

Coupling mechanism between parametric generation and ceramic ornament design aesthetics

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Article Info	Abstract
Article History: Received 18 Aug 2026 Accepted 10 Oct 2026 Keywords: Parametric generation; Ceramic ornament; Design aesthetics; Coupling mechanism; Generative adversarial networks	To address the disconnection between aesthetic requirements and parameter configuration in ceramic ornament design, this study proposes a bidirectional coupling model acting as an algorithmic bridge connecting aesthetic artistic expectations and ceramic firing physical constraints, integrating aesthetics and parameters. The model uses the Analytic Hierarchy Process to quantify indicator weights, employs a Generative Adversarial Network for ornament generation, and integrates Particle Swarm Optimization for global parameter optimization, forming a closed-loop framework. Experimental results show that the model achieves a style feature matching rate of $92.53 \pm 0.97\%$, a decorative detail restoration degree of $97.41 \pm 0.75\%$ (N=5 independent replicates, 95% confidence interval, $p < 0.05$), and a process parameter compliance rate of $91.47 \pm 1.18\%$ in the simple style of Song Dynasty ornaments. Compared with other models, it outperforms the Variational Autoencoder–Analytic Hierarchy Process–Particle Swarm Optimization model ($87.42 \pm 1.35\%$ style matching), the Generative Adversarial Network with elitist strategy and non-dominated sorting genetic algorithm II ($82.43 \pm 1.58\%$ detail restoration), and the Generative Adversarial Network–Particle Swarm Optimization model ($73.34 \pm 1.81\%$ process compliance). The model achieves over 90% accuracy in recognizing multiple ceramic styles. Note that the present model is only validated against Song-Ming-Qing Chinese ceramic styles and its generalization to other ceramic cultural systems remains limited. These results demonstrate its effectiveness in coupling aesthetic requirements with parameter configuration and supporting digital inheritance and innovative ceramic ornament design.

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1. Background

Chinese Song-dynasty celadon represented by Ru-kiln and Guan-kiln pursues subtle, implicit and harmonious form aesthetics; Ming-dynasty blue-and-white ornaments carry rich symbolic semantics of auspicious culture. These historical aesthetic principles lay the theoretical foundation for the three-layer AHP evaluation indicators of form aesthetics, cultural aesthetics and functional aesthetics adopted in this work. There exists intrinsic aesthetic tension between the irregular imperfection of hand-crafted traditional ceramic art and mathematically “perfect” parametric outputs. This study treats parametric generation as an auxiliary design tool rather than a full replacement for hand-crafted subtlety. Ceramic ornaments carry aesthetic thoughts, cultural meanings, and craft techniques from different eras. As a core carrier of traditional Chinese ceramic culture, different ornament styles reflect the deep integration of craftsmanship and aesthetics under specific historical backgrounds [1-2]. However, the inheritance and innovation of traditional ornaments face dual challenges in contemporary ceramic design. On one hand, traditional manual design suffers from long design cycles, low parameterization levels, and insufficient precision in style reproduction [3]. On the other hand, most existing intelligent design methods focus on the

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"visual similarity" of ornament generation, thus neglecting the synergistic coupling between aesthetic requirements and process parameters [4-5]. Although the ornaments generated by some methods visually approximate traditional styles, they failed to consider the matching relationship between glaze material properties and glaze thickness, making them impractical for actual firing production.

With the extensive application of deep learning and optimization algorithms in the design field, research on intelligent generation of ceramic ornaments has achieved significant progress. In existing studies, some models based on variational autoencoders can achieve probabilistic generation of ornaments, but they have relatively low fidelity in restoring details of certain ornament styles, such as the line rhythm of Song Dynasty minimalist ornaments and the brushstroke texture of Ming Dynasty blue-and-white porcelain [6-7]. Generative Adversarial Networks (GANs) can learn ornament features through unsupervised or semi-supervised training methods in scenarios where ceramic ornament annotation data are scarce. The Analytic Hierarchy Process (AHP) can decompose complex problems such as ceramic ornament aesthetic evaluation into clear hierarchical structures and adapt to a wide range of application scenarios. Particle Swarm Optimization (PSO) can rapidly iterate to locate optimal parameter combinations in ceramic ornament parameter optimization.

Currently, most models focus on single-dimensional parameter optimization and have not established bidirectional correlations among aesthetic requirements, parameter design, and process implementation, which easily leads to insufficient model precision and limited practicality [8]. From a theoretical and technical perspective, the core aesthetic requirements of ceramic design have long lacked efficient digital support. The adversarial training mechanism and feature learning capabilities of GANs precisely align with the aesthetic demands of "style transfer" and "creative generation" in ceramic decoration. Moreover, the global search and rapid convergence advantages of PSO can precisely match the quantitative requirements of ceramic aesthetics. Current research has not fully exploited the potential of these two algorithms in the quantitative analysis of ceramic aesthetics and the collaborative optimization of parameters. Therefore, to enhance the effectiveness of intelligent generation of ceramic ornaments, this study designed a fusion algorithm that combines GANs with the AHP and PSO (GANs-AHP-PSO). Based on this, a bidirectional coupling model between ceramic ornament aesthetics and parameters was constructed. This model mainly transforms subjective aesthetic requirements into objective weights through AHP, generates ornament images conforming to style characteristics through GANs, and optimizes ornament parameters through PSO. This study aims to provide technical support for intelligent and precise design of ceramic ornaments. The innovation of this model lies in establishing a bidirectional mapping relationship between aesthetic indicators and process parameters to achieve a closed loop where aesthetic requirements drive parameter optimization and parameter adjustments provide feedback on aesthetic effects.

Recent controllable generation approaches including ControlNet, IP-Adapter and latent diffusion constrained networks deliver high-fidelity image synthesis, yet they exhibit two major drawbacks for ceramic ornament parametric design oriented to real firing production. First, these models lack native explicit mapping from aesthetic semantic scores to continuous craft parameters such as glaze thickness and firing temperature. Second, their inference and training overhead is high, and additional post-processing is required to couple with optimization solvers for process constraints, which weakens closed-loop feedback between aesthetic evaluation and parameter searching.

The core research hypotheses of this work are formulated as follows:

- Hypothesis H1: Subjective multi-dimensional ceramic aesthetic requirements quantified by AHP weights can be transformed into objective fitness constraints for PSO parameter searching.
- Hypothesis H2: Initial ornament samples generated by GANs conditioned on traditional style features can reduce invalid particle solutions and accelerate PSO convergence.
- Hypothesis H3: Bidirectional feedback loop among AHP aesthetic scoring, PSO global optimization and GAN latent-space adjustment can simultaneously improve style restoration, cultural symbol integrity and process-parameter compliance.

2. Methods

2.1 Construction of Bidirectional Coupling Model of Ceramic Ornament Aesthetics and Parameters Based on AHP-PSO

In ceramic ornament aesthetics, AHP decomposes the evaluation problem into multiple layers and forms a clear analytical framework. It converts subjective aesthetic evaluations into objective weight values by constructing a judgment matrix. PSO rapidly iterates to find the optimal parameter combination in ceramic ornament optimization, and the collaboration between individual best and global best guides the search to avoid local optima [9-10]. Therefore, this study integrates AHP and PSO to construct a bidirectional coupling model of ceramic ornament aesthetics and parameters. The process of constructing the AHP evaluation system is shown in Figure 1.

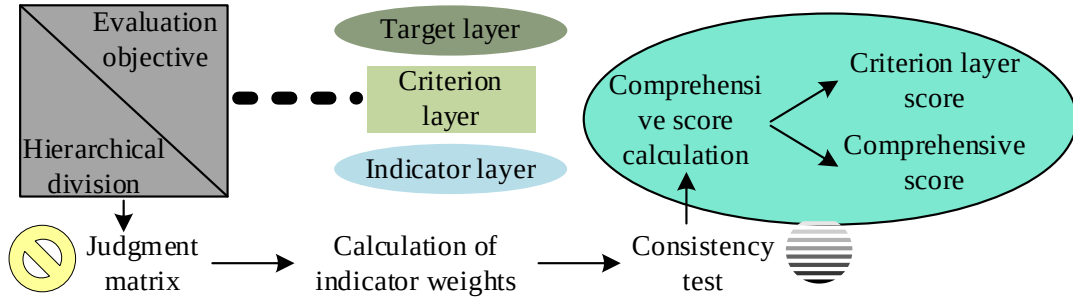


Fig. 1. Construction of AHP evaluation system

In Figure 1, the goal layer reflects the overall matching of parameterized ceramic ornaments with traditional aesthetic standards in terms of form, culture, and function. This layer represents the final output target of the evaluation system. The criterion layer divides ceramic ornament attributes into three dimensions: form aesthetics, cultural aesthetics, and functional aesthetics. The indicator layer is the lowest level and includes measurable indicators derived from the criterion layer. The judgment matrix mainly determines indicator weights through expert scoring. The criterion layer divides the aesthetic attributes of ceramic decoration into three core dimensions, each corresponding to a clear and quantifiable indicator layer, forming a three-level evaluation system of "target layer - criterion layer - indicator layer". The target layer corresponds to the comprehensive matching degree of parametric design of ceramic decoration and traditional aesthetic standards. The criterion layer and the corresponding indicator layer consist of 10 core indicators. Form aesthetics (weight 0.35): smoothness of lines (0.12), color coordination (0.10), balance of layout (0.08), rationality of pattern proportion (0.05). Cultural aesthetics (weight 0.40): compatibility with era style (0.15), completeness of cultural symbols (0.12), degree of traditional craftsmanship restoration (0.08), regional cultural adaptability (0.05). Functional aesthetics (weight 0.25): feasibility of craftsmanship (0.10), compatibility with the shape of the vessel (0.08), coordination of usage scenarios (0.07). AHP converts aesthetic requirements into quantifiable objective functions and constraints, while PSO searches for optimal solutions in the parameter space based on these objectives and constraints. AHP achieves the connection between subjective aesthetics and objective parameters through the path of "aesthetic requirements → indicator mapping → weight quantification → constraint transformation". It maps the abstract aesthetic requirements of users to specific indicators at the indicator layer. The weights are adjusted according to the emphasis of aesthetic requirements. If users emphasize "cultural inheritance", the weight of the "cultural aesthetics" criterion layer is increased from 0.40 to 0.45, and the weight of "form aesthetics" is simultaneously reduced to 0.30. If they focus on "visual effects", the weight of "form aesthetics" is increased to 0.40, and the weight of "functional aesthetics" is reduced to 0.20. The PSO algorithm is selected for global optimization, which precisely meets the requirements of ceramic decorative design. Compared with the crossover and mutation mechanism of the genetic algorithm, PSO can quickly adapt to the multi-objective optimization of ceramic aesthetics and process parameters. Compared with the simulated annealing algorithm, it has stronger global search ability and can effectively avoid getting stuck in local optimal parameter combinations, reducing design failure caused by imbalances in parameters such as glaze layer thickness and pattern density. In ceramic decorative design, the advantages of PSO are particularly prominent.

Firstly, the parameter encoding is flexible, and it can directly map continuous process parameters such as pattern spacing and firing temperature. Secondly, the collaborative search feature is highly compatible with the quantitative aesthetic weights of AHP, and can prioritize the optimization of parameters corresponding to core indicators such as the integrity of cultural symbols. The combination of AHP and PSO is shown in Figure 2.

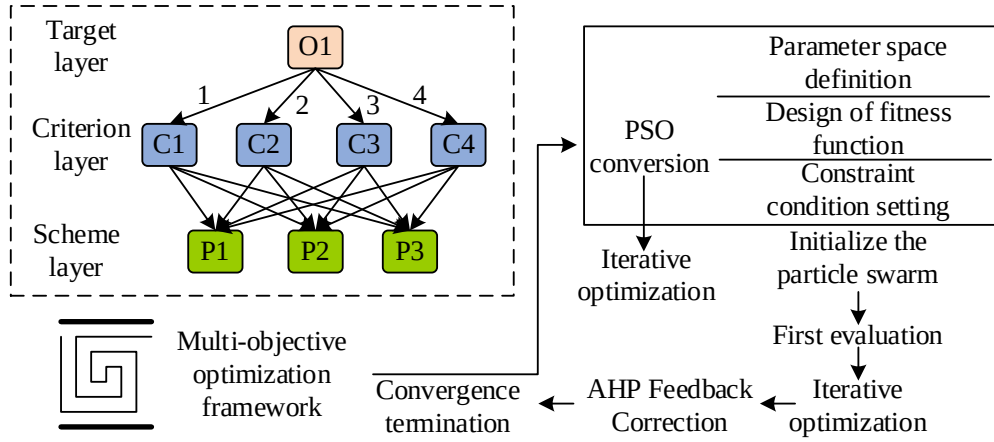


Fig. 2. Schematic of AHP combined with PSO

Figure 2 shows that AHP clarifies optimization targets and priorities through comprehensive aesthetic scores and low-score causes. PSO converts AHP evaluation results into fitness functions and parameter constraints. It iterates through the particle swarm to find optimal parameters that meet aesthetic and process requirements. Optimized parameters from PSO drive ornament regeneration, and AHP evaluates the results until the aesthetic score meets the threshold. In the integration of AHP and PSO, AHP constructs a multi-objective optimization framework, providing PSO with three key pieces of information: core optimization objectives, sub-objective constraints, and optimization priorities. Sub-objective constraints represent the minimum thresholds of criteria and indicator layers. PSO converts AHP objectives into search rules, using parameterized control variables strongly correlated with AHP indicators as optimization variables. The fitness function is calculated by Equation (1) [11].

$$F(X) = \alpha \cdot S(X) + \beta \cdot \sum_{i=1}^m (w_i \cdot I_i(X)) + \gamma \cdot (1 - C(X)/T) \quad (1)$$

In Equation (1), $S(X)$ represents the AHP comprehensive aesthetic score for parameter combination X , $I_i(X)$ is the compliance of the i -th key indicator, $C(X)/T$ is the proportion of process cost, and α, β, γ are weights. Sub-objective constraints from AHP serve as PSO parameter constraints to filter invalid solutions. Where $F(X)$ is the comprehensive fitness value of parameter group X . $\alpha = 0.5, \beta = 0.3, \gamma = 0.2$ are the hyperparameter weighting coefficients for aesthetic score, indicator compliance and process-cost penalty term, respectively. Hard constraints include process compatibility parameters and core cultural parameters, while soft constraints include form aesthetics parameters. The iterative optimization and AHP feedback process begins with PSO randomly generating 100 particles. AHP calculates the comprehensive aesthetic score for each particle and inputs it into the fitness function to determine individual and global best solutions. New particles that violate hard constraints are eliminated; those that comply have their AHP scores recalculated and fitness updated. If the aesthetic score remains below the threshold after 10 iterations, low-score causes are extracted, and PSO search ranges for associated parameters are expanded for feedback correction. When the AHP comprehensive score reaches 90 or higher and shows no improvement over five consecutive generations, the optimal parameters are output. Combining AHP and PSO balances the systematic evaluation of subjective aesthetic cognition with efficient objective parameter optimization. The architecture of the AHP-PSO-based bidirectional coupling model is shown in Figure 3.

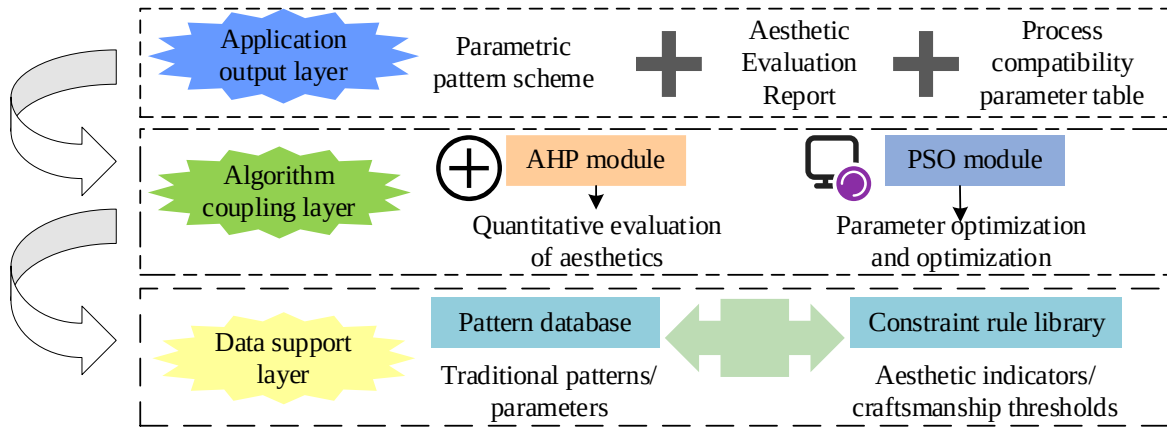


Fig. 3. Architecture of bidirectional coupling model based on AHP-PSO

In Figure 3, the data support layer provides the basis for coupling. The ornament database stores over 5000 traditional ceramic ornament images and their corresponding parameter data, supplying AHP and PSO with aesthetic reference samples and initial parameter ranges. The constraint rules library contains two core types: aesthetic constraints and process constraints. The algorithm coupling layer implements bidirectional coordination of AHP and PSO. The AHP module decomposes measurable indicators based on three criterion dimensions: form aesthetics, cultural aesthetics, and functional aesthetics. Expert scoring and consistency testing determine indicator weights. During evaluation and low-score cause localization, input parameterized ornaments undergo image recognition and expert scoring to obtain indicator scores, which are used to calculate the comprehensive aesthetic score. Scores below 85 trigger output of low-score causes. Aesthetic requirements are converted into PSO-recognizable objective function parameters, including AHP weights of low-score indicators and their minimum thresholds. The PSO module defines the parameter space, designs the fitness function, and provides feedback to AHP. Parameter space definition selects key parameters based on low-score causes and determines value ranges through the process constraint library. The fitness function centers on AHP comprehensive scores and indicator weights. Particle iteration searches for optimal parameters, and the bidirectional coupling interface outputs evaluation scores, low-score causes, indicator weights, and constraint thresholds in JSON format. The application output layer produces digital ornaments that meet aesthetic and process requirements, with parameters compatible with production equipment and directly connectable to ceramic production lines. To investigate the influence of hyperparameters on multi-objective optimization performance, a sensitivity analysis of weighting coefficients α , β , γ is carried out, and the quantitative results are shown in Table 1.

Table 1. Hyper-parameter sensitivity analysis for α , β , γ

(α, β, γ)	Style matching (%)	Process compliance (%)	Symbol completeness (%)
(0.5,0.3,0.2) (baseline)	92.53	91.47	94.58
(0.6,0.2,0.2)	93.11	88.26	94.71
(0.4,0.4,0.2)	90.27	92.84	92.33

It can be observed that increasing α strengthens the weight of aesthetic evaluation and achieves higher style matching, yet weakens the constraint of process indicators and reduces process compliance. Raising β prioritizes process parameter feasibility at the cost of style feature fidelity. The baseline combination ($\alpha=0.5$, $\beta=0.3$, $\gamma=0.2$) achieves a balanced trade-off between aesthetic quality, cultural symbol integrity and manufacturability, and is therefore selected for subsequent experiments. It should be emphasized that the model takes 2D visual ornament features as input and does not directly solve glaze rheological properties such as viscosity or melting point. Hard process constraints are predefined by domain experts and stored in Process-Parameter Constraint Matrix (Table 2) including feasible ranges of glaze-layer thickness, firing-temperature interval, pattern density upper/lower bounds, which serve as PSO hard boundaries.

Table 2. Fragment of process-parameter constraint matrix

Parameter	Min	Max	Unit
Glaze layer thickness	0.15	0.45	mm
Firing temperature	1220	1320	°C
Pattern density ratio	0.10	0.70	-

2.2 Optimization of Bidirectional Coupling Model of Ceramic Ornament Aesthetics and Parameters with GANs

Although the AHP-PSO-based bidirectional coupling model can rapidly iterate in the parameter space to find optimal parameters that balance aesthetic scores and process feasibility, the randomly generated initial parameters in PSO often lead to many initial solutions being eliminated by AHP for deviating from traditional styles [12-13]. GANs can learn aesthetic features from traditional ornaments and provide PSO with initial parameter sets aligned with style cores. GANs can efficiently learn the core aesthetic features of traditional decorations through unsupervised or semi-supervised training in scenarios where the labeled data for ceramic decoration is scarce. For the aesthetic requirements of ceramic decoration such as line rhythm and color gradation, its generator, with a stable architecture consisting of 8 layers of transposed convolutional layers and BatchNorm layers, can quickly convert abstract aesthetic demands into visual decorative images. GAN refers to a single network architecture, while GANs represent multiple network instances or a series of models. Therefore, this study introduces GANs to optimize AHP-PSO, constructing a GANs-AHP-PSO algorithm and a coupling model better aligned with aesthetic requirements and parameter design. The functional positioning and technical design of GANs are shown in Figure 4.

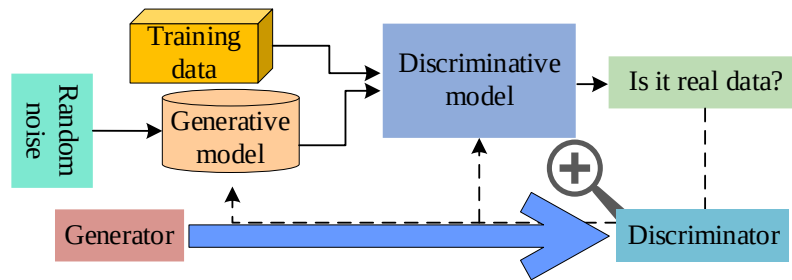


Fig. 4. Functional positioning and technical design of GANs

In Figure 4, GANs serve as the front-end generation layer of the coupling model. Its functions include traditional aesthetic feature extraction, initial ornament generation, and iterative optimization response. Feature extraction learns line rhythm, color matching, and layout rules from the ornament database to construct a style feature library. Ornament generation produces 3 to 5 initial ornaments that meet the style requirements based on user input and outputs corresponding parameterized control variables. In the feature extraction stage, specifically targeting the core aesthetic dimensions of ceramic decoration, we learn from the database the "line blank ratio" of the minimalist style in the Song Dynasty, the "cobalt pigment color intensity and pattern density relationship" of the blue porcelain in the Ming Dynasty, and the "color transition rules of glaze layer superposition" of the pastel color in the Qing Dynasty, to build a detailed style feature library. In the decoration generation stage, based on the aesthetic keywords input by the user, we quickly generate 3-5 sets of initial schemes that meet the precise aesthetic requirements. Compared to the traditional manual design that requires days of iteration, GANs can complete the mapping from aesthetic requirements to visual decoration within minutes, and the generated results include parametric control variables, directly connecting to the subsequent optimization process. The optimization response adjusts generation strategies according to PSO output parameters, ensuring generated variants meet aesthetic evaluation standards. When labeled data is scarce, GANs can efficiently learn the core aesthetic features of traditional ceramic decoration through unsupervised/supervised training. The generator of GANs adopts a stable architecture of 8-layer transposed convolution + BatchNorm, which can quickly convert abstract aesthetic requirements into visual decorative images. The discriminator inputs real or generated ornament images,

containing 7 convolution layers that gradually reduce spatial dimensions. It outputs authenticity probability and style classification probability. Its core design introduces a multi-task loss to identify style categories while discriminating real from fake, allowing the generator to learn style features accurately. The GANs optimization of AHP-PSO is illustrated in Figure 5.

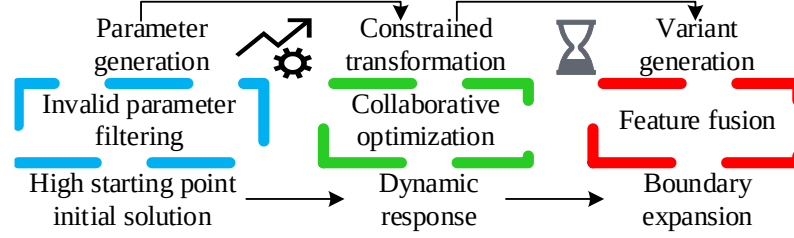


Fig. 5. GANs optimizing AHP-PSO

Figure 5 shows that GANs provide high-quality initial solutions to AHP-PSO. By learning latent features of traditional ornaments, GANs generate initial ornaments that meet style requirements and contain basic parameters. These parameters serve as the initial PSO particle swarm, preventing style distortion caused by random initialization. GANs-generated initial parameters also filter parameters that violate aesthetic rules, reducing the PSO search space to a style-adapted subspace and lowering iteration counts. During optimization, GANs actively adjust generation strategies. When style conformity is low, GANs strengthen target-era feature extraction in the generator. When cultural symbols are missing, GANs focus on cross-branch areas via attention mechanisms. GANs generate variants by adjusting noise intensity based on PSO-optimized parameters. AHP evaluates the novelty of these variants and guides PSO to retain highly innovative solutions. For designs integrating traditional and modern styles, GANs enables feature transfer through multi-style label input. AHP reduces constraints on non-core features, while GANs ensures core feature compliance, producing innovative ornaments. The GANs-AHP-PSO algorithm framework is shown in Figure 6.

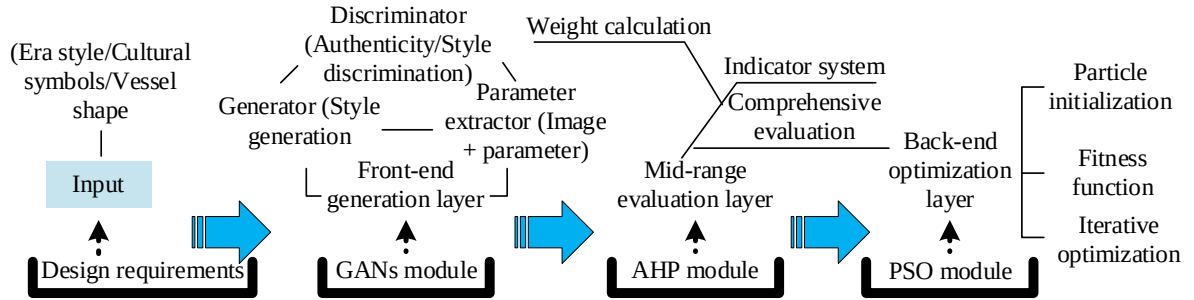


Fig. 6. GANs-AHP-PSO algorithm

Figure 6 shows the front-end generation layer as GANs, converting abstract design requirements into visual ornaments and initial parameters. It includes the generator, discriminator, parameter extractor, and output interface. The parameter extractor derives quantifiable control variables from generated images to form the initial parameter set using OpenCV edge detection and geometric calculations. Weight calculation and consistency testing involve five ceramic experts comparing indicators pairwise, obtaining maximum eigenvalues and weight vectors, and verifying consistency. GANs-generated initial ornaments serve as input, with comprehensive scores, low-score causes, and optimization priorities as output. The PSO module serves as the back-end optimization layer, searching the parameter space for optimal parameters that satisfy aesthetic and process constraints and driving GANs to generate improved ornaments. Parameters associated with low-score AHP indicators encode particle dimensions and initialization. To mitigate mode collapse and vanishing-gradient risks, spectral normalization is applied to discriminator convolutional layers. The total loss combines adversarial loss, style loss and detail loss with weights 1.0, 0.6, 0.4. These weights are determined via small-scale grid search balancing style reconstruction fidelity and local-detail preservation. The detailed layer-by-layer network configurations of the generator and discriminator are summarized in Table 3.

Table 3. A Layer-wise architecture of GAN generator and discriminator

Module	Layer	Operation	Output size
Generator	Layer1-8	TransposedConv + BatchNorm	256×256×3
Generator	Additional	Decorative unit constraint layer	256×256×3
Discriminator	Layer1-7	Conv + SpectralNorm	Classification logits
Discriminator	Output head	Dual-branch: real/fake + style label	2 outputs

Spectral normalization is introduced into discriminator convolution layers to suppress mode collapse and gradient vanishing. The final optimized GANs-AHP-PSO model architecture is shown in Figure 7.

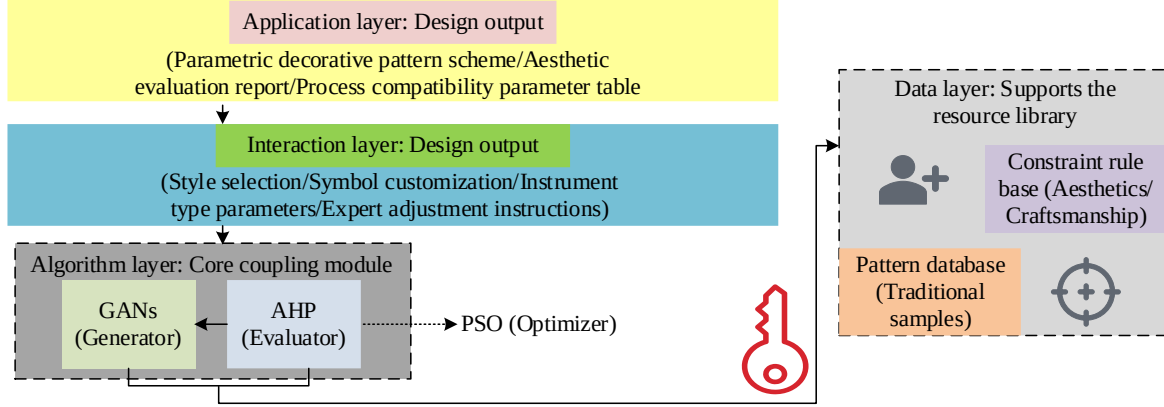


Fig. 7. GANs-AHP-PSO model architecture diagram

In Figure 7, the data layer provides coupling support, storing over 5000 traditional ornament images linked with visual features, cultural tags, and process parameters. The constraint rules library contains aesthetic constraints (AHP thresholds) and process constraints (PSO parameter bounds and GANs-generated style restrictions). The algorithm layer implements bidirectional coordination of GANs-AHP-PSO. GANs transforms abstract aesthetic requirements into visual ornaments and initial parameters. User-encoded demands and random noise input the generator. A style attention mechanism focuses on core features of target ornaments to output initial ornament images. The parameter extractor then generates the initial parameter set. The AHP module converts generated results into quantitative evaluation and optimization instructions. Input GANs-generated ornaments undergo image recognition and expert scoring to calculate the comprehensive aesthetic score. The AHP module converts the results into quantitative evaluation and optimization instructions, with the core logic deeply integrated with aesthetic requirements. For the decorative images generated by GANs, data such as line curvature and color deviation are automatically extracted using image recognition technology, combined with expert ratings, and each of the 10 indicators in the index layer is scored (out of 100 points). If the comprehensive score is less than 85 points, the reasons for the low score are identified and the cobalt pigment concentration parameters and pattern arrangement spacing are adjusted accordingly. Scores below 85 trigger low-score cause output and an optimization priority list. The aesthetic scoring error rate is calculated by Equation (2) [14].

$$ErrorRate = \frac{1}{N} \sum_{i=1}^N \frac{|\hat{S}_i - S_i|}{100} \times 100\% \quad (2)$$

In Equation (2), N is the total number of test samples, $\hat{S}_i$ and S_i are the model-predicted score and expert score for the i -th sample, respectively. The PSO module regulates bidirectional coupling, optimizing parameters based on AHP feedback and driving GANs to generate improved ornaments. The interactive layer provides a visual interface for user selection of era styles, cultural symbols, and vessel parameters. It displays generated ornaments, scores, and optimization suggestions, adjusting PSO constraints in real time. The application layer outputs the coupled results, including parameterized ornaments, aesthetic evaluation reports, and process-compatible parameter tables. After data cleaning, 4862 valid samples were retained. The RGB data was converted to LAB format

and the luminance and color channels were processed separately. Random cropping and flipping were applied for enhancement. The Canny operator ($T1 = 50$, $T2 = 150$) was used to extract line features and generate "image - parameter" mapping data. The GAN generator consists of 8 layers of transposed convolution (channel $512 \rightarrow 3$), with a decorative unit constraint layer, and outputs a 256×256 image. The discriminator has 7 layers of convolution and dual outputs (truth/falseness + style classification). Basic background information for the AHP expert panel participating in pairwise comparison scoring is summarized in Table 4. Consistency-check metrics are computed for each criterion-layer judgment matrix, and results are given in Table 5.

Table 4. Information of AHP expert panel

ID	Professional background	Working years
E1	Ceramic archaeology	18
E2	Traditional ceramic craft master	22
E3	Ceramic art design professor	15
E4	Museum ceramic-collection researcher	13
E5	Digital heritage scholar	11

Note: Five domain experts form the evaluation panel for AHP pairwise-comparison matrix construction.

Table 5. AHP consistency check results

Criterion layer	CI	CR
Form aesthetics	0.027	0.048 (<0.1)
Cultural aesthetics	0.031	0.055 (<0.1)
Functional aesthetics	0.019	0.034 (<0.1)

Note: Valid AHP judgment matrices require Consistency Ratio $CR < 0.10$. All matrices satisfy this acceptance criterion.

PSO is an 8-dimensional process/aesthetics parameter, with 100 particles and 300 iterations, dynamic inertia weight ($0.9 \rightarrow 0.4$), and the fitness function includes aesthetic, process, and cost weights ($0.5/0.3/0.2$), with hard constraint filtering and soft constraint penalty. The style constraint loss uses the VGG19 network to extract 3 layers of features, and the total loss includes adversarial, style, and detail losses (weights of 1.0, 0.6, and 0.4 respectively). The process by which PSO feedback adjusts aesthetic indicators through the GAN hidden space is shown in Figure 8.

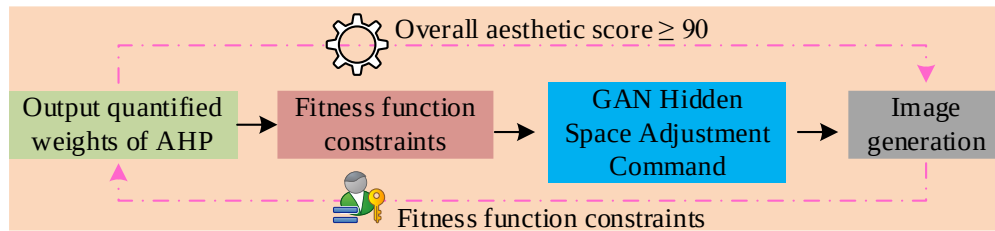


Fig. 8. The process of adjusting aesthetic indicators through the hidden space of the feedback mechanism of PSO using GAN

As shown in Figure 8, the quantified weights output by AHP and the low-scoring indicators clearly define the priority of parameter optimization. PSO converts the weights and scores into a fitness function constraint, focusing on the core parameters corresponding to "color coordination". Through dynamic inertia weight search, it optimizes the parameter combination. The optimal parameters are transformed into adjustment instructions for the GAN hidden space via the coupling interface. To address the insufficient color coordination, the channel weights of the transposed convolution layers in the generator's 3rd to 5th layers are adjusted to enhance the extraction of color features. At the same time, the weight proportion of the "color hierarchy" dimension in the style label vector is corrected. The GAN generates the optimized decorative image based on the adjustment results in the hidden space, and is re-scored by AHP until the comprehensive aesthetic score is ≥ 90 points, completing the two-way closed loop of "weights - parameters - generation". The AHP weights have a clear targeting effect on the regulation of GAN generation. The high weight of the core aesthetic indicators will guide GAN to prioritize the

strengthening of feature extraction in the corresponding hidden layers through PSO. To mitigate cultural hallucination and historically-wrong symbolic patterns, a cultural-symbol dictionary built upon Jingdezhen Ancient Ceramic Gene Bank is embedded. After GAN generates ornament image, symbol detection module matches extracted graphic primitives against dictionary entries. Patterns containing unregistered fabricated symbolic motifs will be assigned low scores on the “completeness of cultural symbols” indicator by AHP and filtered in PSO hard-constraint screening.

The transformation from 2D edge features extracted by Canny operator to continuous ceramic decorative parameters is implemented via heuristic geometric computation. The complete mapping algorithm is given in the pseudocode below.

```
# Pseudocode: Canny edge feature to ceramic pattern parametric mapping
# Input: RGB ornament image I; Canny thresholds T1=50, T2=150
# Output: Normalized pattern parameters for PSO particle initialization
import cv2
import numpy as np
def extract_ceramic_params(I, T1, T2):
    # Step 1 Preprocess input image
    gray_img = cv2.cvtColor(I, cv2.COLOR_RGB2GRAY)
    blur_img = cv2.GaussianBlur(gray_img, ksize=(3,3), sigmaX=1.2)

    # Step2 Canny edge detection
    edge_map = cv2.Canny(blur_img, threshold1=T1, threshold2=T2)
    H, W = edge_map.shape
    total_pixel = H * W
    edge_pixel = np.count_nonzero(edge_map)

    # Step3 Calculate pattern density
    pattern_density = edge_pixel / total_pixel

    # Step4 Contour extraction and line rhythm statistics
    contours, _ = cv2.findContours(edge_map, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
    contour_length_list = []
    contour_centers = []
    for cnt in contours:
        length = cv2.arcLength(cnt, closed=True)
        contour_length_list.append(length)
        M = cv2.moments(cnt)
        cx = int(M['m10'] / (M['m00'] + 1e-8))
        cy = int(M['m01'] / (M['m00'] + 1e-8))
        contour_centers.append([cx, cy])

    # Line rhythm: standard deviation of contour lengths
    line_rhythm_std = np.std(contour_length_list) if len(contour_length_list)>0 else 0

    # Step5 Pattern spacing: minimum Euclidean distance between different contour centers
    min_spacing = float('inf')
    for i in range(len(contour_centers)):
        for j in range(i+1, len(contour_centers)):
            dist = np.linalg.norm(np.array(contour_centers[i]) - np.array(contour_centers[j]))
            if dist < min_spacing:
                min_spacing = dist
    pattern_spacing = min_spacing / max(H,W) # normalize

    # Step6 Output normalized parameters for PSO optimization
    param_set = {
        "pattern_density": pattern_density,
        "line_rhythm_std": line_rhythm_std,
        "pattern_spacing": pattern_spacing
    }
    return param_set
```

This algorithm extracts geometric statistical features from edge images. It should be noted that this mapping only reflects visual pattern characteristics and cannot directly calculate glaze rheological parameters such as viscosity or melting temperature.

3. Results

3.1 Performance Comparison of GANs-AHP-PSO Model

To validate the performance of the proposed GANs-AHP-PSO model, this study selected the following models as comparison models. They were the coupling models based on Variational Autoencoder-AHP-PSO (VAE-AHP-PSO), GANs-Non-dominated Sorting Genetic Algorithm II (GANs-NSGA-II), and GANs-PSO. The experimental dataset was the Chinese traditional ceramic dataset Cart 15K, which this study divided into training and test sets at a ratio of 7:3. This dataset contained 4,096 image-text pairs, covering various ceramic categories from the Stone Age to modern times. The Cart 15K dataset (4096 image-text pairs) is adopted for the 5-fold cross-validation experiment in Table 6. Strict sample-level splitting is implemented: all images belonging to the same ceramic artifact are assigned entirely to either training fold or test fold, which avoids cross-fold data leakage. The Jingdezhen Ancient Ceramic Gene Bank dataset (4862 cleaned samples) is used for multi-style performance tests in Table 7 and is never involved in model training or parameter tuning. The experiment was equipped with NVIDIA GeForce RTX 3090 (24 GB memory), and the CPU was Intel Core i9-12900K (3.2 GHz, 16 cores and 32 threads). The experimental operating system was Ubuntu 20.04 LTS, using PyTorch 1.12.0 as the deep learning framework, and NumPy 1.23.5, SciPy 1.9.3, and scikit-learn 1.2.2 as the required dependency libraries for the experiment. First, this study compared the loss value changes in the training set and test set when the learning rate was 0.0001 and 0.001 under the task scenarios of ceramic ornament style generation and aesthetic parameter optimization. The results are shown in Figure 9.

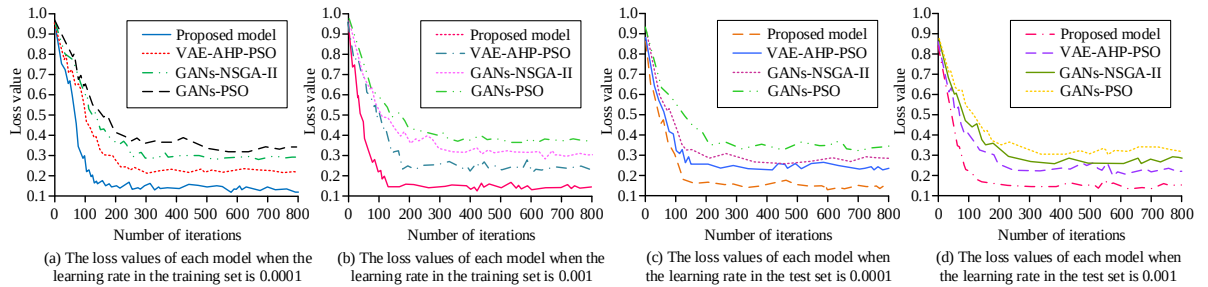


Fig. 9. Loss value changes of the four models

From Figure 9, it can be seen that the ceramic ornament coupling model proposed in this study, in the training set and test set, when the learning rate was 0.0001, had loss values of 0.158 and 0.172 respectively at 500 iterations. Under the same conditions, VAE-AHP-PSO had loss values of 0.232 and 0.267 respectively at 500 iterations, and the loss values of GANs-NSGA-II and GANs-PSO were also much higher than those of the proposed model. When the learning rate changed to 0.001, the loss value of the proposed model still showed the fastest decreasing trend and eventually stabilized at a lower level, with faster loss convergence speed compared to the other three comparison models. The loss value of this model converges more quickly and remains at a relatively low level. The reason for this is that GANs accurately extract the traditional decorative style features, AHP clearly defines the aesthetic optimization goals and priorities, and PSO conducts efficient search in the parameter space based on bidirectional constraints. The collaboration of these three elements reduces the ineffective iterations in feature learning and parameter optimization. The above results indicated that the proposed model was more efficient in learning ceramic ornament style features and optimizing aesthetic parameters. Next, this study compared the aesthetic scoring error rates of the four models under different ceramic ornament styles. In the figure, the colors from light to dark represented the ceramic ornament styles of Song Dynasty minimalism, Yuan Dynasty blue-and-white, Ming Dynasty complexity, and Qing Dynasty polychrome porcelain. The comparison results are shown in Figure 10.

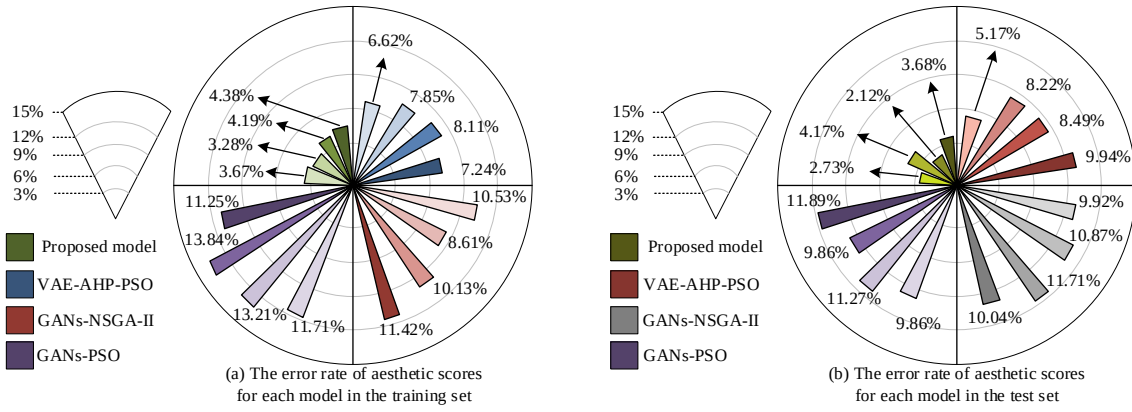


Fig. 10. Aesthetic scoring error rates

Figure 10(a) showed that the aesthetic scoring error rate of the proposed model in the training set was much lower than that of the comparison models. When the style was Song Dynasty minimalism, the aesthetic scoring error rate of the proposed model was only 3.67%. At this time, the aesthetic scoring error rates of VAE-AHP-PSO, GANs-NSGA-II, and GANs-PSO reached 6.62%, 10.53%, and 11.71% respectively, significantly higher than the proposed model. From Figure 10(b), it can be found that in the test set, the aesthetic scoring error rates of the model for the four styles of Song Dynasty minimalism, Yuan Dynasty blue-and-white, Ming Dynasty complexity, and Qing Dynasty polychrome porcelain were still lower than those of the comparison models. When the style was Qing Dynasty polychrome porcelain, the aesthetic scoring error rates of VAE-AHP-PSO and GANs-NSGA-II were 9.94% and 10.04% respectively, the aesthetic scoring error rate of GANs-PSO was 11.89%, while the aesthetic scoring error rate of the proposed model was the lowest at 3.68%. This model has a lower error rate in aesthetic scoring across various styles. The main reason is that AHP converts subjective aesthetic requirements into quantitative weights through expert scoring, and combines PSO for iterative feedback correction of low-scoring items, thereby reducing the subjective bias in aesthetic evaluation. The above data results indicated that the proposed model effectively reduced the prediction deviation of aesthetic scoring through the synergistic mechanism and had high accuracy in ceramic ornament aesthetic quantification. Next, this study analyzed the symbol extraction completeness rates of the four models under the task scenarios of ceramic ornament style generation and aesthetic parameter optimization. The results are shown in Figure 11.

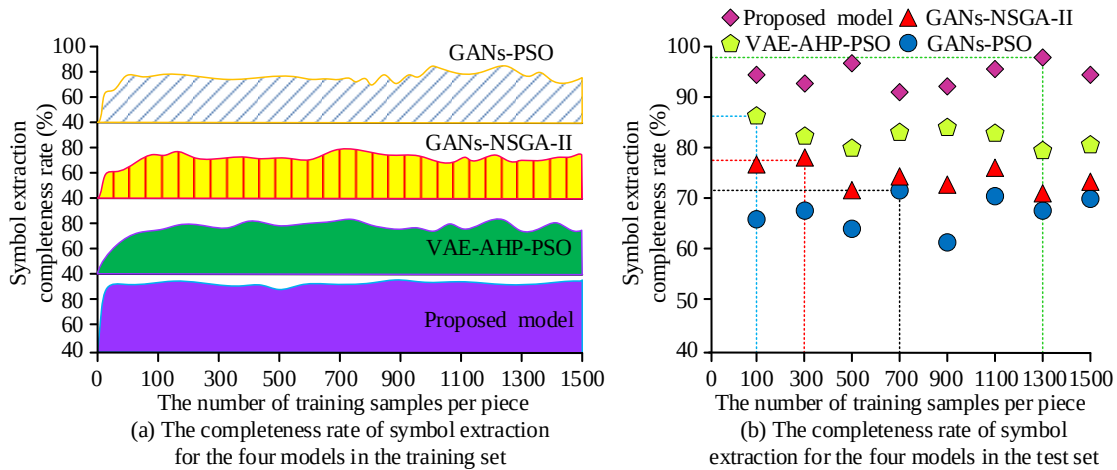


Fig. 11. Symbol extraction completeness rates

As shown in Figure 11(a), the symbol extraction completeness rate of the proposed model in the training set consistently maintained a high level under different numbers of training samples, while the completeness rates of the comparison models were not as good as the proposed model. When the number of training samples was 1,100, the symbol extraction completeness rate of the proposed model was 94.58%, and the symbol extraction completeness rates of VAE-AHP-PSO,

GANs-NSGA-II, and GANs-PSO were 76.49%, 70.16%, and 79.72% respectively. From Figure 11(b), it can be concluded that the highest symbol extraction completeness rate of the proposed model was 97.12%, the highest symbol extraction completeness rate of VAE-AHP-PSO was 85.86%, and the highest symbol extraction completeness rates of GANs-NSGA-II and GANs-PSO were 77.23% and 72.06% respectively. The symbol extraction accuracy rate of this model is significantly higher than that of the comparison model. This is attributed to the decorative unit constraint layer of GANs, which uses customized convolution kernels to capture the detailed associations of cultural symbols. At the same time, the high weight assignment of AHP to cultural aesthetic indicators strengthens the model's priority in identifying and extracting the core cultural symbols in traditional patterns. This indicated that the proposed model had stronger effectiveness in extracting cultural symbols from ceramic ornaments, with higher recognition stability. Finally, this study tested the ceramic ornament performance of each model in the training set and test set. The results are shown in Table 6.

Table 6. Comparison of ceramic ornament performance indicators

Dataset	Model	Process parameter adaptation rate (%)	Style transfer similarity (%)	Ornament detail fidelity (%)	Color reproduction accuracy (%)
Training	Proposed model	91.23±1.25	92.34±0.98	92.74±1.03	94.11±0.87
	VAE-AHP-PSO	82.36±1.58*	78.59±1.32*	78.59±1.45*	81.51±1.21*
	GANs-NSGA-II	76.84±1.83*	72.48±1.67*	76.12±1.52*	79.63±1.38*
	GANs-PSO	78.94±1.65*	80.13±1.41*	76.81±1.57*	77.84±1.43*
Test	Proposed model	89.71±1.32	88.74±1.05	89.35±1.12	91.68±0.93
	VAE-AHP-PSO	79.15±1.62*	75.28±1.48*	78.16±1.53*	82.58±1.29*
	GANs-NSGA-II	73.58±1.91*	69.41±1.75*	72.94±1.64*	80.15±1.45*
	GANs-PSO	76.24±1.73*	77.28±1.54*	73.47±1.61*	74.33±1.52*

*Note: All data are reported as mean ± standard deviation from 5 independent repeated experiments. Two-tailed independent t-tests are performed for pairwise comparisons between baseline models and the proposed model, with Bonferroni correction for multiple hypothesis testing. * Denotes adjusted $p < 0.05$. 5-fold cross-validation is applied for train-test partitioning on the Cart 15K dataset.*

As shown in Table 6, in the training set, the adaptability rate of the process parameters of the research model was $91.23 \pm 1.25\%$, while the similarity of style transfer and the restoration degree of decorative details were $92.34 \pm 0.98\%$ and $92.74 \pm 1.03\%$ respectively, and the accuracy rate of color restoration reached $94.11 \pm 0.87\%$. However, the adaptability rate of the process parameters of VAE-AHP-PSO was only $82.36 \pm 1.58\%$, and the accuracy rates of color restoration of GANs-NSGA-II and GANs-PSO were lower than that of the research model, being $79.63 \pm 1.38\%$ and $77.84 \pm 1.43\%$ respectively. In the test set, the similarity of style transfer of the research model reached $88.74 \pm 1.05\%$, and its adaptability rate of process parameters and the restoration degree of decorative details were higher than those of the comparison models. This model outperforms others comprehensively in terms of parameters adaptation rate, style transfer similarity, etc., because the bidirectional coupling of AHP and PSO ensures the synergy between aesthetic requirements and process constraints, while the multi-task loss design of GANs enhances color restoration and detail fidelity, avoiding the limitations of a single algorithm in optimizing aesthetics or process in a single dimension. Through comparison, it can be concluded that the proposed model achieved comprehensive improvements in multiple aspects of performance including process adaptation and color reproduction.

3.2 Analysis of Practical Application Effects of Bidirectional Coupling Model of Ceramic Ornament Aesthetics and Parameters

To validate the effectiveness of the model in practical application scenarios, this study selected real data from the Jingdezhen Ancient Ceramic Gene Bank in Jiangxi as experimental data. Based on archaeological expert annotations, the ornaments were divided into 6 typical styles: Song Dynasty minimalism, Ming Dynasty Yongle-Xuande blue-and-white complexity, Qing Dynasty Qianlong polychrome porcelain intricacy, Qing Dynasty Kangxi blue-and-white wash painting, Republican period new famille rose patterns, and modern simplicity. First, this study compared the style recognition accuracy of the four models for these 6 styles. The results are shown in Figure 12.

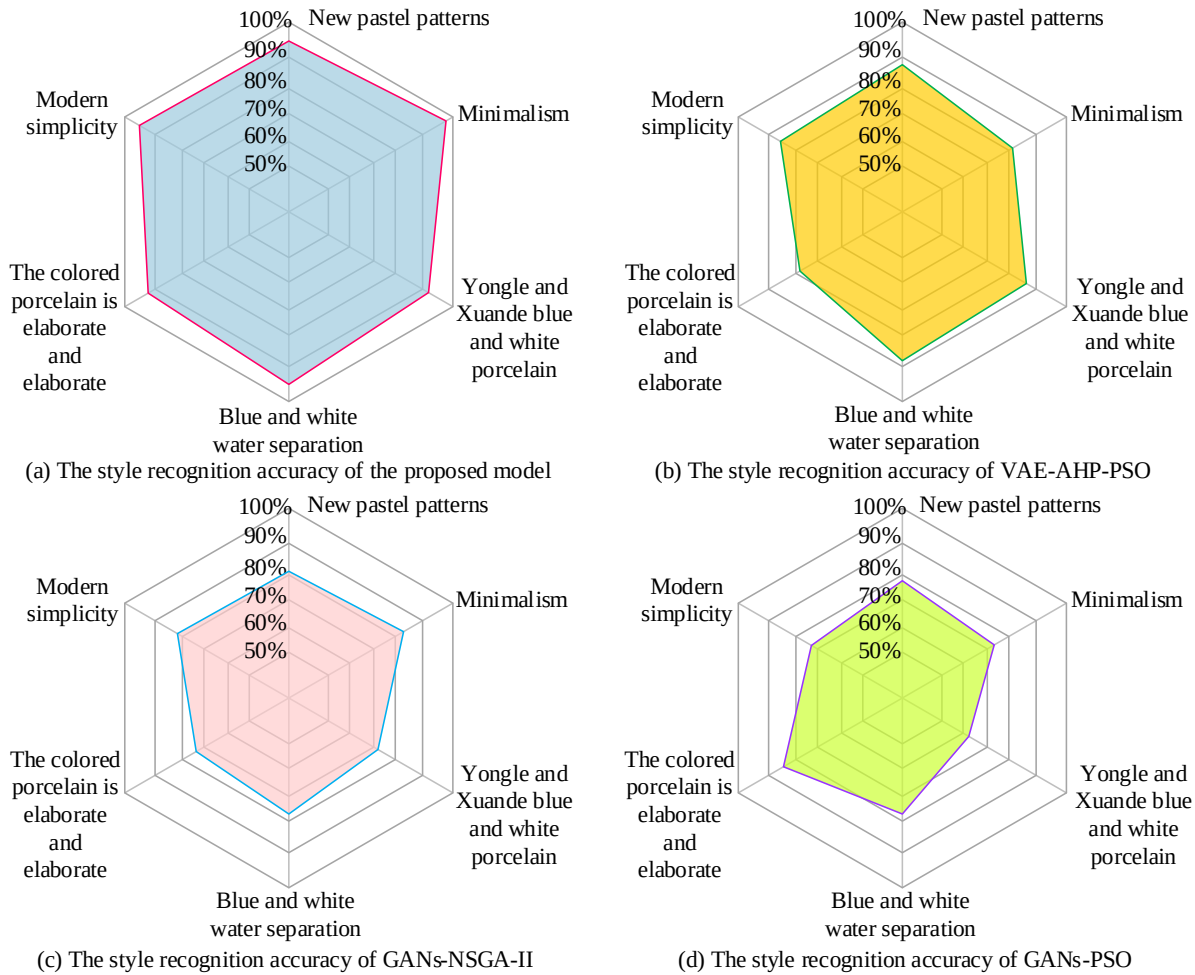


Fig. 12. Style recognition accuracy of different models

In Figure 12, VAE-AHP-PSO had a recognition accuracy rate of only 82.12% for Song Dynasty minimalism style, GANs-NSGA-II had a recognition accuracy rate of 72.27% for Ming Dynasty Yongle-Xuande blue-and-white complexity style, and GANs-PSO had a recognition accuracy rate of 84.97% for Qing Dynasty Qianlong polychrome porcelain intricacy style. This model achieves an accuracy rate of over 90% for the identification of all styles. The key reason for this is that GANs can precisely capture the latent genes of different styles, while the three-level evaluation system of AHP provides clear standards for quantifying style features, thereby reducing the ambiguity in style identification. Through comparison, it can be found that the proposed model could more precisely capture implicit style genes such as the line rhythm of Song Dynasty minimalism and the color hierarchy of Qing Dynasty polychrome porcelain, and had superiority in style-based ornament generation and aesthetic optimization. Next, this study compared the style transfer effects under the task scenarios of ceramic ornament style generation and aesthetic parameter optimization. The results are shown in Figure 13.

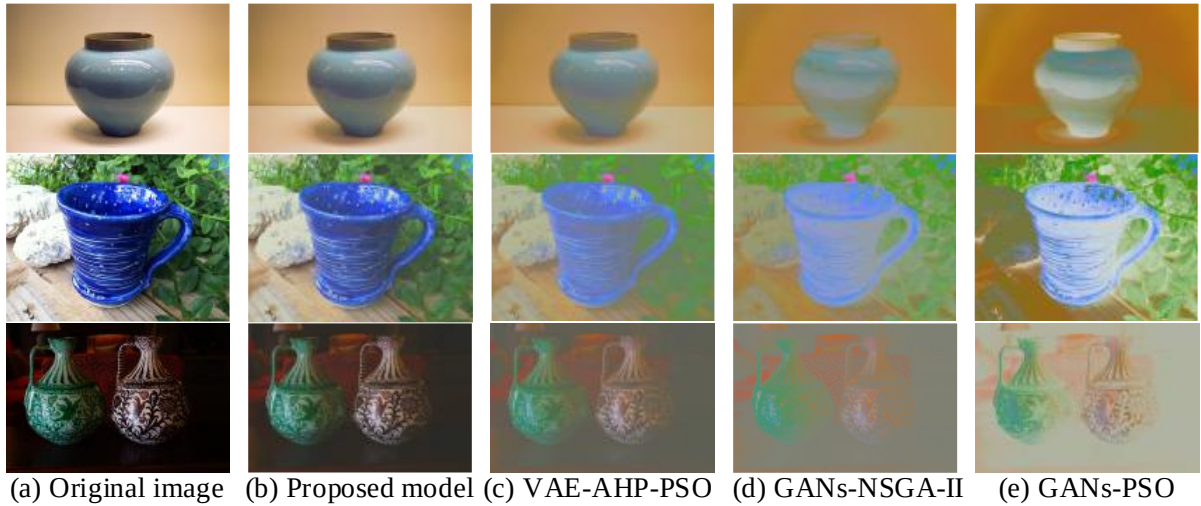


Fig. 13. Style transfer effects of the four models (Image source from: <https://www.1001freedownloads.com/free-photos/?q=Ceramic&page=2>)

In Figure 13, The proposed model's style transfer effect was most prominent in terms of the glaze color hierarchy of celadon jars, the texture quality of blue-glazed cups, and the ornament details of polychrome porcelain vases, with no obvious color distortion and detail loss. However, VAE-AHP-PSO, GANs-NSGA- II, and GANs-PSO all had varying degrees of color deviation and texture blurring problems, and their style transfer effects were not as good as the proposed model. The style transfer of this model is highly consistent with the original image in terms of color, texture and details, with no obvious distortion. This is because the generator of GANs introduces a style attention mechanism, focusing on the core visual features of the target style. At the same time, the optimized process parameters of PSO are deeply matched with the aesthetic features, ensuring that no details are lost during the transfer process. The above results indicated that the coupling model proposed in this study could precisely restore the texture details of ceramic ornaments in style transfer tasks. Subsequently, this study analyzed the aesthetic scoring results of the four models under the task scenarios of ceramic ornament style generation and aesthetic parameter optimization. The results are shown in Figure 14.

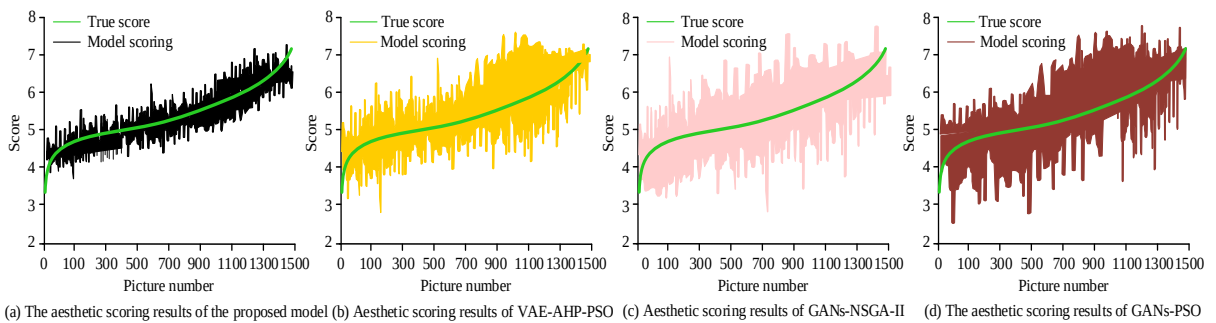


Fig. 14. Aesthetic scoring results of the four models

In Figure 14(a), the aesthetic scoring results of the proposed model were highly consistent with the actual score trends, with good fit, and its average error rate was only 5.29%. This indicated that this model had higher prediction accuracy for ceramic ornament aesthetic scores. Figure 14(b) showed that VAE-AHP-PSO had a large deviation between the scores and actual scores, with an average error rate of 8.73%. In Figure 14(c), the average error rate of GANs-NSGA- II reached 11.38%. As shown in Figure 14(d), the aesthetic scoring results of GANs-PSO differed significantly from the actual scores, with an average error rate of 12.57%. The aesthetic score of this model closely matches the actual score. The reason for this is that the judgment matrix constructed by AHP integrates the professional experience of ceramic experts and cultural scholars, converting abstract aesthetics into calculable objective indicators. Moreover, the iterative feedback of PSO continuously corrects the low-score indicators, narrowing the gap between the model's prediction and the actual aesthetic evaluation. Through comparison, it can be known that the proposed model

could provide reliable quantitative support for aesthetics-driven ornament design. Finally, this study compared the performance of each model under different ceramic ornament styles. The results are shown in Table 7.

Table 7. Performance comparison of each model under different ceramic ornament styles

Decorative style	Model	Feature matching degree (%)	Ornament detail fidelity (%)	Process parameter compliance rate (%)
Song Dynasty minimalism style	Proposed model	92.53±0.97	97.41±0.75	91.47±1.18
	VAE-AHP-PSO	87.42±1.35*	86.14±1.42*	80.47±1.56*
	GANs-NSGA- II	82.51±1.63*	82.43±1.58*	76.58±1.72*
	GANs-PSO	83.69±1.48*	85.48±1.49*	73.34±1.81*
Ming Dynasty Yongle-Xuande blue-and-white complexity style	Proposed model	91.59±1.02	95.74±0.83	92.41±1.15
	VAE-AHP-PSO	85.31±1.41*	83.26±1.54*	84.72±1.43*
	GANs-NSGA- II	81.47±1.68*	85.47±1.51*	80.11±1.67*
	GANs-PSO	79.84±1.57*	80.13±1.63*	78.46±1.75*
Qianlong colored porcelain	Proposed model	95.97±0.85	93.34±0.92	91.47±1.09
	VAE-AHP-PSO	83.64±1.49*	87.43±1.38*	85.03±1.41*
	GANs-NSGA- II	81.47±1.72*	82.91±1.65*	82.47±1.58*
	GANs-PSO	80.75±1.61*	80.42±1.73*	76.63±1.84*
Blue and white-water separation	Proposed model	93.66±0.91	92.26±0.98	95.54±0.89
	VAE-AHP-PSO	87.34±1.38*	82.54±1.57*	83.34±1.49*
	GANs-NSGA- II	85.21±1.59*	79.68±1.71*	81.58±1.62*
	GANs-PSO	81.04±1.65*	73.33±1.87*	74.28±1.92*
New pastel patterns	Proposed model	92.52±1.05	91.57±1.01	89.54±1.23
	VAE-AHP-PSO	87.14±1.43*	82.24±1.59*	82.74±1.54*
	GANs-NSGA- II	82.65±1.67*	78.53±1.76*	81.33±1.65*
	GANs-PSO	80.13±1.72*	72.19±1.93*	72.46±1.89*

Note: All data are reported as mean ± standard deviation from 5 independent repeated experiments. Two-tailed independent t-tests are used for pairwise comparisons between baseline models and the proposed model, with Bonferroni correction for multiple hypothesis testing. * Denotes adjusted $p < 0.05$. Results are tested on the Jingdezhen Ancient Ceramic Gene Bank dataset.

As can be seen from Table 7, the style feature matching degree of the research model in the minimalist style of the Song Dynasty reached $92.53 \pm 0.97\%$, while the restoration degree of decorative details and the compliance rate of process parameters were $97.41 \pm 0.75\%$ and $91.47 \pm 1.18\%$ respectively. In contrast, in the comparison model, VAE-AHP-PSO had a style feature matching degree of only $87.42 \pm 1.35\%$ in the minimalist style of the Song Dynasty, GANs-NSGA-II had a restoration degree of decorative details of $82.43 \pm 1.58\%$, and GANs-PSO had a compliance rate of process parameters of $73.34 \pm 1.81\%$, which was much lower than that of the research model.

Table 8. Computational overhead comparison on RTX 3090 (24 GB)

Model	Peak GPU memory (GB)	Wall-clock time per single ornament (s)	Native output of continuous craft parameters
Proposed GANs-AHP-PSO	10.7	28.4	Yes
VAE-AHP-PSO	8.9	22.1	Yes
GANs-NSGA- II	13.2	41.6	Yes
GANs-PSO	9.5	24.7	Yes
ControlNet-based baseline	18.3	72.6	No

From the perspective of the dense style of blue and white porcelain in the Yongle and Xuande periods of the Ming Dynasty, the various indicators of the research model still showed the highest level and had obvious advantages. This model maintains high performance indicators across various styles. This is because the model dynamically adjusts the feature extraction weights of

GANs and the parameter search range of PSO according to the aesthetic characteristics of different styles, achieving a unified balance between style adaptability and performance stability. The above data results indicated that the proposed model performed excellently in style restoration, detail preservation, and process adaptation, and had good universality under different ceramic ornament styles. To further analyze model computational cost and justify why diffusion-based methods are not adopted as main baselines, computational overhead is benchmarked on RTX 3090 (24 GB). Peak GPU memory usage and wall-clock generation time for single ornament are reported in Table 8, alongside comparison with a ControlNet-based baseline.

4. Discussion

The study selected VAE-AHP-PSO and GANs-NSGA-II models as the comparison cases, with the core based on "algorithm logical consistency" and "adaptability to ceramic design scenarios". The selected comparison models all followed the core framework of "generation/optimization + aesthetic quantification", and had direct comparability with the technical path of the proposed model, facilitating the precise dissection of the collaborative advantages of AHP, GANs, and PSO. The diffusion models and style transfer networks that have become popular in recent years were not included. The main reasons were as follows: First, although diffusion models have high generation quality, their training and inference costs are significantly higher than GANs, and their ability to map the process parameters of ceramic decoration is weak, making it difficult to directly connect with the parameter optimization process of PSO. Second, traditional style transfer networks focus on image style transfer and lack targeted adaptation to ceramic cultural symbols and process constraints, resulting in a deviation from the research's bidirectional coupling goal.

The research model demonstrated excellent performance in various performance tests. From the test results of style feature matching degree, the style feature matching degree of the research model in the elaborate style of Qing Dynasty's Qianlong colored porcelain reached $95.97 \pm 0.85\%$, significantly higher than $83.64 \pm 1.49\%$ of VAE-AHP-PSO, $81.47 \pm 1.72\%$ of GANs-NSGA-II, and $80.75 \pm 1.61\%$ of GANs-PSO. This is due to the precise extraction of implicit features such as color layers and decorative layout by GANs and the quantitative weighting of cultural beauty indicators by AHP, enabling the model to accurately capture the core genetic elements of the style. In the test results of decorative detail restoration degree, the research model performed well in different ceramic decorative styles. When the decorative style was Song Dynasty's minimalism, the decorative detail restoration degree of the research model reached $97.41 \pm 0.75\%$, while GANs-NSGA-II was only $82.43 \pm 1.58\%$, and GANs-PSO was $85.48 \pm 1.49\%$. This was mainly due to the model's ability to capture details such as line rhythm and brush texture through convolution kernels, avoiding the generation of disordered decorative patterns. In the test of process parameter compliance rate, the compliance rate of the research model in the Qing Dynasty's Kangxi cobalt blue shading style reached $95.54 \pm 0.89\%$, while the compliance rate of VAE-AHP-PSO was $83.34 \pm 1.49\%$ at this time. This is inseparable from the two-way coupling of AHP and PSO, where PSO efficiently searches for solutions in the parameter space that meet the actual firing requirements, such as glaze thickness and shading material matching parameters, effectively avoiding generating decorative patterns that meet aesthetic standards but are not feasible in terms of craftsmanship.

The aesthetic scoring error rate test results showed that the average error rate of the proposed model in the test set was only 5.29%, far lower than 8.73% for VAE-AHP-PSO, 11.38% for GANs-NSGA-II, and 12.57% for GANs-PSO, and the error rate was also only 3.68% in the Qing Dynasty polychrome porcelain category with complex ornament styles. This was attributed to the proposed model constructing judgment matrices through ceramic experts and cultural scholars, enabling subjective aesthetic requirements to be transformed into objective weights, while combining PSO's iterative feedback to correct low-standard indicators and reduce scoring deviation. From the results of the style transfer similarity test, it can be seen that the research model maintains excellent performance in both the training set and the test set. The style transfer similarity within the training set is as high as $92.34 \pm 0.98\%$. Although the style transfer similarity in the test set slightly decreases, it still remains at $88.74 \pm 1.05\%$, which is more in line with the original style in terms of color reproduction and texture consistency compared to the comparison model. This is inseparable from the multi-task loss design of the discriminator in GANs, which strengthens the

generator's learning of specific style features and further ensures that the transferred style does not deviate.

From the perspective of model structure differences, the core flaw of the comparative model lies in its single-function orientation, while the proposed model achieves full-process collaboration. In the VAE-AHP-PSO model, the core limitation of VAE is the ambiguity of generating features. By modeling with probability distributions, it generates decorative images but has difficulty precisely capturing the deterministic aesthetic features in ceramic decoration. The proposed model combines the decoration unit constraint layer and multi-task loss design, which can force learning of the deterministic aesthetic features of ceramic decoration. The GANs-NSGA-II model's defect lies in the inefficiency of multi-objective optimization. The crossover and mutation mechanism of NSGA-II is prone to causing the parameter search to fall into local optimum, and it cannot respond quickly to the aesthetic weight priority quantified by AHP. The GANs-PSO model only relies on PSO for single-dimensional optimization of process parameters and cannot convert the subjective aesthetic requirements of ceramic design into objective weights and constraints. However, AHP constructs a three-level evaluation system, which decomposes abstract aesthetic requirements into quantifiable indicators and weights, providing a clear optimization direction for PSO, avoiding the problem of disconnection between parameter optimization and aesthetics. From the perspective of the specific contributions of the algorithms to ceramic design, GANs provide efficient aesthetic mapping capabilities for ceramic decoration. In response to the pain points of difficult style replication and slow creative generation in ceramic design, GANs can extract style features from 5000+ traditional ceramic decoration samples, quickly generate initial solutions that meet the target aesthetic requirements, and support multi-style fusion innovation, expanding the creative boundaries of ceramic design. AHP solves the core problem of difficult quantification of aesthetic requirements in ceramic design. Through expert scoring and consistency verification, subjective demands such as cultural inheritance and visual aesthetics are transformed into clear indicator weights, enabling ceramic design to shift from experience-driven to data-driven, and improving the scientificity of design decisions. PSO achieves precise balance between aesthetics and craftsmanship in ceramic design. For key process parameters in ceramic firing, PSO can quickly search for the optimal combination that meets AHP aesthetic constraints, improving the feasibility of ceramic design.

Further characterization of theoretical computational complexity is conducted for the GANs-AHP-PSO model. Computational overhead is affected by three major components: image generation from the adversarial network, iterative parameter searching of the particle swarm algorithm, and aesthetic evaluation procedures. Model runtime increases with larger particle population size, higher parameter dimension and more optimization iterations. Storage consumption is mainly determined by network parameter volume and particle-swarm data storage.

The "aesthetics-parameter-process" bidirectional coupling architecture constructed in this study broke through the limitations of traditional single-dimensional optimization. It innovatively added an ornament unit constraint layer in the GANs network design, capturing detail correlations of ceramic ornaments through customized convolutional kernels, providing technical support for innovative ornament design while digitally preserving traditional ceramic culture genes. The system supports human-in-the-loop intervention for craft artists. Within the interactive layer, craft masters can manually override PSO parameter boundaries, adjust AHP indicator weights, or reject individual generated ornaments, so human artistic experience can participate in the closed-loop optimization workflow. From artistic perspective, the model can perform two kinds of output: style-faithful imitations of traditional ornaments and cross-style innovative ornaments by mixing multi-era feature vectors. It acts as a generative assistant; final artistic judgment still relies on designers and craftspeople.

5. Summary

Current ceramic ornament design methods suffer from poor process adaptability and low generation efficiency. This study constructs a bidirectional coupling model of ceramic ornament aesthetics and parameters based on the GANs-AHP-PSO algorithm. The model uses AHP to provide

clear objectives for parameter optimization. The GANs module accurately extracts latent features of traditional ornaments through the ornament unit constraint layer and multi-task loss design. PSO efficiently searches the parameter space for optimal solutions based on AHP constraints. Results show that the model achieves higher style feature matching, ornament detail restoration, and process parameter compliance than comparative models. The model maintains high performance even in complex styles such as Qing dynasty Qianlong polychrome ornaments and Kangxi blue-and-white patterns, demonstrating its stability and superiority across different style scenarios. In practical application tests, generated ornaments closely match traditional ceramic features in color reproduction and style transfer, showing stronger restoration capability than comparative models. However, the model mainly focuses on the ceramic styles of the Song, Ming and Qing dynasties, and its applicability and scalability in other cultural contexts have not been fully verified. The visual outputs are digital 2D renderings. Physical firing experiments are not fully completed in current stage; future work will carry out physical 3D-printing-and-firing validation for generated parametric ornaments for comparison between 2D digital design and final fired artifacts. Besides, the dataset is dominated by Chinese imperial court ceramics from Song-Ming-Qing; folk ceramics such as Cizhou-kiln and non-East-Asian ceramic traditions are insufficiently covered by samples. In the future, the model's applicability and scalability in different cultural contexts will be enhanced by expanding the database of ceramic patterns from multiple cultural backgrounds, optimizing the cross-cultural feature transfer module of GANs, and adjusting the cultural adaptability weights of the AHP evaluation system. Further expand the scope of industrial experiments, collaborate with ceramic enterprises to establish a "model parameters - production process" mapping database, and optimize the adaptability of parameters to different production lines. At the same time, deepen the application of coupling mechanisms in interdisciplinary fields, explore their universality in the digital inheritance of other traditional processes, and construct a more complete theoretical system for cultural heritage computing. In addition to technical optimization, further research will consider the model's application in craft-person training and the digital-transformation requirements of small-scale ceramic workshops.

For industrial integration, a three-phased actionable roadmap is defined: Phase-1: Expand the "model-parameter-firing-record" mapping database through cooperation with ceramic enterprises. Phase-2: Achieve format adaptation between model parameter outputs and digital-manufacturing equipment interfaces. Phase-3: Carry out small-batch pilot production for iterative tuning of process-constraint thresholds.

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References

- [1] Li L, Huang Y, Wu J, Yang Y, Li Y, Guo Y. Theme-Aware Visual Attribute Reasoning for Image Aesthetics Assessment. *IEEE Trans Circuits Syst Video Technol.* 2023;33(9):4798-4811. <https://doi.org/10.1109/TCSVT.2023.3249185>
- [2] Zhu H, Shi J, Shao Z, Yao R, Sun K, Li L. Progressively Generated Text-Assisted Image Aesthetic Quality Assessment. *IEEE Trans Fuzzy Syst.* 2025;33(9):2899-2911. <https://doi.org/10.1109/TFUZZ.2025.3566145>
- [3] Wu S, Yan X, Liu W, Xu S, Zhang S. Self-Driven Dual-Path Learning for Reference-Based Line Art Colorization Under Limited Data. *IEEE Trans Circuits Syst Video Technol.* 2024;34(3):1388-1402. <https://doi.org/10.1109/TCSVT.2023.3295115>
- [4] Liu L, Zhang H, Zhou D, Shi J. Toward Fashion Intelligence in the Big Data Era: State-of-the-Art and Future Prospects. *IEEE Trans Consum Electron.* 2024;70(1):36-57. <https://doi.org/10.1109/TCE.2023.3285880>
- [5] Liu DM, Li SW, Zhou RY, Liang LL, Hong YG, Zeng YZ. NADM: Noise-Aware Diffusion Model for Landscape Painting Video Generation. *IEEE Trans Cybern.* 2025;55(8):3686-3698. <https://doi.org/10.1109/TCYB.2025.3576752>

- [6] Chen H, Li W, Xiao B, Gao X. MDFA: A Quantitative Framework for the Analysis of Multimodal Facial Esthetics. IEEE Trans Neural Netw Learn Syst. 2025;36(9):15779-15793. <https://doi.org/10.1109/TNNLS.2025.3570389>
- [7] Wei T, Chen H, Jiang Q. Dual-Stream Interaction Network for Assessing Image Technique and Aesthetic Quality. IEEE Trans Consum Electron. 2025;71(1):453-466. <https://doi.org/10.1109/TCE.2024.3510930>
- [8] Zhang K, Zhu D, Min X, Gao Z, Zhai G. Synergetic Assessment of Quality and Aesthetic: Approach and Comprehensive Benchmark Dataset. IEEE Trans Circuits Syst Video Technol. 2024;34(4):2536-2549. <https://doi.org/10.1109/TCSVT.2023.3303933>
- [9] Qin X, Liu Y, Yang D, Pan D, Meng F, Cao Y. Quantitative Characterization of Highway Landscape Space Visual Perception Based on Deep Learning. IEEE Trans Intell Transp Syst. 2024;25(12):21157-21171. <https://doi.org/10.1109/TITS.2024.3454482>
- [10] Guo C, Lu Y, Dou Y, Wang FY. Can ChatGPT Boost Artistic Creation: The Need of Imaginative Intelligence for Parallel Art. IEEE-CAA J Autom Sinica. 2023;10(4):835-838. <https://doi.org/10.1109/JAS.2023.123555>
- [11] Habash O, Singh S, Mizouni R, Otrók H. Multiple Source Localization in IoT: A Conditional GAN and Image-Processing-Based Framework. IEEE Internet Things J. 2024;11(4):7059-7070. <https://doi.org/10.1109/JIOT.2023.3313887>
- [12] Chen H, Li W, Gao X, Xiao B. Novel Multi-Feature Fusion Facial Aesthetic Analysis Framework. IEEE Trans Big Data. 2023;9(5):1302-1320. <https://doi.org/10.1109/TBDATA.2023.3255582>
- [13] Li L, Sheng X, Chen P, Wu J, Dong W. Towards Explainable Image Aesthetics Assessment with Attribute-Oriented Critiques Generation. IEEE Trans Circuits Syst Video Technol. 2025;35(2):1464-1477. <https://doi.org/10.1109/TCSVT.2024.3470870>
- [14] Li J, Lai C, Zhang H, Yuan X. PM-Vis: A Visual Analytics System for Tracing and Analyzing the Evolution of Pottery Motifs. IEEE Trans Vis Comput Graph. 2024;30(6):3022-3034. <https://doi.org/10.1109/TVCG.2024.3388525>