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Article

Research on Multidimensional Evaluation Method of Digital Art Works Based on Multimodal Data Fusion Technology

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Abstract: Aiming at the problems that the traditional evaluation model does not realize the full use of information, resulting in poor generalization ability and low prediction accuracy, this paper combines the BPNN algorithm with the Self-attention mechanism, and puts forward a multi-dimensional evaluation model for digital art works based on SA-BPNN multimodal fusion. A multi-dimensional evaluation index system for digital art works is constructed, in which the weights of the indexes are obtained through the hierarchical analysis method. It is found that the aesthetic value is the most important in the final rating of digital art works, and emotional resonance and creative autonomy are also important evaluation elements. The study validated the weights of the AHP method by constructing a back-propagation neural network, and after validation, the prediction accuracy of the evaluation model reached 98.85%, which proved the effectiveness of the evaluation model. This paper provides theoretical support and tools for the realization of multi-dimensional evaluation of digital art works by using multimodal data fusion technology.

Keywords: BPNN; Self-attention mechanism; multimodal fusion; hierarchical analysis method; multidimensional evaluation; digital art work

1. Introduction

Digital art is an art form that integrates digital technology with art, featuring diverse forms of expression, including but not limited to computer-generated art, digital imagery, virtual reality, and interactive art [1-2]. The use of digital tools facilitates the creation of digital art, particularly through the use of computer-aided design software, digital color grading software, animation production software, and other tools to process, composite, and enhance images and audio [3-5]. Additionally, one feature of digital tools is their ease of use for collaborative work, enabling collective creation of a single piece [6]. Digital art can also be created using computer programs, which requires creators to possess programming skills. Compared to the use of digital tools, programming offers greater creative freedom and enables the realization of more intricate and complex artistic effects [7-9]. As digital tools continue to evolve, the creation of digital artworks will become increasingly diverse, personalized, and convenient. The digital elements incorporated into digital artworks will significantly enrich the expressive forms of art, while also better meeting the needs of audiences and deepening the interaction between artworks and viewers [10-12]. Therefore, digital artworks have a broad future prospects. To promote artistic innovation, expand creative directions, and foster the healthy development of the digital art market, it is necessary to evaluate digital artworks.

Research on the evaluation of digital artworks is limited. Literature [13] utilized the K-median algorithm to construct an evaluation system for digital art effects, providing support for the quality and understanding of digital art creation, as well as the interpretation of abstract images. Literature [14] developed an artificial intelligence artworks evaluation system, which established multi-dimensional evaluation criteria including aesthetics, color, texture, detail, lines, and style. Literature [15] designed an indicator named “ArtScore” to assess the similarity between AI-generated images and human-created works, and combined pre-trained models and neural networks to evaluate AI-generated images.

Literature [16] revealed that the creation process influences viewers' evaluations of AI artworks, and this influence increases with the richness of color. Literature [17] designed an evaluation model integrating Prilogian, neutrality, forest soft structure, expert opinion, hierarchical attributes, and fuzzy logic to assess the innovation of digital media art, considering different dimensions of innovation evaluation. The evaluation of digital artworks involves three major dimensions: material aspects such as image clarity and audio quality; meaningful aspects such as depth of content and thematic expression; and experiential aspects such as the emotional enjoyment the artwork brings to the audience. Compared to traditional art, digital artworks have more interactive forms of presentation, offering audiences more personalized experiences and immersive sensations [18-19]. Therefore, the evaluation of digital artworks also involves multimodal data such as text, images, speech, and video, which need to be integrated to comprehensively evaluate the artwork.

With the continuous development of technology, the data we face is becoming increasingly diverse, and different types of data are interconnected and influence each other. To better utilize this data, multimodal data fusion technology has emerged [20]. Taking a digital painting as an example, the artwork contains visual elements such as color, shape, and lines, as well as textual descriptions of the artwork and audio/video introductions about its creation background. Multimodal data fusion integrates these visual, textual, and audio data into a more complete and valuable whole, enabling a deeper understanding of the artwork and a more comprehensive evaluation of the work [21-23].

Based on traditional art work evaluation standards and related literature, this paper constructs a multi-dimensional evaluation system for digital art works including 10 dimensions and 30 indicators, and realizes the evaluation indicator assignment through hierarchical analysis method. At the same time, based on the multimodal data fusion technology, a multidimensional evaluation model for digital art works combining BP neural network and self-attention mechanism is proposed, and the weights sought by the hierarchical analysis method are experimentally verified using the SA-BPNN model.

2. Evaluation Method for Digital Artworks Based on Multimodal Data Fusion

In order to realize the multi-dimensional evaluation of digital art works, this paper constructs a multi-dimensional evaluation index system of digital art works, and uses the hierarchical analysis method to find the index weights, and finally combines the BPNN algorithm with the Self-attention mechanism to construct a digital art work evaluation model based on the fusion of multi-modal data.

2.1. BPNN Algorithm

The idea of artificial neural network algorithm initially comes from the way of neuron cell information transmission when the human brain deals with the problem, the back propagation neural network (BPNN) [24] as an important algorithm in the artificial neural network, its main feature lies in the proposal of the back propagation of the reverse back to the way of adjusting the parameters of the network, through which the performance of artificial neural network has been greatly improved, and thus has been applied to many practical scenarios. At the same time, it also promotes the development of complex networks such as CNN, RNN, etc. The network structure of BPNN is shown in Figure 1, and its basic components mainly include: input layer, hidden layer, and output layer.

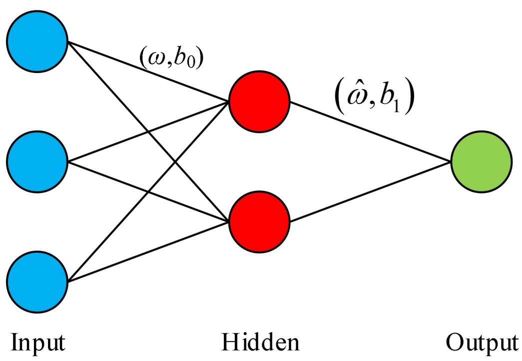


Figure 1. BPNN network structure.

The idea of BPNN algorithm is mainly as follows: firstly, calculate the error of the network through forward propagation, then find the partial derivatives of the parameters in the network with the help of the chain rule for the error function, and then use the direction of the partial derivatives to determine the adjustment value of the parameters, and then finally achieve the purpose of reverse back propagation to gradually optimize the parameters in the network. In forward propagation, the value of the weights between the neurons of the current layer and the neurons of the neighboring layers is first calculated to obtain the inputs of the neurons of the next layer. This is then represented nonlinearly using a nonlinear activation function to characterize the complexity of the input information.

Commonly used nonlinear activation functions in BPNN are: sigmoid function, tanh function, and relu function. sigmoid function is mainly characterized by the ability to map the continuous values of the input to the [0,1] interval, but it has the disadvantage of easy saturation, i.e., when the input is too large or too small, the gradient of the back-propagation is close to 0, which results in the slow updating speed of the weights. The tanh function achieves nonlinear activation by mapping continuous values of the input to the [-1,1] interval, but has the same disadvantage of easy gradient saturation as the sigmoid function. The relu function is a segmented linear function, so there will be no gradient saturation in the network back propagation, thus convergence speed is faster, but it will have the problem of neuron necrosis.

Taking the network structure in Fig. 1 as an example, the steps of the BPNN algorithm are as follows:

Input: sample data set X .

Output: predicted value $\hat{y}$.

Step1: Initialize the parameters (ω, b_0) , $(\hat{\omega}, b_1)$ in the network.

Step2: Forward propagation, calculate the loss function $E(\theta)$:

$$\begin{cases} H = \sigma(\omega \cdot X + b_0) \\ y = \hat{\omega} \cdot H + b_1 \\ E(\theta) = \frac{1}{2}(\hat{y} - y)^2 \end{cases} \tag{1}$$

where H denotes the hidden layer output, σ denotes the activation function, θ represents all the parameters in the network, and $\hat{y}, y$ denotes the predicted and true values respectively.

Step3: Calculate the partial derivatives of the loss function $E(\theta)$ with respect to the network parameters (ω, b_0) , $(\hat{\omega}, b_1)$, based on the chain rule method:

$$\begin{cases} E_{\hat{\omega}^{(k)}}(\theta) = \frac{\partial E(\theta)}{\partial \hat{\omega}}, E_{b_1^{(k)}}(\theta) = \frac{\partial E(\theta)}{\partial b_1} \\ E_{\omega^{(k)}}(\theta) = \frac{\partial E(\theta)}{\partial \omega}, E_{b_0^{(k)}}(\theta) = \frac{\partial E(\theta)}{\partial b_0} \end{cases} \tag{2}$$

Step4: Update of network weights and biases:

$$\begin{cases} \hat{\omega}^{(k)} = \hat{\omega}^{(k-1)} - \eta E_{\hat{\omega}^{(k)}}(\theta), b_1^{(k)} = b_1^{(k-1)} - \eta E_{b_1^{(k)}}(\theta) \\ \omega^{(k)} = \omega^{(k-1)} - \eta E_{\omega^{(k)}}(\theta), b_0^{(k)} = b_0^{(k-1)} - \eta E_{b_0^{(k)}}(\theta) \end{cases} \tag{3}$$

where η is the learning rate.

Step5: λ is the set threshold, determine whether the error $E(\theta) < \lambda$ is valid, if it is valid then stop training, otherwise repeat Step2-Step4.

2.2. Self-Attention Mechanism

In traditional neural network models, each input feature is treated as equally important information, but in practice, certain features may be more important than others. For this reason, the Attention mechanism is proposed to allow the model to weight certain parts of the input sequence when processing it in order to better capture important information.

Typically, the Attention mechanism can be divided into three steps: calculating the Attention weights, weighting the scores, and convergence. Among them, calculating the Attention weights is to generate an Attention matrix based on the input data and the model parameters, which indicates how much attention the model pays to each element in the input data. In the weighted score step, the weights are multiplied and summed element-by-element with the input data to calculate the weighted score. Finally, in the aggregation step, the weighted score is used to summarize all the input data and use it as the output.

Attention extracts the temporal and spatial correlation of the sample data by attention calculation and is widely used in sequential information processing.Self-attention [25] is a variant of Attention, which reduces the dependence on external information and is more adept at capturing internal correlations between the input variables of the neural network.The computational equation of Self-attention is:

$$Attention(Q,K,V) = soft\ \max\left(\frac{QK^T}{\sqrt{d_K}}\right)V \tag{4}$$

The Self-attention computation process is to encode the input sample data into embedding vectors, and learn the information in them by training the sample data to obtain three vectors Q, K and V. Next, an indicator parameter α expressing the correlation between the other input data and it is calculated for each input sample data, $\alpha = Q \times K$ When the dimension of the input vectors is relatively high, the α usually has a relatively large variance, which leads to the gradient of the Softmax function will be smaller, this is mitigated by dividing α by $\sqrt{d_K}$ to improve the stability of the gradient.

After applying an activation function Softmax to α and then dot-multiplying the information vector V obtained by self-learning from the input sample data, the optimized features are finally obtained after Self-attention to extract the correlation of the sample parameters for subsequent classification applications. The Self-attention model used in this paper is shown in Fig. 2. By introducing the Self-attention model, we can capture the dependencies between long sequences, self-attend to the features at different locations thus learning the global information, and at the same time avoiding the problem of information decay and paying more attention to the parts that are useful for solving the task.

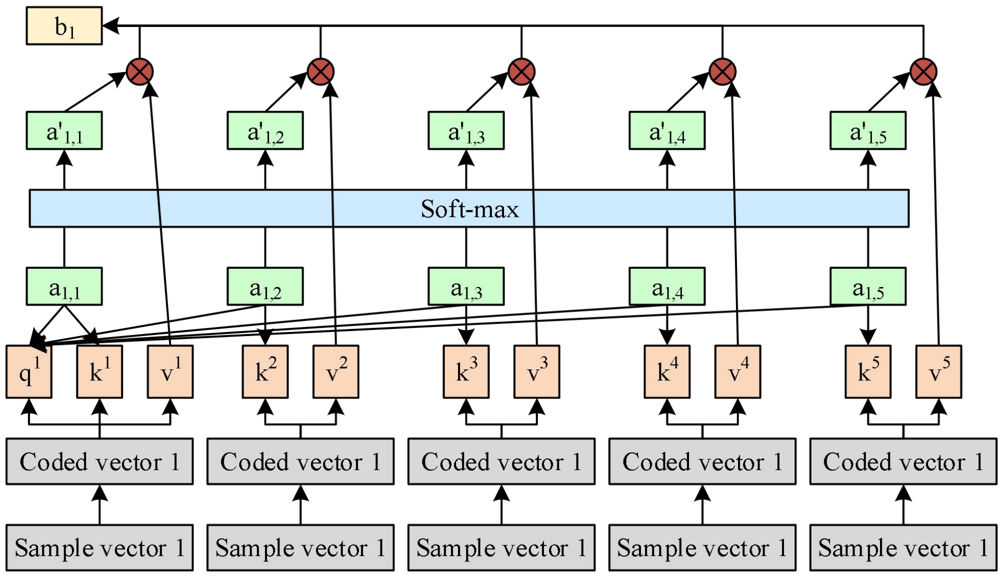


Figure 2. Self-attention model structure.

At the same time, the Self-attention model can be more easily parallelized. Because each time step can be computed independently, the Self-attention model is well suited for parallelized computation on GPUs, which can significantly reduce the time consumption for training and prediction. In addition, combining the input sequences through multiple parallel attention mechanisms yields a multi-head attention mechanism, which allows the model to better utilize the sequence information and capture the key features in the input sequences. By dividing the query vector into multiple sub-vectors, and then performing separate attention computations for each sub-vector, a final output vector can be obtained by weighted summation, which contains an aggregation of all the heads with different representations and different weights in the input sequence.

2.3. Establishment of Multi-Dimensional Evaluation Index System for Digital Art Works

2.3.1. Multi-Dimensional Evaluation System for Digital Artworks

When constructing the evaluation system of digital artworks, this paper draws on the multi-dimensional methods of traditional artwork evaluation and the evaluation indicators proposed by existing researches, and combines the characteristics of digital artworks to form a multi-dimensional evaluation system of digital artworks, as shown in Table 1. The evaluation system includes 10 dimensions: aesthetic value (A1), technical execution (A2), imaginative expression (A3), socio-cultural influence (A4), audience feedback (A5), interactivity and participation (A6), interdisciplinary integration (A7), emotional resonance (A8), creative autonomy (A9), ethics and responsibility (A10), and is subdivided into 30 indicators: visual impact (B1), aesthetic harmony (B2), style innovation (B3), Technical Accuracy (B4), Technical Complexity (B5), Creative Efficiency (B6), Creative Uniqueness (B7), Depth of Expression (B8), Innovation Interpretation (B9), Cultural Sensitivity (B10), Social Issue Reflection (B11), Cultural Inheritance and Innovation (B12), Audience Acceptance (B13), Discussion Triggering (B14), Emotional Touch (B15), Participation Mechanism Design (B16), Interactive Experience Quality (B17), Post-Engagement Impact (B18), Breadth of Knowledge Integration (B19), Depth of Integration (B20), Cross-border Influence (B21), Emotional Expression (B22), Resonance Trigger Point (B23), Emotional Continuity and Response (B24), Independent Creative Decision-making (B25), Independent Thinking Ability (B26), Independence of Creative Style (B27), Ethical Code Compliance (B28), Transparency and Explainability (B29), and Social Responsibility (B30).

Table 1. Multi-dimensional evaluation index system for digital art works.

Target layer	Criterion layer	Index layer
Multi-dimensional evaluation of digital art works (O)	A1	B1
		B2
		B3
	A2	B4
		B5
		B6
	A3	B7
		B8
		B9
	A4	B10
		B11
		B12
	A5	B13
		B14
		B15
	A6	B16
		B17
		B18
	A7	B19
		B20
		B21
	A8	B22
		B23
		B24
	A9	B25
		B26
		B27
	A10	B28
		B29
		B30

2.3.2. Determination of Indicator Weights for AHP-Based Evaluation System

In the process of multi-dimensional evaluation of digital art works, each evaluation index plays a different role in the evaluation results, and the weight value is usually used to describe the role of each evaluation index on the evaluation results, and this paper uses the hierarchical analysis method (AHP) [26] to determine the index weights.

(1) Expert scoring to establish judgment matrix

According to the multi-dimensional evaluation index system of digital art works in Table 1, 25 experts are invited to make two-by-two comparisons of the indicators governed by the same upper level indicators in the same level starting from the second level of the evaluation index system. The judgment matrix scale and meaning are shown in Table 2.

Table 2. Judgment matrix scale and its meaning.

Scale a_{ij}	Meaning
1	Factors i and j are equally important
3	Factor i is slightly more important than factor j
5	Factor i is significantly more important than factor j
7	Factor i is strongly more important than factor j
9	Factor i is extremely important than factor j
2, 4, 6, 8	The scale values corresponding to the intermediate states between the above judgments
Countdown	Factor i is compared with j to obtain a_{ij}, then factor j is compared with i to obtain $a_{ji} = 1/a_{ij}$, a_{ii}=1

The relative importance of the peer indicators was scored according to Table 2, and the comparisons were transformed into a quantitative judgment matrix $A = (a_{ij})_{n\times n}$:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{5}$$

where a_{ij} is the relative importance of the i indicator to the j indicator, which is scored by experts, and n is the number of indicators.

According to the expert scoring situation, the judgment matrix of the first-level indicator $A_1 \sim A_{10}$ of the multi-dimensional evaluation index system of digital art works constructed in this paper relative to the top-level total target of the multi-dimensional evaluation of digital art works is $A_a = (a_{ij})_{10\times 10}$, the judgment matrix of the second-level indicator $B_1 \sim B_3$ relative to the first-level indicator A_1 is $A_1 = (a_{ij})_{3\times 3}$, the judgment matrix of $B_4 \sim B_6$ relative to A_2 is $A_2 = (a_{ij})_{3\times 3}$,... The judgment matrix $A_9 = (a_{ij})_{3\times 3}$ of $B_{25} \sim B_{27}$ relative to A_9 , and the judgment matrix $A_{10} = (a_{ij})_{3\times 3}$ of $B_{28} \sim B_{30}$ relative to A_{10} .

(2) The weight vector of the index is calculated and the consistency test is carried out

1) Normalize each column element of the judgment matrix A :

$$a'_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad i, j = 1, 2, \cdots, n \tag{6}$$

2) Sum each column of the normalized judgment matrix by column:

$$w_{i'} = \sum_{j=1}^{n} a'_{ij} \quad j = 1, 2, \cdots, n \tag{7}$$

3) Normalize the vector $W' = \left(w'_1, w'_2, \cdots, w'_n\right)^T$:

$$w_{ij} = \frac{w'_i}{\sum_{i=1}^{n} w'_i} \quad i = 1, 2, \cdots, n \tag{8}$$

Get $W = \left(w_1, w_2, \cdots, w_n\right)^T$ which is the desired eigenvector.

4) Calculate the maximum eigenvalue of the judgment matrix $\lambda_{\max}$:

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^{n} \frac{AW}{w_i} i = 1, 2, \cdots, n \tag{9}$$

5) Sorting consistency test:

$$CR = \frac{CI}{RI} \tag{10}$$

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{11}$$

where CR is the consistency ratio, CI is the consistency indicator, and RI is the average random consistency indicator. The values of RI according to the number of indicators n are shown in Table 3.

Table 3. The value of the average random consistency index *RI*.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

When $CR < 0.10$, it can be considered that the judgment matrix A meets the consistency requirements, indicating that the importance judgment of each criterion is reliable, and its eigenvector can be used as its weight vector, otherwise the judgment matrix should be appropriately amended.

The weights of the middle tier m indicators $A_1 \sim A_m$ to the overall goal Z were calculated $W = \left(a_1, a_2, \cdots, a_m\right)^T$ and the weights of the bottom tier n indicators to the $A_j (j = 1, 2, \cdots, m)$ indicators in the middle tier were $W_{Aij} = \left(b_{1j}, b_{2j}, \cdots, b_{nj}\right)^T$ calculated.

According to the above calculation method, after using Eqs. (6) to (11) to calculate and consistency check the judgment matrix constructed in this paper, the indicator weight vector $W_a = \left(a_1, a_{21}, a_3, a_4\right)^T$, $W_1 = \left(b_{11}\right)$, $W_2 = \left(b_{12}, b_{22}\right)^T$, $W_2 = \left(b_{13}\right)$ and $W_4 = \left(b_{14}\right)$.

6) Calculate the indicator combination weight vector:

$$B_n = \sum_{j=1}^{m} a_j a_{ij} \quad i = 1, 2, \cdots, n; j = 1, 2, \cdots, m \tag{12}$$

where: a_j is the weight value of indicator A_j in A layer and b_{ij} is the weight value of indicator B_i on indicator A_j in B layer.

2.4. Multi-Dimensional Evaluation Model Design for Digital Art Works

In this paper, for three kinds of digital artwork evaluation data modalities, namely, manual scoring, digital artwork design platform and VR video, a hierarchical model structure is adopted to obtain the information characteristics of each modality separately and then hybrid fusion is carried out to realize the multimodal fusion evaluation. This paper proposes a multimodal fusion digital artwork evaluation model based on self-attention mechanism and improved BP neural network. The model contains four components: self-attention mechanism, modal feature extraction, multimodal feature fusion and evaluation prediction.

2.4.1. Data Pre-Processing

(1) Evaluation data collection

For manual modal data, this paper sets collection indexes based on the evaluation questionnaire of digital art works. For platform modal data, this paper analyzes big data with a variety of software that generally has the function of designing digital art works. For video modal data, this paper uses VR video dataset of digital art works to collect evaluation data.

(2) Data Normalization

Due to the different evaluation units between different indicators, this paper uses the maximum-minimum value method to normalize the data, and expresses the normalized modal data as $X_i = [e_{11}, e_{12}, \cdots, e_{1i}], X_j =$, $X_j = [e_{11}, e_{12}, \cdots, e_{1j}]$ and $X_k = [e_{11}, e_{12}, \cdots, e_{1k}]$, where X_i denotes the manual modal input data, X_j denotes the platform modal input data, and X_k denotes video modal input data.

2.4.2. Modal Feature Extraction

The SA-BPNN module aims to capture the feature information of 3 different modalities. The self-attention mechanism is introduced to enhance the feature learning and relationship modeling capabilities in the multidimensional evaluation system of digital artworks. The self-attention mechanism effectively captures the correlations between different evaluation metrics while assigning dynamic weights to each metric, highlighting important information and adapting to long-range dependencies. These weighted representations are re-inputted as high-level features to enhance model performance and prediction accuracy.

The core idea of the self-attention mechanism is “non-local averaging” to enhance the attention of important information and the overall connection between features. The core idea is to convey information by calculating the similarity of information between the target location Q and other non-local locations K . The weighted summation takes place in the non-localized region, thus effectively correcting the information of the target location. The mechanism is divided into 3 steps and there exist Q , K and $V3$ matrices for each feature.

First, the modal a are $Q_i = WX_i^a W_1$, $K_i = WX_i^a W_2$, $V_i = WX_i^a W_3$. The similarity between the calculated features is shown in equation (13):

$$S_j = \frac{Q_i \times K_j}{\sqrt{d_k}} \tag{13}$$

where: X_i^a denotes the i th eigeninformation of the a th modality. Q_i denotes the Q matrix of the i th eigeninformation. K_i denotes the K matrix for the i th feature. The $\sqrt{d_k}$ denotes the value at which the similarity is scaled to ensure that the similarity calculation is within the appropriate range. S_j denotes the similarity between the i th feature information and the j th feature information. W , W_1 , W_2 and W_3 are the introduced trainable parameters used to train the model for a specific task.

Secondly, the Softmax function is applied to normalize the similarity to obtain the weight representation. These weights represent the weight distribution of similarity in the overall input, which sums up to 1. The weight values Z_i are shown in equation (14):

$$Z_i = \frac{\exp S_j}{\sum_{j=1}^{m} \exp S_j} \tag{14}$$

where: the variable m denotes the number of features of the modality a, and $\exp$ denotes the exponential function with the natural constant e as the base.

Finally, the attention value f_{a_i} between the i th feature of the modality a and the other features is calculated as shown in equation (15):

$$f_{a_i} = \sum_{j=1}^{m} Z_j V_j \tag{15}$$

Similarly, the final calculation of the high-level feature information of the three modes is shown in Equation (16):

$$\begin{cases} F_a = \left[f_{a1}, f_{a2}, f_{a3}, \cdots, f_{an}\right] \\ F_p = \left[f_{p1}, f_{p2}, f_{p3}, \cdots, f_{pn}\right] \\ F_v = \left[f_{v1}, f_{v2}, f_{v3}, \cdots, f_{vn}\right] \end{cases} \tag{16}$$

This high-level feature information is passed as input to the subsequent BP neural network as shown in equation (17):

$$\overline{f}_j = g\left(\sum_{i=1}^{m} W_{ij} f_{ai}\right) \quad (17$$

where: W_{ij} denotes the weight matrix, f_{ai} denotes the information of the i th high-level feature of the modal a, the function $g(\cdot)$ is the activation function and $\overline{f}_j$ represents the information of the j th neuron.

Ultimately, the obtained artificial modal, platform modal and video modal feature information $\overline{f}$ is represented as shown in equation (18):

$$\begin{cases} \overline{F}_a = \left[\overline{f}_{a1}, \overline{f}_{a2}, \overline{f}_{a3}, \cdots, \overline{f}_{am}\right] \\ \overline{F}_p = \left[\overline{f}_{p1}, \overline{f}_{p2}, \overline{f}_{p3}, \cdots, \overline{f}_{pm}\right] \\ \overline{F}_v = \left[\overline{f}_{v1}, \overline{f}_{v2}, \overline{f}_{v3}, \cdots, \overline{f}_{vm}\right] \end{cases} \quad (18$$

where: m denotes the dimension of the modal feature information.

2.4.3. Feature Fusion Strategy

The MF-BPNN module is a trainable hybrid fusion structure for cross-modal information fusion, which improves the prediction of the model in the case of partial modal absence.

It is known that before hybrid fusion in this paper and when the modal information is complete, the input information is composed as shown in equation (19):

$$\left\{F_{input}\right\} \begin{cases} \overline{F}_a = [\overline{f}_{a_1}, \overline{f}_{a_2}, \overline{f}_{a_3}, \cdots, \overline{f}_{a_m}] \\ \overline{F}_p = [\overline{f}_{p_1}, \overline{f}_{p_2}, \overline{f}_{p_3}, \cdots, \overline{f}_{p_m}] \\ \overline{F}_v = [\overline{f}_{v_1}, \overline{f}_{v_2}, \overline{f}_{v_3}, \cdots, \overline{f}_{v_m}] \end{cases} \tag{19}$$

The feature information is mixed and fused, and the input information of the j th neuron in the input layer of the prediction model is calculated as shown in equation (20):

$$\left\{F_{input}\right\}_j = \frac{1}{n}\sum_{i=1}^{n}\overline{f}_{ij} \tag{20}$$

where: n denotes the number of input modalities of the test sample, and i denotes the i th modality.

In this paper, the input information after mixing and fusing the 3 modalities of manual, platform and video is shown in equation (21):

$$\left\{F_{input}\right\} = \begin{cases} \overline{F}_1 = [\overline{f}_{a_1} + \overline{f}_{p_1} + \overline{f}_{v_1}]/3 \\ \overline{F}_2 = [\overline{f}_{a_2} + \overline{f}_{p_2} + \overline{f}_{v_2}]/3 \\ \vdots \\ \overline{F}_3 = [\overline{f}_{a_m} + \overline{f}_{p_m} + \overline{f}_{v_m}]/3 \end{cases} \tag{2}$$

2.4.4. Multidimensional Evaluation Prediction of Digital Artworks

The multidimensional evaluation prediction model for digital art works is based on the BP neural network structure. The first layer is the input layer containing m neurons, the input is denoted as $F_{input} = \left\{\overline{F}_1, \overline{F}_2, \cdots, \overline{F}_j\right\}$, and the second layer is the hidden layer containing p neurons. neurons, and the last layer is the output layer containing q neurons with an output value of $y_{score} = y$. The computation process of input layer and hidden layer neurons is shown in equation (22):

$$h_i = \varphi\left(\sum_{j=1}^{m} w_{ij}\overline{F}_j + \theta_i\right), i = 1, 2, \cdots, p \tag{22}$$

where: h_i denotes the output value of the i th neuron, φ denotes the activation function Sigmoid, θ_i denotes the linear bias of the i th neuron, and w_{ij} denotes the connection weights between the i th neuron and the j th neuron.

The Tansig function is a nonlinear monotonic function, which is commonly used to represent nonlinear relationships, and at the same time meets the requirement of differentiability of the gradient descent algorithm in the backpropagation neural network. In this paper, the Tansig function is chosen as the activation function, denoted as $\varphi(x)$, and the relationship between the hidden layer and the neurons in the output layer is shown in equation (23):

$$o_k = \varphi\left(\sum_{i=1}^{p} w_{ik}h_i + \theta_k\right), k = 1, 2, \cdots, q \tag{23}$$

The essence of neural network training is to learn the correlation between data by comparing the error between the network output and the target output. Commonly used evaluation metrics include mean square error (MSE), cross-entropy loss, accuracy and R^2. In the training phase, MSE is used for the loss function, as shown in equation (24):

$$MSE_j = \frac{1}{2m}\sum_{k=1}^{n}(y_k - o_k)^2 \tag{24}$$

where: y_k denotes the true value of the rating result, o_k denotes the predicted value of the rating result, m denotes the number of test samples modal, and n is the number of test samples.

Repeat the training steps, the final output is the predicted value of multidimensional rating for digital art works, and the trained neural network can realize the mapping from input to output.

3. Measuring the Validity of Evaluation Methods for Digital Artworks

This chapter measures the effectiveness of the proposed evaluation method for digital art works, including the applicability measurement of the evaluation system, the calculation of AHP-based indicator weights, and the validation of SA-BPNN-based evaluation indicator weights.

3.1. Measurement of the Applicability of the Evaluation System

3.1.1. Evaluation of Digital Artworks Based on the AIGC Platform

Based on the constructed evaluation system of digital artworks, this study selects the current popular AIGC platform 1 and platform 2 for evaluation, and verifies the scientificity of the evaluation system with actual cases. In this study, "Chinese landscape painting" and "Europeoil painting" were used as prompts, and 12 paintings were drawn for each painting category of platform 1 and platform 2 to avoid the error of a single painting, and cross-evaluation experiments were carried out based on this.

According to the different types of variables in the multidimensional evaluation system of digital artworks, the study recruited two content coders to code the 30 dimensions in detail in 48 image materials, and the assessment scoring was done by the two coders.

The scoring consisted of three components: subjective user scoring, cue word test scoring, and social legitimacy scoring. The six dimensions of aesthetic value, emotional resonance, imaginative expression, socio-cultural impact, audience feedback, and interdisciplinary integration were derived from subjective user scoring. The 3 dimensions of technical execution, interactivity and participation, and creative autonomy come from the cue word test scoring. Ethics and responsibility were derived from social legitimacy scoring. Coders score based on basic socio-cultural ethics. The specific rules of scoring are that the total score of the evaluation system is 150 points, 10 first-level dimensions, 30 second-level dimensions, and 15 points for each first-level dimension. Take "aesthetic value" as an example, "the picture has complete visual impact (5 points), aesthetic harmony (5 points), stylistic innovation (5 points)", scoring 15 points, and so on for other dimensions.

The study ended up with 48 scores, each of which is the sum of the scores of the 30 digital artwork evaluation dimensions for each painting. The study calculates and averages the scores of Chinese landscape paintings (CLP) and European oil paintings (EP) on Platform 1 and Platform 2 respectively, and finally obtains the data of the evaluation scores of the dimensions of Chinese landscape paintings and European oil paintings design on Platform 1 as shown in Figures 3 and 4 respectively.

It can be clearly observed that the Chinese landscape paintings and European oil paintings created by Platform 1 and Platform 2 perform well in the dimensions of aesthetic value, technical execution, creative autonomy, and imaginative expression, and these scores significantly indicate that the AIGC technology has already reached or even surpassed the cognitive level of some human artists to a certain extent.

Although both Platform 1 and Platform 2 perform well in the area of digital artwork creation, Platform 2 significantly outperforms Platform 1 in the creation of Chinese landscape paintings and European oil paintings, mainly due to the unique design of the platform's algorithms, which makes it particularly good in the area of image generation. Platform 2, as a leading image generation platform, demonstrates higher aesthetic value, technical execution and creative autonomy.

When evaluating the socio-cultural impact of Chinese landscape paintings and European oil paintings created by Platform 1 and Platform 2, it was unexpectedly found that European oil paintings were generally higher than Chinese landscape paintings in terms of the socio-cultural impact indicators, a result that differed from the assumptions made prior to the evaluation. The original hypothesis was that since the coders were all of Chinese nationality, they would rate the socio-cultural impact of Chinese landscape painting higher. This phenomenon may reveal a deep-rooted cultural psychological mechanism: viewers may hold higher expectations and stricter evaluation standards for more familiar cultural backgrounds, while they may show higher acceptance for relatively unfamiliar cultures.

In addition, the high scores of Platform 1 and Platform 2 on ethics and responsibility reflect the deep consideration of social order and morality in the design of the Big Model algorithms, a "domestication" process that ensures that the algorithms avoid using unethical content in the creation of digital artworks.

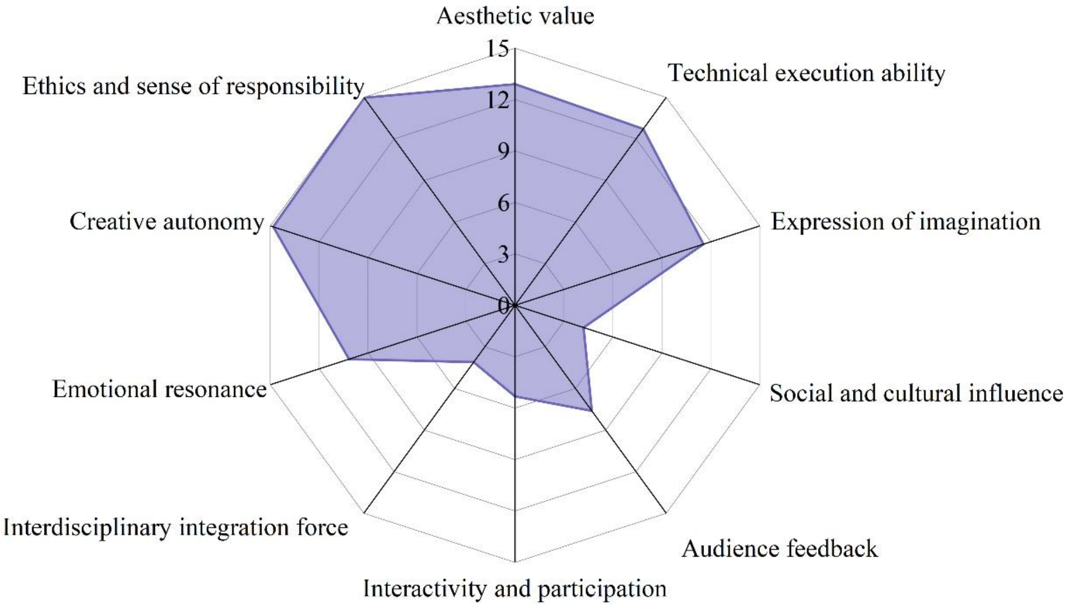


Figure 3. The scores of various dimensions of CLP design art on Platform 1.

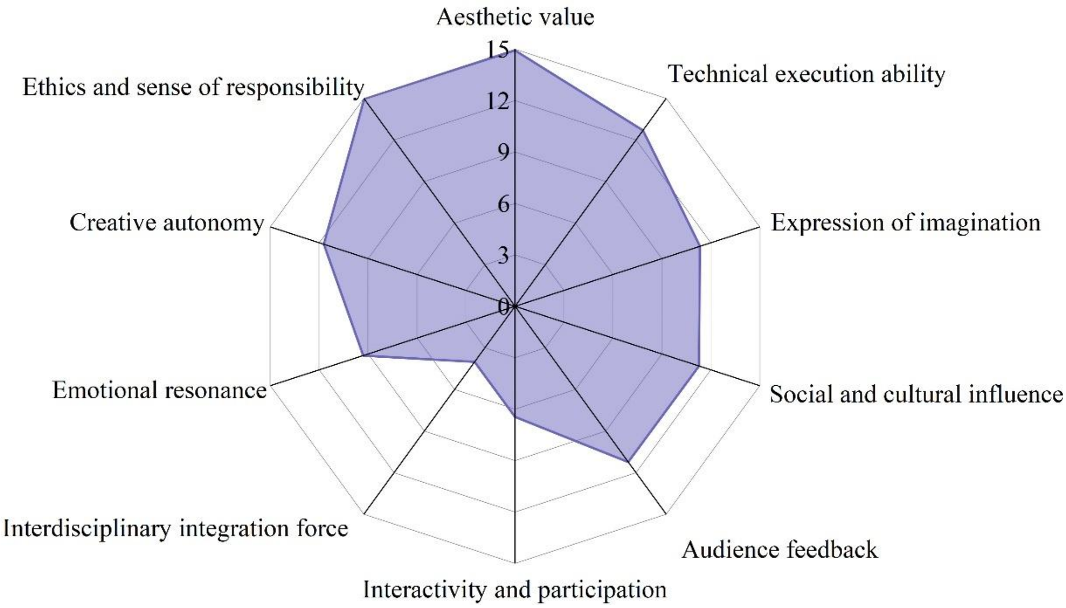


Figure 4. The scores of various dimensions of EP design art on Platform 1.

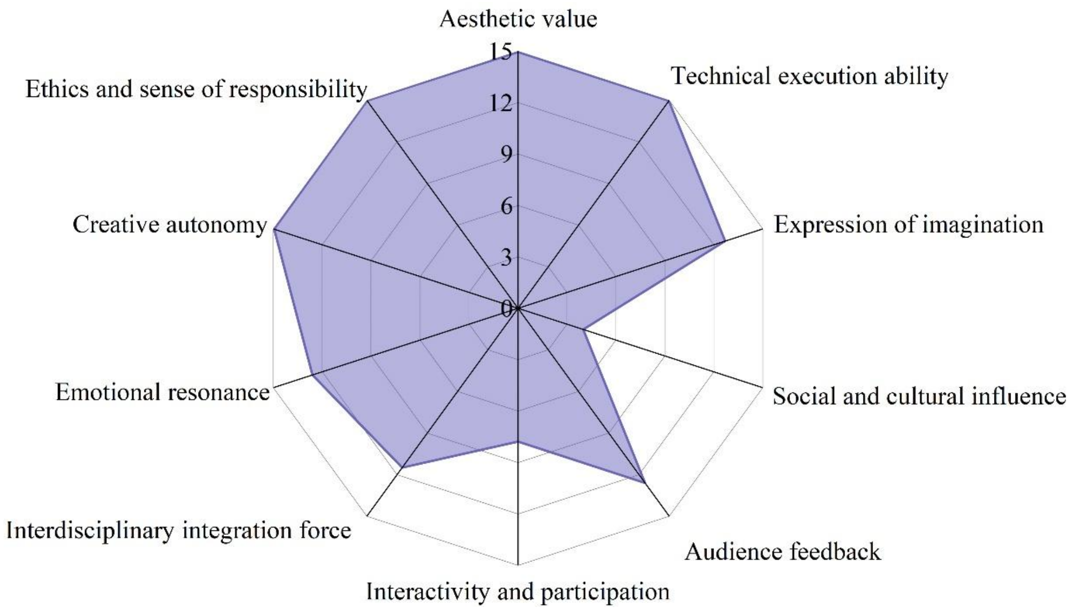


Figure 5. The scores of various dimensions of CLP design art on Platform 2.

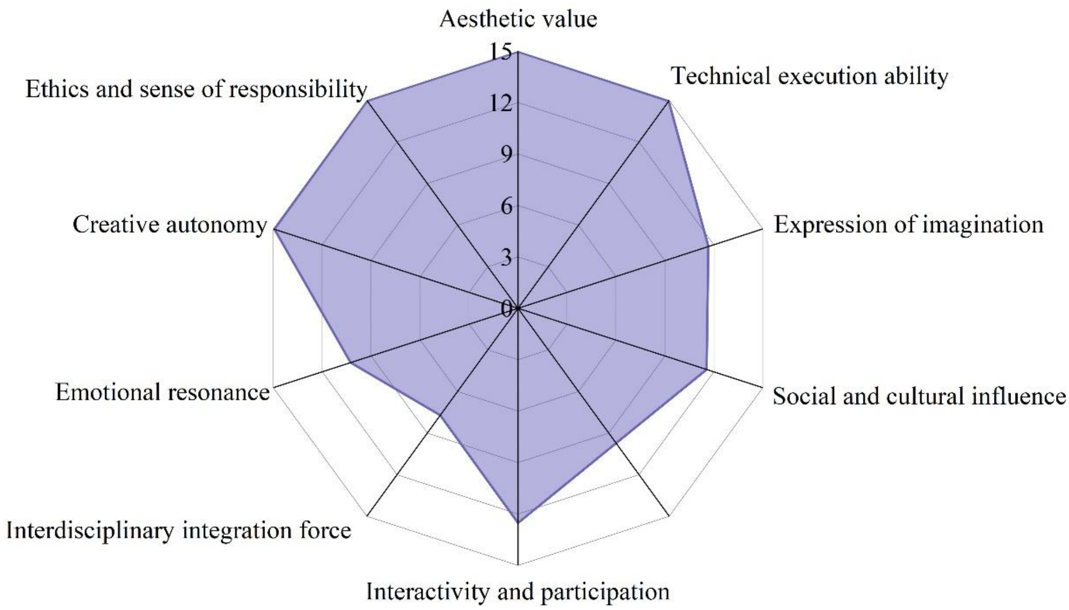


Figure 6. The scores of various dimensions of EP design art on Platform 2.

3.1.2. Factor Analysis and Regression Analysis of Evaluation Indicators

In order to construct a more intuitive and effective evaluation model, this study conducts factor and regression analysis based on the evaluation indexes of digital art works. In order to collect enough sample data, this paper randomly adopts the method of snowball sampling among college students who have used AI drawing, and finally obtains 400 questionnaires. The questionnaire items were centered around 30 evaluation indicators, and the questionnaire was measured by a five-point Likert scale method. After cleaning these data, some invalid samples were eliminated and finally 375 valid samples were retained. The 30 evaluation criteria of these 375 samples were factor analyzed, and the results of the factor loadings of the first four dimensions are shown in Figure 7. Aesthetic value, emotional resonance, creative autonomy, and imaginative expression are the top four topics that respondents are most concerned about, and the factor loadings of these four factors in each evaluation criterion are slightly different. Among them, the loadings of the aesthetic value of digital artworks are relatively high on multiple criteria, indicating that the factor is highly comprehensive and representative.

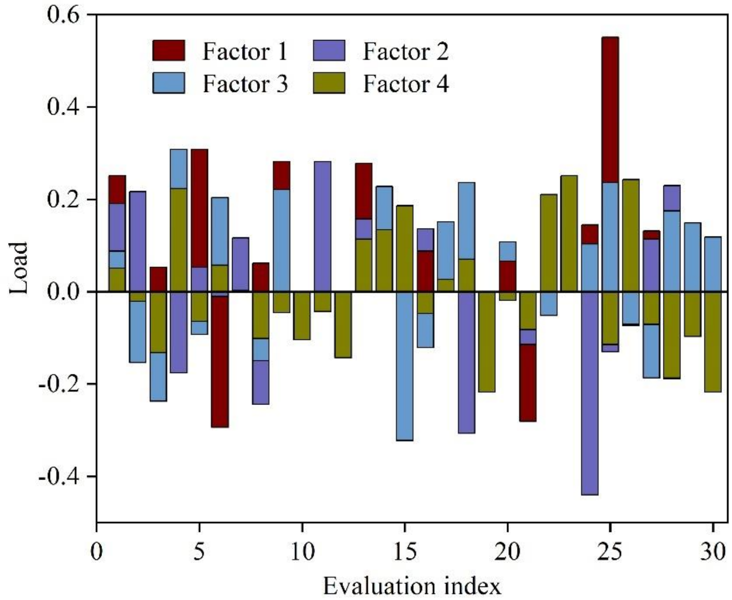


Figure 7. The factor payloads of the first four dimensions.

Based on the results of the factor analysis, this study further developed a regression model with the aim of determining the degree of influence of each factor on the final rating. The results of the factor regression analysis of the 10 dimensions of digital artwork evaluation are shown in Table 4. Where * indicates P<0.05, ** indicates P<0.01, and *** indicates P<0.001.

These coefficients indicate that there is a significant difference in the explanatory power of the different factors on the final score. The final equation obtained from the regression analysis is: digital artwork evaluation score = 2.8 (constant) + 0.92 × aesthetic value + 0.14 × technical execution + 0.51 × imaginative expression + 0.24 × socio-cultural impact + 0.09 × audience feedback + 0.35 × interactivity and engagement + 0.18 × interdisciplinary integration + 0.72 × emotional resonance + 0.55 × creative Autonomy + 0.17 × Ethics and Responsibility. In this equation, the regression coefficient of aesthetic value is 0.92, which is significantly higher than the other factors, indicating that aesthetic value occupies the most important position in the final score. The regression coefficients for emotional resonance and creative autonomy were 0.72 and 0.55, respectively, also indicating their importance in the model.

Table 4. Factor regression analysis of evaluation index.

Model	Taste standardization coefficient (B)	Standard error	Standardized coefficient (Beta)	T	Sig.
Constant	2.8	0.16	0.22	17.26	0.000
Aesthetic value	0.92***	0.11	0.83	9.8	0.000
Technical execution ability	0.14*	0.12	0.13	1.12	0.284
Expression of imagination	0.51***	0.14	0.48	4.15	0.000
Social and cultural influence	0.24*	0.15	0.22	1.71	0.102
Audience feedback	0.09	0.16	0.08	0.54	0.621
Interactivity and participation	0.35*	0.18	0.32	2.24	0.029
Interdisciplinary integration force	0.18	0.19	0.17	1.03	0.327
Emotional resonance	0.72***	0.20	0.7	4.11	0.000
Creative autonomy	0.55**	0.21	0.6	2.89	0.004
Ethics and sense of responsibility	0.17	0.23	0.16	0.81	0.442

3.2. Calculation of Indicator Weights and Analysis of Results

3.2.1. Weighting Results

Using the hierarchical analysis method based on the index scale a^n , the full frequency of each indicator is regarded as the relative importance of the indicator, and the difference of the full frequency between the indicators is converted into a two-by-two scale to construct the judgment matrices of the two levels respectively. As most of the common hierarchical analysis software on the market only supports the calculation of 1-9 scale matrix weights, this paper adopts the sum and product method, using Excel software for the calculation of indicator weights and matrix consistency test, and ultimately obtains the weights of the indicators of the multi-dimensional evaluation system of digital art works and the synthetic weights as shown in Table 5, and the judgment matrices all pass the consistency test.

Table 5. Multi-dimensional evaluation index system and weights for digital art works.

First-level indicator	Weight	Secondary indicators	Weight	Synthetic weight
A1	0.2377	B1	0.4264	0.1014
		B2	0.1958	0.0465
		B3	0.3778	0.0898
A2	0.0362	B4	0.3854	0.0140
		B5	0.2795	0.0101
		B6	0.3351	0.0121
A3	0.1318	B7	0.5193	0.0685
		B8	0.2044	0.0269
		B9	0.2763	0.0364
A4	0.0620	B10	0.2472	0.0153
		B11	0.3581	0.0222
		B12	0.3947	0.0245
A5	0.0233	B13	0.5743	0.0134
		B14	0.2152	0.0050
		B15	0.2105	0.0049
A6	0.0904	B16	0.2234	0.0202
		B17	0.6127	0.0554
		B18	0.1639	0.0148
A7	0.0465	B19	0.2468	0.0115
		B20	0.3513	0.0163
		B21	0.4019	0.0187
A8	0.1861	B22	0.4024	0.0749
		B23	0.2298	0.0428
		B24	0.3678	0.0684
A9	0.1421	B25	0.1624	0.0231
		B26	0.2673	0.0380
		B27	0.5703	0.0810
A10	0.0439	B28	0.4251	0.0187
		B29	0.2623	0.0115
		B30	0.3126	0.0137

3.2.2. Analysis of the Importance of Indicators

The weights of the first-level indicators are ranked from high to low, which are A1 aesthetic value (0.2377), A8 emotional resonance (0.1861), A9 creative autonomy (0.1421), A3 imaginative expression (0.1318), A6 interaction and participation (0.0904), A4 sociocultural influence (0.0620), A7 interdisciplinary integration (0.0465), A10 ethics and responsibility (0.0439), and A2 technical execution (0.0362) , A5 audience feedback (0.0233). It can be seen that the two dimensions of "aesthetic value" and "emotional resonance" add up to more than 0.4, which is the fundamental difference between digital artworks and other AIGC works in the context of artificial intelligence. Creative autonomy is the basis for the free creation of digital artworks, and imaginative expression is the technical guarantee for the quality of digital artworks, which together ensure the creative expression of digital artworks, and are also the two dimensions that directly affect the quality of digital artworks and audience satisfaction. The next two dimensions are "interactivity and participation" and "socio-cultural influence", whether digital artworks can get good feedback is achieved through active interaction with the audience and a high degree of participation of the audience, while socio-cultural impact reflects the influence and popularity of digital artworks, both of which occupy a certain position in the evaluation of digital art. Finally, there are four dimensions: "interdisciplinary integration", "ethics and responsibility", "technical execution" and "audience feedback", which can reflect the design effect of digital artworks to a certain extent, but are not important dimensions to consider in the process of continuous large-scale design.

The composite weights of the secondary indicators are listed in descending order as shown in Figure 8. Among the 6 secondary indicators under the two dimensions of "aesthetic value" and "emotional resonance", a total of 4 ranked in the top 50%, among which, "B1 visual impact" had the highest weight of 0.1014, indicating that experts pay the most attention to the visual impact effect of digital artworks, and the three specific evaluation contents of "B3 style innovation", "B22 emotional expression" and "B24 emotional continuity and resonance" ranked second, fourth and sixth respectively, indicating that experts pay attention to the innovation and emotional rendering ability of works.

Under the two dimensions of "creative autonomy" and "imaginative expression", "B27 creative style independence" and "B7 creative uniqueness" have the highest weight among the six secondary indicators, and these two indicators also rank in the top 10 in the overall indicators, indicating that in these two dimensions, the unique creative ideas and creative styles in the works are the most important, which affects whether the digital artworks can stand out and attract attention among the many works. At the same time, the weight of "B26 independent thinking ability" is also high, indicating that independent thinking ability is required when designing digital artworks.

Among the six secondary indicators under the two dimensions of "interactivity and engagement" and "socio-cultural influence", "B17 interactive experience quality" occupies the highest weight, while "B10 cultural sensitivity" and "B18 post-participation impact" have a lower weight, indicating that experts pay attention to whether the interactive experience of digital artworks meets the needs and preferences of the audience, but do not pay attention to cultural sensitivity issues and the continuous impact of participation and interaction. The "B12 cultural inheritance and innovation" indicator also has a high weight, indicating that experts pay more attention to whether digital artworks can realize the inheritance and innovation of traditional culture. Therefore, when designing works, it is necessary to focus on improving the cultural carrying capacity.

Under the four dimensions of "interdisciplinary integration strength", "ethics and responsibility", "technical execution" and "audience feedback", the usability weights of "B21 cross-border influence", "B28 ethical code compliance" and "B20 integration depth" are higher, followed by "A4 socio-cultural impact", "B30 social responsibility", "B13 audience acceptance" and "A6 interaction and participation". On the whole, the weights of the evaluation indicators of "interdisciplinary integration strength" and "ethics and responsibility" are slightly higher than those of "technical execution" and "audience feedback". It can be seen that digital artworks need to consider technical execution and incorporate audience feedback into the design of the work while ensuring interdisciplinary integration and ethical responsibility.

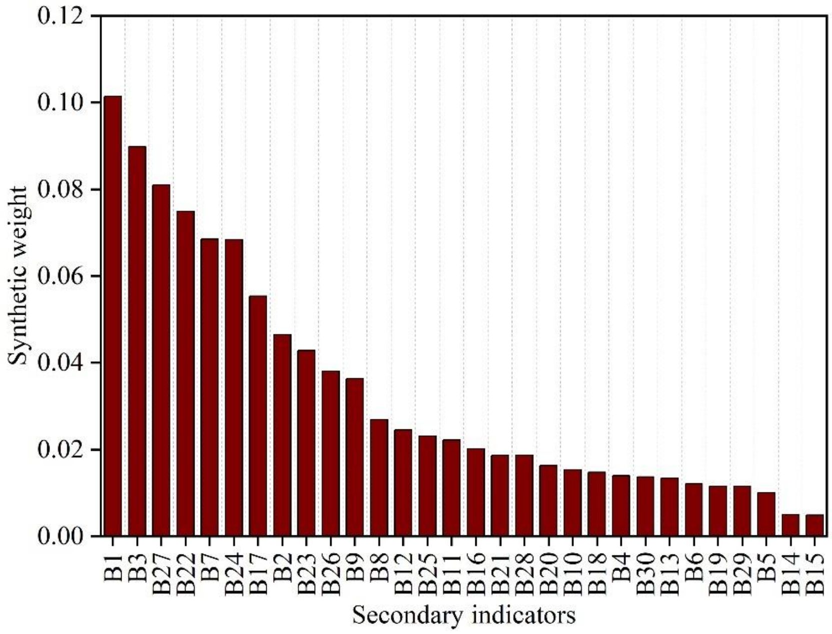


Figure 8. Synthetic weights of secondary indicators.

In summary, the index system constructed in this study reflects the experts' judgment on the relative importance of the dimensions examined in digital art works, which can be used to guide the setting and weight allocation of the evaluation dimensions of subsequent digital art works. At the same time, it can also enlighten the work designers that they need to firstly consider how to comprehensively and deeply carry out the excavation and utilization of internal and external digital resources to develop art works that meet the aesthetics of the audience and have a unique style; secondly, they should consider the cultural connotation and social value of the works; and next, they should consider how to optimize the design effect of the digital art works and the audience satisfaction as much as possible in the dimensions of interaction, feedback, technology, and so on.

3.3. Validation of Evaluation Index Weights Based on SA-BPNN

Due to the cognitive limitations of individuals, there is a certain subjective bias in the calculation of indicator weights of the AHP method for the evaluation system of digital art works. To solve this problem, this study introduces the SA-BPNN method, so as to effectively make up for the lack of information and cognitive bias, and to improve the scientificity and reliability of the calculation of evaluation index weights.

3.3.1. Data Collection: Questionnaires and Test Questions

In order to construct a neural network model suitable for the multi-dimensional evaluation of digital artworks, this study first developed the Questionnaire for the Evaluation of Digital Artworks. The questionnaire contains a total of 30 questions and answers, corresponding to the established 30 secondary indicators. Each question is measured using a five-point Likert scale with five options: "Very Good", "Relatively Good", "Fair", "Poor", and "Very Poor". The survey subjects of this questionnaire are 256 undergraduates, 9 master's students and 15 doctoral students in a university, of which 71.79% are male students and 28.21% are female students, with an average age of 20.65 years and an age standard deviation of 2.504. The evaluation object is 20 digital artworks generated by the AIGC platform. A total of 280 questionnaires were distributed in this survey, 280 questionnaires were recovered, 280 questionnaires were valid, and no invalid questionnaires were obtained.

3.3.2. Digital Artwork Evaluation System SA-BPNN Model Construction

The evaluation index system of digital art works collected in this study contains 30 secondary data indexes, so the number of neurons in the input layer is set to 30, so that it corresponds to each index one by one. Since the goal of the neural network is to generate a comprehensive assessment value based on the data of the Digital Art Work Evaluation Questionnaire, the number of neurons in the output layer is set to 1.

MATLAB provides a wealth of numerical computation functions and tools to quickly build and train SA-BPNN for data analysis and visualization. Therefore, this study utilizes the neural networktoolbox toolbox provided by MATLAB to build SA-BPNN and follows the following steps for concrete implementation.

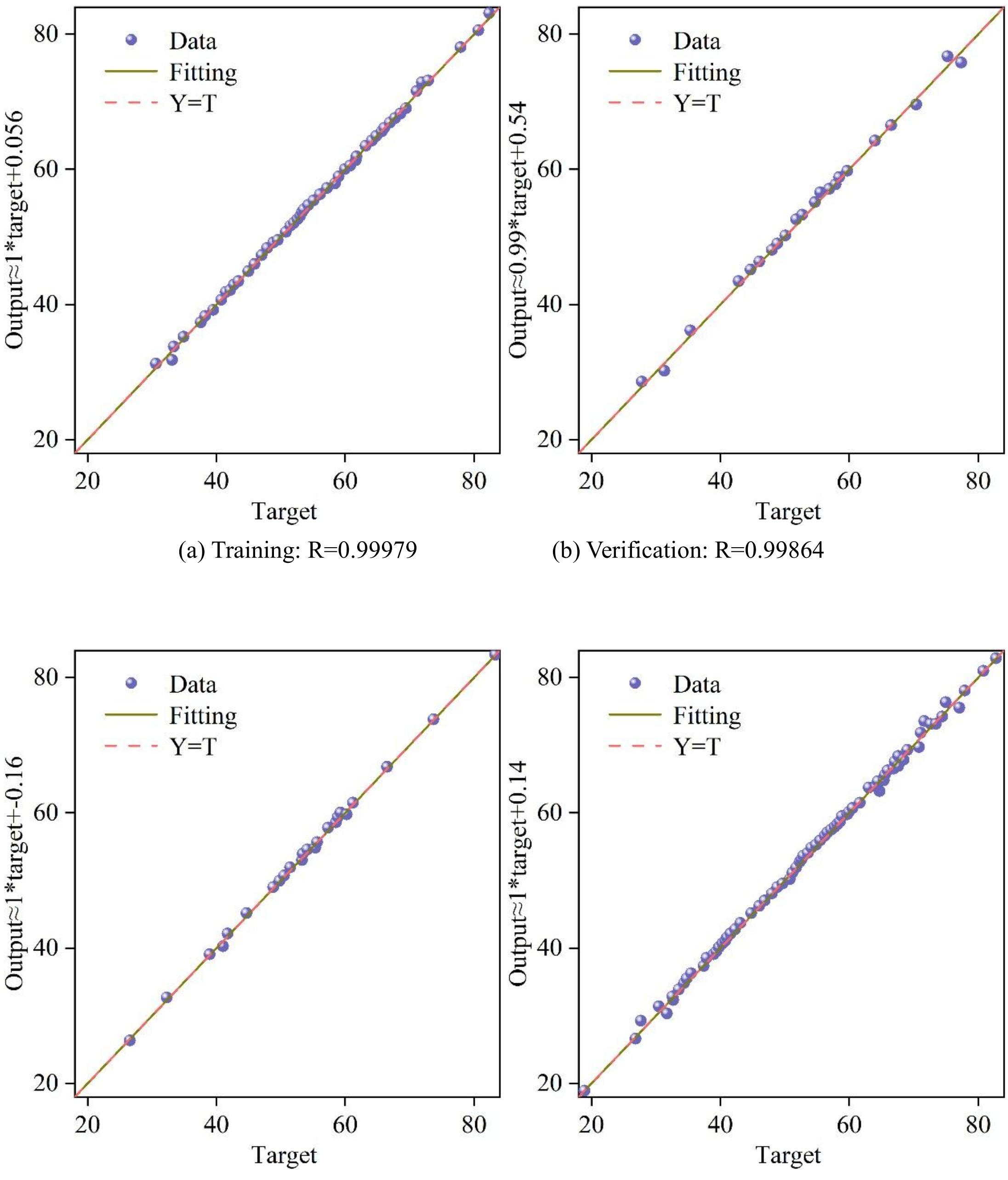
First, the processed data were read and vectorized and divided into training and testing sets in the ratio of 7:3. Subsequently, a four-layer structure of SA-BPNN is created using the function.After several experiments, this study found that the four-layer SA-BPNN performs better in terms of both training effect and convergence speed. Therefore, a four-layer neural network structure with one input layer, two hidden layers and one output layer is finally adopted, in which the number of neurons in the first hidden layer is 6, and the number of neurons in the second hidden layer is 4. In terms of the network parameter settings, the activation function between the input layer and the hidden layer is tansig, and that between the hidden layer and the output layer is purelin, and the maximum number of iterations is set at 4000, and the error target is set to 0.01. Finally, the SA-BPNN is trained using the training set, and the trained SA-BPNN model is used to predict the test set data.

3.3.3. Experimental Results of SA-BPNN Modeling

In this study, the scores of college students on the 30 secondary indicators corresponding to the questionnaire questions were used as model inputs, and the scores of each question were multiplied with the weight values of the secondary indicators calculated by the AHP method and then accumulated as the output of the model, so as to construct the SA-BPNN model.

The network regression fitting results are shown in Figure 9, which visualizes the relationship between the predicted values and the true values and helps to assess the fitting effect of the model. Among them, (a) to (d) are the fitting results of training, validation, testing, and all, respectively.

The observed results show that the output values of digital artwork evaluation in the neural network model obtained from training are highly compatible with the real values, and the accuracy of the trained model is as high as 99.95%. This is a good indication that the model shows great accuracy in predicting the output variables and has excellent fitting results.



(a) Training: R=0.99979 (b) Verification: R=0.99864

(c) Teat: R=0.99957 (d) All: R=0.99954

Figure 9. SA-BPNN regression fitting.

The trend of the SA-BPNN model's error during training is shown in Figure 10. It can be clearly seen that the training error gradually decreases with the increase in the number of training times, indicating that the model is continuously learning and optimizing. Similarly, the validation error shows a corresponding decreasing trend. At the 8th round of training, both the training error and the validation error reach the current optimal value, and the optimal value of the mean square error (MSE) of validation is 15.4635. By now, the SA-BPNN model has successfully converged.

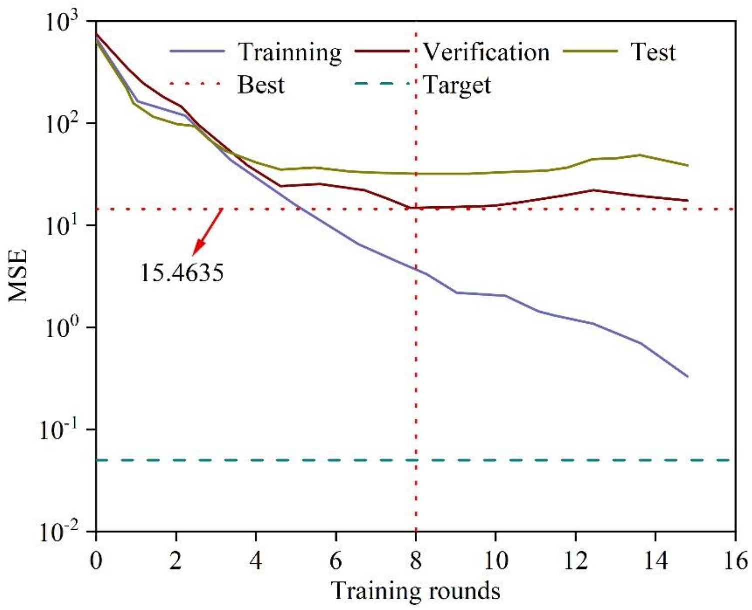
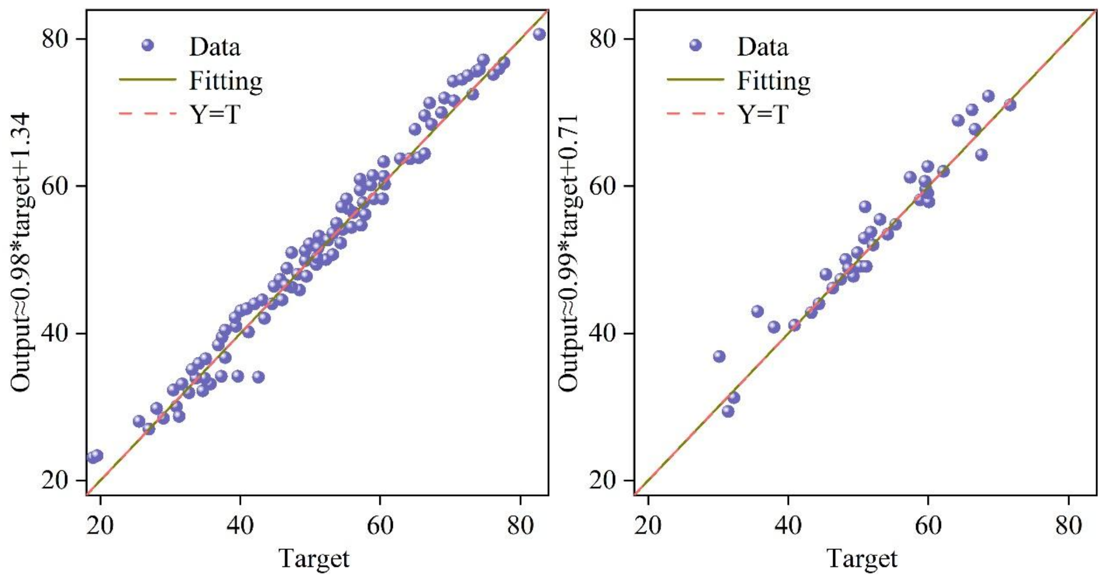


Figure 10. SA-BPNN error transformation.

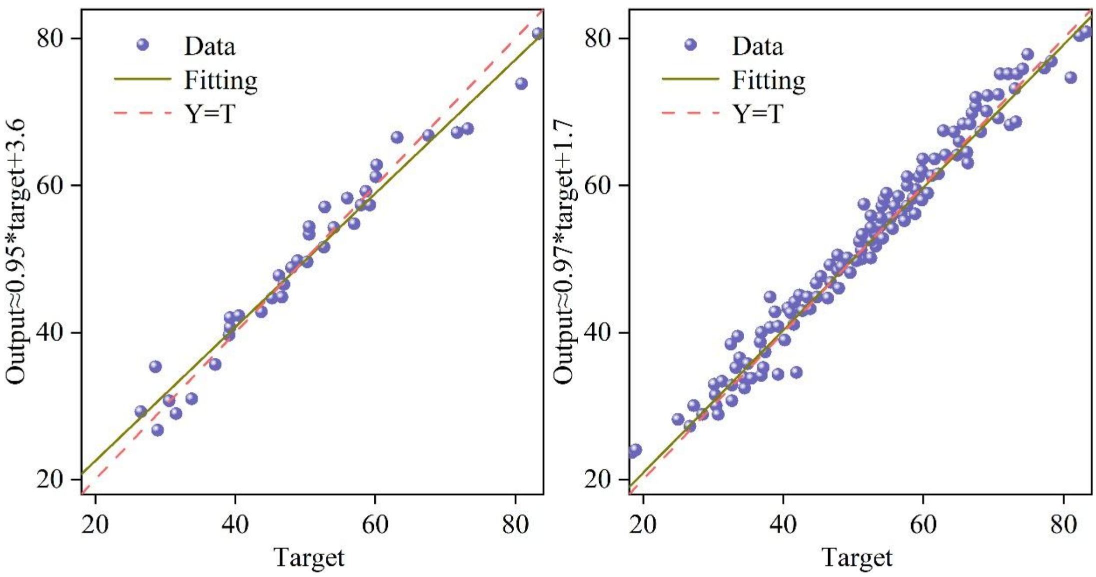
3.3.4. Validation of SA-BPNN Model for Evaluation Index Weights

Although the SA-BPNN model trained on the Digital Artwork Evaluation Questionnaire dataset possesses high accuracy and good fitting effect, students may be affected by subjective cognition, self-perception bias, or depth of understanding, and it is difficult to make completely objective judgments because the questionnaire questions are all subjective single-choice questions. Therefore, based on the previously constructed SA-BPNN model, this study further validates the SA-BPNN model with the help of the answering results of the Test Questions for Evaluation of Digital Artworks.

The neural network validation regression fitting results are shown in Figure 11. It can be seen that after rigorous validation based on the objective dataset, the prediction accuracy of the model reaches 98.85%, indicating that it can accurately fit the output variable values. The good fitting effect of the model is mainly reflected in two aspects: firstly, the high accuracy rate implies that the model fits the data well and is able to effectively capture the patterns and trends in the data. Second, the model shows strong adaptability and reliability in dealing with real data, and can effectively deal with complex data situations.



(a) Training: R=0.98992 (b) Verification: R=0.97496



(c) Teat: R=0.98483

(d) All: R=0.98852

Figure 11. SA-BPNN verify regression fitting.

The results of the neural network validation error transformation are shown in Figure 12. It can be found that the model performs best when the number of training reaches 12 times, and the mean square error of validation is only 6.1842, after which continued training leads to an increase in the error instead. This phenomenon suggests that over-training may trigger the overfitting problem, which reduces the generalization ability of the model. This finding provides an important reference for determining the optimal number of training times for the model in practical applications.

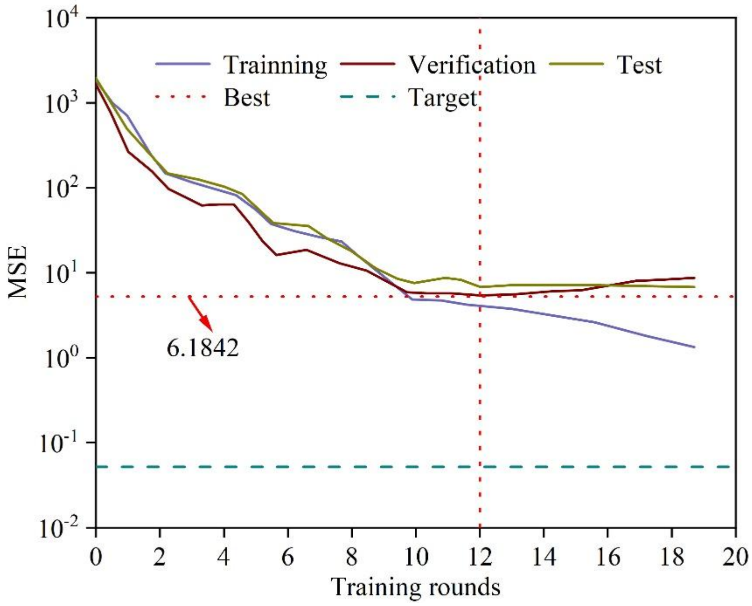


Figure 12. SA-BPNN verification error transformation.

4. Conclusion

This paper constructs a multi-dimensional evaluation system for digital art works, employs hierarchical analysis for indicator assignment, and proposes a SA-BPNN evaluation model based on multimodal data fusion technology.

Through factor analysis and regression analysis of the evaluation indexes, aesthetic value, emotional resonance, creative autonomy, and imaginative expression are the top four topics that respondents are most concerned about, and the loadings of the aesthetic value of digital art works are relatively high on multiple criteria, which is highly comprehensive and representative. Meanwhile, the regression equation of the evaluation indexes of digital art works was obtained through regression analysis, in which the regression coefficient of aesthetic value was 0.92, significantly higher than other factors, and the regression coefficients of emotional resonance and creative autonomy were 0.72 and 0.55 respectively, which were also important in the model.

Based on the importance analysis of indicator weights, this paper draws the following conclusions: in the process of designing digital art works, it is necessary to first consider how to comprehensively and deeply explore and utilize internal and external digital resources to develop art works that meet the aesthetics of the audience and have a unique style, then consider the cultural connotation and social value of the works, and then consider the level of interaction, feedback, and technology to optimize the design effect and audience satisfaction of the digital art works as much as possible. Then consider the interaction, feedback, technology and other levels to optimize the design effect and audience satisfaction of the digital art works as much as possible.

Using the SA-BPNN model to validate the weights sought by the AHP method, the final prediction accuracy of the model reaches 98.85%, which is able to realize the objective evaluation of digital art works. Meanwhile, the model performs best when the number of training times reaches 12, after which continued training leads to an increase in error instead. This suggests that over-training may trigger the overfitting problem, which reduces the generalization ability of the model. This finding provides an important reference for determining the optimal number of training times for the model in practical applications.

References

1. McConaghy, M., McMullen, G., Parry, G., McConaghy, T., & Holtzman, D. (2017). Visibility and digital art: Blockchain as an ownership layer on the Internet. Strategic Change, 26(5), 461-470.
2. Strukov, V. (2021). Digital art: A sourcebook of ideas for conceptualizing new practices, networks and modes of self-expression. The Palgrave Handbook of Digital Russia Studies, 241.
3. Tang, B., & Ge, C. (2021). Application of Computer Software Technology in Art and Technology Creation. World Scientific Research Journal, 7(6), 356-363.
4. Cardinali, M. (2019). Digital tools and technical views: The intersection of digital art history and technical art history in a digital archive on the painting technique of Caravaggio and his followers. Visual Resources, 35(1-2), 52-73.
5. Appukuttan, A. (2021). Digital art-a useful tool for medical professionals to create medical illustrations. JPRAS open, 28, 97-102.
6. Candy, L. (2019, November). Creating with the digital: tool, medium, mediator, partner. In International Conference on ArtsIT, Interactivity and Game Creation (pp. 13-28). Cham: Springer International Publishing.
7. Zhao, B., Zhan, D., Zhang, C., & Su, M. (2023). Computer-aided digital media art creation based on artificial intelligence. Neural Computing and Applications, 35(35), 24565-24574.
8. Liu, Y., Liang, C., Xu, H., Wang, F., Hao, Y., Dong, J., ... & Yu, P. (2022). Digital art pattern design based on visual material colouring intelligent programming system. Mathematical Problems in Engineering, 2022(1), 2450074.
9. Gai, Z., & Yang, T. (2024). Digital art creation and visual communication design driven by internet of things algorithm. Computer-Aided Design and Applications, 135-149.
10. Li, P. (2022). Interpretation of online artworks of digital art design in the new media environment. Journal of Environmental and Public Health, 2022(1), 9566844.
11. Taheri Qomi, S. M. (2024). An Analysis of the Interactive Engagement of the Audience with Interactive Computer Art from David Rokeby's Perspective. Glory of Art (Jelve-y Honar) Alzahra Scientific Quarterly Journal, 16(3), 76-90.
12. Suhr, H. C. (2018). The audience and artist interactivity in augmented reality art: The solo exhibition on the flame series. Critical Arts, 32(3), 111-125.
13. Luo, X. (2022). Digital Art Design Effectiveness Model System Based on K-Medoids Algorithm. Advances in Multimedia, 2022(1), 2901815.
14. Wang, Q., Dai, H. N., Yang, J., Guo, C., Childs, P., Kleinsmann, M., ... & Wang, P. (2024). Learning-based Artificial Intelligence Artwork: Methodology Taxonomy and Quality Evaluation. ACM Computing Surveys, 57(3), 1-37.
15. Chen, J., An, J., Lyu, H., Kanan, C., & Luo, J. (2024). Learning to evaluate the artness of AI-generated images. IEEE Transactions on Multimedia.
16. Xu, R., & Hsu, Y. (2020). Will the process of creation impact the viewer's appraisal of the creativeness of artificial intelligence artworks?. In Human Interface and the Management of Information. Interacting with Information: Thematic Area, HIMI 2020, Held as Part of the 22nd International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings, Part II 22 (pp. 418-429). Springer International Publishing.
17. Hong, M., Xue, S., & Zhou, X. (2025). A hyperdimensional adaptive plithogenic-neutrosophic forestsoft superhypersoft set model for innovation evaluation in virtual reality based digital media art design. Neutrosophic Sets and Systems, 86, 89-104.

18. Jackson, K. (2017). Where qualitative researchers and technologies meet: Lessons from interactive digital art. Qualitative Inquiry, 23(10), 818-826.
19. Xu, L., Xu, H., Luo, J., Zhang, R., Pan, Y., & Xu, J. (2025). Immersive Digital Art Experience: An Empirical Study on Audiences' Switching Intention to Metaverse Online Art Museum. IEEE Access.
20. Pawłowski, M., Wróblewska, A., & Sysko-Romańczuk, S. (2023). Effective techniques for multimodal data fusion: A comparative analysis. Sensors, 23(5), 2381.
21. Khramova-Baranova, O. (2023). Digital painting: Formation and prospects. Culture and Contemporaneity, 1(25), 49-55.
22. Huang, C. (2024, January). The Transformation Strategy and Innovative Application of Multisource Information Fusion in Art Painting. In Proceedings of the 3rd International Conference on Computer, Artificial Intelligence and Control Engineering (pp. 417-421).
23. Guo, K. (2022). Study on Digital Painting Art Based on Computer Virtual Technology. Mobile Information Systems, 2022(1), 5687835.
24. Ben Jin & Hanwen Li. (2025). Construction of teaching quality evaluation model of online dance teaching course based on improved PSO-BPNN. Nonlinear Engineering,14(1),20240078-20240078.
25. Muhammad Salman Haleem, Owain Cisuelo, Martina Andellini, Rossana Castaldo, Massimiliano Angelini, Matteo Ritrovato... & Leandro Pecchia. (2024). A Self-Attention Deep Neural Network Regressor for real time blood glucose estimation in paediatric population using physiological signals. Biomedical Signal Processing and Control,92,106065-.
26. Caio Robert Santos Barbosa, Luiz Alberto Vedana, Rossano Belladona & Tiago de Vargas. (2025). Assessing groundwater recharge potential in the Sergipe River Basin using the Analytical Hierarchy Process (AHP). Journal of South American Earth Sciences,162,105595-105595.