Contemporary Art Practice Path to Build a Strong Community Consciousness—Digital Regeneration Design Based on the Ethnic Mural Heritage Along the Belt and Road

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ABSTRACT This study investigates the visual symbol system of ethnic murals along the Belt and Road and proposes a digital regeneration framework to address material degradation and semantic discontinuity in cultural heritage preservation. Based on cultural memory theory and symbolic cross-media narrative, the framework integrates cultural gene extraction, cross-media translation, and community narrative reconstruction through high-precision multimodal acquisition, deep semantic analysis, and generative design techniques. Multispectral digital acquisition and computational visual modeling provide reliable information capture strategies that are conceptually relevant to electromagnetic imaging and intelligent sensing applications, offering methodological references for data acquisition and feature representation in antenna-assisted cultural heritage monitoring. Visual anthropology and ethnic identity mechanisms are employed to establish structured fusion rules, while generative artificial intelligence and parametric design transform mural symbols into textile patterns. Experimental evaluation using a five-dimensional perception framework and semantic resonance analysis demonstrates high immersion (8.86), visual beauty (8.90), and narrative resonance (93/100) for the regenerated designs. The proposed framework effectively preserves mural cultural genes while enabling their contemporary textile transformation, providing a reproducible digital paradigm for cultural heritage regeneration and offering valuable insights for multidisciplinary applications involving multimodal sensing, computational imaging, and digital communication technologies.

INDEX TERMS digital regeneration, multispectral imaging, cultural heritage sensing, textile pattern design, visual symbol system

I. INTRODUCTION

THE textile industry is shifting from functional to culture-driven models. By reinterpreting ethnic mural heritage, textiles gain enhanced cultural value, aesthetic innovation, and sustainability for national brands. Along the Belt and Road corridors, ethnic murals—sharing patterns, color systems, and compositional logic with textile arts—have attracted increasing attention in heritage and textile design studies [1,2]. Accordingly, 24 representative mural sites in Western China and Central Asia were selected to extract symbolic motifs and construct a methodological framework for digital regeneration. As witnesses of multi-ethnic exchange, these murals record visual memories of civilization and convey ethnic identity [3,4]. However, generational gaps and misunderstandings of their religious, mythological, and ritual contexts weaken their narrative functions [5]. Although mural patterns, colors, and symbols are rich resources for textile innovation, their poor alignment with contemporary aesthetics reduces appeal [6,7]. Moreover, the lack of an integrated mechanism limits the refinement of shared cultural elements and their role in fostering Chinese national identity [8,9]. A "systematic visual language integration mechanism," based on morphological coordination, Lab color encoding, and semantic fusion, could establish a unified multi-ethnic visual grammar, yet current practices focus mainly on restoration rather than cross-cultural narrative re-creation [10,11]. Therefore, scientifically reconstructing mural visual expression while respecting original meanings is essential for building a shared visual symbol system of multi-ethnic identity and resonance [12,13].

Recent studies emphasize art's role in cross-cultural exchange, cultural identity, and social cohesion. Linuwih linked Chinese murals in Surabaya Chinatown to community memory and identity [14], Khan highlighted art's bridging function in multicultural societies [15], and Al-Zadjali showed its power to challenge stereotypes and empower marginalized groups [16]. However, most research remains conceptual, lacking practical and quantitative frameworks to translate regional culture into textile design. This study addresses this gap by constructing a reproducible mural-based visual language system with cross-cultural aesthetic consistency.

In cultural heritage digital regeneration, Mason proposed a people-oriented museum design framework stressing digital enhancement [17]. Liu examined intangible heritage protection through modern technology and systematic platforms [18], and Paschalidou et al. built a sustainability-oriented digital protection model [19]. Existing studies focus on museums, intangible heritage, and archiving, but rarely reconstruct cultural genes into visual narratives or multi-ethnic visual language systems. This study uses mural motifs for textile design to build a digital-to-pattern workflow that enhances Chinese community consciousness.

This paper proposes a mural-based textile pattern innovation method following "cultural gene extraction– cross-media translation–community narrative reconstruction." Belt and Road murals are digitized to build a dataset of texture, color, and composition, and a symbolic database is constructed using image recognition and NLP. Cross-ethnic commonalities are mapped, motifs are adapted through multimodal generation, and AR supports narrative reconstruction. The study demonstrates the value of mural motifs, color, and composition for contemporary textile design and multi-ethnic identity.

CONSTRUCTION OF ART PRACTICE PATH FOR DIGITAL REGENERATION DESIGN OF NATIONAL MURAL HERITAGE

DIGITAL EXTRACTION TECHNOLOGY OF MULTI-ETHNIC CULTURAL GENES

DEEP SEMANTIC ANALYSIS OF MURAL ONTOLOGY INFORMATION

Deep semantic analysis integrates multispectral imaging and ResNet to construct a cross-modal semantic map for textile design, supporting topology, color distribution, and composition analysis. A 16-channel multispectral system (400–1000 nm) corrects illumination effects and establishes the murals' spectral reflectance function.

$$R(\lambda)=\frac{DN_{\text{raw}}(\lambda)-DN_{\text{dark}}(\lambda)}{E(\lambda)\cdot t} \tag{1}$$

DN_{raw} represents the original digital value, DN_{dark} is the dark current compensation, E(λ) is the irradiance per band, and t is the integration time. The 16-dimensional spectral data is reduced using principal component analysis to create a multimodal data cube that captures material composition and drawing process features, enabling precise analysis of mural pattern, color, and composition characteristics:

$$PC_k=\sum_{i=1}^{16} w_{ki}\cdot R(\lambda_i) \tag{2}$$

Among them, w_{ki} is the weight coefficient of the k-th principal component in the λ_i band. The ResNet-152 architecture uses a cross-layer feature fusion mechanism and optimizes parameters through transfer learning with the ImageNet pre-training model. During forward propagation, the residual module performs feature transformation.

$$H(x)=F(x,\{W_i\})+x \tag{3}$$

Among them, F(x) is the residual function composed of stacked convolutional layers, and x is the input feature. Wi represents the convolutional weight matrix of the i-th residual block, which determines the feature transformation strength at each layer. A multi-scale attention module is designed based on mural pattern features, with a spatial pyramid pooling layer added after the final residual block to extract topological invariant features of the pattern contour.

$$A_{ij}=\frac{\exp(s(Q_i,K_j))}{\sum_{j=1}^{N}\exp(s(Q_i,K_j))} \tag{4}$$

Among them, Qi is the query vector; Kj is the key vector; s(·) is the similarity calculation function. The multispectral and visual morphological features are fused via tensor concatenation to form a 3D semantic association map:

$$G=\operatorname{ReLU}\left(W_g\cdot[F_{\text{spec}}\oplus F_{\text{vis}}]+b_g\right) \tag{5}$$

Among them, Fspec∈ResNet-256 is the spectral feature vector; Fvis∈ResNet-512 is the visual feature vector; Wg is the 512×768 weight matrix. bg represents the bias term introduced in the fusion process, which ensures the stability of feature alignment between spectral and visual modalities. The symbolic map is built by aligning BERT-encoded semantic nodes from mural texts with ResNet-152 visual features. Graph attention layers analyze structural correspondence via co-occurrence and edge weight similarity across ethnic groups. Containing 120 motifs and 340 relationships, the map is iteratively optimized with a graph attention network, where the node update formula is:

$$h_i^{(l+1)}=\sigma\left(\sum_{j\in N(i)}\alpha_{ij}^{(l)}W^{(l)}h_j^{(l)}\right) \tag{6}$$

Among them, α_{ij} is the attention coefficient, and $N(i)$ is the neighborhood of node i. $h_j^{(l)}$ represents the feature vector of neighbor node j in layer l; $W^{(l)}$ represents the learnable weight matrix of layer l, which is used to apply linear transformation to the neighbor feature vector and participate in the aggregation operation after weighting the attention coefficient. Finally, the fully connected layer outputs the classification probability of cross-ethnic motifs, with a weighted cross-entropy loss:

$$L = -\sum_{c=1}^{C} w_c y_c \log(p_c) \tag{7}$$

Among them, $w_c = 1/\sqrt{N_c}$ is the inverse square root weight of the number of samples of category c, and N_c is the number of samples of category c in the training set. y_c is the true label indicator variable for the sample in category c. It takes a value of 1 if the sample belongs to category c and 0 otherwise. p_c is the probability value predicted by the model that the sample belongs to category c. It is used together with y_c to calculate the cross-entropy loss. The experiment uses a batch size of 32, learning rate 0.001, and Adam optimizer for end-to-end training. The resulting semantic map and database form the 'mural-pattern gene digital resource library' for subsequent textile pattern design.

VALUE DIMENSION ENCODING OF CULTURAL SYMBOLS

To encode the value dimension of cultural symbols, a three-layer system is built on Saussure's 'signifier– signified' model, extended to an (S, R, V) triple: S denotes formal traits, R the cultural image, and V the spiritual value. Formal features are quantified via image analysis (e.g., line density, contour curvature, node distribution) to capture morphological complexity and structural characteristics. Assuming that the input image is I(x, y), and its gradient is $\nabla I = (\partial I/\partial x, \partial I/\partial y)$, then the local line density D is defined as the trace of the structural tensor $J = \nabla I \cdot \nabla I^T$, that is, $D = Tr(J) = (\partial I/\partial x)^2 + (\partial I/\partial y)^2$, which is used to describe the morphological complexity of the pattern in a specific area.

Image connotation encoding builds a semantic embedding space from symbol–image mappings, using BERT (further pretrained on 10,000 mural documents) for textual encoding and a GNN for semantic dependency extraction. Annotations are organized into literal, symbolic, and cultural layers. Contrastive learning aligns ResNet-152 visual features with BERT embeddings, while the GNN integrates multimodal features into a unified semantic graph of nodes (concepts) and edges (contextual relations). Each cultural symbol, represented by node vector hi, aggregates adjacent nodes via $\phi(h_i)=\sigma(\sum j\in(i)Wh_j)$ to form a nested semantic feature, which is multimodally fused with image features to produce vector R quantifying cultural symbolism.

The spiritual value layer uses PCA and semantic scoring to map high-dimensional cultural traits. Principal components project each symbol's spiritual vector via expert-annotated scoring. A three-layer nested value vector $C_i=[D_i,R_i,V_i]$ enables semantic alignment, visual reconstruction, and narrative fusion, quantitatively representing form, symbolism, and spiritual connotation for standardized input in mural modeling and community narrative reconstruction.

VISUAL GENERATION MECHANISM OF CROSS-MEDIA TRANSLATION

MORPHOLOGICAL TRANSLATION ALGORITHM OF DIGITAL MEDIA

The multimodal framework combines StyleGAN2 with semantic conditioning: ResNet-152 encodes visual features, BERT extracts cultural semantics, and cross-modal attention fuses them to generate patterns that retain mural form and meaning. Adversarial, perceptual, and consistency losses guide training. A parametric system incorporating L-system grammar, polar layouts, and Lab color optimization enables controllable style, scale, color, and composition, producing textile-ready outputs with repeatability and print fidelity for cultural continuity and contemporary adaptation.

Five models—ResNet-152, StyleGAN2, Bi-LSTM, GRU, and GAT—are compared under unified settings for training time, GPU memory, and inference efficiency (Table 1).

TABLE 1. Comparison of core model computing power performance

Model	Training Time (hrs)	GPU Memory (GB)	Avg Inference Time (ms/sample)
ResNet-152	14.2	10.8	7.6
StyleGAN2	26.5	23.4	18.2
Bi-LSTM	6.9	4.3	4.1
GRU	5.3	3.9	3.7
GNN (GAT)	11.4	8.6	9.8

StyleGAN2 is the most resource-intensive due to deep adversarial architecture and high-resolution synthesis, while ResNet-152 also incurs high training cost; GATs show moderate consumption but slower inference, and Bi-LSTM and GRU are comparatively lightweight, with GRU the most efficient. Overall, generative models require the greatest resources, whereas sequence models are more efficient. The generative pipeline follows three stages: StyleGAN2 pretraining on 12,000 mural patches, semantic conditioning with hybrid losses, and UNet-based refinement for edge and color enhancement. Architecturally, the generator maps G:Z→W→X, where latent vectors are transformed into style embeddings and injected via AdaIN to synthesize mural-based images.

In the feature transfer mechanism, the low-frequency and high-frequency decoupling representation method of the pattern semantic structure is adopted to define the content mapping function S(x) and the style mapping function T(x), extracting the spatial composition tensor and the decorative pattern tensor of the input image x, respectively. The goal is to maintain the corresponding relationship of S(x)≈S(G(z)) and T(x)→T(G(z)).

Style fidelity is constrained by minimizing the difference between the multi-layer Gram matrix, and its style loss function is defined as:

$$L_{\text{style}} = \sum_{l} w_l \cdot \left\| G(F_s^l) - G(F_t^l) \right\|_F^2 \tag{8}$$

Among them, F_s^l and F_t^l are the feature maps of the source image and the generated image after convolution at the l-th layer, respectively; $G(F)$ is the corresponding Gram matrix; $\|\cdot\|_F$ represents the Frobenius norm; w_l is the layer weight coefficient.

To strengthen the content semantics of the generated image, the structural consistency loss is applied:

$$L_{\text{struct}} = \sum_l \left\| F_c^l(x) - F_c^l(\hat{x}) \right\|_2^2 \tag{9}$$

Among them, F_c^l represents the content feature extraction function of the l-th layer; $\hat{x}$ is the model output image; x is the input mural sample.

The coordinated optimization of style and structure is achieved through the joint loss function:

$$L_{\text{total}} = \lambda_1 \cdot L_{\text{style}} + \lambda_2 \cdot L_{\text{struct}} \tag{10}$$

Among them, λ_1=1.0 and λ_2=0.8 control the relative optimization weights of style transfer and structure preservation losses, respectively, to balance the aesthetic transformation of visual symbols and the context restoration of narrative semantics.

To validate style (λ_1) and structure (λ_2) weights, six configurations are tested under fixed settings. Outputs are evaluated by five experts (10+ years) on style consistency and structural clarity (0–10), with averaged scores reported in Table 2.

TABLE 2. Style Consistency and Structural Accuracy Scores of Pattern Generation under Different λ_1/λ_2 Weight Combinations (Full Score: 10)

No.	λ1 (Style)	λ2 (Structure)	Style Consistency Score	Structural Accuracy Score
1	1.5	0.3	8.3	7.2
2	1.2	0.6	8.6	8.1
3	1.0	0.8	8.9	9.1
4	0.8	1.0	8.5	9.0
5	0.6	1.2	8.1	8.3
6	0.3	1.5	7.4	8.6

Group 3 (λ_1=1.0, λ_2=0.8) performs best (style 8.9, structure 9.1), balancing morphology and cultural stability. High λ_1 blurs structure, while high λ_2 distorts style. Overall,λ_1=1.0, λ_2=0.8 ensures stable, adaptable pattern generation for cross-media use.

The style control vector z_s and the structure control vector z_c are applied into the latent variable space and mapped to the generating function $f(z_s, z_c) = \hat{x}$, respectively, to achieve dual controllable scheduling of the pattern style and layout composition in the generated image. The perceptual quality dimension applies the perceptual loss based on the pre-trained VGG19 model:

$$L_{\text{percep}} = \sum_{i=1}^{N} \|\phi_i(x) - \phi_i(\hat{x})\|_2^2 \tag{11}$$

Among them, ϕ_i represents the feature mapping function of the i-th layer, and N is the number of perceptual layers.

The final training effect is calculated by calculating the statistical distance between the generated image and the feature distribution of the real mural image:

$$FID = \|\mu_r - \mu_g\|_2^2 + \operatorname{Tr}\left(\Sigma_r + \Sigma_g - 2(\Sigma_r \Sigma_g)^{1/2}\right) \tag{12}$$

Among them, μ_r and Σ_r are the mean and covariance matrix of the real image set, respectively, and μ_g and Σ_g are the corresponding statistics of the generated image set. This indicator comprehensively measures the visual naturalness and structural similarity of the image. The outputs span static textile patterns (core), dynamic images, and virtual displays, enabling semantic mapping from 2D murals to multimodal textile design. The algorithm supports efficient generation of ethnic patterns that blend cultural heritage with modern style.

Technology of Spatiotemporal Reconstruction of Cultural Images A four-dimensional narrative modeling method reconstructs static mural images into spatiotemporal scenes with historical and cultural semantics. Cultural content is encoded as an event vector set E={e1,e2,...,en}, where each ei=(ti,li,ai,si) includes time (ti), location (li), action (ai), and symbolic meaning (si). These vectors are extracted from mural image–text pairs through sequence annotation: Bi-LSTM identifies temporal labels, spatial data derive from geotagged sources, GRU classifies actions, and graph-based motif embeddings are aligned with BERT semantics, then verified through historical records and expert review. The timeline employs a Bi-LSTM sequence annotation model to extract temporal relations from mural text and form the event time mapping function T:ei→ti, while spatial modeling integrates a spatial weight function via a semantic geographic annotation system:

$$L(e_i) = \sum_{j=1}^{m} \omega_j \cdot d(e_i, g_j) \tag{13}$$

Among them, ωj represents the cultural relevance weight of the location gj, and d is the Euclidean distance function, which realizes the matching reconstruction of events and geographic nodes.

A GRU-based action migration network generates interactive character action sequences for dynamic expression of the image behavior layer.Assuming that A(ei)={ai1,ai2,...,aik}, The action embedding matrix models cultural intentions, while a GNN encodes symbolic semantics with motifs as nodes, co-occurrence/similarity as edges, and weights defining propagation G=(V,E,W).

By integrating four-dimensional data, a cross-temporal, spatial, behavioral, and semantic cultural narrative model is built. Dynamic mural narratives are reconstructed with voxel time axis V(x,y,z,t) and real-time semantic annotation, creating a spatiotemporal database that supports cross-cultural visual design, such as pattern-based textiles.

RECONSTRUCTION AND COMMUNICATION PATH OF COMMUNITY NARRATIVE

DESIGN OF CROSS-CULTURAL SYMBOL FUSION RULES

This study establishes a structural-level fusion method for cross-ethnic textile motifs through topological similarity and geometric mapping, promoting aesthetic compatibility and cultural identity. Each ethnic pattern element is set as a morphological vector $S_i = \{s_{i1}, s_{i2}, ..., s_{in}\}$, where each dimension represents its topological characteristic parameter, such as boundary curvature κ, node density ρ, and symmetry factor σ. The topological similarity function is defined as:

$$T(S_i, S_j) = \frac{\sum_{k=1}^{n} w_k \cdot \left(1 - \frac{|s_{ik}-s_{jk}|}{\max(s_{ik}, s_{jk})}\right)}{\sum_{k=1}^{n} w_k} \tag{14}$$

Among them, w_k is the weighted coefficient of each topological dimension, which is obtained by normalizing the core element proportion matrix in the visual language of each ethnic group. If $T(S_i, S_j) \geq 0.85$, it enters the fusion candidate set for subsequent geometric registration and visual adaptation.

In the fusion process, a visual balance function is applied to maintain aesthetic stability, using the golden ratio as the structural control parameter. With the main composition axis length as L, the maximum nesting unit is set to 0.618L to regulate spatial tension, and the pattern arrangement follows a spiral trajectory defined by a path function:

$$r(\theta) = ae^{b\theta} \tag{15}$$

This function effectively guides the rhythmic layout of continuous textile patterns (two-way, four-way) in fabrics, scarves, and carpets. Among them, r is the polar diameter; θ is the rotation angle; Constants a and b control scale and density, determined by boundary overlap and visual complexity feedback to ensure rhythmic structure under cross-cultural aesthetics. Color fusion uses the ΔE color difference minimization path in the Lab color model (CIELab color model) for transition regulation. The fusion trajectory of any two pattern color blocks $C_i = (L_i, a_i, b_i)$ and $C_j = (L_j, a_j, b_j)$ is defined by the ΔE_{2000} color difference formula:

$$\Delta E_{2000} = \sqrt{\begin{aligned}&\left(\frac{\Delta L}{k_L S_L}\right)^2 + \left(\frac{\Delta C}{k_C S_C}\right)^2 + \left(\frac{\Delta H}{k_H S_H}\right)^2 \\ &+ R_T \left(\frac{\Delta C}{k_C S_C}\right)\left(\frac{\Delta H}{k_H S_H}\right)\end{aligned}} \tag{16}$$

Among them, ΔL, ΔC, and ΔH are brightness, chromaticity, and hue differences, respectively; S_L, S_C, and S_H are the perceptual weight coefficients of each channel; k_L, k_C, and k_H are adjustment coefficients; R_T is the interaction correction factor. In color fusion, a ΔE_{2000} tolerance of 2.3—based on human perception and textile printing stability—ensures smooth transitions and visual consistency. Lab-based color paths are optimized, and designs are verified to stay within this threshold, supporting multi-color overprinting and gradients. Finally, the fused visual motif set is double-evaluated by the structural consistency kernel function $K(S_i, S_j) = \exp(-\gamma\|S_i - S_j\|^2)$ and the color perception similarity function $C(C_i, C_j) = 1 - \Delta E_{00}(C_i, C_j)/100$. Fusion pairs with scores above 0.9 are used for narrative construction. Through topological mapping, spatial coordination, and color path optimization, mural symbols along the 'Belt and Road' are reorganized into a unified visual language, providing a basis for modern textile designs—printed, jacquard, or embroidered (Figure 1).

Figure 1 patterns vary in shape, color, and balance. Axial symmetry and circular layouts aid positioning, continuous filling suits printed or jacquard surfaces, and saturation levels convey ethnic identity or multicultural blending. Linear trends and node density enable parametric control, preserving morphology and smooth style transitions, demonstrating controllable digital regeneration and cross-cultural visual fusion.

To evaluate the golden ratio layout in multi-pattern fusion, three structures—axial symmetry (S1), central rotation (S2), and boundary expansion (S3)—are applied to eight pattern sets (F1–F8) under 0.618L control. Effects are measured by Tension Index, Visual Center Offset, and expert-rated Stability Score (Table 3).

TABLE 3. Summary of pattern composition evaluation results under different structural types and layout strategies

Structural Type	Golden Ratio Applied	Tension Index	Visual Center Offset (px)	Stability Score
S1	No	0.167	78.3	7.2
S1	Yes	0.094	35.6	9.1
S2	No	0.184	92.5	6.9
S2	Yes	0.102	39.1	8.8
S3	No	0.196	101.4	6.5
S3	Yes	0.108	44.7	8.5

Golden ratio control reduces Tension Index by 44.5%, Visual Center Offset by 56.1%, and raises Stability Score by 1.9 points across all structures. The 1.9-point increase is the average Stability Score improvement acrossS1–S3:(9.1-7.2+8.8-6.9+8.5-6.5)/3. The results show the golden ratio effectively improves symmetrical, rotational, and boundary-expansion layouts, supporting its broad applicability in cross-ethnic pattern fusion for both composition and aesthetic stability.

AUGMENTED REALITY NARRATIVE INTERACTION SYSTEM

The AR narrative system combines spatial mapping, gesture tracking, and multi-linear storytelling to deliver immersive mural experiences through spatial anchoring, interaction sensing, and dynamic narrative reconstruction.

Spatial positioning uses Visual-Inertial Odometry (VIO) and SLAM to construct a 3D coordinate system $F_s = \{x, y, z\}$, tracking user position $P_t \in R_3$ and viewpoint V_t

FIGURE 1. Digital fusion design samples of multi-ethnic mural patterns

in real-time. A spatial state function $\phi(P_t, V_t)$ dynamically activates relevant mural narrative branches.

Gesture recognition employs a CNN combined with temporal convolution to encode user gestures as a $g_t \in R^d$ time-series vector $G = \{g_1, g_2, \ldots, g_t\}$, where each Actions are classified into categories $A = \{a_1, a_2, \ldots, a_n\}$ via a Softmax classifier:

$$P(a_i|G) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \tag{17}$$

A mapping function $M : A \rightarrow N$ links gestures to narrative events $E_i = (\tau_i, \lambda_i, \psi_i)$, which drive virtual content generation.

Narrative reconstruction uses a Hidden Markov Model with state set $S = \{s_1, s_2, \ldots, s_k\}$ and transition matrix $A = [a_{ij}]$, updated via user interaction sequence $O = \{o_1, o_2, \ldots, o_T\}$. The forward-backward algorithm computes optimal narrative paths.

Content rendering uses a Shader-based style mapping function in Unity:

$$I_{AR} = F_{\text{style}}(T_i, S_j) = \alpha T_i + (1 - \alpha) S_j \tag{18}$$

where T_i is the original texture, S_j is the style-mapped result, and $\alpha \in [0, 1]$ controls fusion. The system runs at >60 FPS, ensuring real-time responsiveness.

User behavior data is collected to train an LSTM network with attention, optimizing narrative recommendations via cross-entropy loss:

$$L = -\sum_{i=1}^{m} y_i \log \hat{y}_i \tag{19}$$

This feedback refines narrative relevance, supporting cross-cultural and cross-generational engagement.

II. EFFECTIVENESS VERIFICATION OF COMMUNITY CONSCIOUSNESS CONSTRUCTION IN DIGITAL REGENERATIVE DESIGN

EVALUATION OF DIGITAL COLLECTION METHODS FOR MURALS

A digital regeneration system combining multimodal imaging and deep learning (ResNet-152 with graph attention) captures material, color, structure, and techniques, building a multidimensional visual–semantic database that outperforms traditional photography in preserving cultural information (Figure 2).

Figure 2 shows multimodal data collection outperforms traditional methods in mural restoration: honeysuckle and scroll patterns reach 95% and 94% accuracy, pigment recognition improves ~40%, sub-millimeter point cloud registration enhances overlapping brushstrokes, and implicit cultural information extraction achieves 92%–90%. Multimodal perception with intelligent decoding overcomes semantic loss, ensures high-fidelity reproduction, and provides reliable data for modern textile design.

VERIFICATION OF CULTURAL GENE EXTRACTION INDICATORS

Four models—ResNet-152, EfficientNet-B0, Inception-v3, and DenseNet-121—are compared on accuracy, diversity retention, semantic and universal matching, and convergence efficiency to assess adaptability in cultural symbol analysis (Figure 3).

Figure 3 shows ResNet-152 leads in accuracy (93.6%) and semantic matching (91.8%), EfficientNet-B0 converges fastest (91.2%) but with lower accuracy (89.7%), Inception-v3 retains diversity (88.1%) but has weaker universal matching (86.6%), and DenseNet-121 balances convergence

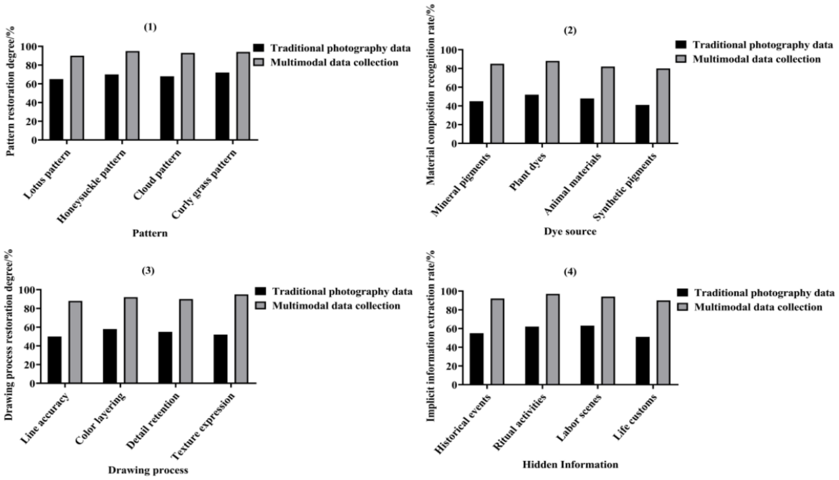

FIGURE 2. Comparative analysis of the performance of digital collection methods for ethnic murals. (1) Comparison of pattern restoration; (2) Comparison of material composition recognition rate; (3) Drawing process restoration; (4) Implicit information extraction rate

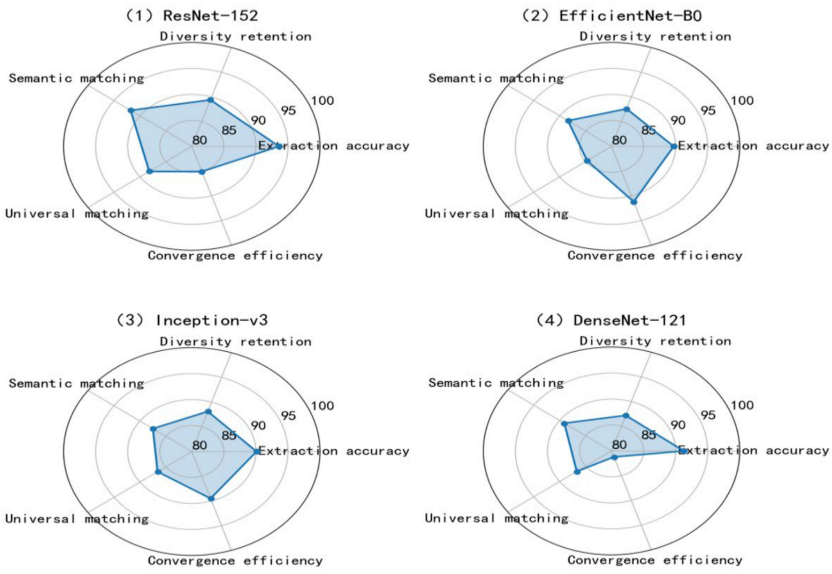

FIGURE 3. Multimodal cultural gene analysis model performance radar chart. (1) ResNet-152; (2) EfficientNet-B0; (3) Inception-v3; (4) DenseNet-121

(81.2%) and universal matching (86.7%), highlighting each architecture's strengths for cultural gene analysis and cross-media translation.

MULTI-DIMENSIONAL EVALUATION OF CROSS-ETHNIC SYMBOL FUSION

A deep learning–based framework uses multimodal data and intelligent decoding for digital regeneration of mural heritage, reorganizing ethnic symbols and quantitatively evaluating cultural identity and aesthetic compatibility across eight fused mural–textile designs (F1–F8, Table 4).The specific meanings are as follows: F1 represents the textile pattern design scheme of the Tibetan "propitious cloud pattern" and the Han "cloud pattern"; F2 represents the fusion of the Uyghur "octagonal-star pattern" and the Hui "lotus petal" pattern; F3 is the fusion of the Kazakh "ram's horn pattern" and the Han "connected thunder pattern"; F4 combines the Zhuang "bronze drum pattern" and the Hezhe "fishnet pattern"; F5 refers to the fusion pattern of the honeysuckle pattern and the Central Asian vortex pattern; F6 represents the fusion of the Miao "dragon scale pattern" and the Hui "lotus leaf pattern"; F7 refers to the fusion design of the Tibetan "mandala" structure and the Xinjiang "sun pattern"; F8 is the combination of the Han "round longevity pattern" and the Central Asian "geometric halo pattern". Five experts from national art universities ($\geq$10 years in textile design or mural heritage) scored the designs on morphology, symbolism, and aesthetics (100-point scale).

Inter-rater reliability was high (ICC(2,5) = 0.89).

TABLE 4. Expert cultural fit score table

Expert \ Fusion ID	F1	F2	F3	F4	F5	F6	F7	F8
Expert 1	90	85	92	88	94	87	91	89
Expert 2	91	86	93	87	95	85	90	88
Expert 3	88	84	91	86	92	86	89	90
Expert 4	92	87	94	89	96	88	92	91
Expert 5	89	83	90	85	93	84	88	87

Table 4 shows F5 ranks highest (94) in cultural adaptability due to plant-form abstraction and rotational logic, F2 lowest (85) due to motif tension; SDs within ± 4 confirm fusion rules balance cultural recognition and visual consensus, validating digital regeneration feasibility.

To counter weakened cultural identity in Belt and Road murals, a deep learning–based cross-ethnic symbol fusion system reorganizes form, color, and narrative, quantified via a multimodal model (Figure 4). Figure 4 shows F5 achieves highest cross-ethnic cognitive similarity (Tibetans 0.96, Uyghurs 0.95, Kazakhs 0.94) and excels in boundary curvature (96), symmetry (95), and spatial balance (96) via a golden-ratio layout. Its $\Delta E2000$ (1.9) is within textile tolerance (2.3), confirming effective color reproduction, while most other schemes exceed 2.3, with the exception of F3 which achieved 2.1. These results validate the fusion rule system's balance of aesthetic consensus and cultural recognition.

COMMUNITY NARRATIVE ACCEPTANCE

A multi-dimensional AR-based framework assessed immersive experience, cultural identity, and aesthetic resonance of mural regeneration and textile applications in 150 participants (18–60 yrs, 63 F/87 M), grouped by audience type (youth, elderly, minority, Han, foreign) using a four-dimensional system (Figure 5). Cross-national data (China, Kazakhstan, Kyrgyzstan, Pakistan, Iran, Turkey) support Tables 5–6.

Figure 5 shows youth audiences score highest in interactivity (9.3), ethnic minorities in information communication (9.1), while foreign audiences lag in emotional expression recognition (78.3%) and symbol comprehension (75.2%). The AR system bridges these gaps with contextual explanations and visual cues. All groups report high immersion (8.86) and visual beauty (8.9), confirming cross-cultural empathy and support for Chinese national community consciousness.

Audience scores from six groups across five dimensions were tested for normality (Shapiro–Wilk) and analyzed by one-way ANOVA with Tukey HSD, reporting 95% confidence intervals and p-values (Table 5).

TABLE 5. Statistical significance analysis of cross-national audience resonance evaluation

Dimension	F-value	p-value	Significant Differences Detected	95% CI for Mean Scores (China)
Graphic Resonance	4.73	0.005	Yes	[91.1, 93.3]
Content Resonance	3.89	0.011	Yes	[85.9, 88.3]
Value Resonance	5.56	0.002	Yes	[93.5, 95.3]
Aesthetic Resonance	2.14	0.072	No	[90.1, 92.5]
Narrative Resonance	4.18	0.007	Yes	[91.8, 94.2]

COMPREHENSIVE CULTURAL IDENTITY EFFECTIVENESS EVALUATION

An AR interactive system was built to present regenerated mural culture immersively, using a five-dimensional framework to evaluate cross-national audience resonance (Table 6).

TABLE 6. Multi-level resonance scores of audiences in different countries on the cultural content of recycled murals and their textile applications

Country	Graphic resonance	Content resonance	Value Resonance	Aesthetic resonance	Narrative Resonance
China	92.2	87.1	94.4	91.3	93.0
Kazakhstan	89.6	86.5	91.0	88.2	89.7
Kyrgyzstan	88.9	85.4	90.1	87.4	88.6
Pakistan	87.5	84.8	89.6	86.7	87.9
Iran	90.3	86.2	92.4	89.1	90.2
Turkey	88.7	85.9	90.7	88.3	89.0

Table 6 shows Chinese audiences excel in graphic (92.2), value (94.4), and narrative (93.0) resonance with local cultural symbols, especially textiles. Iranian audiences rank second in value resonance (92.4), while Turkey (89.0) and Kazakhstan (89.7) differ in narrative logic. Overall, high aesthetic (88.5) and graphic (89.5) scores indicate that digital regenerative textile design fosters cross-regional visual empathy and strengthens Chinese national community consciousness.

The study builds a digital regeneration system—cultural gene extraction, cross-media translation, and community narrative reconstruction—and evaluates identity activation across ethnic groups using the multi-dimensional system in Figure 6.

Figure 6 shows spatial narrative composition achieved high identification among Tibetans (92.6%), Uyghurs (91.8%), and Zhuangs (89.1%), outperforming language and history dimensions, while Han participants showed lower historical improvement (19.4%). Video and interactive textile applications received over 85% positive feedback, indicating that multimodal, culturally adaptive designs effectively foster identity formation.

III. CONCLUSION

This paper presents a digital regeneration path—cultural gene extraction, cross-media translation, and community narrative reconstruction—using multimodal acquisition and deep learning to extract core visual genes from Belt and Road murals for modern textile transformation. Application

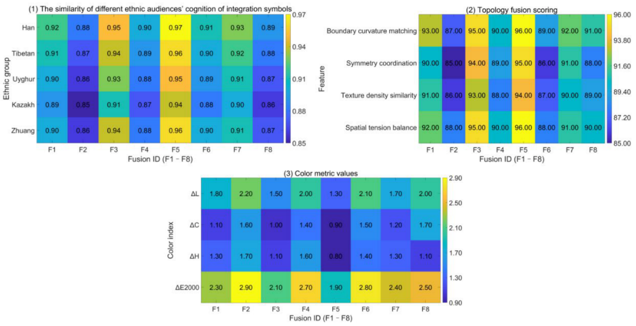

FIGURE 4. Multi-dimensional evaluation heat map of cross-ethnic symbol fusion design. (1) Cognitive similarity of fusion patterns applied to textiles among audiences of different ethnic groups; (2) Topological structure fusion score. (3) Value of color measurement

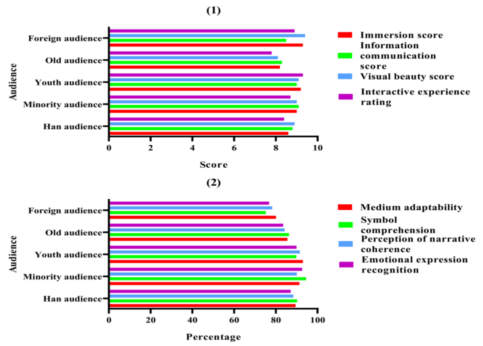

FIGURE 5. Analysis of multi-level resonance of different audience groups on regenerated murals. (1) Comparison of multi-dimensional experience scores; (2) Comparison of cultural cognitive adaptability percentages

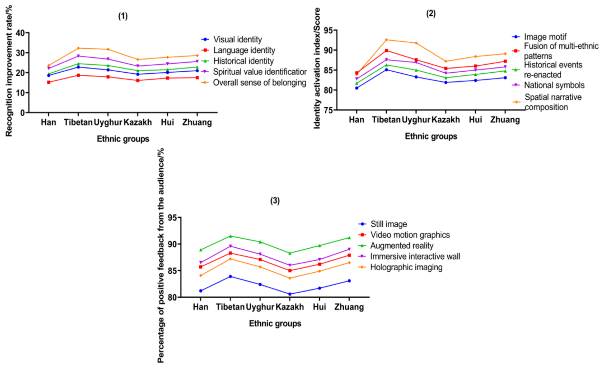

FIGURE 6. Comparison of identity activation effectiveness of different ethnic groups in multicultural narrative elements and textile product carriers. (1) Comparison of the improvement rate of different ethnic groups in multiple identification dimensions; (2) Impact analysis of cultural narrative components on audience identification efficacy; (3) Feedback score of identification efficacy under different display media.

tests showed strong engagement (youth 9.3, minorities 9.1). Contributions include a cross-cultural pattern fusion method, a high-fidelity mural database, and an effective textile transformation path.

ENGINEERING FEASIBILITY VERIFICATION

A small-scale test on a partner textile line showed 30% lower sampling costs, 0.3 mm regenerated line widths, 25 yarns/cm density control, and Grade 4+ color fastness with $\Delta E \leq 2.1$, confirming the system's feasibility and industrial adaptability.

LIMITATIONS AND FUTURE WORK

This study is limited by high data dependence, abstract symbol recognition challenges, and region-specific evaluation. Future work will apply adaptive learning, expand semantic databases, extend AR validation, and integrate multi-sensory feedback.

AUTHOR CONTRIBUTIONS

All work in this study was independently completed by Guofu HE.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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REFERENCES

[1] Y. Wang and X. Wu, "Current progress on murals: Distribution, conservation and utilization," Heritage Science, vol. 11, no. 1, pp. 61, 2023, doi: 10.1186/s40494-023-00904-9.

[2] Z. Li and S. Champadaeng, "Study of Cultural Heritage and Digital Preservation: The case of Murals of the Northern Yue Temple," International Journal of Education and Literacy Studies, vol. 13, no. 2, pp. 262-268, 2025, doi: 10.7575/aiac.ijels.v.13n.2p.262.

[3] A. MOHAMED ALI SHAHIN, "The Mural Design Derived from Heritand its Impact on the Development of Community Culture," International Journal of Multidisciplinary Studies in Heritage Research, vol. 4, no. 1, pp. 69-103, 2021, doi: 10.21608/ijmshr.2021.189655.

[4] O. O. Merekina and O. S. Panova, "Perception of the Mogao Caves' Art Heritage in Republican China (1911– 1949): From Obscurity to National Treasure," Actual Problems of Theory and History of Art, vol. 12, pp. 574-584, 2022, doi: 10.18688/aa2212-06-45.

[5] A. Youzbashi, S. R. Hoseini, and A. Chareie, "Identifying the Causes of the Emergence of Religious Themes and Its Important Components in the Murals of Religious Monuments of the Qajar Era (Case Study: Sacred Shrines of Guilan Province)," Negareh Journal, vol. 17, no. 61, pp. 25-47, 2022, doi: 10.22070/negareh.2021.5789.2581.

[6] C. Bolong, Y. Zongren, S. Manli, S. Zhong, Z. Jinli, S. Biwen, et al., "Virtual reconstruction of the painting process and original colors of a color-changed Northern Wei Dynasty mural in Cave 254 of the Mogao Grottoes," Heritage Science, Art. no. . 10(1):164, 2022, doi: 10.1186/s40494-022-00785-4.

[7] X. Lu, Y. Yang, L. Wang, and L. Wang, "Cultural and creative design of Dunhuang murals in Xixia period based on deep learning," Wireless Communications and Mobile Computing, vol. 2022, no. 1, Art. no. 7161593, 2022, doi: 10.1155/2022/7161593.

[8] G. Ma, "Cultural significance of the Baoning temple murals in Shanxi, China: Perspectives from artists and art historians influenced by cultural heritage," Herança, vol. 7, no. 1, pp. 136-153, 2024, doi: 10.52152/heranca.v7i1.774.

[9] H. Liao and T. Wechkama, "The Folk Murals in Pingnan County of Guangxi: Protection and Inheritance for Cultural Heritage," Journal of Modern Learning Development, vol. 9, no. 10, pp. 151-161, 2024, [Online]. Available: https://so06.tci-thaijo.org/index.php/jomld/article/view/277654.

[10] Y. Jia, H. Li, J. Fang, X. Chen, L. Ji, and N. Wang, "Image inpainting of thangka murals using edge-assisted feature fusion and self attention based local refine network," IEEE Access, vol. 11, pp. 84360-84370, 2023, doi: 10.1109/ACCESS.2023.3299876.

[11] T. Ning, G. Huang, J. Li, and S. Huang, "Complex image inpainting of cultural relics integrating multi-stage structural features and spatial textures," Pattern Analysis and Applications, vol. 28, no. 2, pp. 1-18, 2025, doi: 10.1007/s10044-025-01434-9.

[12] E. Pietroni and D. Ferdani, "Virtual restoration and virtual reconstruction in cultural heritage: Terminology, methodologies, visual representation techniques and cognitive models," Information, vol. 12, no. 4, pp. 167, 2021, doi: 10.3390/info12040167.

[13] T. Sun, T. Jin, Y. Huang, M. Li, Y. Wang, Z. Jia, et al., "Restoring dunhuang murals: Crafting cultural heritage preservation knowledge into immersive virtual reality experience design," International Journal of Human–Computer Interaction, vol. 40, no. 8, pp. 2019-2040, 2024, doi: 10.1080/10447318.2023.2232976.

[14] E. R. Linuwih, S. Harijanto, and E. Fadilah, "Semiotic Landscape of Chinese Murals in Kya-Kya, Surabaya," Indonesian Journal of EFL and Linguistics, vol. 10, no. 1, pp. 145-157, 2025, doi: 10.21462/ijefl.v10i1.883.

[15] N. Khan, "Art Across Cultures: Bridging Divides and Building Connections," Journal of Religion and Society, vol. 1, no. 1, pp. 1-12, 2023, [Online]. Available: https://islamicreligious.com/index.php/Journal/article/view/18.

[16] Z. Al-Zadjali, "The significance of art in revealing a culture's identity and multiculturalism," Open Journal of Social Sciences, vol. 12, no. 1, pp. 232-250, 2024, doi: 10.4236/jss.2024.121015.

[17] M. Mason and G. Vavoula, "Digital cultural heritage design practice: A conceptual framework," The Design Journal, vol. 24, no. 3, pp. 405-424, 2021, doi: 10.1080/14606925.2021.1889738.

[18] Y. Liu, "Application of digital technology in intangible cultural heritage protection," Mobile Information Systems, vol. 2022, no. 1, Art. no. 7471121, 2022, doi: 10.1155/2022/7471121.

[19] E. Paschalidou, C. Fafet, and L. Milios, "A strong sustainability framework for digital preservation of cultural heritage: Introducing the eco-sufficiency perspective," Heritage, vol. 5, no. 2, pp. 1066-1088, 2022, doi: 10.3390/heritage5020058.