International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-1115
Article

Coupling of Traditional Handicraft Skills Intangible Cultural Heritage and Cultural Industry Agglomeration under the Background of Big Data

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Abstract: The transmission of traditional folk craft skills and educational innovation are key to achieving the living transmission of cultural heritage. This paper takes China's 31 provinces as its research subjects and constructs an evaluation index for the competitiveness of China's cultural heritage. It comprehensively employs the Analytic Hierarchy Process (AHP) and the Entropy Weighting Method to determine the weights of the indicators. This approach effectively integrates subjective expert experience with objective data, thereby avoiding the biases associated with single-weight determination methods. A BP neural network-based evaluation model for China's cultural heritage competitiveness was established. The model was trained using 2014 data on China's cultural heritage competitiveness, generating evaluation results for each province and overcoming the limitations of traditional linear evaluation methods. Empirical results indicate that the model exhibits good fit, with a maximum error of only 0.0006 in the test sample. Between 2014 and 2019, the overall level of cultural heritage competitiveness across Chinese provinces improved, with the mean rising from 0.1744 to 0.2393; however, the disparity in development levels of cultural heritage competitiveness among provinces remains significant. Therefore, this paper proposes specific strategies in areas such as digital technology capabilities, distinctive development advantages, and educational innovation, providing methodological support and practical strategies for the transmission of traditional folk craft skills and educational innovation.

Keywords: Analytic Hierarchy Process; Entropy Weighting Method; Backpropagation Neural Network; Cultural Heritage Competitiveness Evaluation; Skill Transmission; Educational Innovation

1. Introduction

Traditional folk crafts are an integral part of Chinese culture, embodying the wisdom and craftsmanship of ancient China [1–2]. With the advancement of modern technology and the rise of industrialized production, many traditional folk crafts have gradually disappeared and even face the risk of being lost forever [3–4]. How to protect and preserve these traditional crafts while infusing them with new relevance in the modern era has become an urgent issue that demands attention. With the continuous advancement of artificial intelligence technology, the application of neural network algorithms has emerged as a breakthrough in addressing the challenges of inheriting traditional folk crafts [5-6]. A neural network is a machine learning model designed to simulate biological neural networks. It utilizes a large number of computational nodes to process complex tasks, enabling machines to learn automatically and ultimately make autonomous decisions [7-9]. Regarding the transmission of traditional folk crafts, neural networks construct deep learning models to automatically identify data such as the movements and voices of craft masters. This enables the creation of craft-specific parametric models and facilitates visual replication in educational settings, thereby innovating teaching methods [10–13].

This paper establishes an evaluation index system for the competitiveness of China's cultural heritage. It employs a combined AHP-entropy weighting method to determine the weights of the evaluation indicators, thereby enhancing the scientific rigor and reliability of the weighting. A cultural heritage competitiveness evaluation model based on a Backpropagation (BP) neural network was designed. By leveraging the self-learning and nonlinear fitting capabilities of the BP neural network, the model improves the accuracy of cultural heritage competitiveness evaluations, providing data-driven decision-making support for the skill transmission and educational innovation of traditional folk crafts. The study selected China's 31 provinces as the research subjects. The model was trained using relevant data from five provinces in 2014. The trained model then generated cultural heritage competitiveness scores for each Chinese province in both 2014 and 2019, thereby advancing the intelligent transmission of traditional folk craft skills and educational innovation.

2. Indicator System for Cultural Heritage Competitiveness

2.1. Establishment of an Evaluation Indicator System

This paper uses the six key elements of the theory of cultural heritage competitiveness—cultural heritage productivity, cultural heritage consumption capacity, cultural heritage support capacity, cultural heritage dissemination capacity, cultural heritage management capacity, and cultural heritage innovation capacity—as secondary indicators to conduct a comprehensive assessment of cultural heritage competitiveness at the provincial level in China. Based on this, the paper identifies several indicators that influence cultural heritage competitiveness, which together form the Chinese Cultural Heritage Competitiveness Indicator System, as shown in Table 1.

Table 1. China's cultural heritage competitiveness index system

Primary indicator	Secondary indicator	Tertiary index
China's cultural heritage competitiveness	Cultural inheritance	World cultural heritage
		The number of representative projects of national intangible cultural heritage
		Number of key cultural relics in the country
		The number of village in the famous city of national historical and cultural city
	Cultural heritage	The cultural relics industry
		Total sales of cultural relics
		Cultural added value of GDP
		The amount of consumer expenditure per capita of residents per capita
	Cultural heritage support	Number of national museums
		The number of literary goods stores
		Traffic facilitation
		Number of star hotels
	Cultural heritage communication	The number of exhibitions in the cultural relics industry
		The website is a number of visitors
		Sign agreement or memorandum of memorandum with foreign literary and blog agencies
		The number of activities organized by the group of wenbo
	Cultural heritage management	The regulations and regulations of local cultural relics are introduced at this level
		The amount of financial funds of the cultural relics department
		Number of cultural relics protection management institutions
		Number of authorities in the administrative department of cultural relics
	Cultural innovation	Number of scientific and cultural research institutions
		The professional talents of cultural relics protection research institutions are compared
		The number of patent systems in wenbo system
		Type of cultural and creative products of wenbo system

2.2. Determining the Weighting of Indicators

The Analytic Hierarchy Process (AHP) is a subjective weighting method. Developed by American operations researchers in the 1970s, it is a multi-criteria decision-making analysis method that combines qualitative and quantitative approaches. Its key feature lies in simplifying and making practical complex decision-making problems influenced by multiple factors through the construction of an AHP model and quantitative analysis. The specific steps are as follows: First, scores are assigned to indicators at each level using a 1–9 rating scale, and these indicators are organized into pairwise comparison matrices. Matrix $A-B$ serves as the first-level comparison matrix, while matrices $B1-C$, $B2-C$, $B3-C$, and $B4-C$ serve as second-level comparison matrices. Next, consistency tests are conducted using the consistency index (CI) and the random consistency index (CR). Finally, the weighted results are derived.

After normalizing the initial data, the weights for each indicator are first obtained by calculating the average of each row of the indicator. Next, the maximum eigenvalue of each judgment matrix is calculated using formula $\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n}\frac{(EW)_i}{W_i}$, followed by the calculation of the consistency index (CI) using formula $CI = \frac{\lambda_{\max}-n}{n-1}$. The random consistency index (RI) is then derived by comparing the values, and the layer consistency index (CR) is calculated using formula $CR = \frac{CI}{RI}$. If $CR < 0.1$ holds, the consistency test is passed. Finally, if the CR values of each judgment matrix pass the consistency test, the data is sorted by level and overall rank, and the weights for each indicator are calculated.

The entropy weighting method is an objective weighting technique applied to multi-criteria evaluation. Its fundamental approach involves utilizing differences in information to assign objective weights, and its evaluation results primarily depend on the dispersion of the data itself, making them less susceptible to human bias. Since the use of the Analytic Hierarchy Process (AHP) to determine indicator weights, as discussed earlier, is prone to being influenced by experts' subjective judgments, applying the entropy weighting method to adjust these weights ensures the objectivity and fairness of the evaluation results. To eliminate the influence of physical units, and since all indicators selected in this paper are positive indicators, the extreme value method is adopted. Specifically, the raw data is made dimensionless using formula $X'_{ij} = \frac{X_{ij}-m_j}{M_j-m_j}$, where X_{ij} represents the value of sub-indicator j within indicator i, and M_j and m_j represent the maximum and minimum values of the respective sub-indicator data within indicator i. Next, to eliminate the influence of zero and negative values without affecting the usability of the data, the data is shifted by 0.0001 units using formula $Y'_{ij} = X'_{ij} + \beta$. Then, the characteristic weight is calculated using formula $P_{ij} = \frac{Y'_{ij}}{\sum_{i=1}^{n} Y_{ij}}$, the entropy value is calculated using formula $e_j = -\frac{1}{\ln n} P_{ij} \ln P_{ij}$, the information utility value is calculated using formula $d_j = 1 - e_j$, and finally, the evaluation index weights are determined using formula $Q_j = \frac{d_j}{\sum_{i=1}^{n} d_j}$.

Based on the results of the two methods described above, the indicator weights obtained from the AHP and the entropy weighting method were combined; specifically, the formula $D_j = \frac{WQ_j}{\sum_{i=1}^{n} WQ_j}$ was used to determine the composite weights for each indicator. The composite weights for the Chinese Cultural Heritage Competitiveness Index System are shown in Table 2. Among these, the indicator for the number of World Cultural Heritage sites has the highest weight, at 0.1344.

Table 2. Comprehensive weight of cultural heritage competitiveness

Primary indicator	Secondary indicator	Weight	Tertiary index	Weight
China's cultural heritage competitiveness	Cultural inheritance	0.2225	World cultural heritage	0.1344
			The number of representative projects of national intangible cultural heritage	0.0479
			Number of key cultural relics in the country	0.0258
			The number of village in the famous city of national historical and cultural city	0.0144
	Cultural heritage	0.1385	The cultural relics industry	0.024
			Total sales of cultural relics	0.1089
			Cultural added value of GDP	0.0027
			The amount of consumer expenditure per capita of residents per capita	0.0029
	Cultural heritage support	0.1486	Number of national museums	0.1001
			The number of literary goods stores	0.0336
			Traffic facilitation	0.0087
			Number of star hotels	0.0062
	Cultural heritage communication	0.1295	The number of exhibitions in the cultural relics industry	0.0051
			The website is a number of visitors	0.0428
			Sign agreement or memorandum of memorandum with foreign literary and blog agencies	0.0480
			The number of activities organized by the group of wenbo	0.0336
	Cultural heritage management	0.1647	The regulations and regulations of local cultural relics are introduced at this level	0.0795
			The amount of financial funds of the cultural relics department	0.0278
			Number of cultural relics protection management institutions	0.0294
			Number of authorities in the administrative department of cultural relics	0.028
	Cultural innovation	0.1962	Number of scientific and cultural research institutions	0.0091
			The professional talents of cultural relics protection research institutions are compared	0.0031
			The number of patent systems in wenbo system	0.1332
			Type of cultural and creative products of wenbo system	0.0508

3. A Model for Evaluating the Competitiveness of Cultural Heritage Based on a Backpropagation Neural Network

3.1. BP Neural Network Method

Based on the theoretical principles of the Backpropagation (BP) neural network, the number of nodes in the input layer, output layer, and hidden layers of the evaluation model was determined, and the structural model was trained and tested for stability using MATLAB software. In this evaluation process, the BP neural network structure was first initialized, followed by the adjustment of weights and thresholds based on the network's prediction errors. The trained BP neural network was then applied to evaluate the competitiveness of cultural heritage.

Practical research demonstrates that the BP neural network-based evaluation of cultural heritage competitiveness achieves a high degree of accuracy. This method effectively integrates theory with practical issues in a scientific and efficient manner, providing valuable support for enhancing cultural heritage competitiveness. The evaluation process can be broadly divided into the following three steps:

construction of the evaluation model, training of the network structure, and evaluation and analysis of the BP neural network's output results. The evaluation steps are illustrated in Figure 1:

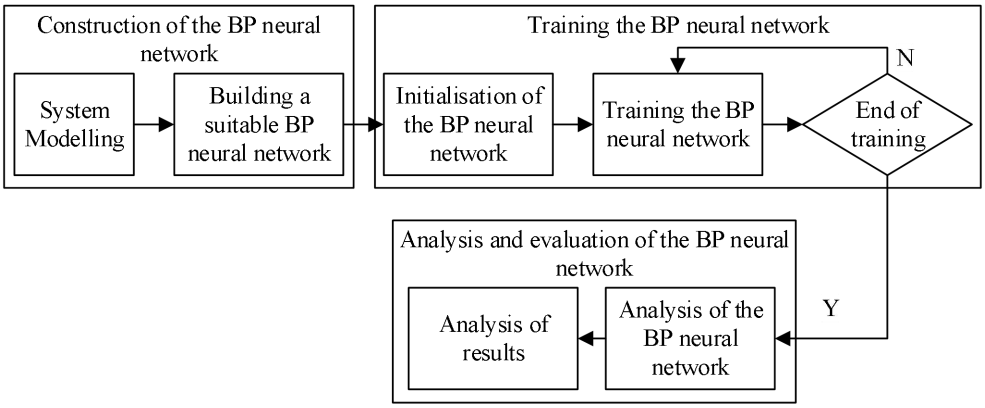

Figure 1. Evaluation procedure based on bp neural network

The structure of a Backpropagation (BP) neural network consists of a combination of multi-layer feedforward neural networks, characterized by forward signal propagation and backpropagation of errors. The topological structure of a BP neural network includes an input layer, hidden layers, and an output layer, as shown in Figure 2.

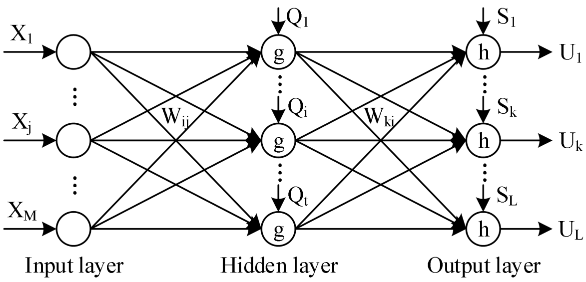

Figure 2. Diagram of a BP neural network topology

(1) The forward propagation of a signal

In the topological diagram, $X_1, X_1, \cdots, X_m$ represents the input values of the BP neural network, m represents the number of nodes in the input layer, and the input changes to $X_i(P)(i=1,2\cdots,n)$. ω_{ij} represents the connection weights between the input layer and the hidden layer; $\omega_{ij}=(i=1,2,\cdots,n;j=1,2,\cdots,l)$ and θ_i represent the thresholds of node i in the hidden layer; $g(x)$ is the activation function of the hidden layer; ω_{ki} represents the connection weights between the hidden layer and the output layer; $\omega_{ki}=(k=1,2,\cdots,n;i=1,2,\cdots,l)$; S_k represents the threshold of the k th node in the output layer, $k=1,2,\cdots L$; $h(x)$ represents the activation function of the output layer; and $U_1 \cdots U_k \cdots U_l$ represents the output values of the BP neural network.

The forward propagation process of the signal is as follows:

Input to the i th node in the hidden layer:

$$net_i = \sum_{j=1}^{M} \omega_{ij} x_j + q_i \tag{1}$$

Output of node i in the hidden layer:

$$y_i = g(net_i) = g\left(\sum_{j=1}^{M} \omega_{ij} x_j + q_i\right) \tag{2}$$

Input to the k th node in the output layer:

$$net_k = \sum_{i=1}^{t} \omega_{ki} y_i + s_k = \sum_{i=1}^{t} \omega_{ki} g\left(\sum_{j=1}^{M} \omega_{ij} x_j + q_i \right) + s_k \tag{3}$$

Output from the k th node in the output layer:

$$u_k = h(net_k) = h\left(\sum_{i=1}^{t} \omega_{ki} y_i + s_k \right) = h\left(\sum_{i=1}^{t} \omega_{ij} x_j + q_i \right) + s_k \tag{4}$$

(2) The Backpropagation Process

By calculating the error values from the output layer to the hidden layers, then calculating the output errors of the neurons in each layer from the hidden layers to the input layer, and finally using gradient descent to continuously optimize the weights and thresholds of each layer, the process iterates until the error between the network's output and the expected value falls within a reasonable range. The expression for the error criterion function is as follows:

$$E_b = \frac{1}{2} \sum_{k=1}^{L} (D_k - u_k)^2 \tag{5}$$

The expression for the error criterion function for the training samples is as follows:

$$E = \frac{1}{2} \sum_{b=1}^{B} \sum_{k=1}^{L} (D_k^B - u_k^B)^2 \tag{6}$$

Using the error gradient descent method, adjust the weights of the output layer, the threshold of the output layer, the weights of the hidden layer, and the threshold of the hidden layer in that order:

$$\Delta\omega_{ki} = -\eta \frac{\partial E}{\partial \omega_{ki}} \tag{7}$$

$$\Delta s_k = -\eta \frac{\partial E}{\partial s_k} \tag{8}$$

$$\Delta\omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}} \tag{9}$$

$$\Delta q_i = -\eta \frac{\partial E}{\partial q_i} \tag{10}$$

The formula for adjusting the output layer weights is:

$$\Delta\omega_{ki} = -\eta \frac{\partial E}{\partial \omega_{ki}} = -\eta \frac{\partial E}{\partial net_k} \frac{\partial net_k}{\partial \omega_{ki}} = -\eta \frac{\partial E}{\partial u_k} \frac{\partial u_k}{\partial net_k} \frac{\partial net_k}{\partial \omega_{ki}} \tag{11}$$

The formula for adjusting the output layer threshold is:

$$\Delta s_k = -\eta \frac{\partial E}{\partial s_k} = -\eta \frac{\partial E}{\partial net_k} \frac{\partial net_k}{\partial s_k} = -\eta \frac{\partial E}{\partial u_k} \frac{\partial u_k}{\partial net_k} \frac{\partial net_k}{\partial s_k} \tag{12}$$

The formula for adjusting the hidden layer weights is:

$$\Delta\omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}} = -\eta \frac{\partial E}{\partial net_i} \frac{\partial net_i}{\partial \omega_{ij}} = -\eta \frac{\partial E}{\partial y_i} \frac{\partial y_i}{\partial net_i} \frac{\partial net_i}{\partial \omega_{ij}} \tag{13}$$

The formula for adjusting the hidden layer threshold is:

$$\Delta\omega_{ij} = -\eta \frac{\partial E}{\partial q_i} = -\eta \frac{\partial E}{\partial net_i} \frac{\partial net_i}{\partial q_i} = -\eta \frac{\partial E}{\partial y_i} \frac{\partial y_i}{\partial net_i} \frac{\partial net_i}{\partial q_i} \tag{14}$$

Because:

$$\frac{\partial E}{\partial u_k} = -\sum_{b=1}^{B} \sum_{k=1}^{L} (D_k^B - u_k^B) \tag{15}$$

$$\frac{\partial net_k}{\partial \omega_{ki}} = y_i \tag{16}$$

$$\frac{\partial net_k}{\partial s_k} = 1 \tag{17}$$

$$\frac{\partial net_k}{\partial \omega_{ki}} = x_j \tag{18}$$

$$\frac{\partial net_i}{\partial q_i} = 1 \tag{19}$$

$$\frac{\partial E}{\partial y_i} = -\sum_{b=1}^{B}\sum_{k=1}^{L}(D_k^B - u_k^B)h'(net_k)\omega_{ki} \tag{20}$$

$$\frac{\partial y_i}{\partial net_i} = g'(net_i), \frac{\partial u_k}{\partial net_k} = h'(net_k) \tag{21}$$

Result:

$$\Delta\omega_{ki} = \eta\sum_{b=1}^{B}\sum_{k=1}^{L}(D_k^B - u_k^B)h'(net_k)y_i \tag{22}$$

$$\Delta s_k = \eta\sum_{b=1}^{B}\sum_{k=1}^{L}(D_k^B - u_k^B)h'(net_k) \tag{23}$$

$$\Delta\omega_{ij} = \eta\sum_{b=1}^{B}\sum_{k=1}^{L}(D_k^B - u_k^B)h'(net_k)\omega_{ki}g'(net_i)x_j \tag{24}$$

$$\Delta q_i = \eta\sum_{b=1}^{B}\sum_{k=1}^{L}(D_k^B - u_k^B)h'(net_k)\omega_{ki}g'(net_i) \tag{25}$$

The computational process of a backpropagation (BP) neural network primarily consists of the following steps: First, initialization is performed. Based on the theoretical principles of the BP neural network, the number of neurons in each layer—specifically, the number of nodes in the input layer, hidden layers, and output layer—is set. Connection weights and the training threshold function are then determined. Sample data is input to train the BP neural network model, and the expected output is generated. Through continuous training and error calculation by the BP neural network, training of the model can be concluded when the error is controlled within an acceptable range. If the error requirements are not met, the weight values must be adjusted, and a new round of training must be conducted.

3.2. Design of a Competitiveness Evaluation Model

The number of nodes in the input layer corresponds to the number of parameters presented to the network as inputs. Based on the evaluation index system for the competitiveness of China's cultural heritage established above, the number of secondary indicators is equal to the number of nodes in the input layer.

Since the study of the competitiveness of China's cultural heritage ultimately requires calculating its competitiveness output value, the output layer contains only one value, and the number of nodes in the output layer is 1.

The neurons in the hidden layer are primarily responsible for feature extraction. The number of hidden layers and hidden neurons is unknown; there may be one or more. Hidden layers and hidden neurons can provide higher dimensions and adapt to tasks such as classification and pattern recognition. However, to obtain efficient, accurate, and reasonable results within a limited timeframe, it is essential to determine a reasonable number of hidden layer nodes. Since there is no universally applicable method for determining the number of hidden layer neurons, the following three expressions can be used as a reference:

$$1)\ \sum_{i=0}^{n} C_M^i > k \tag{26}$$

$$2)\ M = \sqrt{n+m} + a \tag{27}$$

$$3)\ M = \log_2 n \tag{28}$$

Here, k represents the number of samples, M represents the number of neurons in the hidden layer, and m and n represent the number of neurons in the output layer and input layer, respectively; a is a constant between $[0,10]$.

It is present within each neuron of a neural network and is used to process data. After the data is processed, each output is combined with the corresponding weight, and this new value is fed into the next processing neuron in the next layer, continuing until the final output neuron.

Generally, BP neural networks commonly use linear functions and nonlinear sigmoid functions (S -type functions). S -type functions include logarithmic and tangent functions, whose ranges are between $[0,1]$ and $[-1,1]$, respectively.

$$\phi(x) = \frac{1}{1+e^{-x}} \tag{29}$$

$$\phi(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{30}$$

When dealing with nonlinear problems, to ensure the range of output values, a nonlinear function is typically used from the input layer to the hidden layer, while a linear function is used from the hidden layer to the output layer. After data normalization, the input layer falls within the range of $[0,1]$, satisfying the range requirements for the logarithmic sigmoid function. Therefore, this paper selects the logarithmic sigmoid function for the connection from the input layer to the hidden layer, and the purelinear function for the connection from the hidden layer to the output layer.

The operation process of the activation functions is as follows:

1) For the s th data point, the input to the j th hidden neuron is:

$$net_{ij}^{s} = \sum_{i=1}^{16} w_{ij} I_i^s \tag{31}$$

2) The corresponding output is:

$$h_j^s = \phi(net_j^s) = \phi\left(\sum_{i=1}^{16} w_{ij} I_i^s\right) \tag{32}$$

3) Therefore, the input to the kth output unit is:

$$Q_k^s = \phi(net_k^s) = \phi\left(\sum_{j=1}^{14} \overline{w}_{jk} h_j^s\right) = \phi\left(\sum_{j=1}^{14} \overline{w}_{jk} \phi\left(\sum_{i=1}^{16} w_{ij} I_i^s\right)\right) \tag{33}$$

4) Accordingly, the kth output of the neural network is:

$$net_k^s \equiv \sum_{j=1}^{14} \overline{w}_{jk} h_j^s = \sum_{j=1}^{14} \overline{w}_{jk} \phi\left(\sum_{i=1}^{16} w_{ij} I_i^s\right) \tag{34}$$

The training function is also a critical parameter of the BP neural network, with each training function corresponding to its own algorithm. The training algorithm must be selected based on specific conditions such as the research problem itself and the training samples. Different training algorithms vary in terms of memory usage, search methods, number of iterations, computational complexity, computational speed, convergence speed, and generalization ability; therefore, selecting an appropriate training function is crucial. This paper uses the training function `trainingdx` for network training.

The selection of training samples for the BP neural network must be reasonable and representative, and data collection must be objective, scientific, and fact-based. Since data on the competitiveness of China's cultural heritage is open and transparent, this paper utilizes relevant indicator data on the development of China's cultural industry from 2014 to 2019. Taking China's 31 provinces, municipalities, and autonomous regions as the basic units, the sample data for this study was primarily obtained through the following channels.

Statistical Yearbooks and Statistical Bulletins: These primarily include the "China Statistical Yearbook" (2014–2019), provincial statistical yearbooks (2014–2019), the "Report on the Development of China's Cultural Heritage Sector", the "China Tourism Statistical Yearbook", the "China Urban Statistical Yearbook", the "Report on the Development of China's Tourist Attractions", the "China Cultural and Cultural Relics Statistical Yearbook", the "China Cultural and Related Industries Statistical Yearbook", as well as the 2014–2019 Statistical Bulletins on National Economic and Social Development for each province.

Online Sources: These primarily include the official websites of UNESCO (UNESCO), the Ministry of Culture and Tourism, the National Cultural Heritage Administration, the departments (bureaus) of culture and tourism in various provinces, municipalities, and autonomous regions, as well as China Economic Net.

Data normalization ensures consistency in both the content and format of data types represented within the system. Furthermore, data standardization facilitates efficient and consistent data mapping and output. Data standardization determines data quality; high-quality data should meet certain standards, namely accuracy, completeness, and consistency. This paper collected data on the competitiveness of China's cultural heritage based on specific evaluation indicators. However, due to differences in the units and definitions of these indicators, the raw data is not comparable. In this context, data standardization is necessary to eliminate these barriers.

This paper uses the maxmin function to standardize the raw data, converting it into values ranging from $(0,1)$ to facilitate the training and learning of the BP neural network described below. The formula for the maxmin function is as follows:

$$y_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{35}$$

In this context, x_i represents the original data, $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of the same metric, respectively, and y_i represents the result of the standardization process.

4. Results of the Empirical Analysis and Evaluation

4.1. Model Training

Data related to the competitiveness of China's cultural heritage was input into the input layer, and the data was trained using the `train` statement. After six training iterations, the model stopped training, indicating that the error had reached an acceptable range. The specific numerical accuracy was 6.02e-06, and the training convergence is shown in Figure 3.

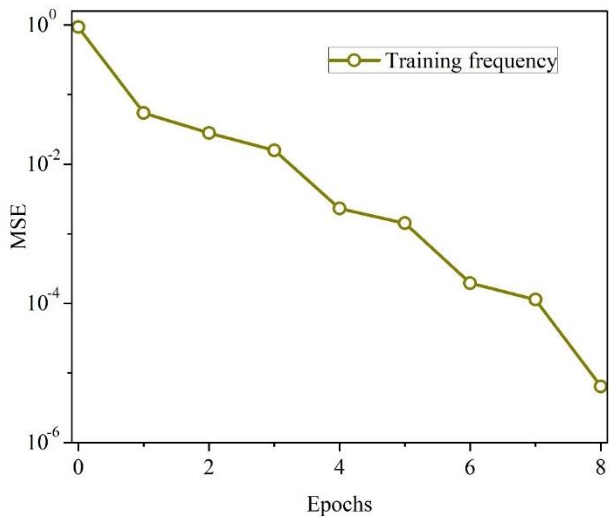

Figure 3. Training convergence

Next, we examined the results of the model fit to conduct a correlation analysis. The fit is shown in

Figure 4. The results obtained from the neural network model align closely with the actual values; there is significant overlap between the target output values and the model output values, indicating that the model fits the data well. Next, to further verify the model's accuracy and prevent issues such as underfitting or overfitting, we selected data on cultural heritage competitiveness from five provinces—Shandong, Beijing, Henan, Jiangsu, and Shaanxi—as a validation sample. We input the 2014 data from these five provinces into the model for training. The comparison of target values and predicted values is shown in Table 3.

It was found that there is a certain degree of error between the predictions of the constructed neural network model and the actual values; however, the error remains within an acceptable range, with the maximum error being only 0.0006. This indicates that the model is effective, capable of fitting the sample data to a certain extent, reflecting the patterns in the data, and enabling evaluations of the competitiveness of China's cultural heritage.

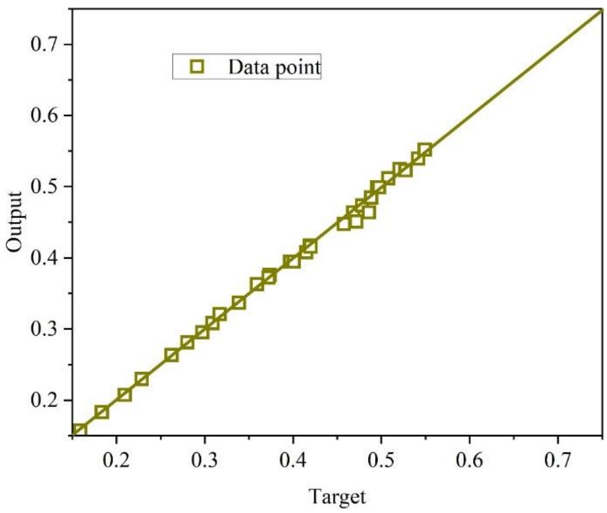

Figure 4. Make sense

Table 3. Comparison of target and forecast values

	Shandong	Beijing	Henan	Jiangsu	Shaanxi
Target value	0.3875	0.3684	0.3687	0.3491	0.3134
Output value	0.3872	0.3688	0.3682	0.3495	0.3128
Error value	0.0003	0.0004	0.0005	0.0004	0.0006

4.2. Evaluation Results

Once the model has been trained, the next step is to evaluate the sample data on China's cultural heritage competitiveness. This involves simply entering the relevant data from the sample into the input layer. The trained neural network model then processes this data to calculate the cultural heritage competitiveness scores for each province and rank them, thereby producing a ranking of the cultural heritage competitiveness across all 31 provinces. Additionally, it is possible to rank and compare enterprises within the same category, making the process user-friendly, clear, and straightforward.

The following rankings of cultural heritage competitiveness for the 31 provinces from 2014 to 2019 were generated using the trained model. The ranking results for 2014 and 2019 are shown in Table 4.

In 2014, the top five provinces, municipalities, and autonomous regions in China's provincial-level cultural heritage competitiveness index were, in order, Jiangsu, Shaanxi, Shandong, Beijing, and Henan, while the bottom five were Qinghai, Guangxi, Ningxia, Tianjin, and Hainan; In 2019, the top five provinces, municipalities, and autonomous regions in China's provincial-level cultural heritage competitiveness index were, in order, Shandong, Beijing, Henan, Jiangsu, and Shaanxi, while the bottom five were Qinghai, Heilongjiang, Tianjin, Ningxia, and Hainan. Specifically, the average composite score for China's provincial-level cultural heritage competitiveness in 2014 was 0.1744. Among the 31 study subjects analyzed in this paper, only the top 13 provinces had composite scores above the average, indicating that the disparity in China's provincial-level cultural heritage competitiveness was relatively significant in 2014, with a considerable number of provinces still scoring below the average. In 2019, the average comprehensive score for provincial-level cultural heritage competitiveness in China was 0.2393. Among the 31 provinces analyzed in this study, the top

16 provinces had comprehensive scores above the average, indicating that the gap in the level of provincial-level cultural heritage competitiveness in China gradually narrowed in 2019, with the competitiveness of cultural heritage in most regions showing steady improvement.

Overall, whether looking at the comprehensive scores for provincial cultural heritage competitiveness in 2014 or 2019, there is a significant disparity in the development levels of cultural heritage competitiveness among China's provinces. Shandong, Beijing, Henan, Jiangsu, and Shaanxi rank in the top tier due to their concentration of resources, talent, technology, and other factors, while Hainan, Ningxia, and Tianjin rank at the bottom. Among the top ten provinces in terms of cultural heritage competitiveness, the eastern region dominates, the central region ranks second, and the western region is relatively weaker. In other words, from a spatial perspective, China's provincial cultural heritage competitiveness generally increases gradually from west to east. However, it was also found that the varying levels of cultural heritage competitiveness across provinces are influenced not only by objective factors such as the distribution of cultural heritage resources but also by management capabilities regarding the protection and utilization of cultural heritage. Therefore, different provinces can use their scores across various classification indicators to clarify specific strategies and objectives for the inheritance of cultural heritage skills and the innovative development of education.

Table 4. The cultural heritage of 31 provinces in 2014 and 2019

	2014			**2019**	
Ranking	Province	Score	Ranking	Province	Score
1	Shandong	0.3872	1	Jiangsu	0.4703
2	Beijing	0.3688	2	Shaanxi	0.4372
3	Henan	0.3682	3	Shandong	0.4332
4	Jiangsu	0.3495	4	Beijing	0.4205
5	Shaanxi	0.3128	5	Henan	0.3827
6	Shanxi	0.3032	6	Sichuan	0.3664
7	Hupei	0.2960	7	Shanxi	0.3644
8	Zhejiang	0.2747	8	Zhejiang	0.3430
9	Sichuan	0.2412	9	Guangdong	0.3310
10	Hebei	0.2386	10	Hupei	0.3211
11	Shanghai	0.2282	11	Hebei	0.3145
12	Guangdong	0.2227	12	Liaoning	0.3038
13	Guizhou	0.2053	13	Tibet	0.2965
14	Liaoning	0.1505	14	Fujian	0.2852
15	Fujian	0.1451	15	Chongqing	0.2509
16	Kansu	0.1436	16	Kansu	0.2438
17	Hunan	0.1435	17	Hunan	0.1874
18	Xinjiang	0.1054	18	Shanghai	0.1867
19	Jiangxi	0.1026	19	Jiangxi	0.1739
20	Anhui	0.1007	20	Xinjiang	0.1590
21	Yunnan	0.1004	21	Yunnan	0.1404
22	Tibet	0.1001	22	Guizhou	0.1383
23	Jilin	0.0768	23	Anhui	0.1301
24	Inner Mongolia	0.0719	24	Heilongjiang	0.1252
25	Guangxi	0.0697	25	Jilin	0.1232
26	Chongqing	0.0688	26	Inner Mongolia	0.1230
27	Qinghai	0.0669	27	Ginghai	0.0927
28	Heilongjiang	0.0604	28	Guangxi	0.0822
29	Tianjin	0.0539	29	Ningxia	0.0661
30	Ningxia	0.0286	30	Tianjin	0.0633
31	Hainan	0.0195	31	Hainan	0.0620

5. Strategies for the Transmission of Traditional Folk Craft Skills and Educational Innovation

5.1. Enhancing the region's digital capabilities

We should prioritize the steady enhancement of regional digital technology capabilities and, from a multi-dimensional perspective, use achievements in digital technology to drive the development of the cultural heritage industry in traditional folk crafts. On the one hand, from the government's perspective:

First, fully leverage the government's service and regulatory functions to further improve the institutional mechanisms for scientific and technological innovation, providing comprehensive policy safeguards for digital technological progress in the preservation of traditional folk crafts; second, increase guidance and policy support for the research and application of key technologies in the cultural heritage industry; third, strengthen the construction of regional digital infrastructure to provide technical support and platform guarantees for the development of cultural heritage industries related to the preservation of traditional folk crafts. On the other hand, from the perspective of the industry and enterprises: First, prioritize the consolidation and enhancement of digital technology capabilities, harness the dynamic potential of digital innovation, and encourage market entities and research institutions to actively promote and apply digital technology achievements; second, reinforce the central role of enterprises in scientific and technological innovation, increase investment in innovation factors within the cultural heritage industry, and elevate the levels of intelligence, connectivity, and knowledge-based content in digital cultural products and services.

5.2. Leverage the unique strengths of regional development

There are significant disparities in cultural heritage competitiveness across China's various regions, with uneven development among provincial-level areas. Analysis shows that regions with weaker competitiveness are primarily located in central, western, and northeastern China, where provinces and cities generally lag behind in terms of scientific and technological capabilities, economic strength, and educational resources. Therefore, it is essential to strengthen cooperation and foster mutual benefit among China's various regions. First, efforts should be made to accelerate the construction of and integration into the unified national market, gradually eliminating market barriers and spatial-temporal constraints in the cultural heritage industry to achieve coordinated economic development and mutual progress. Second, provinces and cities with strong competitiveness should benchmark against leading countries and regions in the international cultural heritage industry, adhere to the principle of "the strong getting stronger," and achieve the aggregation of factors such as capital and talent. Third, provinces and cities with relatively strong competitiveness should strengthen the research, development, application, introduction, absorption, and innovative upgrading of technologies related to the regional cultural heritage industry, capitalizing on their strengths while mitigating weaknesses to amplify their advantages and achieve exponential growth and efficiency gains in industrial development; Fourth, provinces and cities with average competitiveness can adopt a tailored approach to leverage their comparative advantages in cultural heritage, thereby further narrowing the competitiveness gap among provinces and cities.

5.3. Strengthening Educational Innovation in Traditional Folk Crafts

Based on the results of an evaluation of cultural heritage competitiveness across China's provinces using a Backpropagation (BP) neural network, we will precisely identify the strengths and weaknesses of different regions in the transmission of traditional folk craft skills and establish a tiered, categorized, and dynamically adaptive educational innovation system. By utilizing the BP neural network model to conduct quantitative analysis and predictions regarding transmission efficiency, learner acceptance, and the risk of skill loss, we will provide data-driven decision support for curriculum design, teaching method optimization, and faculty allocation.

We will promote in-depth collaboration among universities, vocational colleges, craft inheritors, and intangible cultural heritage protection organizations. We will incorporate the core factors identified by the neural network evaluation into a digital teaching resource repository and develop blended online-offline training modules and intelligent assessment tools. Concurrently, we will establish a quality feedback mechanism for skill transmission, regularly evaluate the effectiveness of educational interventions, dynamically adjust training programs, and enhance the sustainable transmission capacity and educational innovation level of traditional folk crafts.

6. Conclusion

This study examines the cultural heritage competitiveness of China's 31 provinces. It constructs an evaluation system comprising multidimensional indicators, including cultural heritage productivity, and employs a combination of the AHP and entropy weighting methods to determine the comprehensive weights of the evaluation indicators. Furthermore, a model for evaluating China's cultural heritage competitiveness is established based on a BP neural network. The algorithm was validated and empirically analyzed using training data from 2014 and 2019.

The BP neural network effectively captures the complex nonlinear relationships among the various indicators of cultural heritage competitiveness and the composite scores. The model demonstrated good convergence during training, with a maximum error of only 0.0006 between the target values and the output values in the validation sample. This indicates that the model possesses high predictive accuracy and generalization ability, providing reliable data support for the inheritance of traditional folk craft skills and educational innovation.

The evaluation results show that the overall level of cultural heritage competitiveness among China's provinces improved between 2014 and 2019, with the average score rising from 0.1744 to 0.2393 in 2019. Furthermore, the number of provinces with composite scores above the average increased from 13 to 16, indicating that the gap in cultural heritage competitiveness among China's provinces gradually narrowed over the six-year period. There is a significant polarization in the development levels of cultural heritage competitiveness across provinces. Shandong, Beijing, Henan, Jiangsu, and Shaanxi rank in the top tier, while Hainan, Ningxia, and Tianjin rank lower. Among the provinces with higher cultural heritage competitiveness, those in the eastern region dominate, those in the central region rank in the middle, and those in the western region have relatively weaker competitiveness. These results provide quantitative evidence for formulating categorized strategies for the inheritance and educational innovation of traditional folk craft skills.

Based on the above analysis, this paper proposes strategies to enhance regional digital technology capabilities, leverage regional development strengths and characteristics, and strengthen educational innovation in traditional folk crafts, thereby achieving data-driven, targeted inheritance and educational innovation of traditional folk craft skills.

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