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Digitalization of Zhejiang Yueqing Fine-Paper-Cutting Empowered by Artificial Intelligence: Integrated Application of F-AHP and RIME-BPNN Algorithms

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Abstract The preservation and modernization of traditional paper-cutting art face significant challenges due to its reliance on manual craftsmanship and subjective evaluation. This study proposes a computational framework integrating fuzzy analytic hierarchy process (F-AHP) and a Rime Optimization Algorithm-Back Propagation Neural Network (RIME-BPNN) to digitize and op-timize the design process for Yueqing intricate paper-cutting. First, we formalize the design op-timization problem as a multi-criteria decision-making task, where F-AHP quantitatively extracts key emotional dimensions ("Exquisite-Rough", "Modern-Traditional", "Elegant-Rustic") from both artists' expertise and consumer preferences. Second, we introduce RIME-BPNN, a metaheuristic-enhanced neural architecture that demonstrates superior prediction performance over conventional BPNN and SVR models through adaptive parameter optimization. Third, we implement a Generative Adversarial Network (GAN) that automatically generates design solu-tions by learning the mapping between F-AHP-derived parameters and visual features. Quanti-tative evaluations demonstrate the framework's effectiveness: user studies show higher emo-tional resonance scores and greater satisfaction compared to conventional methods. The pro-posed system's key innovations include: (1) a data-driven F-AHP method bridging subjective art evaluation with computable metrics, (2) RIME-BPNN's superior convergence in modeling non-linear aesthetic preferences, and (3) an end-to-end pipeline from perceptual analysis to AI-generated design. This work provides a scalable computational paradigm for intangible cul-tural heritage digitization, demonstrating how hybrid AI techniques can address challenges in traditional art preservation and innovation.

Index Terms zhejiang yueqing fine line paper-cutting, RIME-BPNN algorithm, cultural heritage preservation, kansei engineering, F-AHP

I. Introduction

China, an ancient Eastern nation with a civilization spanning over five millennia, boasts a rich history that has given rise to a brilliant cultural heritage [1]. Among its many treasures, the art of paper-cutting shines as a dazzling gem. Recognized as a UNESCO Intangible Cultural Heritage, Chinese paper-cutting stands out in the global art scene for its unique artistic charm and profound cultural significance [2]. It has also become an important symbol of Chinese cultural identity. Across China's vast landscape, numerous schools of paper-cutting have emerged, each with distinct characteristics [3]. One notable branch is Yueqing fine-line paper-cutting from Zhejiang Province [4]. Renowned for its intricate craftsmanship, exquisite patterns, and strong regional flavor, it holds a prominent place in Zhejiang's paper-cutting tradition. In May 2006, Yueqing fine-line paper-cutting was inscribed on the National List of Intangible Cultural Heritage, solidifying its status as an indispensable treasure in the repository of Chinese paper-cutting art [5].

Although Zhejiang's paper-cutting art, particularly Yueqing fine-line paper-cutting, has garnered widespread acclaim for its exquisite craftsmanship and unique artistic style, it faces significant challenges in its development and inheritance [6]. Currently, most of the folk artisans proficient in this ancient craft are elderly, while the younger generation shows diminishing interest and enthusiasm for traditional paper-cutting art. This has created a risk of a break in the chain of transmission [7]. While the skills of the older generation have been preserved, the continuous evolution and elevation of societal aesthetics have rendered traditional paper-cutting less capable of fully meeting the visual and aesthetic demands of the new era. Consequently, it struggles to effectively convey contemporary cultural values and spiritual connotations. Moreover, most paper-cutting works remain confined to purely handmade production processes that are intricate, time-consuming, and ill-suited to modern fast-paced production and consumption patterns. If traditional development pathways and models continue to be relied upon without innovation or transformation, traditional paper-cutting culture will inevitably lose its vitality and market competitiveness, ultimately facing obsolescence. Therefore, how to integrate modern design concepts and technological approaches while preserving the essence of tradition has become a critical issue for the inheritance and development of Zhejiang's paper-cutting art [8].

With the increasing abundance of material life and the advent of the era of emotional consumption, product homogenization in the market has become increasingly prominent. When purchasing products, users not only focus on functionality but also place greater emphasis on emotional resonance and aesthetic value conveyed by the product [9]. Therefore, in the process of product development, designers must address not only "hard issues" at the technical level but also "soft issues" such as consumer satisfaction, aesthetic demands, and emotional intentions [10], [11]. They need to integrate users' aesthetic psychology and cultural preferences into the details of product design. Kansei Image, which represents the sum of users' emotions, feelings, and psychological impressions toward a product, serves as a bridge for emotional connection between users and products [12]. It encompasses multidimensional psychological responses such as aesthetic perception, cultural identity, emotional resonance, and usage experience. In today's highly competitive market environment, functionality is no longer the sole determining factor for success; shaping Kansei Image has become critical to enhancing product value and fostering user loyalty. A successful product design must not only meet users' basic needs but also evoke emotional resonance through Kansei Image transmission, creating a sense of psychological identification and belonging for users [13].

To assist designers in developing products that more precisely and efficiently meet users' emotional needs, Kansei Engineering (KE) emerged as a solution. Originating in Japan during the 1970s, KE was introduced by Japanese scholar Mitsuo Nagamachi [14], [15]. It aims to scientifically transform users' emotional needs into specific design elements [16]. Over the past few decades, KE has been widely applied across various fields, including automobiles [17], home appliances [18], fashion [19], and electronic products [20]. It has become an essential tool for bridging the emotional connection between products and users. Not only has it significantly enhanced the emotional value and market share of products, but it has also provided new perspectives and methodological support for design innovation. This enables products to not only fulfill functional requirements but also establish deeper emotional resonance with users. Scholars have made notable progress in integrating pattern design with KE. For instance, in the field of spatial design, researchers have used KE methods to analyze users' emotional responses to interior decoration patterns, constructing relational models between color, texture, and users' Kansei cognition [21]. In interaction design, KE has been applied to optimize user interface patterns, enhancing users' emotional experiences [22]. Similarly, in industrial design, scholars have explored the relationship between product appearance patterns and users' emotional needs through Kansei Image analysis, providing scientific foundations for product design [23]-[25]. These research achievements demonstrate the feasibility and effectiveness of KE theory in pattern design. However, despite its significant advancements in other fields, research on the Kansei evaluation of paper-cutting patterns remains relatively scarce. Existing studies largely focus on the inheritance of paper-cutting techniques and discussions of their cultural value but lack in-depth analysis of consumer emotional needs [26]. Nevertheless, the successful application of KE in spatial design, interaction design, and industrial design offers important theoretical support and practical references for studying the Kansei Image of paper-cutting patterns. In exploring the relationship between design elements and Kansei cognition, scholars often employ statistical methods such as factor analysis, regression analysis, and cluster analysis. While these methods can reveal correlations between users' Kansei Images and design features to some extent, they are limited by their reliance on manual feature extraction and the restricted interpretability and predictive accuracy of their models. With the development of artificial intelligence technologies, some researchers have begun leveraging deep learning algorithms to construct mapping models. For example, studies have utilized support vector regression (SVR) and backpropagation neural networks (BPNN) to predict and analyze user emotional data, automatically extract design features, and build Kansei Image models. Others have adopted Generative Adversarial Networks (GANs) to generate designs that align with users' emotional needs, introducing new technical approaches to research in KE [27].

In summary, current research on the Kansei Image design of Yueqing fine-line paper-cutting in Zhejiang exhibits the following limitations: (1) Existing studies on patterns and paper-cutting art largely rely on designers' subjective aesthetics, lacking scientific analysis of consumers' psychological needs and emotional preferences. This makes it challenging to meet the modern consumer demand for personalized products. (2) Most existing research employs statistical methods to construct Kansei Image models. While these methods can reveal correlations between user emotions and design features to some extent, they rely on manual feature extraction, making it difficult to fully capture the complex characteristics of patterns. This reliance limits both the depth and accuracy of the research. (3) With the rapid development of artificial intelligence technologies, deep learning algorithms (e.g., SVR, BPNN) have demonstrated significant advantages. Combining various deep learning algorithms with KE and conducting comparative studies to identify the optimal intelligent approach offers a new research direction and technical support for paper-cutting pattern design. This approach holds great potential to drive the modernization and innovative development of traditional paper-cutting art.

Therefore, this study proposes a modernized design evaluation system for paper-cutting that integrates F-AHP and Rime Optimization Algorithm-Back Propagation Neural Network (RIME-BPNN), based on KE theory and artificial intelligence technology. The aim is to accurately capture users' emotional needs regarding Yueqing fine-line paper-cutting in Zhejiang and to generate design schemes that combine traditional artistic aesthetics with modern aesthetic demands using GANs. This research not only provides a theoretical foundation for the modernization of traditional paper-cutting art but also explores a new technological pathway for the inheritance and innovation of intangible cultural heritage.

II. Relevant Methods and Implementation Steps

II. A. Theory and Development of Kansei Engineering

KE, originating in the 1970s in Japan, was first introduced by Japanese scholar Mitsuo Nagamachi. It is a scientific method for transforming users' emotional needs (Kansei Images) into specific product design elements. By employing systematic research methods, KE aims to capture users' emotional responses to products and quantify and visualize these responses to guide design practices [28]. The core of KE lies in establishing a mapping relationship between users' Kansei Images and design features [29]. Through the analysis of users' emotional data, key design elements are extracted to achieve emotionally-driven product designs. The development of KE has evolved from qualitative research to quantitative analysis. In its early stages, traditional methods such as surveys and semantic differential analysis were primarily used [30]. Later, the integration of statistical tools and computer technologies significantly enhanced the precision and efficiency of research. KE has been widely applied across various fields, including automotive design [31], home appliance design [32], service design [33], [34], and interaction design [35]. In these domains, it helps designers optimize the appearance, functionality, and user experience of products by analyzing users' emotional needs, thereby significantly improving market competitiveness and user satisfaction. These successful applications provide valuable references for extending KE into the realm of traditional craftsmanship. Applying KE theory to the design research of Yueqing fine-line paper-cutting holds significant theoretical and practical value. As a form of traditional paper-cutting art, Yueqing fine-line paper-cutting has long relied on designers' subjective aesthetics and experience for pattern creation while lacking scientific analysis of consumer emotional needs. By introducing KE, it becomes possible to systematically explore users' Kansei Images related to paper-cutting patterns and establish a mapping relationship between design elements and user emotions. This approach enables the creation of works that better align with modern consumers' aesthetic preferences and emotional requirements. Such an application not only facilitates the modernization of Yueqing fine-line paper-cutting but also provides scientific foundations and technical support for its inheritance and innovation in contemporary markets. By bridging traditional artistry with modern consumer demands through KE, this initiative can breathe new life into this cultural heritage while ensuring its relevance in today's society.

II. B. Fuzzy Analytic Hierarchy Process

The Fuzzy Analytic Hierarchy Process (F-AHP) is an extension of the Analytic Hierarchy Process (AHP) that combines fuzzy mathematics theory to address uncertainty and vagueness in decision-making problems [36]. F-AHP uses fuzzy numbers, such as triangular fuzzy numbers, to represent the relative importance of expert judgments, thereby more accurately reflecting the fuzzy nature of human subjective assessments [37]. F-AHP is widely applied in multi-criteria decision-making problems, particularly in the field of KE, where it is used to quantify the relationship between users' Kansei Images and design features [38], [39]. The main steps of F-AHP are as follows:

(1) Establishing a hierarchical structure model: The decision problem is broken down into three levels: the goal layer, the criteria layer, and the alternatives layer.

(2) Constructing a fuzzy judgment matrix: Experts and consumers are invited to comprehensively evaluate and perform pairwise comparisons of Kansei vocabularies in the criteria layer. Triangular fuzzy numbers (l,m,u) are used to represent their relative importance. The meanings of these parameters are as follows: l : The lowest possible value, m : The most likely value, u : The highest possible value.

$$\tilde{A}=\begin{pmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n1} & \cdots & \tilde{a}_{nn} \end{pmatrix} \quad (1)$$

Among them, $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ represents the importance of the i Kansei vocabulary relative to the j Kansei vocabulary.

(3) The geometric mean method is used to calculate the fuzzy weight of each Kansei vocabulary. The specific steps are as follows:

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij} \right)^{\frac{1}{n}} \tag{2}$$

where $\tilde{a}_{ij}$ is the triangular fuzzy number in the fuzzy judgment matrix.

$$\tilde{w}_i = \frac{\tilde{r}_i}{\sum_{j=1}^{n} \tilde{r}_j} \tag{3}$$

Among them, $\tilde{w}_i = (l_i, m_i, u_i)$ represents the fuzzy weight of the i Kansei vocabulary.

(4) Defuzzification is performed using the centroid method to convert fuzzy weights into specific numerical values. The formula is:

$$w_i = \frac{l_i + m_i + u_i}{3} \tag{4}$$

(5) The consistency check is performed on the fuzzy judgment matrix to ensure the rationality of expert judgments. The formulas for the Consistency Index (CI) and the Consistency Ratio (CR) are as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{5}$$

$$CR = \frac{CI}{RI} \tag{6}$$

If $CR < 0.1$, the judgment matrix is considered to have acceptable consistency.

II. C.Back Propagation Neural Network

BPNN is a type of multilayer feedforward neural network trained using the error backpropagation algorithm. It has strong nonlinear mapping capabilities and self-learning abilities [40]. The core idea of BPNN is to calculate the output results through forward propagation and then adjust the network weights through error backpropagation, thereby gradually optimizing model performance. In product design, BPNN can effectively handle complex nonlinear relationships, such as the correlation between users' Kansei Images and design features. By training a BPNN model, it is possible to predict users' emotional responses to specific designs, thus providing data support for design optimization [41]. Compared to traditional statistical methods, BPNN can automatically extract features and build high-precision predictive models, significantly improving the efficiency and accuracy of design research [42]. The BPNN neural network process is shown in Figure 1.

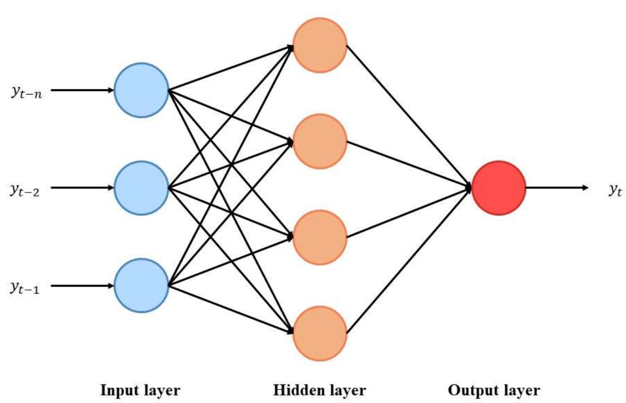


Figure 1: BPNN Process Structure

II. D.RIME Optimization Algorithm

The Rime Optimization Algorithm (RIME) is a heuristic optimization algorithm inspired by the natural process of rime ice formation, proposed by researcher Hang Su in February 2023 [43]. Its inspiration comes from the physical phenomenon of rime ice forming through the condensation of water vapor in low-temperature environments. The rime ice formation process exhibits randomness, dynamism, and adaptability, which are abstracted as search strategies within the optimization algorithm [44]. The RIME algorithm simulates the crystallization process of rime ice, treating the solution space of the optimization problem as the environment for rime ice formation. By leveraging the random growth characteristics of rime ice, it performs global search and local optimization [45]. The core idea of the RIME algorithm is to balance exploration (global search) and exploitation (local optimization) capabilities through random sampling and dynamic adjustment strategies. Its core steps and mathematical models are as follows:

Step 1: Initial Population Generation

(1) Randomly generate the initial population, where each individual represents a potential solution to the optimization problem. The population size is N, and the position of each individual is represented as $X_i = \left(x_{i1}, x_{i2}, \ldots, x_{iD}\right)$, where D is the dimensionality of the problem.

$$X_i = lb + \left(ub - lb\right) \cdot rand() \tag{7}$$

Here, lb and ub represent the lower and upper bounds of the search space, respectively, and $rand()$ is a random number within the range [0,1].

(2) Calculate the fitness value of each individual, $f\left(X_i\right)$, to evaluate the fitness of each individual.

Step 2: Simulation of Rime Ice Growth

(1) Generate new candidate solutions through random sampling to simulate the random formation process of rime ice. The position update formula for the new solution is:

$$X_{new} = X_i + \alpha \cdot \left(X_j - X_k\right) \tag{8}$$

In the formula, X_j and X_k are two randomly selected individuals from the population, and α is a random step size factor.

(2) Based on the growth characteristics of rime ice, dynamically adjust the search step size and direction. The update formula for the step size factor α is:

$$\alpha = \alpha_{\max} - \left(\alpha_{\max} - \alpha_{\min}\right) \cdot \frac{t}{T} \tag{9}$$

Here, $\alpha_{\max}$ and $\alpha_{\min}$ represent the maximum and minimum values of the step size factor, t s the current iteration number, and T is the maximum number of iterations.

(3) Balance global search and local optimization through the crystallization mechanism of rime ice. The position update formula for the new solution is:

$$X_{new} = X_i + \beta \cdot \left(X_{best} - X_i\right) \tag{10}$$

Step 3: Population Update

(1) Compare the fitness values of the new solution and the current solution, and retain the better solution.

$$X_i = \begin{cases} X_{new}, if \ \mathrm{f}\left(X_{new}\right) < \mathrm{f}\left(X_i\right) \\ X_i, \ otherwise \end{cases} \tag{11}$$

(2) Repeat Steps 2 and 3 until the maximum number of iterations T is reached.

II. E. Rime Optimization Algorithm-Back Propagation Neural Network

Although the BPNN possesses strong nonlinear mapping and self-learning capabilities, it still has certain limitations in practical applications [46]. Therefore, this study introduces RIME to optimize the initial weights and biases of BPNN, thereby improving the training efficiency and prediction accuracy of the network. The RIME-BPNN algorithm is a hybrid optimization method that combines the Rime Ice Optimization Algorithm with the Backpropagation Neural Network, offering the following advantages: (1) The RIME algorithm, through random sampling and dynamic adjustment strategies, effectively avoids BPNN falling into local optima and enhances the model's global search capability. (2) During optimization, the RIME algorithm dynamically adjusts the step size factor, enabling rapid convergence to the optimal solution and significantly reducing BPNN's training time. (3) The RIME algorithm can adapt to complex nonlinear problems, especially for optimizing high-dimensional, multi-modal functions, providing a better solution for BPNN's weight initialization. (4) By optimizing initial weights and biases with the RIME algorithm, BPNN's prediction accuracy is significantly improved, allowing it to more accurately capture the relationship between users' perceptual intentions and design features. Below are the detailed steps and formula explanations of the RIME-BPNN algorithm.

Step 1: Divide the dataset into a training set and a test set. Normalize the input and output data, mapping them to the range [-1, 1]:

Step 2: Use the RIME algorithm to optimize the initial weights and biases of BPNN to generate the optimal solution:

$$X_{best} = \arg\min_{X_i} f\left(X_i\right) \tag{12}$$

In the formula, X_{best} represents the optimal weights and biases.

Step 3: Initialize the BPNN using the optimal weights and biases obtained from RIME optimization, and update the network parameters through the error backpropagation algorithm:

$$w_{ij} = w_{ij} + \eta \cdot \delta_j \cdot h_j \tag{13}$$

In the formula, η represents the learning rate, δ_j is the error term, and h_j denotes the output of the hidden layer.

Step 4: To evaluate the performance of the RISE-BPNN algorithm, this study uses the coefficient of determination (R^2) and Root Mean Square Error (RMSE) as evaluation metrics. The R^2 value is used to measure the goodness of fit between the predicted values and the actual values, and its formula is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2} \tag{14}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of the actual values. The closer R^2 is to 1, the better the model's fit [47].

RMSE is used to measure the deviation between the model's predicted values and the actual values, and its formula is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{15}$$

The smaller the RMSE, the higher the prediction accuracy of the model (Figure 2) [48].

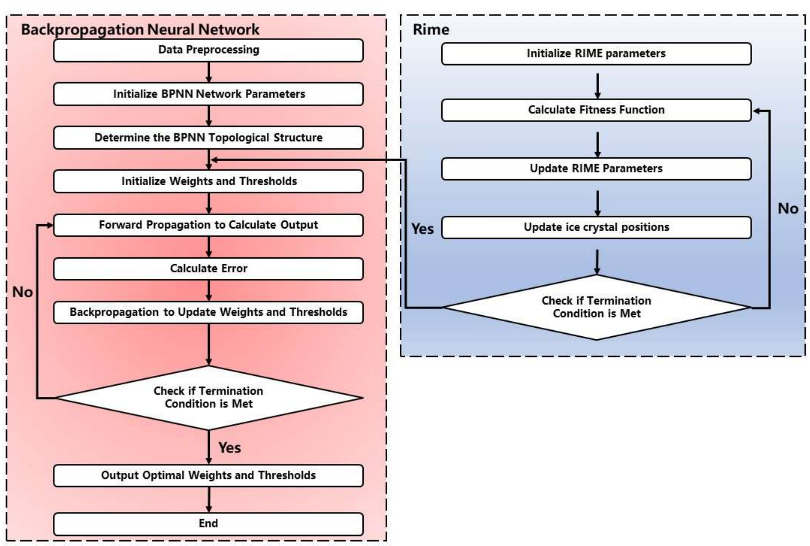


Figure 2: RIME-BPNN Process Structure

III. A Case Study on the Digital Design of Paper-Cutting

This study focuses on Yueqing fine line paper-cutting from Zhejiang, combining KE theory with artificial intelligence technologies to construct a systematic research framework aimed at achieving the modernization and innovative inheritance of traditional paper-cutting art. The research framework consists of the following four main components: to begin with, extracting key emotional needs based on the F-AHP, integrating the dual demands of paper-cutting artists and consumers; next, constructing a RIME-BPNN affective mapping model, which is a Backpropagation Neural Network optimized by the RIME algorithm, to accurately predict users' affective intentions; then, utilizing GANs to generate design schemes that combine traditional artistic aesthetics with modern aesthetic demands; and finally, validating the practical effectiveness of the design schemes through user evaluations, providing scientific evidence and practical guidance for the modern transformation of traditional paper-cutting art. The research framework is shown in Figure 3.

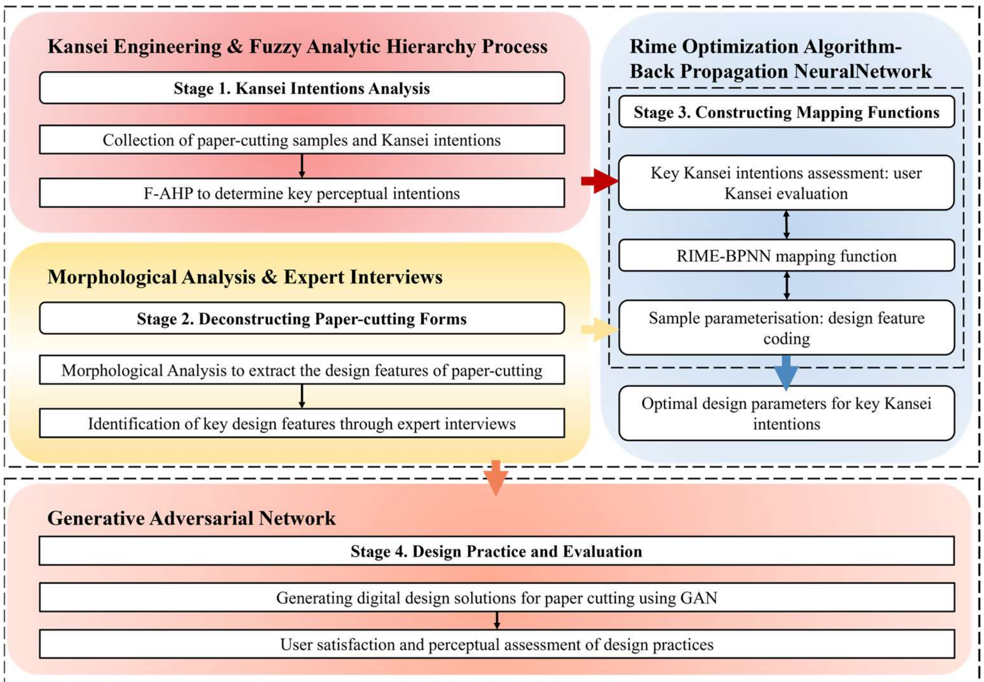
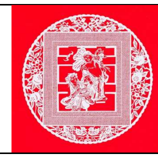
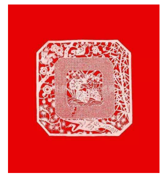
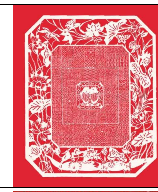
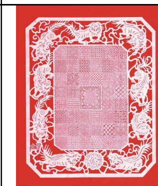
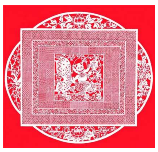
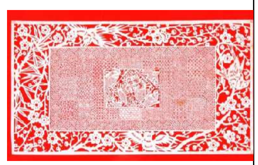
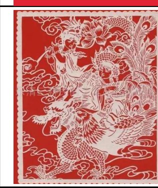
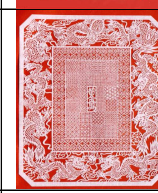
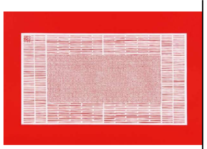
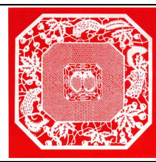
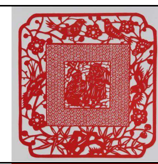
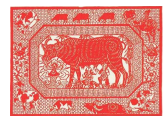
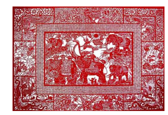
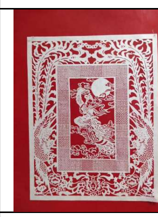
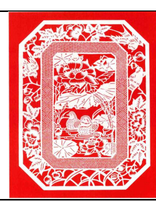
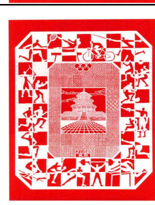
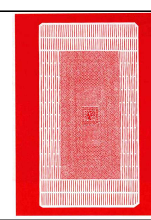


Figure 3: A Research Framework for the Digital Design of Yueqing Fine Line Paper-Cutting in Zhejiang

III. A. The Collection of Paper-Cutting Image Samples

To comprehensively study the emotional intention design of Yiquan fine line paper-cutting from Zhejiang, this research first collected 70 representative samples of Yiquan fine line paper-cutting through various channels. The sources of these samples include museums and art exhibitions, folk art works, digital resource libraries, and modern design works. Among the initially collected 70 samples, the research further screened the samples through a panel of experts (including 6 paper-cutting art researchers, 5 designers, and 2 cultural scholars) and user surveys. The expert panel scored the samples based on dimensions such as artistic value, cultural representation, pattern complexity, and visual expressiveness. Additionally, user surveys were conducted to understand the emotional perceptions and preferences of ordinary viewers regarding the samples. Ultimately, combining expert scores and user feedback, 43 samples that were most representative and valuable for research were identified (Table 1). These 43 samples encompass various styles, including traditional and modern, simple and complex, natural and abstract, which can comprehensively reflect the artistic characteristics and cultural connotations of Yiquan fine line paper-cutting. These samples will serve as the foundational data for subsequent emotional engineering research and deep learning algorithm analysis to construct a relationship model between user emotional intentions and design features.

Table 1: Zhejiang Yueqing Fine Paper-Cut Sample Library

No.	Paper-cutting	No.	Paper-cutting	No.	Paper-cutting	No.	Paper-cutting	No.	Paper-cutting
1		2		3		4		5	
6		7		8		9		10	
11		12		13		14		15	
16		17		18		19		20	
21		22		23		24		25	
26		27		28		29		30	
31		32		33		34		35	
36		37		38		39		40	
41		42		43					

III. B. Collection of Kansei Intentions in Paper-Cutting Images

To scientifically explore consumers' emotional needs regarding Yiquan fine line paper-cutting from Zhejiang, this study first conducted literature analysis, user interviews, and market research to preliminarily collect 30 pairs of emotional vocabulary. These words encompass various dimensions, including users' aesthetic feelings, cultural identity, and emotional experiences related to paper-cutting patterns, providing a comprehensive reflection of users' emotional perceptions of Yiquan fine line paper-cutting. Subsequently, the study invited an expert panel to screen and optimize these vocabulary pairs. Through discussion and scoring, the expert panel considered the representativeness, applicability, and operability of the vocabulary, ultimately determining 8 pairs of the most representative emotional vocabulary. These vocabulary pairs are as follows (Table 2).

Table 2: Kansei Vocabulary of Yiquan Fine Line Paper-Cutting from Zhejiang

No.	Kansei Vocabulary	No.	Kansei Vocabulary
1	Traditional – Modern	2	Complex - Simple
3	Elegant - Rustic	4	Vivid - Stale
5	Exquisite - Rough	6	Warm - Cold
7	Interesting - Boring	8	Cultural - Ordinary

III. C. Extraction of Key User Emotional Intentions Using F-Ahp

To extract the emotional vocabulary that has the greatest impact on user satisfaction, this study employs F-AHP to calculate the weights of the 8 pairs of emotional vocabulary. The goal layer is set as user satisfaction, the criterion layer consists of the 8 pairs of emotional vocabulary, and the alternative layer includes 43 paper-cutting patterns. First, an expert panel consisting of 6 paper-cutting art researchers and 6 consumers was invited to conduct pairwise comparisons of the emotional vocabulary, constructing a fuzzy judgment matrix. The relative importance is represented using triangular fuzzy numbers (l,m,u), as shown in Table 3.

Subsequently, the fuzzy weights of each emotional vocabulary were calculated using the geometric mean method, and defuzzification was performed using the centroid method to obtain specific weight values (Table 4). Additionally, a consistency test was conducted on the fuzzy judgment matrix to ensure the rationality of expert judgments, resulting in CI = 0.04 and CR =0.028. Since CR < 0.1, it demonstrates that the judgment matrix has acceptable consistency.

The weight calculation results (Table 5) indicate that "Exquisite - Rough" (weight: 0.170), "Traditional - Modern" (weight: 0.160), and "Elegant - Rustic" (weight: 0.130) are the emotional vocabularies that have the greatest impact on user satisfaction. These emotional vocabularies play a significant role in users' evaluations of fine-line paper-cutting in Yueqing, Zhejiang, and can significantly influence overall user satisfaction. Therefore, during the design optimization process, attention should be focused on these emotional vocabularies by enhancing the sense of exquisiteness, traditionality, and elegance of the patterns, as well as increasing their interestingness and simplicity to meet users' emotional needs, thereby improving user satisfaction with the design.

Table 3: F-AHP Expert Judgment Matrix

Kansei Vocabulary No.	Kansei Vocabulary No.							
	1	2	3	4	5	6	7	8
1	(1, 1, 1)	(1.5, 2, 2.5)	(1.2, 1.5, 1.8)	(2.5, 3, 3.5)	(1, 1, 1)	(1.8, 2.2, 2.6)	(1.3, 1.6, 1.9)	(2.7, 3.2, 3.7)
2	(0.4, 0.5, 0.6)	(1, 1, 1)	(1.1, 1.4, 1.7)	(1.6, 2, 2.4)	(0.6, 0.8, 1)	(1.2, 1.5, 1.8)	(1, 1, 1)	(1.7, 2.1, 2.5)
3	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(1, 1, 1)	(1.3, 1.6, 1.9)	(0.7, 0.9, 1.1)	(1.1, 1.3, 1.5)	(1, 1, 1)	(1.8, 2.2, 2.6)
4	(0.3, 0.4, 0.5)	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)	(1, 1, 1)	(0.4, 0.5, 0.6)	(1.2, 1.4, 1.6)	(1, 1, 1)	(1.6, 2, 2.4)
5	(1, 1, 1)	(1.2, 1.5, 1.8)	(0.9, 1.1, 1.3)	(1.7, 2, 2.3)	(1, 1, 1)	(1.4, 1.7, 2)	(1, 1, 1)	(2.2, 2.6, 3)
6	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)	(1, 1, 1)	(1, 1, 1)	(1.5, 1.8, 2.1)
7	(0.5, 0.6, 0.7)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1.7, 2, 2.3)

Table 4: F-AHP Fuzzy Weight Normalization Values

Kansei Vocabulary	Weight Normalization Values (l,m,u)	Kansei Vocabulary	Weight Normalization Values (l,m,u)
Traditional – Modern	(0.13, 0.16, 0.19)	Exquisite - Rough	(0.15, 0.17, 0.19)
Complex - Simple	(0.09, 0.11, 0.13)	Warm - Cold	(0.08, 0.10, 0.12)
Elegant - Rustic	(0.11, 0.13, 0.15)	Interesting - Boring	(0.10, 0.12, 0.14)
Vivid – Stale	(0.07, 0.09, 0.11)	Cultural - Ordinary	(0.06, 0.08, 0.10)

Table 5: Comprehensive Weight of Affective Vocabulary

Kansei Vocabulary	Weight	Ranking	Kansei Vocabulary	Weight	Ranking
Traditional – Modern	0.160	2	Exquisite - Rough	0.170	1
Complex - Simple	0.110	5	Warm - Cold	0.100	6
Elegant - Rustic	0.130	3	Interesting - Boring	0.120	4
Vivid – Stale	0.090	7	Cultural - Ordinary	0.080	8

III. D. Morphological Deconstruction and Coding of Engraved Paper Images

To deeply explore the design characteristics of fine line engraved paper from Yueqing, Zhejiang, and to establish a relational model between these characteristics and users' affective intentions, this study systematically deconstructed and coded 43 finalized samples. By analyzing the visual features and cultural connotations of the samples, and referencing cultural knowledge provided in books, several potential design elements were initially proposed. Subsequently, an expert group was invited to review and optimize these elements. Through multiple rounds of discussion and evaluation, the expert group comprehensively considered the artistic characteristics, cultural value, and research feasibility of Yueqing fine line engraved paper, ultimately identifying five key design elements: shape outline, composition form, modeling technique, pattern theme, and engraving technique. These elements encompass multidimensional features of paper-cutting works, ranging from overall structure to detailed expression, effectively reflecting the artistic characteristics and cultural value of Yueqing fine line engraved paper. By systematically deconstructing and coding these five design elements (Table 6), this study transforms the complex design features of Yueqing fine line engraved paper into quantifiable and analyzable data, laying a solid foundation for subsequent research.

Table 6: Morphological Deconstruction of Fine Line Engraved Paper from Yueqing, Zhejiang

Design features	1	2	3	4	5
Shape Outline	Octagon	Square	Circle	Irregular Combination	
Composition Form	Enclosed Composition				
Modeling Technique	Realistic	Exaggerated	Symbolized		
Pattern Theme	Landscape	Figures	Flora and Fauna	Religion	Mythology
Engraving Technique	Circular Knife Method	Square Knife Method	Knife Stabbing Method	Needle Stabbing Method	Comprehensive Method

III. E. Construction of the Engraved Paper Affective Mapping Model Using Rime-Bpnn

To deeply explore the affective intention design of fine line engraved paper from Yueqing, Zhejiang, this study first conducted systematic design coding for 43 design schemes. Through expert evaluations, the design elements were categorized and quantified based on detailed coding rules. Subsequently, 100 users were invited to assess each sample's three main Kansei intentions (Exquisite - Rough, Modern - Traditional, and Elegant-Rustic) using a 10-point Likert scale. The assessment was conducted offline, and each user was fully informed of the questionnaire content and assessment criteria before the assessment. The specific assessment questionnaire is shown in Figure 4. The average affective scores were calculated. Based on the user evaluation data, an affective mapping matrix was constructed (Table 7), with design elements as input variables and affective intentions as output variables. This matrix describes the complex relationship between user affective intentions and design characteristics. To construct a more accurate affective mapping model, this study adopted the RIME-BPNN method and utilized the MATLAB 2024Rb platform for model construction and training. During the development of the RIME-BPNN affective mapping model, detailed parameter settings were implemented to ensure prediction accuracy and generalization capability. First, the dataset was divided into training and testing sets in a ratio of 90% to 10%, with random shuffling ensuring randomness in sample distribution. The input features included five key design elements, while the output dimensions corresponded to three key affective intentions. The network training parameters were set as follows: 1,000 training iterations, a target error of 1e-6, and a learning rate of 1e-3. The optimization algorithm employed was RIME, with a population size of 30 and a maximum of 50 iterations. The optimization parameters' lower and upper bounds were set to -1 and 1, respectively. The optimal weights and biases obtained through the RIME algorithm were assigned to connections between the input layer and hidden layer as well as between the hidden layer and output layer. Finally, the model was trained using data from the training set and validated using data from the testing set. Performance evaluation metrics included RMSE and R^2 to ensure both generalization capability and prediction accuracy of the model.

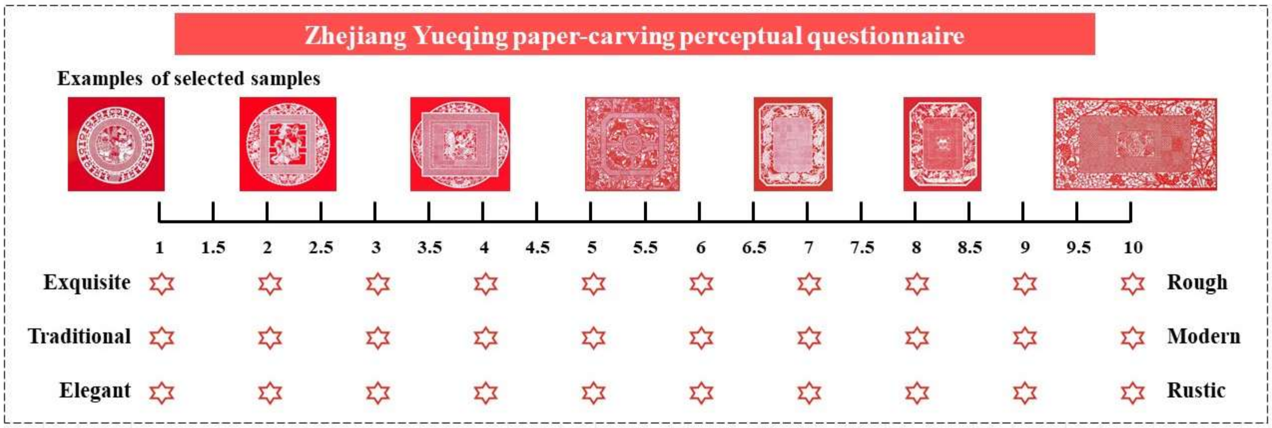


Figure 4: Example of Kansei evaluation questionnaire

Table 7: RIME-BPNN mapping function model dataset

No.	Paper-cutting design feature code					Key Kansei intentions		
	Shape Outline	Composition Form	Modeling Technique	Pattern Theme	Engraving Technique	Exquisite - Rough	Traditional – Modern	Elegant-Rustic
1	1	1	1	3	5	3.317	6.083	2.217
2	3	1	3	2	2	3.317	5.196	2.363
3	3	1	1	2	5	3.464	6.325	2.076
4	2	1	1	3	5	3.464	6.325	2.280
5	1	1	2	5	5	3.742	7.483	2.860
6	2	1	2	5	1	3.317	5.916	2.812
7	2	1	3	3	2	3.317	5.196	2.520
8	2	1	1	3	2	3.000	4.359	2.196
9	2	1	3	3	5	3.742	6.928	2.582
10	2	1	3	5	5	4.000	8.000	3.015
11	4	1	2	4	5	4.000	7.874	2.688
12	2	1	3	2	5	3.606	6.557	2.404
13	2	1	2	3	5	3.606	6.557	2.404
14	4	1	2	4	1	3.464	6.164	2.587
15	1	1	2	5	1	3.162	5.657	2.774
16	2	1	3	4	2	3.464	5.831	2.740
17	1	1	3	3	1	3.000	4.583	2.419
18	4	1	3	2	1	3.317	5.568	2.330
19	2	1	2	4	5	3.742	7.071	2.645
20	2	1	2	4	5	3.742	7.071	2.645
21	2	1	3	3	5	3.742	6.928	2.582
22	1	1	3	3	5	3.606	6.708	2.535
23	1	1	3	3	5	3.606	6.708	2.535

24	4	1	2	5	1	3.606	6.856	2.849
25	2	1	2	3	5	3.606	6.557	2.404
26	2	1	2	2	1	2.828	3.742	2.018
27	2	1	2	5	1	3.317	5.916	2.812
28	4	1	3	3	5	4.000	7.746	2.626
29	2	1	2	5	1	3.317	5.916	2.812
30	2	1	2	3	1	3.000	4.359	2.271
31	2	1	1	6	5	3.873	8.185	3.082
32	1	1	1	3	5	3.317	6.083	2.217
33	4	1	3	1	5	3.742	7.211	2.339
34	2	1	2	2	1	2.828	3.742	2.018
35	2	1	1	1	5	3.162	5.657	1.838
36	1	1	1	1	5	3.000	5.385	1.730
37	1	1	1	1	5	3.000	5.385	1.730
38	2	1	1	6	5	3.873	8.185	3.082
39	2	1	2	5	1	3.317	5.916	2.812
40	2	1	3	4	2	3.464	5.831	2.740
41	2	1	2	4	1	3.162	5.099	2.541
42	2	1	1	3	1	2.828	4.000	2.128
43	2	1	2	1	1	2.646	3.317	1.822

Through the training and testing of the RIME-BPNN affective mapping model, excellent performance evaluation results were achieved. For the " Exquisite - Rough " dimension, the R^2 values for the training set and testing set were 0.9995 and 0.9977, respectively, while the RMSE values were 0.0077 and 0.0186, respectively. For the "Traditional-Modern" dimension, the R^2 values were 0.9959 and 0.9997, with RMSE values of 0.0747 and 0.0253, respectively. For the "Elegant-Rustic" dimension, the R^2 values were 0.9991 and 0.9977, with RMSE values of 0.0100 and 0.0181.

Based on the experimental results (Table 8), it can be concluded that the R^2 values for all affective intention dimensions are close to 1, indicating excellent fitting performance, while the RMSE values are relatively small, reflecting minimal prediction errors. The fitting plot of the Kansei values for the training set and test set of the RIME-BPNN mapping model is shown in Figure 5. This demonstrates that the constructed RIME-BPNN affective mapping model possesses high prediction accuracy and strong generalization capability, effectively capturing the mapping relationship between design elements and affective intentions.

Table 8: RIME-BPNN mapping model parameter results

Key Kansei intentions	R^2		RMSE	
	The training set.	The testing set.	The training set.	The testing set.
Exquisite - Rough	0.9995	0.9977	0.0077	0.0186
Traditional – Modern	0.9959	0.9997	0.0747	0.0253
Elegant-Rustic	0.9991	0.9977	0.0100	00181

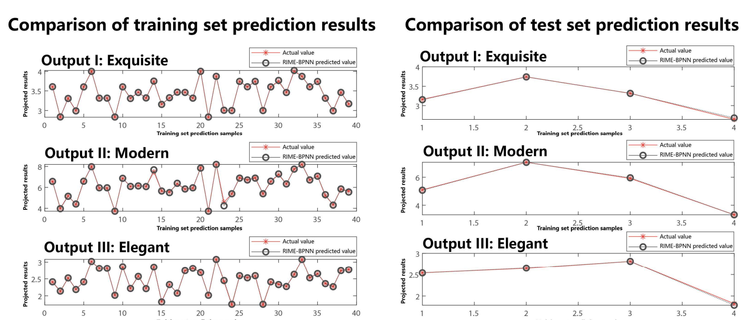


Figure 5: RIME-BPNN Mapping Model Prediction Fitting Plot

To further develop design schemes that meet users' specific emotional needs, a total of 360 design coding schemes were generated by combining various design features (4×1×3×6×5=360) and input into the trained RIME-BPNN affective mapping model to generate corresponding affective intention predictions. Leveraging the model's efficient computational capabilities, the predicted values for each design coding scheme across the three key affective intention dimensions were quickly obtained. Based on suggestions from the expert group regarding future directions for paper-cutting needs, this study selected vocabulary dimensions more aligned with future trends as the design practice goals for each pair of affective needs: " Exquisite," "Modern," and "Elegant." The design coding schemes with the highest predicted values for these dimensions were selected, with detailed schemes as follows: (1) " Exquisite ": Octagonal shape outline, realistic modeling technique, landscape pattern theme, circular knife engraving technique. (2) "Modern": Irregular combination shape outline, symbolic modeling technique, historical pattern theme, comprehensive engraving technique. (3) "Elegant": Irregular combination shape outline, symbolic modeling technique, historical pattern theme, needle-stabbing technique.

In the design practice process, traditional paper-cutting techniques were not directly used. Instead, a series of digitally collectible-type design schemes were generated using GANs-based image generation tools [49]. These designs aim to serve as references for paper-cutting artists in completing their final creations while also attracting younger audiences to appreciate and accept traditional paper-cutting techniques. By integrating the professional creative experience of paper-cutting artists and undergoing multiple rounds of iterative optimization, three sets of paper-cutting design schemes were ultimately developed that balance traditional artistic aesthetics with modern aesthetic demands (Figure 6).

To validate the practical effectiveness and user experience of these designs, 100 users were invited to participate in an evaluation of affective needs and satisfaction levels using a 10-point Likert scale. The evaluation results are shown in Table 9. The results indicate that the emotional assessment results had an error margin within ±0.5 compared to the model's predictions, and satisfaction scores exceeded 7.5 points. This further validates both the success of the design practice and the practical applicability of the model's predictive results. This process not only demonstrates the potential for integrating traditional craftsmanship with artificial intelligence technologies but also provides new perspectives for the future development of paper-cutting art. Furthermore, it offers innovative pathways for modernizing traditional arts and promoting them among younger generations.

Exquisite Modern Elegant

Figure 6: NEV steering wheel design solution

Table 9: User Kansei Evaluation and Satisfaction Evaluation

Digital Design Plan for Paper-Cutting	Predictive Kansei evaluation	User Kansei evaluation	Satisfaction evaluation
Exquisite - Rough	4.311459254	4.085	8.425
Traditional – Modern	9.002961812	8.625	7.535
Elegant-Rustic	3.299126561	2.635	8.045

IV. Discussion

This study explores the modernization design path of Yueqing fine line engraved paper from Zhejiang by integrating KE with artificial intelligence technologies. The research not only developed an affective mapping model based on RIME-BPNN but also utilized GANs to create design schemes that balance traditional artistic aesthetics with modern aesthetic demands. The results indicate that artificial intelligence technology can effectively enhance the design efficiency and user satisfaction of traditional paper-cutting art, while also offering new possibilities for the inheritance and innovation of traditional arts. The discussion is elaborated below from two perspectives: the inheritance of traditional arts and the performance comparison of artificial intelligence models.

IV. A. Artificial Intelligence Empowering the Modernization and Youthful Revitalization of Paper-Cutting Art

As an intangible cultural heritage, traditional paper-cutting art carries profound cultural connotations and artistic value [49]. However, in modern society, it faces significant challenges in terms of inheritance and preservation. The younger generation's interest in traditional craftsmanship is gradually waning, and the design and dissemination methods of traditional paper-cutting art urgently require innovation. This study introduces artificial intelligence technologies to provide new perspectives for the modernization and transformation of paper-cutting art. Firstly, by integrating KE theory with the RIME-BPNN model, this research accurately captured users' emotional needs for paper-cutting designs, providing a scientific basis for the modernization of traditional art (Figure 7). This fusion of technology and art not only enhances the efficiency and quality of paper-cutting design but also injects new vitality into the preservation of traditional arts. Secondly, the digital collectible-type design schemes generated using GANs retain the artistic essence of traditional paper-cutting while incorporating modern aesthetic elements. This digital design practice provides creative references for paper-cutting artists while lowering the learning barriers to traditional craftsmanship, enabling more people to participate in the creation and dissemination of paper-cutting art. The rise of digital collectibles has brought new vitality to traditional arts. Through blockchain technology and virtual exhibition platforms, paper-cutting artworks can be permanently preserved and widely disseminated in digital form, capturing the attention of younger generations. With AI technologies, designers can respond more quickly to user needs, generating design schemes that align with modern aesthetic trends. This promotes the popularization and application of paper-cutting art in contemporary society. In the future, as technologies such as digital collectibles and virtual reality continue to advance, paper-cutting art is expected to explore broader application scenarios in the digital domain, achieving a deeper integration between tradition and modernity [50]. This innovative approach to inheritance not only protects intangible cultural heritage but also breathes new life into it, allowing it to shine anew in modern society.

Figure 7: Zhejiang Yueqing Paper-Cutting Digital Collectibles Design

IV. B. RIME-BPNN Performance Comparison with BPNN and SVR

To validate the performance of the RIME-BPNN model, this study constructed SVR and BPNN models on the MATLAB R2024b platform for comparative analysis with RIME-BPNN.

(1) For the SVR model, MATLAB's fitrsvm function was used, and the kernel function type (Radial Basis Function, RBF) and regularization parameter (C) were optimized using a grid search method. Although SVR demonstrates stable performance when handling high-dimensional data, its ability to capture complex nonlinear relationships is limited. This limitation becomes particularly evident in affective intention prediction tasks, where it struggles to accurately reflect the intricate mapping between user emotional needs and design features.

(2) For the BPNN model, MATLAB's feedforwardnet function was employed to construct a single-hidden-layer structure with five hidden nodes and a Sigmoid activation function. While BPNN has strong nonlinear fitting capabilities, its training process is prone to getting stuck in local optima and is sensitive to initial weights. Despite multiple training iterations and parameter adjustments that improved its prediction accuracy, BPNN still fell short of achieving the performance level of RIME-BPNN.

Experimental results indicate that RIME-BPNN outperformed both BPNN and SVR in affective intention prediction tasks, as evidenced by significantly better RMSE and R^2 values (as shown in Table 10). These results strongly demonstrate the superiority of RIME-BPNN in the field of KE. In comparison, RIME-BPNN leverages the RIME algorithm to optimize initial weights and biases, effectively avoiding the local optima problem inherent in BPNN. The RIME algorithm employs random sampling and dynamic adjustment strategies to balance global search and local optimization capabilities, significantly improving both prediction accuracy and convergence speed. Furthermore, during training, RIME-BPNN exhibited greater robustness and was able to more accurately capture the complex relationships between user affective intentions and design features. Therefore, RIME-BPNN demonstrates significant advantages in KE applications, providing robust technical support for optimizing traditional art designs. Its superior performance highlights its potential as an effective tool for bridging traditional craftsmanship with modern technological innovation.

Table 10: The model parameter results for BPNN and SVR

Mapping model	Key Kansei intentions	R^2		RMSE	
		The training set.	The testing set.	The training set.	The testing set.
BPNN	Exquisite - Rough	0.9928	0.9718	0.029481	0.053435
	Traditional – Modern	0.9701	0.8895	0.20798	0.40937
	Elegant-Rustic	0.9980	0.9768	0.016144	0.042083
SVR	Exquisite - Rough	0.9987	0.9878	0.10763	0.18618
	Traditional – Modern	0.9873	0.9401	0.35569	0.48736
	Elegant-Rustic	0.9945	0.9991	0.10763	0.18618

V. Conclusions

This study explored the modernization design path of Yueqing fine line engraved paper from Zhejiang by integrating KE theory with artificial intelligence technologies, providing new ideas for the inheritance and innovation of traditional arts. Traditional paper-cutting design research often relies on the subjective aesthetics of paper-cutting artists and inheritors, lacking scientific analysis of consumer emotional needs, which makes it difficult for design schemes to meet the personalized needs of modern users.

Firstly, this study used the F-AHP to extract key emotional needs, synthesizing the dual demands of paper-cutting artists and consumers, and identified "Delicate," "Modern," and "Elegant" as core objectives for design practices. Secondly, to accurately capture the relationship between users' affective intentions and design features, this study proposed the RIME-BPNN model. Compared with traditional BPNN and SVR, RIME-BPNN demonstrated significant advantages in affective intention prediction tasks, with RMSE and R^2 values outperforming BPNN and SVR. By optimizing initial weights and biases, RIME-BPNN effectively avoided the local optima problem of traditional BPNN models, significantly improving prediction accuracy and convergence speed. Finally, using GANs, this study generated design schemes that combine the artistic beauty of traditional arts with modern aesthetic demands. The evaluation results showed that the error between evaluation results and model predictions was less than ±0.5, proving the reliability of the proposed method. The main contributions of this study are as follows:

(1) A KE model combining F-AHP, RIME-BPNN, and GANs was proposed, optimizing the creative process of paper-cutting techniques. This model provides creative references for paper-cutting artists, promoting the modernization and youthful revitalization of traditional paper-cutting art.

(2) An emotional needs extraction method based on F-AHP was introduced, integrating the dual demands of paper-cutting artists and consumers. This approach addresses the shortcomings of traditional research that often overlooks consumer needs.

(3) The RIME-BPNN affective mapping model was constructed, significantly improving the accuracy of affective intention predictions. The model outperformed traditional BPNN and SVR models in small-sample nonlinear modeling tasks.

However, this study has certain limitations that will be considered for improvement in the future:

(1) The sample data in this study primarily comes from Yueqing fine line engraved paper from Zhejiang. Future research could expand to include paper-cutting art from other regions to validate the model's generalizability.

(2) Although the designs generated by GANs provide valuable references for paper-cutting artists, the controllability of the generation process still needs improvement. Future work could consider introducing a graphical user interface (GUI) system combined with AI technologies to develop an auxiliary design system. This would allow artists to more intuitively adjust and optimize design schemes, enhancing flexibility and controllability in design creation.

(3) The user samples in this study mainly consist of young people in China. In the future, more diverse user data could be collected, including users of different age groups, cultural backgrounds, and aesthetic preferences, to better reflect a broader range of user needs and further enhance the model's applicability and universality.

In summary, this study combines artificial intelligence technologies with traditional paper-cutting art to explore pathways for modernizing the inheritance of traditional arts while validating the superiority of the RIME-BPNN model in affective intention prediction tasks. In the future, as technology continues to advance, AI is expected to play a greater role in the preservation and innovation of traditional arts, offering new solutions for protecting and promoting intangible cultural heritage.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data used to support the findings of this study are included within the article.

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Conflicts of Interest

The authors declare no conflict of interest.

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