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The Impact of Varying Levels of Figurative Representation on Aesthetic Evaluation: A Computational Aesthetic Analysis of Xu Beihong's Horse Paintings

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Abstract. This study integrates computational aesthetics and experimental aesthetics methods to explore the influence of abstraction and figuration on the aesthetic evaluation of traditional Chinese ink paintings depicting animals. Using Xu Beihong’s horse paintings as a case study, the research employs subjective ratings and machine learning models to quantitatively analyze the aesthetic dimensions of artworks at varying levels of figurative representation and their impact on aesthetic experiences. The results indicate that dimensions such as visual harmony and emotionality play a significant role in predicting aesthetic appreciation. Through regression analysis and principal component analysis, the study reveals distinct mechanisms underlying the aesthetic experiences of figurative and abstract art, providing a novel perspective for the development of computational aesthetics research methodologies.

Keywords: Experimental Aesthetics;Level of Figuration;Xu Beihong’s Horse Paintings;Chinese Ink Painting;Aesthetic Preference.

1. Introduction

Aesthetic perception, as a crucial domain in both psychology and art theory, involves the interaction between visual features, cognitive processes, and emotional experiences. Western theories of abstract and figurative art are based on the influence of complexity on aesthetic preference. Yanagisawa proposed a free energy model based on information theory, which supports the hypothesis of a U-shaped curve for aesthetic pleasure, where works of medium complexity elicit the highest aesthetic preference[1]. Xu Beihong’s horse paintings, which integrate the precision of Western anatomy with the expressive style of Chinese ink painting, are frequently examined from an art historical perspective. However, limited research has quantitatively explored the specific impact of varying levels of figuration on aesthetic evaluation. This study combines subjective ratings and machine learning models to investigate the aesthetic dimensions of artworks at different levels of figuration, revealing their effect on aesthetic experience. The goal is to deepen the understanding of the interaction between abstraction and figuration in traditional Chinese animal ink paintings.

2. Literature Review

2.1 Aesthetic Differences Between Abstract and Figurative Art

The aesthetic differences between abstract and figurative art have long been a central topic in the field of aesthetics. Berlyne's U-shaped hypothesis suggests that aesthetic experiences reach their optimal level when the complexity of the stimulus is moderate[2]. Aesthetic preference declines when the complexity of the artwork is either too low or too high. Cupchik and Winston empirically tested this hypothesis in their study of Western figurative and abstract art and found a "moderate complexity" range where aesthetic experiences are maximized[3]. In figurative art, the detailed representation of objects elicits direct emotional responses; whereas in abstract art, the complexity

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and symbolism of the forms provoke higher-level cognitive processing[4]. Research by Mather et al. revealed that abstract art, due to its visual ambiguity, requires more cognitive reasoning and processing from the viewer, thereby enhancing emotional resonance and subjective interpretation of the artwork[5]. These findings provide important insights into the aesthetic mechanisms within abstract art.

2.2 Art Appreciation from the Cultural Context Perspective

Cultural differences also exhibit significant effects on neural responses to art appreciation. In a cross-cultural experiment, Bao et al. demonstrated that Chinese and Western participants showed distinct brain activation patterns when viewing culturally significant works, indicating that aesthetic evaluation is influenced not only by visual features but also by cultural background[6]. Mikuni et al. conducted a study on the cultural differences in aesthetic judgment between native Japanese and German speakers, finding that Japanese participants preferred simpler, realist works, whereas German participants favored more complex works with strong emotional expression[7].

2.3 Computational Aesthetics: From Visual Features to Higher-Order Aesthetic Concepts

In computational aesthetics research, edge features are considered important factors influencing the visual complexity and degree of figuration in artworks. Figurative art typically exhibits clear form contours and high edge density, while abstract art tends to reduce form clarity, decrease edge density, and enhance form ambiguity[8]. The Canny edge detection algorithm is a widely used technique in image processing that effectively extracts the primary contours of an image, quantifying edge density and line quantity. As a result, the Canny algorithm was selected as the primary method to measure the degree of figuration in Xu Beihong’s horse paintings.

Furthermore, with the development of computational aesthetics, researchers have focused on quantifying visual features of artworks and establishing their relationship with aesthetic preferences. Low-level visual features, such as color harmony, texture complexity, and composition, have become key areas of study in computational aesthetics[9]. Palmer et al. explored the roles of color, spatial structure, and individual differences in aesthetic preference and examined how color harmony influences aesthetic judgments[10]. Brachmann and Redies further combined visual features with subjective ratings to propose a method for predicting aesthetic preferences[11].

2.4 The Predictive Role of Machine Learning Models in Aesthetic Rating

Martindale pointed out that machine learning can quantify high-level aesthetic concepts such as symbolism and emotional resonance through pattern recognition and feature extraction, demonstrating its strong applicability in predicting aesthetic evaluations[12]. Mikuni et al. showed that in machine learning models, high-level concepts such as symbolism and emotional resonance predict aesthetic judgments as effectively as low-level visual features[7]. This suggests that aesthetic experience is multidimensional, influenced not only by visual stimuli but also by more complex psychological mechanisms involving context, emotion, and culture.Breiman’s random forest algorithm has been widely used in aesthetic evaluation research to model the nonlinear relationships between visual features and subjective ratings, revealing the key factors influencing aesthetic preference[13]. Random forests can assess the contribution of different features to aesthetic ratings through variable importance analysis. Wang et al. found that SVM (Support Vector Machine) and decision trees performed well in predicting the aesthetic ratings of photographic images, classifying high and low aesthetic images based on image features[14]. Lin et al. demonstrated that computational aesthetics methods based on the SVM model, combining subjective ratings and neural data, can effectively predict aesthetic ratings for abstract art[15].Spee et al. also utilized machine learning methods to analyze the key factors influencing creativity ratings of Western art paintings. The study, based on 78 participants’ subjective ratings of 17 artistic attributes for 54 paintings, employed a random forest regression model and identified symbolism, emotionality, and imagination as the main predictors of creativity. While abstraction, emotional

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valence, and complexity had some impact on creativity ratings, their effects were weaker, revealing the nonlinear relationship between artistic attribute ratings and creativity judgments[16].

The above research methods provide a new perspective for computational aesthetics, showing that aesthetic experience can be comprehensively explained by starting with visual statistical features and incorporating machine learning models to quantify more complex aesthetic dimensions.

2.5 Experimental Aesthetics: Methods for Quantifying Aesthetic Experience

Experimental aesthetics, as a quantitative approach in aesthetic research, was first proposed by Fechner. Its primary goal is to uncover the patterns of human aesthetic experience through the analysis of experiments and data[17]. Unlike traditional philosophical discussions in aesthetics, experimental aesthetics emphasizes objective measurement, typically employing methods such as behavioral experiments, psychophysical measurements, eye-tracking, and neuroimaging technologies to quantify individual aesthetic evaluations of artworks. In recent years, experimental aesthetics has gradually integrated with computational aesthetics and neuroaesthetics, providing new methodological support for the study of aesthetic experience[18].

In experimental aesthetics research, scholars have identified a range of key factors influencing aesthetic preference and have sought to standardize these factors to allow comparisons across different art forms and cultural contexts. This study will combine the methods of experimental aesthetics, using subjective rating experiments to measure 11 key aesthetic dimensions[19], including visual harmony, complexity, symbolism, cultural context, and emotionality. Additionally, the study will analyze participants' reaction times to each metric in order to explore the cognitive processing demands under different aesthetic factors.

2.6 Aesthetic and Symbolic Analysis of Xu Beihong's Horse Paintings

Xu Beihong's horse paintings are renowned for their unique fusion of Chinese and Western artistic traditions. The works not only embody the precise anatomical expression of Western realism but also incorporate the expressive spirit of Chinese ink painting[20]. In his artworks, the image of the horse is not only a physical representation but also carries significant symbolic meaning, reflecting the cultural spirit of China's modernization process in the early 20th century[21]. However, existing research in China has largely focused on art-historical analysis or qualitative studies, without delving into how the interaction between varying levels of figuration influences viewers' aesthetic evaluations. Therefore, the exploration of aesthetic preferences in Xu Beihong's horse paintings, combining subjective ratings with machine learning techniques, is the focus of this study.

3. Method

This study employs a method based on subjective ratings and machine learning to explore the impact of varying levels of figuration on aesthetic evaluation in Xu Beihong's horse paintings. The experimental design includes the selection and classification of stimulus materials, recruitment of participants, task design, as well as data collection and analysis procedures.

3.1 Stimulus Materials

This study selected 30 of Xu Beihong's horse paintings as experimental stimuli to explore the impact of abstraction on aesthetic evaluation. Bellaiche et al. used 30 paintings generated by the artificial intelligence tool ArtBreeder (15 figurative and 15 abstract) and invited participants to evaluate these artworks. The design of these studies provides a reference for this experiment, supporting the validity and scientific rationale for selecting 30 paintings as stimulus materials[22]. To achieve scientific classification, this study employed the Canny edge detection algorithm to

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process the images, allowing for an objective and scientific quantification of the level of abstraction in the artworks.

The basic computational steps are as follows:

Gaussian filtering: The original image I(x, y) is smoothed using the Gaussian kernel function G(x, y) to remove noise:

$$I_G(x,y) = I(x,y) * G(x,y)$$

Here, G(x, y) represents the two-dimensional Gaussian function:

$$\mathrm{G}(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Gradient Calculation: The gradients in the horizontal and vertical directions are computed as follows:

$$G_x = \frac{\partial I_G}{\partial x}, G_y = \frac{\partial I_G}{\partial y}$$

Next, the gradient magnitude and gradient direction are calculated as follows:

$$G(x,y) = \sqrt{G_x^2 + G_y^2}, \quad \theta(x,y) = \tan^{-1}\left(\frac{G_y}{G_x}\right)$$

To ensure the accuracy of edge detection, this study employs non-maximum suppression to filter out pixels that are not local maximum gradient values, retaining only the points with maximum gradients as edges:

$$\mathrm{G}(\mathrm{x,y}) = \begin{cases} G(x,y), & if\ G(x,y) is\ a\ local\ maximun \\ 0, & otherwise \end{cases}$$

During the calculation process, based on the gradient direction θ(x, y), adjacent pixels along the gradient direction are selected for comparison to ensure that the retained edge pixels are local maxima.

The image after NMS processing may still contain some false edges. Therefore, this study applies a double threshold hysteresis suppression to further filter the edge points. High threshold (TH) and low threshold (TL) values are set to classify the edge pixels:

$$G(x,y) = \begin{cases} Strong\ edge, & G(x,y) > T_H \\ Non-edge, & G(x,y) < T_L \\ Connected\ edge, & T_L \le G(x,y) \le T_H \end{cases}$$

After completing edge detection, a contour detection algorithm is used to extract the main contours of the image, followed by morphological optimization. The contour detection is based on the OpenCV contour finding algorithm:

$C = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$

where C represents the edge contours. This study further removes small-area noise through an area filtering condition:

$$\mathrm{A}(\mathrm{C}) > \mathrm{A}_{\min}$$

In this study, the minimum contour area is set to 100 pixels to retain the main contours, and morphological closing operations are applied to connect broken edges, enhancing edge continuity. The detection results from the Canny algorithm are used to quantify the degree of figuration in the

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artwork. Based on edge density and line quantity, the artworks are categorized into different levels of figuration (Fig. 1):

High-figuration artworks: High edge density, clear line contours, and distinct structural forms.

Medium-figuration artworks: Some contours are retained, but local details are simplified.

Low-figuration artworks: Reduced edge quantity, blurred contours, tending towards an abstract style.

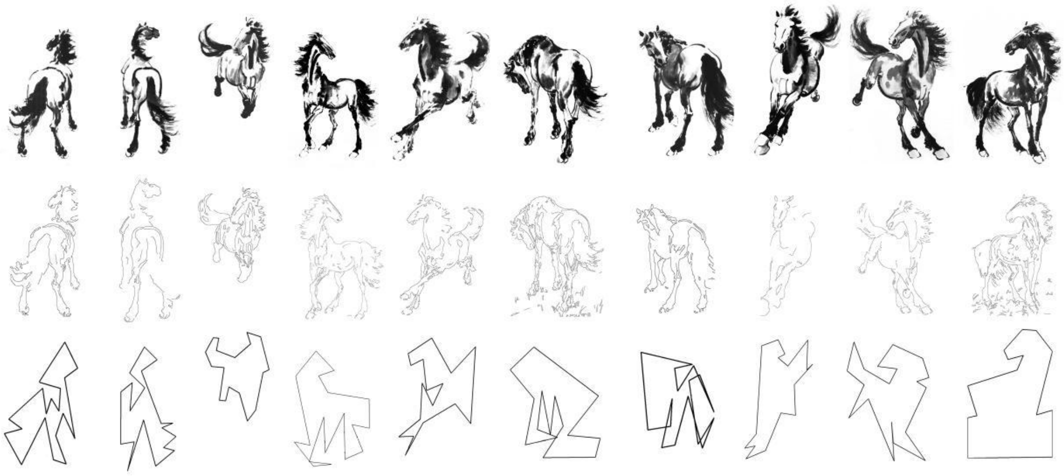

Fig. 1 The abstraction process of Xu Beihong's horse paintings.High-figuration – original Chinese ink painting (top);Medium-figuration – contour extraction results (middle);Low-figuration – geometric abstract representation (bottom).All images are self-drawn by the author.

3.2 Experimental Participants

Thirty experimental participants with an art background were recruited, including graduate students in product design and visual communication design. Chatterjee et al. noted in their study that participants with an art background typically demonstrate higher sensitivity and professional judgment in art evaluation tasks[23]. The participants' ages ranged from 22 to 25 years, with 1 to 5 years of formal art training. All participants signed an informed consent form and were approved to participate in the experiment.

3.3 Experimental Tasks

The experimental participants were required to rate 30 paintings on 11 aesthetic criteria, including aesthetic appreciation, on a scale from 0 to 100[7]. The paintings were presented in a random order to avoid sequence effects. The experimental procedure was programmed in Python to ensure the accuracy and consistency of data recording.

3.4 Rating Criteria

The definitions and rating ranges for the 11 aesthetic criteria are as follows (Table 1)[19]:

Visual Harmony: From "proportion imbalance" to "proportion harmony."

Depth: From "two-dimensional" to "three-dimensional."

Complexity: From "simple" to "complex."

Brushwork: From "delicate" to "Coarse."

Symbolism: From "clear interpretation" to "ambiguous interpretation."

Object Representation: From "Photographic realism" to "painterly style."

Vividness: From "static" to "dynamic."

Emotionality: From "emotionless" to "emotionally rich."

Thoughtfulness: From "simple and intuitive" to "thought-provoking."

Cultural Background: From "culturally resonant" to "forming an independent context."

Aesthetic Value: From "ugly" to "beautiful."

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Table 1. Aesthetic Evaluation Criteria

Rating Criteria	Negative Pole (Minimum Value)	Positive Pole (Maximum Value)
a. Visual Harmony (Balance)	Visual harmony, proportional coordination	Unique, irregular forms
b. Depth	Two-dimensional	Three-dimensional
c. Complexity	Simple	Complex
d. Brushwork	Delicate brushstrokes	Coarse brushstrokes
e. Symbolism	Clear and explicit interpretation	More interpretative space, ambiguous
f. Accurate Object Representation	Photographic realism	Painterly style
h. Vividness	Dynamic	Static
i. Emotionality	Emotionless	Emotionally rich
j. Thoughtfulness	Straightforward and intuitive	Thought-provoking
k. Cultural Background	Evokes cultural resonance	Establishes a unique cultural context
Aesthetic Value	Ugly	Beautiful

This table presents different aesthetic dimensions, with each dimension rated on a scale from the negative extreme (minimum value) to the positive extreme (maximum value). The evaluation criteria cover aspects such as visual balance, complexity, symbolism, and emotionality.

4. Result

4.1 Descriptive Statistics

In this study, the mean, standard deviation, and data distribution for each category of artwork across the 11 aesthetic criteria and aesthetic quality were calculated. Additionally, to visually represent the data distribution characteristics, box plots were created, which are based on quartiles and outliers, providing insights into the central tendency and dispersion of the scores for each category.

The results of the ratings for the 30 Xu Beihong horse paintings (Fig. 2) show that, across all 11 aesthetic evaluation dimensions, visual harmony, complexity, and symbolism received higher scores. In comparisons among the three categories of artworks, high-figuration works scored higher on aesthetic quality, emotional resonance, and visual harmony, indicating that these works generally provide a stronger visual impact and emotional connection.

While the aesthetic quality of medium-figuration works is not as high as that of high-figuration works, they performed better than low-figuration works. Low-figuration works generally received lower scores across all dimensions, especially in complexity and depth, reflecting their weaker visual and emotional appeal.

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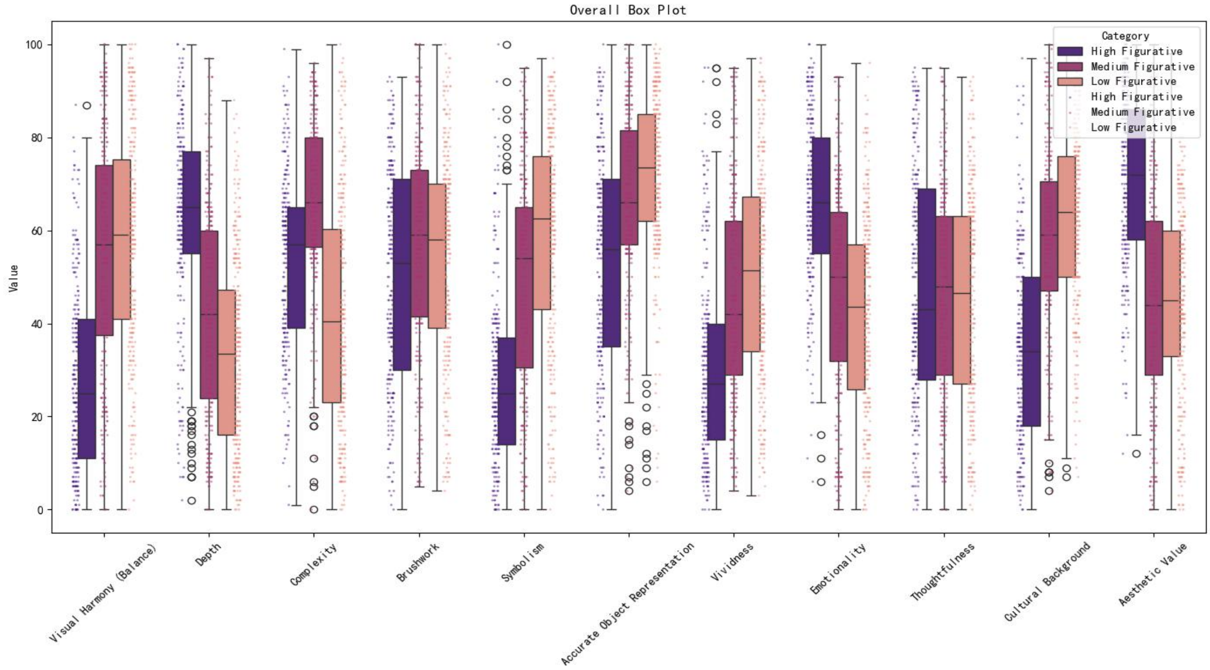

Fig. 2 Distribution of Aesthetic Scores Across Different Levels of Figuration

This figure displays the distribution of scores for high-figuration, medium-figuration, and low-figuration artworks across 11 aesthetic dimensions. The box plot shows the median (black line), interquartile range (IQR, box range), data dispersion (whiskers), and outliers (dots) for each rating dimension.

4.2 Correlation Analysis

In this study, rating time was considered an important cognitive load-related variable, used to assess its role in the aesthetic evaluation process. To explore the potential impact of rating time on subjective rating results, the Spearman correlation coefficient (ρ) between rating time and each aesthetic criterion was calculated[24]. The formula for calculation is as follows:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

In this formula, d_i represents the rank difference for the i-th data point in the sample, and n is the sample size. The results are tested for significance ($p < 0.05$) to reveal the monotonic relationships between rating time and each dimension. The data used in this study do not meet the assumption of normality but are non-parametric. This means that the analysis in this study does not rely on the specific distribution of the data but calculates the correlation between variables through rank differences. Therefore, the results reflect the monotonic relationships between variables rather than linear relationships.

The Spearman correlation analysis results indicate (Fig. 3) that rating time shows significant correlations with several aesthetic dimensions.Significant positive correlations were found for the following dimensions:Symbolism (0.48);Cultural Background(0.48);Vividness (0.47).

These results suggest that viewers require more cognitive processing when evaluating these aesthetic dimensions, particularly symbolism and cultural context, which may involve deeper cultural interpretations, leading to longer rating times.Significant negative correlations were found for the following dimensions:Emotionality (-0.54);Aesthetic Value (-0.69).

The negative correlations between rating time and these dimensions indicate that emotion-driven aesthetic judgments are more intuitive, and viewers are able to make evaluations more quickly.No

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significant correlations were found for the following dimensions:Complexity (0.00);Thoughtfulness(-0.07).

This suggests that although complexity and Thoughtfulness may influence aesthetic judgments, they do not significantly affect rating time. This implies that rating speed may depend more on individual experience or other factors rather than the complexity of the artwork itself.

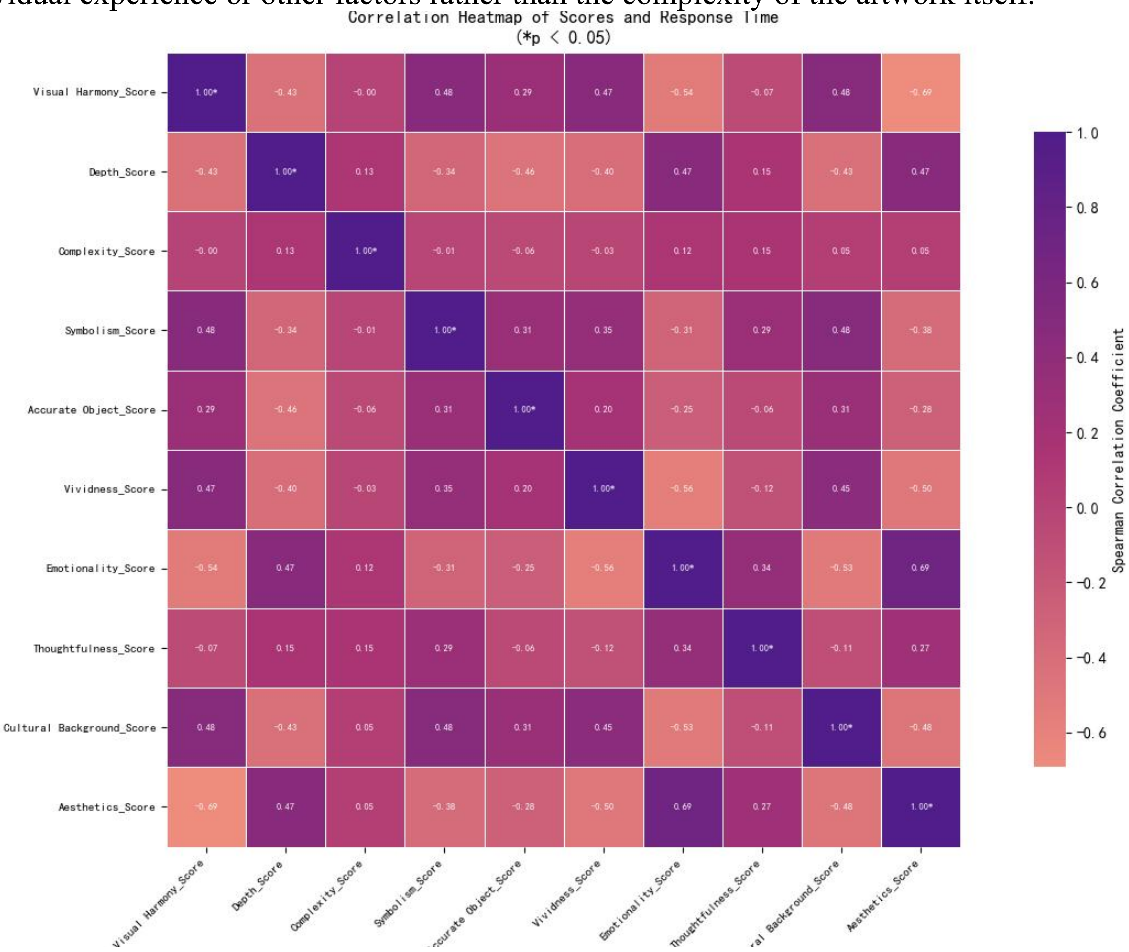

Fig. 3 Spearman Correlation Heatmap of Aesthetic Rating Dimensions and Rating Time

This figure displays the Spearman correlation coefficients (ρ) between the 11 aesthetic rating dimensions, as well as the relationship between these ratings and rating time. The color intensity indicates the strength of the correlation, with deep purple representing a positive correlation (ρ close to 1), deep pink representing a negative correlation (ρ close to -1), and white representing no correlation (ρ close to 0). The significance level is set at $p < 0.05$.

4.3 Machine Learning Model Prediction

This study employs three machine learning methods—Random Forest, Decision Tree, and Support Vector Regression—to simultaneously compare and validate results, in order to assess the impact of 11 aesthetic criteria on aesthetic quality at different levels of figuration and to analyze the feature importance. All models use nested cross-validation, with the outer cross-validation evaluating model generalization, and the inner cross-validation combining Bayesian optimization for hyperparameter tuning. The dataset is split into 80% training set and 20% testing set, and random splitting is performed using Shuffle-Split cross-validation (128 repetitions) to ensure model stability and result reproducibility[19].

In the Random Forest (RF) model, feature importance is calculated using the Gini index, as shown in the following formula:

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$$Gini = 1 - \sum_{i=1}^{n} p_i^2$$

In this formula, p_i represents the proportion of samples in the i-th class, and the Gini index measures the impurity of the data. A smaller Gini index indicates higher purity of the data. In Random Forest (RF), the importance of a feature is calculated as follows:
where FI(f)represents the importance of feature f, wt is the weight at node t , and $\Delta Gini_t$ represents the change in the Gini index before and after the split at the node. Random Forest further combines permutation importance by randomly shuffling features and calculating the change in R^2 to measure the contribution of variables.

The Decision Tree model is based on the principle of recursive splitting, and the splitting criterion can be calculated using the following information gain formula:

$$IG(D, f) = H(D) - \sum_{\upsilon \in v} \frac{|D_\upsilon|}{|D|} H(D_\upsilon)$$

In this formula, IG(D,f)represents the information gain of dataset D at feature f, and H(D) is the entropy of the dataset before the split. D_v refers to the subset of data after splitting on feature f. The entropy is calculated as follows:

$$H(D) = -\sum_{i=1}^{n} p_i \log_2 p_i$$

In this formula, p_i represents the proportion of samples in class i. To avoid overfitting, this study applies pruning to the Decision Tree by setting the minimum sample split size and maximum depth to optimize model complexity. The importance of features is evaluated using Split Gain.

Support Vector Regression (SVR) uses a Radial Basis Function (RBF) kernel to map the data to a higher-dimensional space, improving its ability to fit nonlinear data. The RBF kernel is defined as follows:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$$

In this formula, x_i and x_j represent the input feature vectors, and γ is the kernel function parameter. SVR minimizes the error by optimizing the following objective function:

$$\min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \max(0, |y_i - (w \bullet x_i + b)| - \varepsilon$$

In this formula, w represents the regression coefficients, C is the regularization parameter, and ϵ is the error tolerance margin. This study evaluates the predictive performance of the SVR model using mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2), and tests the statistical significance of features on aesthetic quality through randomization tests.

All analyses were conducted in a Python environment using the Scikit-learn library to ensure the reproducibility and robustness of the model computations.

The prediction of aesthetic ratings was performed using Random Forest, Support Vector Regression, and Decision Trees. The results show that the models in this study performed well in terms of prediction accuracy, with an R^2 value of 0.952. In the feature importance analysis, "visual harmony" and "emotionality" dominated all models, indicating that these two aesthetic dimensions have the most significant impact on aesthetic quality.

The differences in feature importance rankings across models reveal varying focuses on predicting aesthetic quality. Overall, all models indicate that visual harmony and emotionality are the core factors influencing aesthetic ratings, while Cultural Background, as a secondary variable, appears in all three models and somewhat influences the deeper cognitive aspects of aesthetic evaluation.

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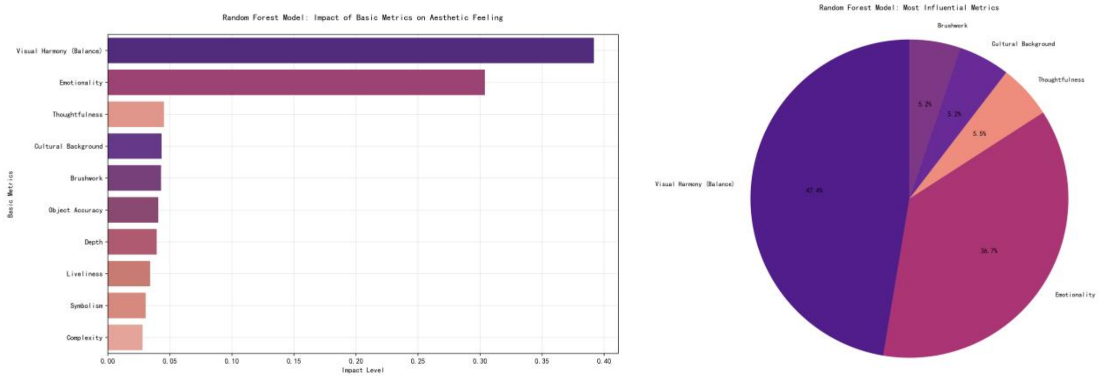

Fig. 4 Key Influencing Factors of Aesthetic Quality Analyzed by the Random Forest Model

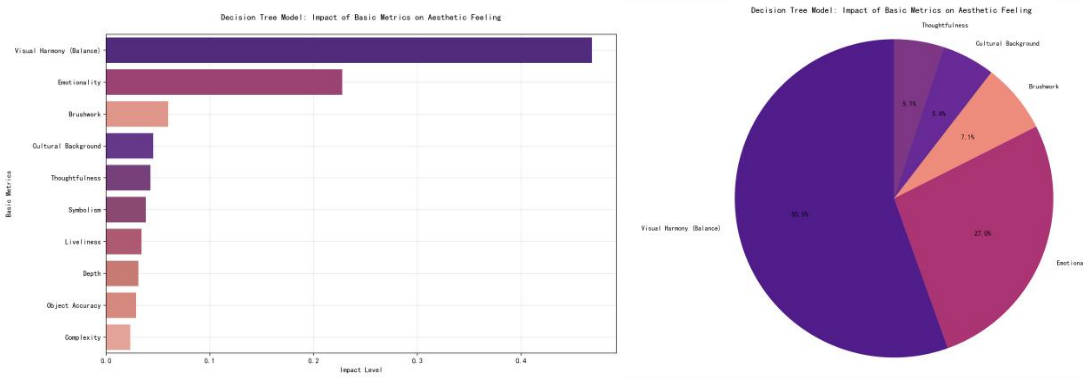

Fig. 5 Key Influencing Factors of Aesthetic Quality Analyzed by the Decision Tree Model

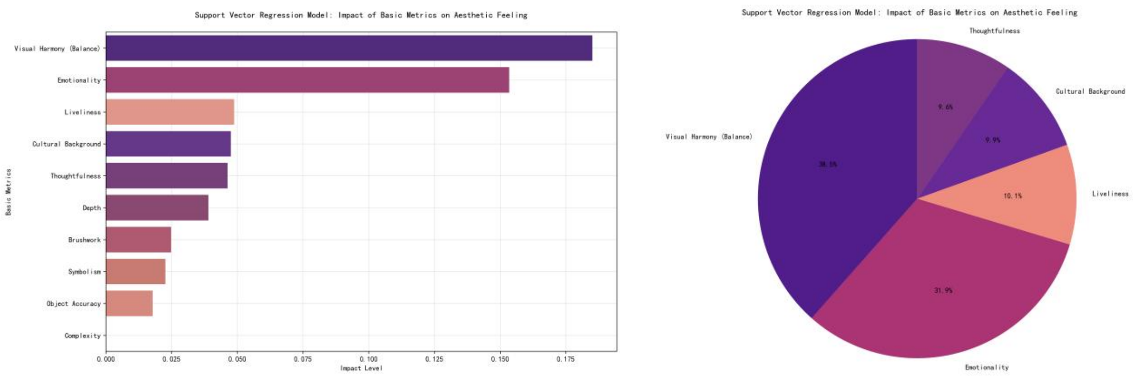

Fig. 6 Key Influencing Factors of Aesthetic Quality Analyzed by the Support Vector Regression Model

4.4 Principal Component Analysis

To further reveal the underlying structure among the 11 aesthetic criteria and to extract the primary aesthetic dimensions influencing aesthetic quality, this study employs Principal Component Analysis (PCA) for dimensionality reduction. This method is widely used in computational aesthetics research to simplify complex features, identify key aesthetic dimensions, and explore data structures[25].

First, the 11 aesthetic criteria are standardized to eliminate the impact of dimensional differences between the indicators. The standardization process can be expressed using the following formula:

$$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j}$$

In this formula, Z_{ij} represents the standardized data, X_{ij} represents the original data, and μ_j and σ_j are the mean and standard deviation of the j-th variable, respectively. Next, the principal

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components are extracted through PCA, and the variance contribution rate for each principal component is calculated. The formula for the variance contribution rate is:

$$\text{Variance Contribution}(\lambda_i) = \frac{\lambda_i}{\sum_{i=1}^{k} \lambda_i}$$

In this study, the first few principal components with a cumulative variance contribution rate exceeding 80% were selected as the main aesthetic dimensions[26].

To visually demonstrate the distribution of different artworks along the primary aesthetic dimensions, a principal component score plot was created. The first principal component (PC1) and second principal component (PC2) were used as the axes, mapping each artwork into a two-dimensional space. The principal component score plot allows for the observation of clustering patterns and differences among high, medium, and low-figuration artworks along different aesthetic dimensions, further revealing the aesthetic characteristics of abstract and figurative art.

Additionally, by analyzing the principal component loading matrix, this study identifies the explanatory power of each principal component for the original indicators. The principal component loading matrix can be calculated using the following formula:

$$\mathrm{P} = \mathrm{V} \bullet \sqrt{\lambda}$$

In this formula, P is the loading matrix, V is the eigenvector matrix, and λ is the square root of the eigenvalue matrix. By analyzing the loading matrix, this study gains insight into the contribution of each principal component to the different aesthetic dimensions. These results reveal the mechanisms through which different aesthetic dimensions influence aesthetic quality and corroborate the findings from the Random Forest, SVR, and Decision Tree models.

This study uses Principal Component Analysis (PCA) to extract the primary dimensions of the 11 aesthetic criteria in order to analyze the key influencing factors for artworks at varying levels of figuration.

The PCA score plot (Fig. 7) shows that:Low-figuration artworks have lower PC1 scores, and their aesthetic experience is primarily influenced by factors such as symbolism and cultural context.High-figuration artworks typically exhibit higher visual realism, and therefore, they are concentrated on the right side of the PC1 axis, associated with visual harmony and accurate object representation.Medium-figuration artworks are positioned in the middle of the PC1 axis, indicating that they possess both figurative and abstract characteristics, featuring clear visual structures while also engaging with symbolism and cultural context. These artworks are likely to evoke diverse aesthetic interpretations, appealing to different viewers' aesthetic preferences.

Furthermore, the PCA loading plot (Figure 8) shows that the second principal component (PC2) is positively correlated with complexity, emotionality, and intellectuality, with relatively balanced distribution trends across artworks of different figuration types. This suggests that both figurative and abstract works are influenced by complexity and emotionality in shaping the viewer's aesthetic experience.

The PCA results reveal the main driving factors in aesthetic experience for artworks at different levels of figuration (Fig. 7 and 8):

Low-figuration artworks are mainly influenced by symbolism, cultural context, and intellectuality, indicating that abstract art tends to stimulate viewers' conceptual associations and cultural interpretations.High-figuration artworks are primarily driven by visual harmony and accuracy of object representation, suggesting that their aesthetic experience relies more on the recognizability of form and structure.Medium-figuration artworks exhibit both figurative and abstract features, indicating that they may serve as a balance point for viewers between cognitive load and aesthetic preference.

This finding complements the results from the machine learning models. Random Forest analysis indicates that visual harmony and emotionality are the most significant factors influencing Aesthetic value, while the PCA results further highlight that symbolism, cultural context, object

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representation accuracy, and Thoughtfulness hold varying weights across artworks with different levels of figuration (Fig. 7 and 8).

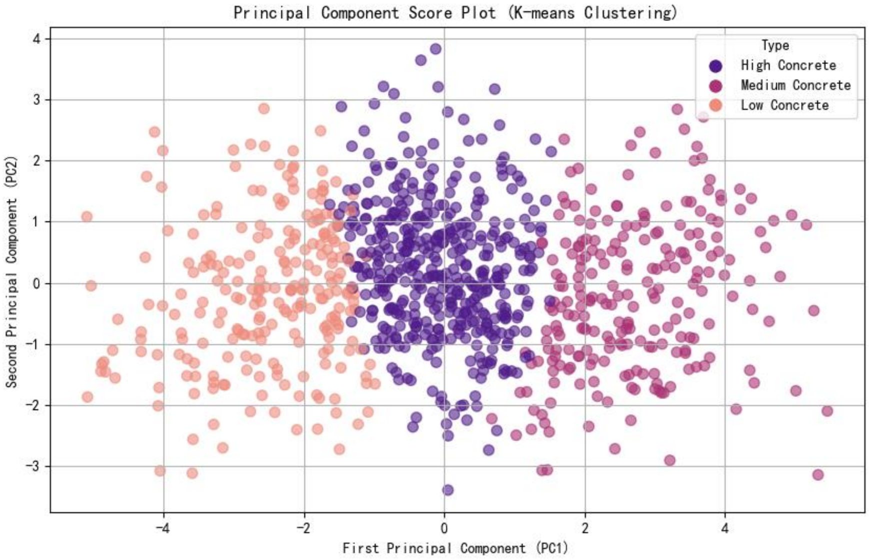

Fig. 7 Principal Component Analysis Score Plot

This figure shows the distribution of artworks with varying levels of figuration along the principal component axes, with classification performed using the K-means clustering method. The first principal component (PC1) primarily distinguishes between figuration and abstraction, while the second principal component (PC2) reflects the variation in complexity and symbolism across the artworks.

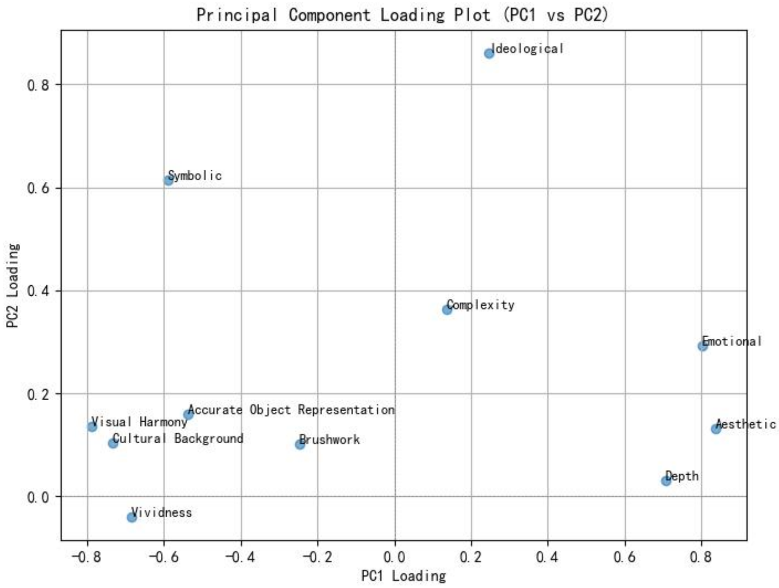

Fig. 8 Principal Component Analysis Loading Plot

Aesthetic quality and emotionality have higher loadings on PC1, indicating that these two dimensions have a significant impact on the variation in PC1. They primarily reflect features of figuration, such as visual harmony and accuracy of form. Symbolism and complexity have higher loadings on PC2, suggesting that these two dimensions significantly influence the variation in PC2, reflecting the importance of abstraction, complex cognitive processing, and emotional response in the artworks.

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5. Discussion

This study found that, for Xu Beihong’s horse paintings, visual harmony and emotionality are the main factors influencing aesthetic evaluation at different levels of figuration. High-figuration artworks scored higher on visual harmony, which is related to the clarity of their contours and well-defined structure, making it easier to evoke emotional resonance in viewers. In contrast, low-figuration artworks rely more on symbolism and cultural context, with viewers interpreting these elements emotionally.

Compared to Western art studies, this research offers a new perspective. Western research often suggests that abstract art triggers cognitive processing through complex forms, while figurative art generates aesthetic pleasure through the representation of forms. This study found that low-figuration artworks received higher emotionality scores, indicating that abstract works can evoke strong emotional reactions through emotional interaction. This demonstrates that aesthetic evaluation is not only influenced by visual features but is also closely related to viewers' emotional and cognitive experiences.

The sample in this study primarily consisted of participants with an art background, which may affect the generalizability of the results. Future studies could broaden the sample to include participants from various backgrounds. Additionally, the study is limited to Xu Beihong's horse paintings; future research could extend to artworks of different artistic styles and cultural contexts to validate the universality of figuration in aesthetic evaluation.

Although this study explored the impact of figuration on aesthetic quality using 11 different criteria, certain limitations still exist. Future research could combine eye-tracking technology to analyze visual attention patterns when viewers appreciate artworks with different levels of figuration, further understanding their effects on emotion and cognition. Additionally, integrating brain imaging techniques (such as fMRI or EEG) could explore the processing mechanisms of artworks with varying levels of figuration in the brain, providing more comprehensive evidence for aesthetic evaluation.

6. Conclusion

This study investigates the impact of different levels of figuration on the aesthetic evaluation of traditional Chinese animal ink paintings. The results indicate that visual harmony and emotionality are core factors influencing aesthetic quality, with high-figuration artworks performing well on these dimensions, while low-figuration artworks rely more on the interpretation of symbolism and cultural context.

The main contribution of this study lies in its systematic exploration of the different mechanisms through which abstraction and figuration influence the aesthetic evaluation of traditional Chinese ink animal paintings, particularly through the use of machine learning models to analyze the predictive ability of aesthetic dimensions. This provides a new perspective for the aesthetic study of traditional Chinese animal ink paintings, especially Xu Beihong's horse paintings, and expands the application of traditional aesthetic theory.

The significance of the study is twofold: on one hand, it reveals the mechanisms through which different levels of figuration in Chinese traditional animal paintings affect aesthetic evaluation, providing theoretical support for understanding the aesthetic differences between figurative and abstract art; on the other hand, the innovative research methods (such as the application of machine learning models) offer new directions for future aesthetic research, particularly in the quantitative analysis of the aesthetic features of artworks.

Overall, this study provides new insights into the aesthetic perception of traditional Chinese animal ink paintings and contributes to the application and development of computational aesthetics methods, offering both academic value and practical significance.

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