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Deconstruction and Reconstruction of Intangible Cultural Heritage Symbols Driven by GraphSAGE: Taking the Intelligent Generation of Bohai Mohe Embroidery Topological Patterns as an Example

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Article

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ABSTRACT

Traditional methods struggle to capture the complex structure and cultural semantics of Bohai Mohe embroidery, leading to distortion in intelligent pattern generation. This study proposes a graph sample and aggregate (GraphSAGE)-based framework that models embroidery patterns as graphs, encoding visual symbols as nodes and connections. A two-layer GraphSAGE network extracts local stitching and global cultural features, followed by feature fusion and dynamic edge adjustment to generate structurally sound, culturally consistent patterns. Experiments on a custom dataset show high pattern symmetry consistency (0.881) and semantic fidelity (up to 0.970), demonstrating the method's effectiveness in digitalizing intangible cultural heritage through structured modeling and multilevel feature perception.

KEYWORDS

GraphSAGE framework, embroidery pattern, visual symbol, cultural feature, semantic fidelity

INTRODUCTION

In the context of globalization and digitalization, intangible cultural heritage faces challenges in inheritance and opportunities for innovation, among which embroidery is one of the key branches [1,2]. Bohai Mohe embroidery, with its unique structural logic and cultural connotation [3], integrates national style and deep semantics in pattern construction and is widely used in clothing, utensils, and rituals. It has distinct functionality and symbolism, and its symbol system shows characteristics such as skirt decoration and spatial association. These patterns not only demonstrate craftsmanship but also carry cultural symbols, forming a two-dimensional graphic system that blends craftsmanship and culture. Traditional manual recording and static archiving hardly reflect its multidimensional craft details and the cultural norms behind the patterns [4]. Existing image generation technology focuses on pixels and style conversion, ignoring the relationship between the structure, craftsmanship, and cultural connotation in embroidery patterns [5,6]. This method is prone to structural distortion, organizational chaos, and cultural loss and has difficulty supporting the digital reconstruction of intangible cultural heritage with inheritance value [7,8]. Bohai Mohe embroidery patterns have a hierarchical structure, and the relationship between elements reflects the spatial connection and functional correspondence of craftsmanship. However, existing generative models have difficulty identifying the topological relationships between symbolic nodes and are unable to model underlying craft rules [9,10]. The stitches, color blocks, and skeletons in the patterns are composed of a set of graph structures composed of craftsmanship, composition, and cultural semantics and do not exist in isolation. Traditional image generation networks simplify these visual elements into image feature vectors [11,12]. In the absence of structural and semantic constraints, the generated patterns are likely to be similar in style but semantically misplaced, deviating from the cultural origin [13]. This superficial imitation makes it difficult to restore the symbols and cultural logic of intangible cultural heritage, limiting its creative digital transformation path.

As a commonly used graph neural network model, GraphSAGE has made remarkable progress in multimodal fusion and graph modeling in recent years [14,15]. It has good adaptability to irregular structures and complex semantics and provides technical support for complex modeling tasks such as intangible cultural heritage. Traditional methods such as convolutional neural network (CNN), generative adversarial network (GAN), and variational autoencoder (VAE) are mostly used for image recognition and pattern generation tasks. CNN lacks topological perception, GAN lacks structural and semantic control, and VAE is prone to degradation and ambiguity, making it difficult to generate complex patterns. Such methods rely on pixel or feature modeling, making it difficult to express node logic and cultural semantics, limiting their application in intangible cultural heritage pattern generation. In response to the limitations of GraphSAGE in the problem of node category imbalance, Huang et al. expanded the sample by generating niche node subgraphs, improved classification performance, and provided a reference for the augmentation of rare patterns in intangible cultural heritage [16]. On this basis, Dai combined GraphSAGE with genetic algorithms in recommendation modeling, mined deep relationships, and provided a reference for preference modeling and style matching in intangible cultural heritage [17]. In addition, Cui et al. found that constructing a graph model helps enhance the data augmentation capability of rare intangible cultural heritage patterns [18]. In summary, GraphSAGE takes into account local attributes and structural semantics and is suitable for modeling complex cultural objects. However, despite the continuous expansion of GraphSAGE applications, its versatility and generalization ability for complex structures remain limited.

Current research is exploring the integration of AI and traditional culture to promote the digitization and intelligent redesign of intangible cultural heritage patterns [19]. Research on image style, cultural extraction, and human–computer collaboration has made progress and has initially expanded the path of intelligent generation of intangible cultural heritage patterns. Chen et al. extracted the Huayao embroidery style through deep learning, achieved intelligent generation with cultural charm, and expanded the path of digitalization of ethnic patterns [20]. In addition, Xie combined regional culture and user perception and intelligently deduced intangible cultural heritage elements based on shape grammar to achieve personalized and culturally integrated generative design [21]. Subsequently, Hu et al. proposed a method for generating intangible cultural heritage patterns based on deep learning, providing new ideas for its digitization and intelligent redesign [22]. The above research covers key links such as style recognition and visual generation and has initially constructed a system framework for the intelligent design of intangible cultural heritage patterns. Although there have been achievements, in the face of irregular structures and cross-context migration, existing methods are insufficient in relational modeling and semantic adaptation, and a new path with structural perception and semantic embedding is urgently needed.

To address the challenges of insufficient structural understanding and semantic expression in the intelligent generation of intangible cultural heritage patterns, this study proposes a generative framework that integrates graph structure perception and cultural semantic embedding. A graph neural network model based on GraphSAGE is constructed, using the topological patterns of Bohai Mohe embroidery as the modeling object, integrating craft rules and cultural semantic structure. The graph structure consists of three types of nodes (needle units, color regions, and pattern skeletons) and three types of connecting edges (process flow edges, structural nesting edges, and semantic mapping edges), reflecting the craft logic and cultural hierarchy of the embroidery patterns. In the feature learning phase, a two-layer GraphSAGE architecture is designed. The bottom layer extracts local stitch features, while the upper layer captures cultural semantics and constructs a mapping relationship between pattern themes and structures. In the structural reconstruction phase, new topological patterns are generated using cross-layer feature aggregation and a dynamic adjustment mechanism for edge weights. Finally, a graph-to-image mapping module completes end-to-end pattern generation. This method breaks through the limitations of traditional image feature-driven modeling, unifies process structure and semantic structure modeling, and improves the controllability and interpretability of intangible cultural heritage pattern generation. Its innovations include ① unifying visual and cultural information through graph structure; ② introducing semantic constraints and edge weight adjustment mechanisms; and ③ constructing a structure-to-image generation pathway, providing a new path for the digital expression and redesign of intangible cultural heritage.

GRAPH STRUCTURE PERCEPTION GENERATION FRAMEWORK OF BOHAI MOHE EMBROIDERY PATTERNS

Construction of the Bohai Mohe Embroidery Thematic Dataset

This study constructed a Bohai Mohe embroidery thematic dataset through hierarchical and multimodal technologies, covering four data sources: pattern images, spectral fiber distribution, process archives, and oral process texts. The pattern images were collected using a 1200DPI industrial scanner and an RGB depth camera to ensure high-fidelity images. The spectral data used a spectral camera in the 400–1000 nm band to scan the silk thread dyeing characteristics pixel by pixel and generate a spectral mapping tensor. The process archives and oral processes were combined with OCR technology and speech transcription, and the text was vectorized using the BERT (Bidirectional Encoder Representations from Transformers) model to construct a cross-modal representation space. Figure 1 below shows some examples of images of the original Bohai Mohe embroidery pattern.

Figure 1. Part of the original Bohai Mohe embroidery pattern

Figure 1 illustrates the diversity of Bohai Mohe embroidery in terms of composition, visual semantics, and symbol density. The pattern structure exhibits a blend of regular and irregular patterns, while color elicits emotion through saturated colors and color blocks. Symbolic units include plants, animals, and abstract totems, providing a classification basis for node abstraction. These characteristics determine the precision requirements for node partitioning and edge weight initialization during graph structure modeling, supporting pattern generation and semantic consistency.

After data collection, it undergoes preprocessing through normalization and denoising. Image data undergo grayscale normalization and adaptive histogram equalization to enhance texture detail. Spectral data are compressed using principal component analysis to preserve key spectral information. Image segmentation uses ResNet-101 and an improved attention module to segment overlapping regions accurately. Text data are filtered using regular expressions and stop words to extract key semantic information and construct process behavior diagrams.

All data are uniformly mapped to the preprocessing space of the pattern structure model. Image data are mapped to visual nodes, spectral data generate material vectors, and text data construct node attribute vectors, forming a multimodal, multiscale fusion dataset that provides a basis for subsequent graph structure modeling and feature extraction.

Pattern Graph Structure Modeling Based on Process Priors

A graphic symbol modeling method based on the dual constraints of visual semantic nesting and process operation hierarchy was adopted to construct the pattern graph structure of Bohai Mohe embroidery. First, through semantic segmentation and feature extraction, the symbol units in the pattern image were converted into node representations with attribute vectors and semantic labels. Each symbol unit corresponds to a node in the graph structure, and the node attribute vector is composed of low-level visual texture features (such as texture gradient and color histogram principal components), process structure attributes (such as needle frequency, edge closure, and thread direction vector), and semantic label embedding vectors. Node types are divided into low-level needle nodes, mid-level color nodes, and high-level pattern skeleton nodes. The initial category encoding of the nodes is one-hot and mapped to the type embedding vector via an embedding matrix.

The attribute consistency of nodes is measured by the Gaussian kernel function, and its formula is:

$$Consistency(u, v) = exp\left(-\frac{||a_u - a_v||^2}{2\sigma^2}\right). \tag{1}$$

In Formula (1), a_u and a_v are the attribute vectors of nodes σ and v, respectively; and u is the standard deviation of the Gaussian kernel. These vectors serves as a priori reference in subsequent topological edge construction and dynamic edge weight initialization. The node abstraction process uses a multiscale sliding window strategy to verify structural consistency, calculate position-sensitive feature centers, and record the spatial anchor points of the nodes to ensure their correct spatial positioning.

Next, when constructing topological edges, the triple relationship measurement of node spatial position constraints, process prior order, and semantic association strength is considered. The calculation formula is:

$$Semantic\ Strength(u, v) = \frac{e_u \cdot e_v}{||e_u|| \cdot ||e_v||}. \tag{2}$$

In Formula (2), e_u and e_v are the semantic embedding vectors of nodes u and v. The spatial distance metric function defines the spatial reachability between nodes. The process sequence is provided by the directed dependency graph in the process knowledge graph, and the semantic association strength is calculated by the cosine similarity of the node semantic embedding vectors. Based on these factors, the topological edge weights are initialized and support the weighted feature aggregation of the subsequent GraphSAGE model.

A grid search strategy is used to tune hyperparameters to optimize the configuration of edge weights. The edge weights are initialized in accordance with the spatial distance between nodes, process sequence, and semantic association strength. The formula is:

$$w_{uv} = \lambda_1 \cdot Spatial\ Distance(u, v) + \lambda_2 \cdot Process\ Order(u, v) + \lambda_3 \cdot Semantic\ Strength(u, v) \quad (3)$$

The final weight configuration chosen was $\lambda_1 = 0.500$, $\lambda_2 = 0.300$, and $\lambda_3 = 0.200$, ensuring optimal graph representation. On this basis, a directed weighted graph structure was constructed, with the edge weight tensor passed as input to the GraphSAGE encoding stage. This process enabled structure-aware feature propagation while ensuring the triple constraints of process rationality, spatial continuity, and semantic consistency.

Two-layer GraphSAGE feature extraction architecture

The local stitch feature encoder is based on GraphSAGE and uses adjacency structure perception to achieve spatial propagation of stitch symbols. Each node represents an embroidery unit, and its raw features include stitch density, orientation angle, stitch length, and color thread thickness. Feature updates are achieved through Klayer stacking, where each layer uses a weighted average to aggregate adjacent node features and performs a nonlinear transformation using the ReLU activation function. The formula is as follows:

$$h_v^{(local,k+1)} = \sigma\left(\sum_{u \in N(v)} \frac{1}{c_{uv}} W^{(k)} h_u + b^{(k)}\right). \quad (4)$$

In Formula (4), $h_v^{(local,k+1)}$ is the feature of the node v at the $k+1$ layer, $N(v)$ is node v's neighbor set, c_{uv} is the normalization factor, $W^{(k)}$ and $b^{(k)}$ are the weight matrix and bias term, respectively, and σ is the ReLU activation function. During the initial feature construction phase, a linear mapping layer is used to unify the feature dimensions and perform Z-score normalization. Long-hop connections and dropout are used to enhance node information propagation and suppress overfitting. The final encoding result is used for cross-level feature fusion, interacting with global cultural features to characterize process relationships within the local structure.

The global cultural semantic extractor is modeled using the GraphSAGE framework, employing multiscale adjacency relationships to encode the cultural semantic attributes of nodes. Each node represents a unit of cultural importance, and its feature vector includes digital information on auspicious semantic encoding, pattern label, craft category, and historical origin. Global semantic updates utilize an extended GraphSAGE mechanism, employing an attention mechanism to enable cross-node cultural semantic flow. The formula is as follows:

$$h_v^{(semantic,k+I)} = Attention\left(\sum_{u \in N(v)} \alpha_{uv} \cdot W^{(k)} h_u\right). \tag{5}$$

In Formula (5), $h_v^{(semantic,k+1)}$ is the cultural semantic feature of the node v at the first layer α_{uv}, and $k+1$ is the attention coefficient calculated on the basis of the attention mechanism. In the initial stage, the cultural and style labels of the nodes are converted into semantic features through the embedding matrix. A skip-layer residual connection structure is used to alleviate the problem of feature attenuation. The final semantic embedding is input into the graph structure reconstruction module to construct a pattern graph with cultural consistency, guiding the semantic-driven control in the generation phase.

Cross-level Feature Fusion and Dynamic Reorganization

This module mainly covers process constraint feature aggregation, dynamic edge weight update and mapping of graph structure to vector, constructing an efficient multiscale graph structure representation for the intelligent regeneration of embroidery crafts and cultural symbols.

First, process-constrained feature aggregation aligns local and global features and maps them into a unified feature space through weighted fusion. Local features are output by the local feature encoder, and global cultural features are generated by the global semantic encoder. Through the feature alignment and weighted fusion process, it can be expressed as follows:

$$h_v=Gate(W_{local}h_{local}+W_{global}h_{global}+b). \tag{6}$$

In Formula (6), h_v is the aggregated feature of the node v, h_{local} and h_{global} are the local and global features, respectively, W_{local} and W_{global} are the weight matrices for feature fusion, b is the bias term, and the gate function is used to adjust the contribution of local and global features. A gating mechanism is then used to optimize feature contributions further, and a structural regularization term is added to ensure the hierarchical diversity of the aggregated features and the consistency of adjacent nodes, thus ensuring the stability and semantic continuity of node features.

On this basis, the dynamic edge weight update module adaptively adjusts the weights of the edges connecting nodes in the graph to construct a topological network with cultural logic constraints. The update formula of its edge weight is:

$$\widehat{w_{uv}}=\alpha\cdot Structural\ Similarity(u,v)+\beta\cdot Semantic\ Consistency(u,v). \tag{7}$$

In Formula (7), α and β are hyperparameters used to control the contribution of structural similarity and semantic consistency to edge weights.

The edge weights of node pairs are optimized using an edge weight adjustment function, and the learning of edge weight updates is enhanced using normalization coefficients and gating adjustment factors. Finally, the normalized adjacency matrix enables adaptive structural updates, improving the graph's responsiveness to embroidery techniques and cultural combinations.

Finally, the graph structure to vector mapping module maps the updated graph structure into a low-dimensional differentiable vector representation. The formula is:

$$z_v=Readout\left(\sum_{u\in N(v)}\alpha_{uv}h_u\right). \tag{8}$$

In Formula (8), z_v is the low-dimensional vector representation of the node v, $N(v)$ is node v's neighbor set, h_u is the feature of the neighboring nodes u and is a graph-level readout function that aggregates node features into a global representation of the graph. This graph-level readout function supports the generation and style control of pattern graphs. Through a learnable graph-level readout function and a global attention mechanism, the contextual dependencies of node features are integrated into the mapping process, forming a unified representation of semantic and topological features. A cosine similarity loss function is introduced to enhance the geometric constraints of the graph structure, thus ensuring the structural consistency of the mapping results. Finally, the mapped vector representation is input into the pattern generation network to promote the generation and rendering of graphic patterns, realizing the intelligent regeneration of embroidery symbols.

This process ensures the deep integration of the graph structure in terms of craft constraints and cultural semantics while optimizing node features, edge weights, and structural representation, supporting the continuous generation and accurate reproduction of embroidery craft symbols.

EXPERIMENTAL VERIFICATION OF INTELLIGENT GENERATION OF BOHAI MOHE EMBROIDERY PATTERNS

The GraphSAGE-driven invisible graph structure generation model proposed in this study is deployed and trained in the following hardware and software environments:

Hardware configuration: Processor, Intel Xeon Gold 6348 @ 2.60 GHz (32 cores); Graphics card, NVIDIA RTX A6000 48 GB GDDR6 (CUDA compute capability 8.6); Memory, 256 GB DDR4 ECC; Storage, 4 TB NVMe SSD; Power supply support, Supports multi-GPU parallel computing but uses a single card training.

Software environment: Operating system, Ubuntu 20.04.6 LTS (64 bit); CUDA version, 11.8; cuDNN version, 8.6.0; Python version, 3.9.18.

Deep learning framework: PyTorch 2.1.0 (including torch_geometric v2.4.0 for graph neural network operations).

Auxiliary toolkits: NumPy 1.24.3, SciPy 1.11.1, NetworkX 2.8.8, scikit-learn 1.3.0, matplotlib 3.7.2.

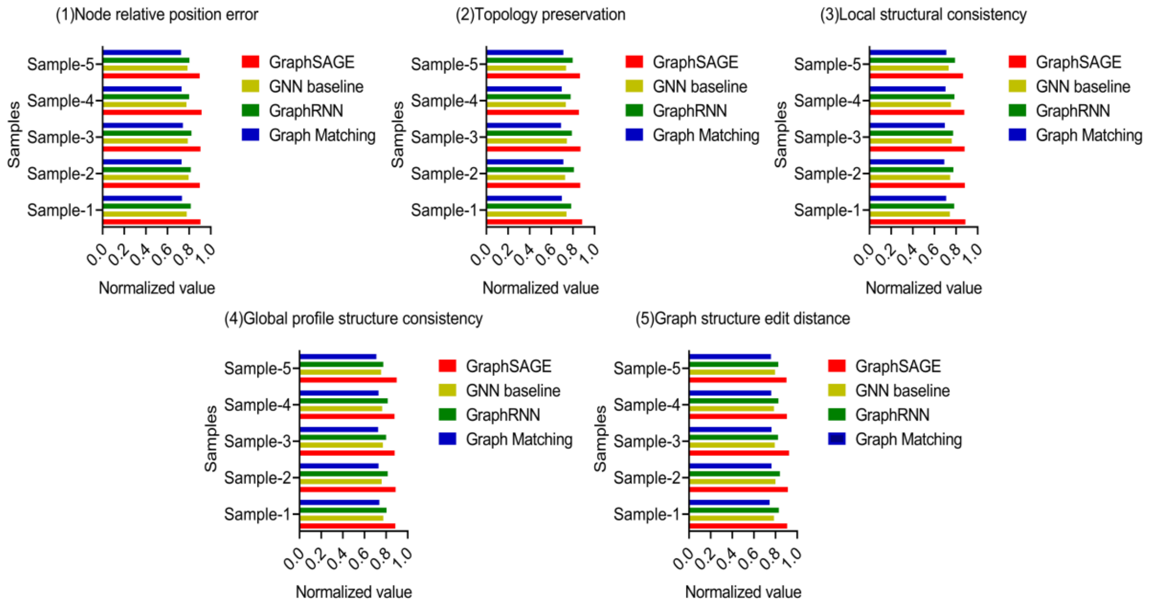
BERT embedding module: BERT-base-Chinese pretrained model (version 4.31.0) from the transformers library.

Visualization tool: Gephi 0.10.1, used to assist in graph structure annotation.

Deployment and Computing Configuration: All experiments were conducted in a local multithreaded environment. Training was performed in single-GPU mode, using mixed precision (AMP) acceleration. Model weight storage and result logging were managed by the Hydra framework. Experimental logs and graph output were uniformly stored using the JSON-LD specification, facilitating subsequent semantic fusion analysis and cross-modal correlation retrieval.

Structural Fidelity Evaluation of Generated Patterns

To verify systematically the comprehensive performance of the proposed GraphSAGE-driven intangible cultural heritage pattern graph structure generation framework in terms of structural restoration and semantic consistency, this experiment constructs a multidimensional evaluation index system and conducts a horizontal comparative analysis of the GraphSAGE model and three comparison methods, namely, graph neural network (GNN) baseline, graph recurrent neural network (GraphRNN), and graph matching, from five levels: node relative position error, topology preservation, local structural consistency, global profile structure consistency, and graph structure edit distance. These three types of models represent the typical ideas of current graph generation technology from the three dimensions of “structural perception ability,” “generation path modeling ability,” and “structural coordinate ability,” and are complementary in methodology. Comparing with the GraphSAGE structure perception, edge weight dynamic reconstruction, and embedding mechanism proposed in the study helps reveal the effect of this method on improving the structure, semantic consistency, and process logic expression in the task of intangible cultural heritage graphics generation. Five groups of typical pattern samples are selected for each dimension, and the actual performance of each model in terms of structural accuracy and semantic restoration is evaluated through standardized quantitative indicators, further revealing the adaptation differences of different modeling mechanisms in the symbolic structure generation task. The relevant comparison results are shown in Figure 2.


(1)Node relative position error

(2)Topology preservation

(3)Local structural consistency

(4)Global profile structure consistency

(5)Graph structure edit distance

Figure 2. Performance comparison of different methods under five types of structural evaluation indicators

Figure 2 shows that in terms of node relative position error indicators, GraphSAGE’s scores in the five groups of samples are maintained at 0.898 and above, which is remarkably higher than the maximum values of 0.796 and 0.743 of GNN baseline and graph matching, indicating that it has stronger structural accuracy in position retention. This advantage mainly comes from the sensitive perception of its local feature aggregation mechanism to the density and direction of needles. In terms of topology preservation, GraphSAGE’s score fluctuates between 0.856 and 0.885, and its average is higher than GraphRNN’s 0.792, reflecting its robustness in topological continuity modeling, which is closely related to its application of process sequence constraints in edge weight initialization. In terms of local structural consistency, GraphSAGE always maintains 0.865 and above, considerably better than the highest value of 0.761 of GNN baseline, indicating that its context information perception ability effectively supports the restoration of the local organizational structure of the pattern. In terms of global profile structure consistency, GraphSAGE has an advantage with a maximum value of 0.898 and an average value of 0.886. Its global semantic encoder shows high adaptability to the graph embedding strategy of cultural themes in this dimension. In the graph structure edit distance indicator, the scores of the five groups of GraphSAGE samples all reach 0.902 or above, with a peak value of 0.925, which is much higher than other methods. This result confirms the optimization ability of its dynamic edge weight adjustment mechanism in structural reorganization. Overall, GraphSAGE has a leading advantage in all five structural evaluation dimensions, reflecting its dual modeling capabilities of craft logic and semantic structure in the task of intangible cultural heritage graph structure generation.

Effectiveness Verification of Cultural Semantic Inheritance

In the study of intelligent generation of intangible cultural heritage patterns, several comparative experiments are constructed on the basis of the Bohai Mohe embroidery dataset to verify the performance of the GraphSAGE-driven model in the four dimensions of cultural theme expression, structural semantics preservation, color image restoration, and style semantic consistency, covering expert manual design schemes and current mainstream models graph convolutional network (GCN) and graph attention network (GAT), and a manually annotated evaluation index system is applied. Starting from the structure of the pattern graph, the comprehensive ability of the model in visual symbol extraction and semantic feature reorganization is systematically quantified, and its dual restoration effect on the cultural depth of intangible cultural heritage symbols and the accuracy of visual forms is evaluated. Figure 3 shows the performance differences of the four types of models under the subdivided indicators of each dimension.

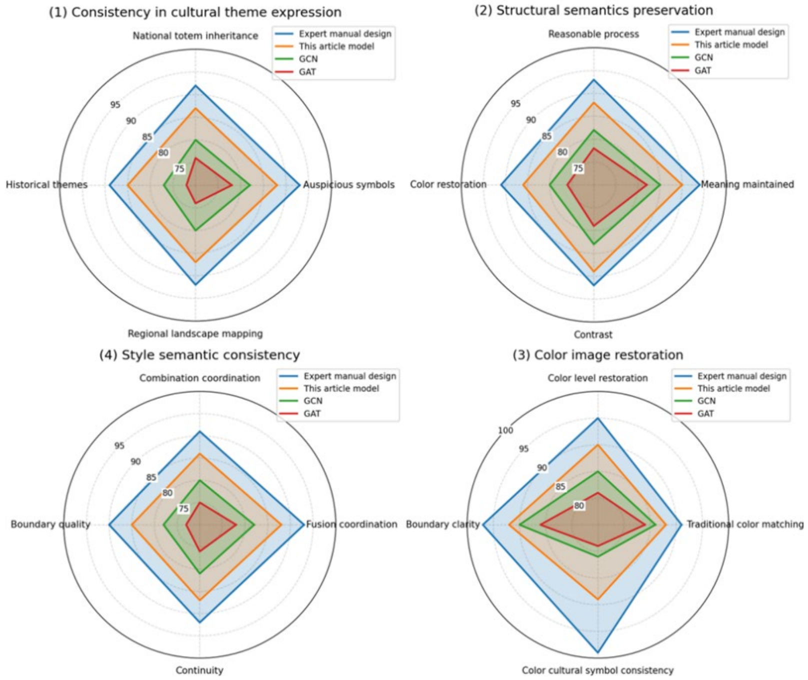
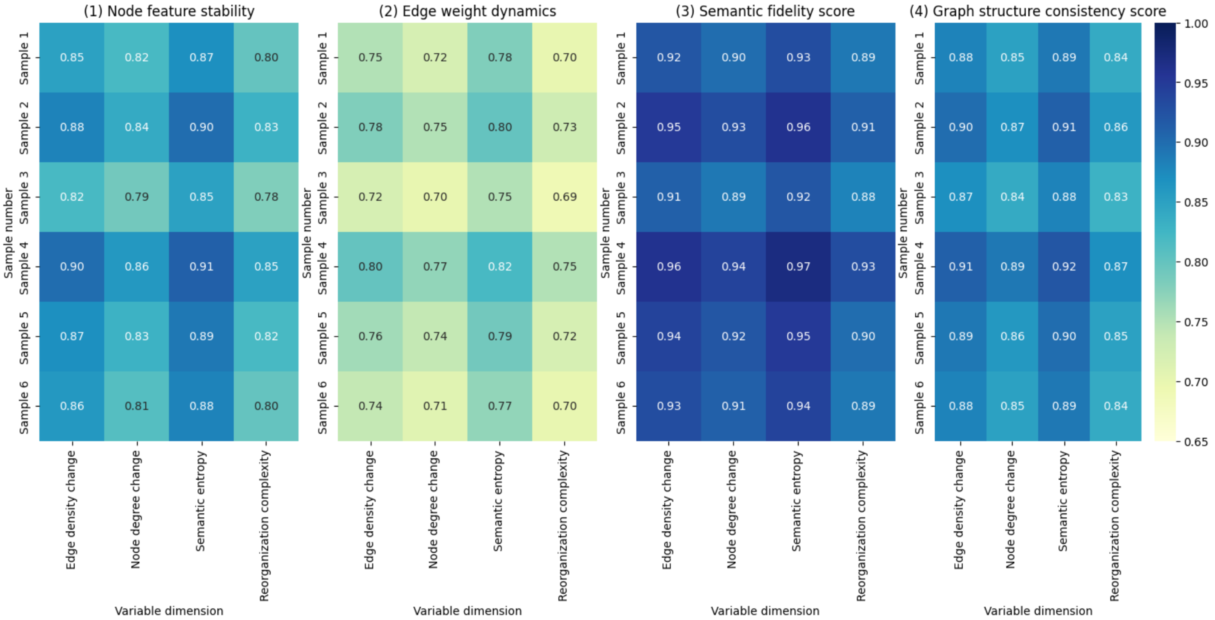


Figure 3. Performance comparison of each model under the four-dimensional indicators of intangible cultural heritage pattern generation

From the data performance in Figure 3, the expert manual design scheme maintains the highest level in all four dimensions, and the average score in the cultural theme expression consistency dimension reaches 91.5%. Among them, “auspicious meaning,” “national totem inheritance,” and “regional landscape mapping” all reach 92.0% and above, showing the advantages of manual schemes in deep semantic construction. Compared with GCN and GAT, the model in this article always maintains a better performance in all dimensions, and the cultural theme consistency score is generally higher than GCN. In terms of structural semantics preservation, “meaning retention” and “color restoration” reach 90.0% and 86.0%, respectively, showing the dual support of GraphSAGE structure for craft semantics and visual details. In the degree of color image restoration, the model presents a score of 88.0% and above for “traditional color matching” and “color level restoration,” indicating that its stability in the process of multilevel color deconstruction and reconstruction is better than other comparison models. In terms of style semantic consistency, although the overall score is slightly lower than that of manual design, the two items of “fusion coordination” and “continuity” remain above 86%, reflecting the certain advantages of the model in semantic fusion strategy. The overall data verify that the comprehensive performance of the GraphSAGE model in structural modeling and semantic generation is better than the current mainstream model.

Visualization of Graph Structure Reorganization Process

To evaluate in depth the performance of the GraphSAGE-driven intangible cultural heritage pattern generation framework in terms of graph structure stability and semantic consistency, this study constructs four types of variable dimension interference scenarios, covering four variables: edge density change, node degree change, semantic entropy perturbation, and reorganization complexity, and measures the four key indicators of node feature stability, edge weight dynamic change, semantic fidelity, and graph structure consistency of the model under different samples. Each test takes the actual generated pattern as the sample unit and studies the model’s robustness to multisource feature perturbations by comparing the degree of variation of the graph structure and semantic attributes before and after the perturbation. Figure 4 shows the heat map scoring results of six groups of typical samples under the above four indicator dimensions.



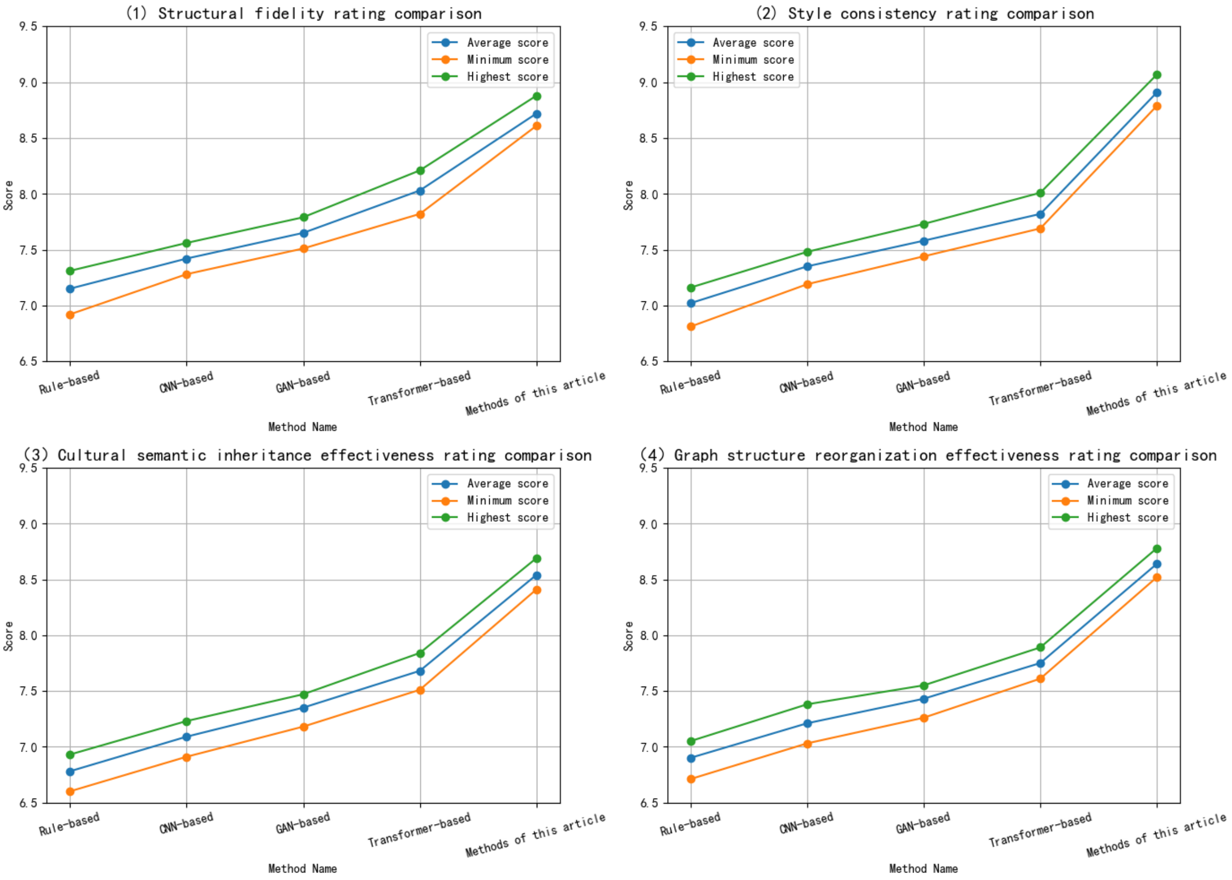
	Edge density change	Node degree change	Semantic entropy	Reorganization complexity
(1) Sample 1	0.85	0.82	0.87	0.80
(1) Sample 2	0.88	0.84	0.90	0.83
(1) Sample 3	0.82	0.79	0.85	0.78
(1) Sample 4	0.90	0.86	0.91	0.85
(1) Sample 5	0.87	0.83	0.89	0.82
(1) Sample 6	0.86	0.81	0.88	0.80
(2) Sample 1	0.75	0.72	0.78	0.70
(2) Sample 2	0.78	0.75	0.80	0.73
(2) Sample 3	0.72	0.70	0.75	0.69
(2) Sample 4	0.80	0.77	0.82	0.75
(2) Sample 5	0.76	0.74	0.79	0.72
(2) Sample 6	0.74	0.71	0.77	0.70
(3) Sample 1	0.92	0.90	0.93	0.89
(3) Sample 2	0.95	0.93	0.96	0.91
(3) Sample 3	0.91	0.89	0.92	0.88
(3) Sample 4	0.96	0.94	0.97	0.93
(3) Sample 5	0.94	0.92	0.95	0.90
(3) Sample 6	0.93	0.91	0.94	0.89
(4) Sample 1	0.88	0.85	0.89	0.84
(4) Sample 2	0.90	0.87	0.91	0.86
(4) Sample 3	0.87	0.84	0.88	0.83
(4) Sample 4	0.91	0.89	0.92	0.87
(4) Sample 5	0.89	0.86	0.90	0.85
(4) Sample 6	0.88	0.85	0.89	0.84

Figure 4. Heat map of relevant index scores of GraphSAGE model under multivariate interference

The data in Figure 4 reflect that the model shows high overall stability and consistency in semantic expression and structural restoration. In the dimension of node feature stability, the scores under semantic entropy perturbation generally remain at 0.850 or above, among which the fourth group of samples reaches 0.910, indicating that the model has a strong abstract retention ability for high-level semantic features. In terms of dynamic changes in edge weights, although the scores of each item are slightly lower, they still remain between 0.700 and 0.820 under the scenarios of semantic entropy perturbation and node degree change, reflecting a certain degree of response flexibility in the process of edge structure adjustment. In the semantic fidelity score, the scores under all variable interferences are stable at 0.880 or above, and the fourth group of samples even reaches 0.970 under semantic entropy perturbation, highlighting the tolerance of semantic encoding mechanism to information redundancy. In terms of graph structure consistency, most samples maintain scores in the range of 0.830 to 0.920 under all variable dimensions, indicating that the model has structural preservation and adaptability in the process of feature fusion and structural reconstruction. The above data together show that the model has excellent overall stability in graph structure and semantic expression in complex interference environments.

Comparative Experiment of Multiple Baseline Methods

To verify the effectiveness and advantages of the method in the intelligent generation of intangible cultural heritage patterns, the experiment compares and evaluates the comprehensive performance of traditional rule-based methods, deep generation methods based on CNN and GAN, Transformer architecture, and the GraphSAGE method proposed in this study from four dimensions: structural fidelity, style consistency, cultural semantic inheritance effectiveness, and graph structure reorganization effectiveness. Each score is scored by multiple experts on the basis of the self-built Bohai Mohe embroidery sample set, covering three levels: average score, minimum score, and maximum score, to reflect the performance differences of each method fully under different conditions. The evaluation results are shown in Figure 5, which presents a quantitative comparison of each method under four indicators.


(1) Structural fidelity rating comparison

(2) Style consistency rating comparison

(3) Cultural semantic inheritance effectiveness rating comparison

(4) Graph structure reorganization effectiveness rating comparison

Figure 5. Comparison of expert scores of various generation methods under relevant indicators

As shown in Figure 5, the proposed method achieves the best results in all four evaluation dimensions. In terms of structural fidelity, the average score of the proposed method reaches 8.720, which is considerably higher than the 8.030 of the Transformer-based method, indicating that it can capture the complex structural relationship of embroidery patterns more accurately. Its highest score is 8.88, and the lowest score is

8.610, with strong scoring stability. In terms of style consistency, the average score of the proposed method is 8.910, which is considerably higher than the 7.820 of the Transformer-based method. This result is mainly attributed to its cross-layer feature aggregation mechanism, which can effectively retain the style characteristics of the pattern. In terms of cultural semantic inheritance effectiveness, the average score of the proposed method is 8.540, which is remarkably better than the 6.780 of the traditional rule-based method, reflecting its advantage in global cultural semantic extraction. In the graph structure reorganization effectiveness score, the average score of the proposed method is 8.640, which is remarkably higher than the 7.430 of the GAN-based method, indicating that its dynamic edge weight adjustment mechanism helps to reconstruct the topological relationship more reasonably. Overall, while maintaining the integrity of structure, style, and semantics, the proposed method also improves the logical rationality of graph structure generation, demonstrating its strong adaptability and practical value in the task of intangible cultural heritage pattern generation.

Process Adaptability

This study verifies the effectiveness of GraphSAGE in the intelligent generation of intangible cultural heritage patterns by constructing a graph structure perception framework, focusing on its ability to capture the multidimensional features of Bohai Mohe embroidery topological patterns. For four typical embroidery process scenarios, namely, linear, curvilinear, segmented, and symmetrical, comparative experiments are conducted from four dimensions: pattern completeness, symmetry consistency, process rule compliance, and style fusion. By quantitatively evaluating the performance differences of different algorithm models in terms of visual structure fidelity and cultural semantic transmission, the adaptation characteristics of feature aggregation mechanism to complex process rules are revealed. The experimental results are shown in Figure 6.

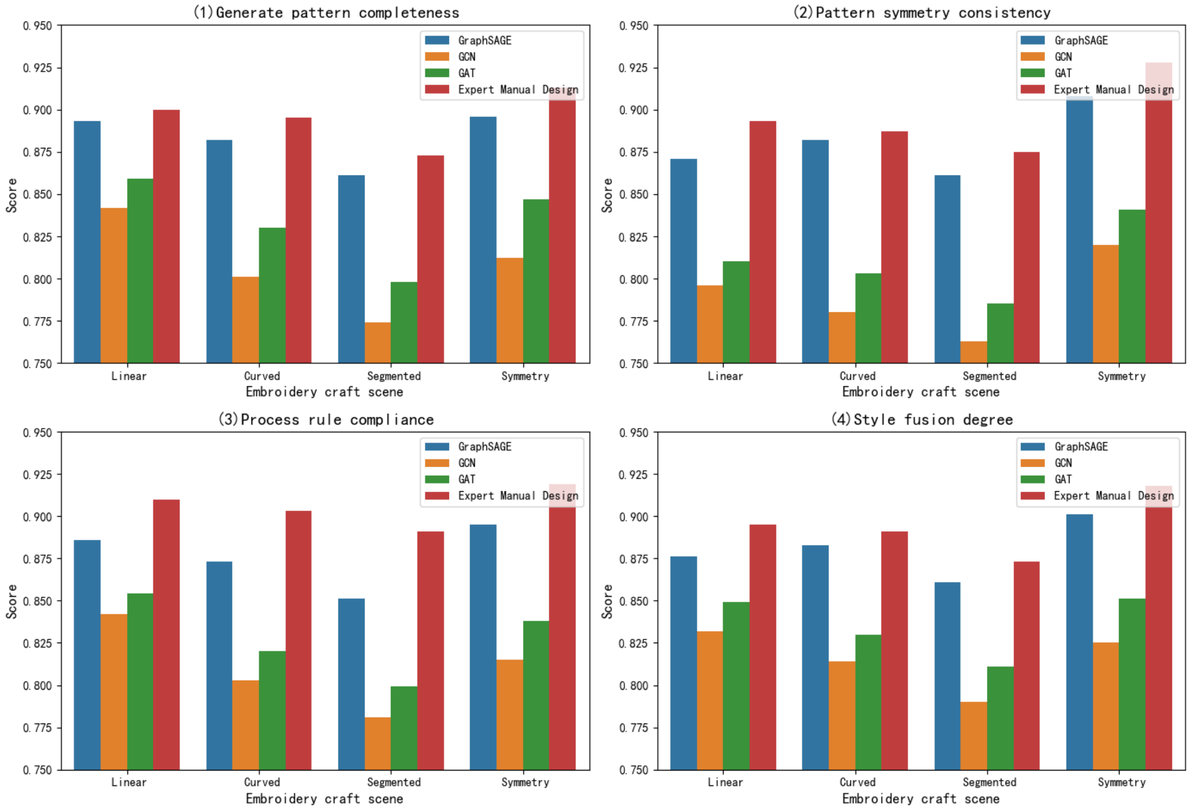


Figure 6. Multidimensional evaluation comparison of Bohai Mohe embroidery topological pattern intelligent generation

The data in Figure 6 show that the average values of various indicators of GraphSAGE are the completeness of generated patterns (0.883), pattern symmetry consistency (0.881), process rule compliance (0.876), and style fusion (0.880), which are better than GCN (0.807/0.790/0.810/0.815) and GAT (0.834/0.810/0.828/0.835) in all four indicators. This advantage stems from its two-layer architecture's ability to model local needlework features and global cultural semantics collaboratively and achieve feature reconstruction under the constraints of process rules through dynamic edge weight adjustment, which effectively solves the expression limitations of traditional methods in the coupling of structural relevance and cultural semantics. In terms of the completeness of the generated patterns, when faced with segmented craft scenes, GraphSAGE can still maintain a completeness score of 0.861, indicating that it has strong learning robustness for the topological relationship of discretized pattern units, which is mainly due to the adaptive aggregation mechanism of differential pooling operations on noncontinuous node features. The error analysis of the four groups of indicators shows that the maximum deviation between GraphSAGE and expert manual design is controlled within 0.040, which verifies the technical feasibility of this framework in the digital inheritance of intangible cultural heritage symbols.

CONCLUSIONS

This study proposes an intelligent generation framework for intangible cultural heritage patterns based on graph structure perception. By constructing a pattern graph model that integrates craft rules and cultural semantics, a two-layer GraphSAGE architecture is used to extract local needle method features and global cultural semantic features, respectively, and a topological pattern with structural rationality and cultural consistency is generated on the basis of a dynamic edge weight reorganization mechanism. The experimental results show that the average process rule compliance of the patterns generated by this method on the Bohai Mohe embroidery dataset reaches 0.876; the score of the generated pattern completeness reaches 0.883; the node relative position error score is controlled at 0.898 or above, which verifies the role of craft prior modeling and multilevel feature fusion mechanism in improving the digital expression of intangible cultural heritage symbols. However, current research still has limitations: the construction of the craft knowledge graph relies on manually annotated data, and the generalization ability is restricted by sample diversity; the computational complexity of the dynamic edge weight update mechanism is high, which may affect the real-time generation of large-scale patterns; in addition, the mapping relationship between the implicit expression of cultural semantics and explicit constraints has not been fully quantified. In the future, weakly supervised learning frameworks must be explored to reduce data annotation costs, the lightweight design of graph neural networks must be optimized to improve generation efficiency, and multimodal data should be combined to enhance the interpretability modeling of cultural semantics and thus promote the in-depth application of intangible cultural heritage digital technology in cultural inheritance and innovative design.

Author Contributions

All work in this study was independently completed by Guanhong ZHAN.

Conflicts of Interest

The author declares no conflict of interest.

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