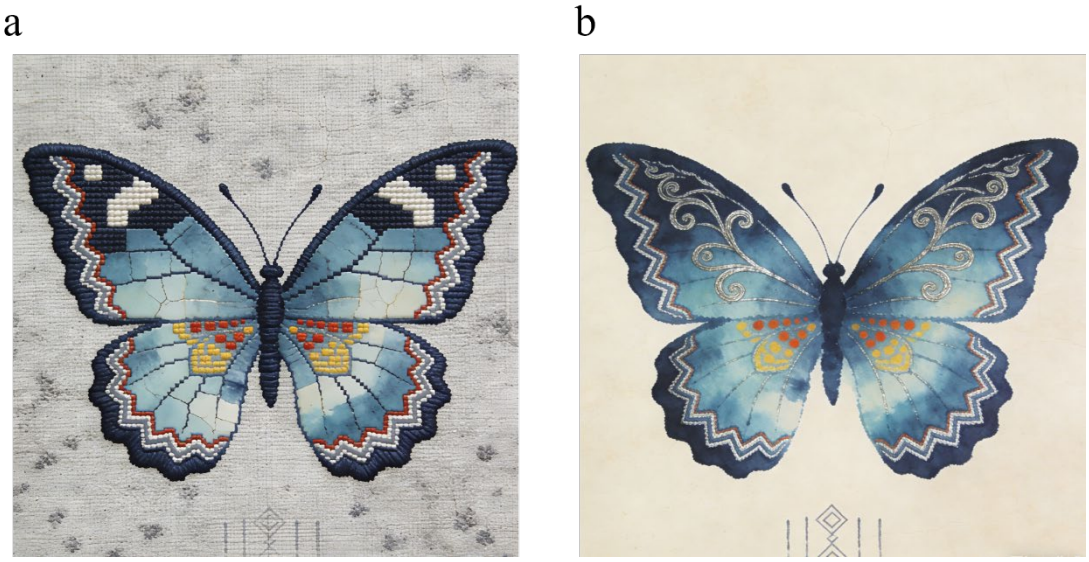

Figure 1. Pixel-Level Nearest Neighbor Comparison for Visual Inspection. A side-by-side comparison of a generated design (a) and its nearest neighbor from the training dataset (b)

The AI model captures the butterfly motif and the characteristic indigo–crimson palette. However, it produces distinct pixel-level textures and stroke morphologies (e.g., a painted effect rather than the original cross-stitch appearance).

Consumer Perception and Market Viability

The results of the consumer survey provided strong statistical evidence supporting the effectiveness of the proposed methodology. The mean Purchase Intention (PI) score for the textile products featuring the AI-generated Miao-inspired designs was significantly higher than for the products with generic ethnic patterns. The AI-generated designs group had a mean PI of 5.82 (SD = 1.05), whereas the control group had a mean PI of 4.15 (SD = 1.20).

An independent samples t-test was conducted to compare the mean PI scores. The results in Table 3 showed a statistically significant difference between the two groups, $t(598) = 18.14$, $p < 0.001$. This p-value is substantially below the predetermined significance level of $\alpha = 0.05$, indicating that the higher purchase intention for the designs created through the culturally grounded digital workflow was not due to chance. The findings suggest that consumers can discern and value the greater authenticity and narrative depth of the designs, which translates directly into higher market viability.

Table 3. Comparison of Consumer Purchase Intention Scores

Group	N	Mean Purchase Intention (1–7 Scale)	Std. Deviation	t-statistic	p-value
AI-Generated Miao Designs	300	5.82	1.05	18.14	< 0.001
Generic Ethnic Designs	300	4.15	1.20		

These combined results validate the entire pathway, from the quantitative analysis of a cultural archive to the AI-driven creative process and its positive reception in a simulated market environment.

DISCUSSION

The findings of this research present substantial evidence for the efficacy of a structured, technology-driven pathway for applying ethnic art archives in textile design. The statistically significant increase in consumer purchase intention for the AI-generated, culturally grounded designs over generic ethnic prints is particularly telling. This suggests that the modern consumer is not merely seeking exotic aesthetics, but is receptive to products that embody authentic cultural narratives and demonstrate a thoughtful design process. The methodology employed in this study—combining quantitative cultural data analysis with creative AI—offers a potent alternative to the superficial appropriation of ethnic motifs. It provides a means to innovate from a tradition rather than simply copying from it, thereby creating products with deeper resonance and market appeal.

The success of this pathway, however, hinges on a nuanced understanding of the interplay among technology, culture, and commerce. The role of AI in this context is not to replace the human designer but to act as a sophisticated tool for cultural translation. By capturing the visual grammar of Miao art—the frequencies of symbols and the relationships between colors—the GAN model was able to generate novel compositions that adhered to the foundational aesthetic principles of the source culture. This process of creative reinterpretation is crucial; it allows for the evolution of traditional art forms, preventing them from becoming static relics. This dynamic preservation ensures that cultural heritage remains relevant and alive, capable of participating in contemporary discourse and economic life.

Furthermore, this research underscores the indispensable need for ethical considerations to be woven into the fabric of the design process. A critical ethical distinction in our methodology lies in the implementation of the expert filter versus community consent. While the Cultural Safety Screening performed by academic historians successfully served as a proxy to prevent overt cultural misappropriation or the misuse of taboos, it remains an etic (outsider) verification. We acknowledge that relying on academic proxies, rather than direct consultation with community bearers, limits the validation to a scholarly verified framework.

Consequently, our claim to cultural sensitivity is limited to the aesthetic and semantic reinterpretation and does not extend to a verified, community-approved ethical framework. The statement provided to survey participants was a mitigating step, not a sufficient methodological solution. A true real-world application of this pathway must integrate community collaboration, data sovereignty, and benefit-sharing agreements prior to any digitization. This ensures that the source communities—not just researchers—are the primary

decision-makers and beneficiaries of their cultural heritage's revitalization, resolving the significant ethical gap present in our current study.

It is critical to acknowledge a significant methodological limitation regarding the expert filter used in our evaluation. As noted, the five-person expert panel's findings are not generalizable. However, this non-generalizable panel served as the sole mechanism for selecting the five top designs (from 100) that were subsequently tested in the main consumer study. This introduces a significant selection bias. The statistically significant consumer preference ($p < 0.001$) does not validate the overall efficacy of the AI-assisted pathway, but rather the efficacy of a highly curated, expert-selected subset of its output. We cannot, from this data, generalize that the entire portfolio of 100 AI-generated designs would outperform the control. A more robust methodology would have presented consumers with a larger, randomly selected sample from the 100 generated designs. Such a design would minimize the expert filter bias and provide a more accurate validation of the pathway itself, rather than just its most successful curated examples. This limitation must be addressed in future work. Finally, a significant limitation of this study is the gap between the digital evaluation and the physical manufacturing process. While our methodology included the step of digitally printed onto cotton fabric samples, our evaluation focused exclusively on the design's aesthetic and market appeal, not on its technical printability. While our color fidelity analysis ($\Delta Ecmc = 2.4$) demonstrated the fundamental feasibility of printing these complex patterns, future research should expand to encompass a broader range of substrates (e.g., silk, polyester) and more complex color management workflows. The current success on cotton serves as a foundational proof of concept for the digitalization-to-production pathway. This is a crucial omission, as the pathway's ultimate goal is to connect archives to contemporary textile manufacturing. Future research must incorporate a formal technical evaluation of the printed textiles to validate the manufacturing feasibility of these AI-generated, culturally grounded designs, thereby fully bridging the gap between the digital archive and the physical product. At the same time, it is critical to acknowledge the limitation of the control group used in the consumer study. The comparison group, defined as commercially available, generic ethnic-inspired patterns, serves as a baseline for current market offerings but is not a precise experimental control. A more rigorous comparison would involve testing the AI-generated designs against designs created by human designers using the same digital archive, or against simple replications of the original patterns.

Therefore, the current results strongly validate the *overall pathway*—which fuses a specific, culturally grounded archive with an AI-generative tool—against generic commercial alternatives. However, the study in

its current form cannot fully isolate the specific contribution of the AI component itself versus the inherent value of the source archive. Future research should aim to conduct this more granular comparison to distinguish the specific value added by the AI-driven reinterpretation process from that of human-led design using the same cultural assets.

Finally, the demographic scope of our consumer survey presents a significant limitation to the generalizability of our market viability findings. As noted in the methodology, our n = 600 sample was sourced entirely from consumers within mainland China. While this provides a strong validation of the pathway within its domestic market, the high PI score may be partially influenced by cultural proximity or existing familiarity with Miao-inspired aesthetics.

Consequently, these findings cannot be generalized to the global textile market referenced in the introduction. Future research is essential to test the reception of these designs among diverse international consumer groups (e.g., European and North American) to determine their true global market potential.

CONCLUSION

This research has successfully designed, implemented, and validated a systematic pathway for the digitization and application of ethnic art image archives in textile product design. By focusing on the specific case of Miao ethnic patterns, this study has demonstrated that a methodology grounded in quantitative analysis and augmented by AI-driven creative tools can produce innovative textile designs that are not only aesthetically compelling, technically reproducible, and commercially viable, but also culturally authentic. The data-driven approach, from the creation of a semantically structured digital archive to the statistically significant results of the consumer evaluation, provides a robust framework that moves beyond anecdotal design inspiration to a replicable, scientific process.

The core contribution of this work is the establishment of an integrated model that bridges the gap between cultural preservation and market-driven innovation. It proves that digital technology can serve as a powerful instrument for the dynamic continuation of cultural heritage, transforming static archives into living resources for creative industries. The findings indicate a clear consumer preference for products that embody genuine cultural narratives, highlighting a significant market opportunity for textiles developed through such considered and respectful methods.

Ultimately, this study provides a blueprint for a more culturally sensitive and sustainable approach to textile

design. It calls for a paradigm shift where designers act not just as creators but as cultural translators, and where technology is leveraged not for mere replication but for meaningful reinterpretation. The future development of this field will depend on strengthening the ethical frameworks surrounding digital cultural heritage and fostering collaborative partnerships with source communities. By embracing such a holistic approach, the textile industry can unlock a wealth of creative potential while playing a proactive role in the preservation and celebration of global cultural diversity.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

Author Contributions

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

Ethics Approval and Consent to Participate

This survey was conducted in compliance with Ethics Committee of Shanxi College of Applied Science and Technology. Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

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Conflict of Interest

The author declares no conflict of interest.

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