Hindawi
Mobile Information Systems
Volume 2023, Article ID 9754217, 1 page
https://doi.org/10.1155/2023/9754217

Retraction

Retracted: Scientific Research Management Helping the Development of Regional Cultural Industry from the Perspective of Artificial Intelligence

Mobile Information Systems

Received 1 August 2023; Accepted 1 August 2023; Published 2 August 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Wang and X. Hu, "Scientific Research Management Helping the Development of Regional Cultural Industry from the Perspective of Artificial Intelligence," *Mobile Information Systems*, vol. 2022, Article ID 1032081, 14 pages, 2022.

Hindawi
Mobile Information Systems
Volume 2022, Article ID 1032081, 14 pages
https://doi.org/10.1155/2022/1032081

Research Article

Scientific Research Management Helping the Development of Regional Cultural Industry from the Perspective of Artificial Intelligence

Jun Wang and Xuying Hu

Quzhou College of Technology, Quzhou 324000, China

Correspondence should be addressed to Xuying Hu; 435689@qzct.edu.cn

Received 9 August 2022; Revised 5 September 2022; Accepted 13 September 2022; Published 3 October 2022

Academic Editor: Jiafu Su

In order to solve the problem that traditional scientific research management is restricted by management methods and tools, and it is difficult to realize the development of cultural industry, this paper proposes a research method that scientific research management helps the development of the regional cultural industry from the perspective of artificial intelligence. Based on a wavelet neural network based on artificial intelligence, this paper establishes the goodwill value evaluation of cultural industry development under scientific research management. Firstly, the paper uses the hierarchical structure theory to construct the theoretical analysis framework and evaluation index system of cultural value and divides the influencing factors of cultural industry value into three levels: input layer network structure, hidden layer network structure, and output layer network structure. Then the wavelet neural network method is used to analyze, and the three-layer network structure is superimposed to reflect the hierarchical relationship between the index systems. Through the combination of normative analysis and empirical analysis, it verifies that the method has unique advantages and feasibility and realizes the promotion of scientific research management to the development of the regional cultural industry.

1. Introduction

The cultural industry has become a new growth pole in the process of global economic development and has gradually become a pillar industry in the economy of some developed countries. How to promote the rapid development of the cultural industry is a problem that all countries in the world are thinking about and discussing at present. However, from the perspective of the general trend of the development of the cultural industry, scientific and technological innovation and management are becoming an important driving force for the rapid development of the cultural industry. National planning outlines have made a comprehensive deployment for the development of cultural industry and proposed to promote the integration of culture and science, and technology. In this macro context, strengthening research on science and technology management and the development of the cultural industry will not only help to broaden the original theoretical scope but also further summarize the practical experience in the development of the cultural industry. From a global perspective, the development of cultural industries and the trade of cultural products are constantly impacting and changing the traditional economic form, which has a sustained and significant impact on the sustainable development of the world economy and the market pattern of world products and has become an important factor in improving the potential and quality of economic development and enhancing the innovation ability of countries or regions. Scientific research management and the development of the cultural industry are of great significance to accelerate the transformation of economic mode, promote the adjustment of industrial structure and industrial transformation and upgrading, improve the national cultural soft power, and build an innovative country [1].

2. Literature Review

Western cultural industry theory is relatively mature in foreign countries. Scholars have carried out extensive research and discussion on the cultural industry from the perspectives of economics, sociology, history, philosophy, and other different disciplines [2]. From the perspective of scientific and technological innovation, foreign scholars' research and exploration of cultural industry mainly focus on three aspects: the relationship between scientific and technological development and cultural communication; the relationship between scientific and technological innovation and cultural industry institutional innovation and the specific form of cultural industry.

Around whether cultural system innovation should be based on technological logic, Zhi and others believe that although technological innovation is a huge driving force for the development of cultural industry, it may also lead to conflicts with the national system, or contradictions between media companies, personal freedom of expression and national system constraints [3]. Czako and others studied the evolutionary relationship between technological innovation and institutional change in the cultural industry and found that the application and promotion of printing technology led to the emergence of the printing media industry and gave birth to the corresponding legal system. Subsequently, the emergence of radio technology and film promoted the emergence of management systems related to content control and access control. Comparatively speaking, the emergence of the latter has made the authority of freedom of speech and expression more restricted [4]. Saeik and others' research on the cultural content industry found that the development of modern network technology not only promotes the enrichment of the forms and contents of the cultural industry, but also provides modern management equipment such as electronic information systems, communication facilities, monitoring systems, etc., which provides favorable external conditions for the reform of management modes and the innovation of management methods, and thus promotes the institutional innovation of many cultural industries. In general, most scholars agree that scientific and technological innovation has a significant impact on the institutional innovation of the cultural industry, but they have not reached a unanimous conclusion on whether to follow the technical logic and choose the same policy objectives, methods, and principles under the unified management framework [5]. Li and others studied the impact of digital technology on the publishing industry. He believed that the most fundamental change brought by digital technology innovation is to separate the published content from the physical carrier carrying it [6].

In the research on the countermeasures for the integrated development of cultural industry and scientific and technological innovation, it analyzes the similarities and differences between scientific and technological innovation and cultural innovation at the macro level, as well as the multi-level impact of science and technology on culture, and puts forward the goals and tasks of the deep integration of science and technology into culture. Some scholars have studied the historical evolution, key issues, and talent requirements of the integration and development of culture and science and technology and have proposed to deal with the mechanism of integration drive, the way of an integration and transformation, the cultivation of integration atmosphere, and the improvement of integration quality. They studied the relationship between scientific and technological development and the cultural industry management system and put forward strategic countermeasures to promote the integrated development of cultural industry and scientific and technological innovation from the perspective of management system innovation. From the five aspects of system innovation, concept innovation, technology innovation, capital innovation, and content innovation, this paper puts forward the relationship that must be handled well to realize the innovative development of the cultural industry. At the regional level, the development situation and mode of the cultural industry in Henan, Hebei, Guangxi, Beijing, Tianjin, Hangzhou, Dalian, Chengdu, Wuhan, Anyang, and other provinces and cities have been deeply studied, and the corresponding specific strategic countermeasures to promote the integration of cultural industry and science and technology and enhance industrial competitiveness that are suitable for the characteristics of each province and city have been put forward [7].

3. Value Analysis of Cultural Industry Based on Artificial Neural Network

3.1. Constituent Factors. Adopting the method of wavelet neural network to establish an index system and a model of cultural industry goodwill value evaluation will better reflect the hierarchy. The evaluation indicators are divided into three layers: input layer, the hidden layer, and the output layer. It can more clearly reflect the relationship between the indicator systems, better measure and determine the impact indicators of the value of cultural industry goodwill, make up for the shortcomings of the previous methods of evaluating the value of goodwill, and better measure the value of cultural industry goodwill. The elements of cultural industry goodwill value evaluation are mainly divided into two factors: soft environment and hard environment: soft environment refers to the sum of external reasons and conditions such as law, policy, system, culture, ideology, and so on in addition to material conditions, including personnel quality, management level, and public influence of cultural industry. The concept of hard environment relative to a soft environment is the sum of geographical conditions, resource conditions, infrastructure, basic conditions, and other external factors and conditions in economic development [8].

3.2. Analysis of Constituent Elements. First, the LM algorithm optimization equation is quoted. Assuming the number of iterations is k, the output layer function of cultural industry goodwill value is defined as $F(z)$, which is expressed as $z_k = [w_{ik}, r_k, a_k, b_k]$ in the matrix.

$$Z_{k+1} = z_k - A_{k-1} g_k. \tag{1}$$

Suppose $F(z) = v(z)^T v(z, v(z))$ is the error vector. Gradient formula of output layer function of goodwill value of cultural industry:

$$\nabla F(z) = 2J^T(z)v(z). \tag{2}$$

Hessaian matrix approximate estimation formula

$$\begin{aligned} &\nabla^2 F(z) \approx 2J^T(z)J(z), \\ &z_{k+1} = zk - \left[J\left(z^J J(z)\right)\right]^{-1} J^T(z)v(z). \end{aligned} \tag{3}$$

Converted into unit matrix, the output layer function gradient equation of cultural industry goodwill value can be expressed as

$$z_{k+1} = zk - \left[J(z)^J J(z) + u_k I\right]^{-1} J(z)^J v(z). \tag{4}$$

We introduce the global optimization algorithm GA to determine the initial state of the neural network so as to achieve the minimum fitting difference. The processing flow of the GA genetic algorithm is shown in Figure 1.

The goodwill value evaluation of the cultural industry based on wavelet neural networks in this paper can not only reflect the characteristics of wavelet neural network that effectively extract the local information of signals, have self-learning, adaptability and fault tolerance, high precision and fast convergence speed, and avoids the blindness of BP neural networks and other structural designs but also evaluate the goodwill value of the cultural industry from the perspective of combining qualitative and quantitative analysis from a unique perspective [9]. The hierarchical structure of the wavelet neural network is more suitable for the hierarchical stratification and classification of the factors affecting the goodwill value of the cultural industry, so as to more effectively and accurately build an evaluation index system and determine the value of the cultural industry in terms of goodwill according to the evaluation index.

3.3. Structural Analysis. The reputation of the cultural industry is the reputation of an enterprise. Its generation is not a gift, but only when the commodity economy develops to a certain stage. It is also gradually formed in the process of commodity producers' production and operators' circulation. The value of goodwill reflects not only the comprehensive evaluation of the enterprise but also the comprehensive evaluation of the enterprise by society, and it is the external overall image of the company. In essence, goodwill is the capitalized value owned by the enterprise, but it cannot be specifically identified. It can enable the enterprise to obtain additional income. In addition, goodwill not only reflects the current development of an enterprise, including its management level, performance, personnel quality, etc., but also reflects the future development of an enterprise. A wavelet neural network is a combination of wavelet analysis and neural network theory. Neural processing units can represent different objects. The processing units in the network can be divided into three types: input units, output units, and hidden layer units. The input unit is connected with external information and data, and the output unit refers to the output of system processing results, but the hidden layer unit is between the input unit and the output unit, which is a unit that cannot be observed outside the system [10].

This paper uses the wavelet neural network method to transform the constituent indicators of cultural industry goodwill value into neurons as evaluation indicators, which are divided into three levels of hierarchy, input layer, hidden layer, and output layer. We regard the factors that affect the goodwill value of the cultural industry as the input, the average value of goodwill value roughly calculated by experts in the industry as the output, and the neuron incentive function selected by the hidden layer as the Morlet wavelet.

$$h(t) = \cos(1.75t)\exp\left(-\frac{t^2}{2}\right). \tag{5}$$

As the input layer function of cultural industry goodwill value evaluation is.

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right)\left(a, b \in R^2\right). \tag{6}$$

The output layer function is

$$y_k = \sum_{j=1}^{n} r_j h\left[\frac{\sum_{i=0}^{m} w_{ij} x_k(i) - b_j}{a_j}\right]. \tag{7}$$

By transforming the indicators of various influencing factors into neurons in the wavelet neural network method, the cultural industry neurons are formed, the hierarchical network structure is formed, and the index system and model are formed, so as to more clearly show the various relationships of the internal composition of the goodwill value of the cultural industry.

4. Empirical Test of Cultural Industry Efficiency of Artificial Intelligence

In order to empirically test the above theoretical analysis of the impact mechanism of artificial intelligence on the efficiency of the cultural industry, this chapter will first use the DEA-Malmquist index method to calculate the efficiency of the cultural industry from 2005 to 2018. Secondly, the principal component analysis method will be used to measure the development level of artificial intelligence. Finally, OLS regression and 2SLS regression will be used to test the impact of artificial intelligence on the efficiency of the cultural industry. At the same time, because the endogenous explanatory variables that may exist in the model will affect the results, this chapter will continue to use the limited information maximum likelihood method LIML, two-step optimal GMM, and iterative GMM to test the stability of the results [11, 12].

4.1. Calculation of Cultural Industry Efficiency

4.1.1. Model Selection. Data envelopment analysis (DEA) is to determine the relatively effective frontier through mathematical programming and statistical data and then

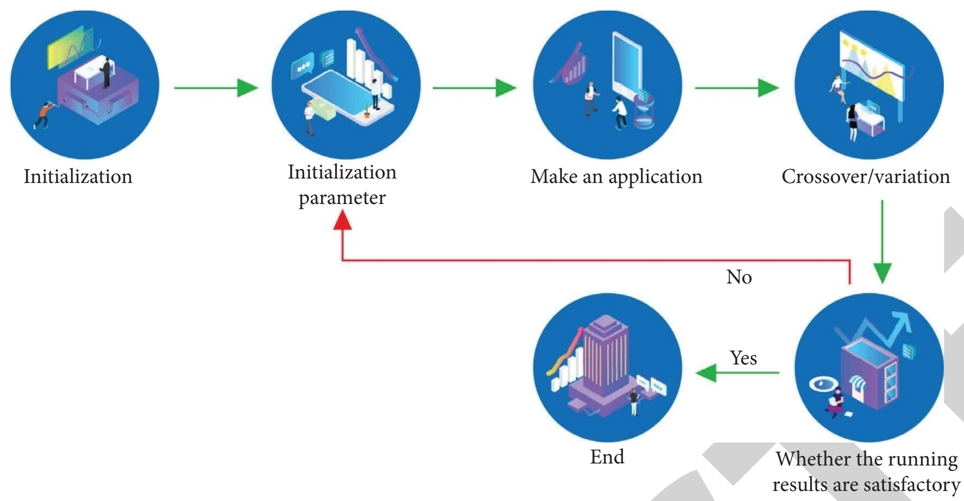

FIGURE 1: GA genetic algorithm processing flow chart.

analyze the deviation degree between the decision-making unit and the frontier of DEA, so as to calculate its relative efficiency. The DEA research method emphasizes the concept of relative efficiency, so as to evaluate the evaluation object, aiming to more effectively reflect the input-output efficiency of the analysis object, and select the best input-output scheme by adjusting the input-output of the analysis object. Because the DEA evaluation method takes relative efficiency as the evaluation index, it can analyze the efficiency of complex systems more simply and conveniently. From the perspective of output, the expressions of the previous $T-1$ period and the current t period of the Malmquist index are as follows:

$$\begin{aligned} M_0^{t-1} &= \frac{D_0^{t-1}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t-1}\left(X^{t}\times Y^{t}\right)},\\ M_0^{t-1} &= \frac{D_0^{t}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t}\left(X^{t}\times Y^{t}\right)}. \end{aligned} \tag{8}$$

According to Fisher's ideal index, the comprehensive production index is the geometric average of the above formula:

$$\begin{aligned} M_0^{t-1,t} &= \sqrt{M_0^{t-1}\times M_0^{t}}\\ &= \sqrt{\frac{D_0^{t-1}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t-1}\left(X^{t}\times Y^{t}\right)}\times\frac{D_0^{t}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t}\left(X^{t}\times Y^{t}\right)}}, \end{aligned} \tag{9}$$

where X^{t-1} and Y^{t-1} represent the input and output vectors of the previous period, X^t and Y^t represent the input and output vectors of the current period, and D_0^{t-1} and D_0^t represent the technical level of the previous period and the current period.

Output oriented total factor productivity (TFP index) can be expressed as

$$\mathrm{TFP} = \sqrt{\frac{D_0^{t-1}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t-1}\left(X^{t}\times Y^{t}\right)}\times\frac{D_0^{t}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t}\left(X^{t}\times Y^{t}\right)}}. \tag{10}$$

TFP can be used to express the efficiency change level of the current period compared with the previous period. When $\mathrm{TFP}>1$, it means that the efficiency of the current period is on the rise; when $\mathrm{TFP}=1$, it means that the efficiency of the current period has not changed; when TFP $G<1$, it means that the efficiency of the current period is in a declining state [13].

Total factor productivity can be further decomposed into technical efficiency (EFFCH) and technological progress efficiency (CTECHCH), so the influence mechanism of total factor productivity of the cultural industry can be further analyzed. The expression is decomposed as follows:

$$\begin{aligned} \mathrm{TFP} &= M_0^{t-1,t} = \frac{D_0^{t-1}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t-1}\left(X^{t}\times Y^{t}\right)}\\ &\quad\cdot\sqrt{\frac{D_0^{t-1}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t-1}\left(X^{t}\times Y^{t}\right)}\times\frac{D_0^{t}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t}\left(X^{t}\times Y^{t}\right)}}\\ &= \mathrm{EFF}\times\mathrm{TECH},\\ EFF &= \frac{D_0^{t-1}\left(X^{t-1}\times Y^{t-1}\right)}{D_0^{t-1}\left(X^{t}\times Y^{t}\right)} = \mathrm{PE}\times\mathrm{SE}. \end{aligned} \tag{11}$$

4.1.2. Construction of Index System. Considering the possibility and accuracy of data acquisition, combined with the above theoretical basis, this paper selects the cultural market's operating institutions as the representative variables of the cultural industry. The decision-making unit set of this paper selects the cost and revenue data of cultural market operating institutions in China's provinces, cities, municipalities directly under the central government and autonomous regions from 2004 to 2018. The data samples involve all provinces of the country. Due to the lack of data in Tibet, this paper will not consider Tibet for the time being. The data are mainly from the statistical yearbook of Chinese culture and tourism, the statistical yearbook of China, and the statistical database of China's economic network. The specific measurement indicators are shown in Table 1.

4.1.3. Calculation Results of Cultural Industry Efficiency

(1) Efficiency of Cultural Industry. The efficiency of the cultural industry in this paper is the total factor productivity of the cultural industry calculated according to the DEA-Malmquist index method. See Table 2 for the specific results of the efficiency of the cultural industry in various provinces and cities from 2004 to 2018.

As can be seen from Table 3, the average efficiency of Beijing's cultural industry from 2004 to 2018 was 1.122, indicating that the efficiency of its cultural industry increased by an average of 12.2%, ranking first. In addition, 20 provinces and cities have increased to varying degrees, and the remaining 10 provinces and cities are in a backward state. Specifically, Beijing and Chongqing are the only two regions where the efficiency of the cultural industry has increased by more than 10%; Fujian and Gansu increased by more than 5%; while Shaanxi and Jiangsu increased by only 0.2%; among the 10 provinces and cities that showed retrogression, the retrogression was not serious, with an average decrease of less than 0.5 in Hubei, Tianjin, Hainan, and Anhui; Qinghai has the largest degree of regression, with a decrease of about 5.3. Although the degree of regression is general, it has a large gap with Beijing, Chongqing, and other places ranking highly.

It can be seen from Table 4 that from 2004 to 2018, there were 6 years when the efficiency of the cultural industry was greater than 1, while there were 8 years when the efficiency was less than 1. Among them, the growth rate during 2006-2007 was the largest compared with other years, reaching 62.6%; during 2011-2012, it was followed by 10.1%; In the four years of 2004-2005, 2005-2006, 2013-2014, and 2016-2017, the growth rate of each year was 2% to 10%; In 2007-2008, 2008-2009, and 2010-2011, the recession was relatively serious, with more than 10% recession. The efficiency of the cultural industry in other years decreased by less than 10%.

(2) Technical Efficiency of Cultural Industry. It can be seen from Table 5 that the technological efficiency of the cultural industry has improved in 9 of the 14 observation periods from 2004 to 2018, and the technological efficiency of the remaining 5 periods has regressed. Among them, the technical efficiency during 2006-2007 has retreated the most. The technical efficiency index can be further divided into scale efficiency and pure technical efficiency, so the improvement of technical efficiency can be started from the aspects of enterprise scale, management and operation, technology, and other factors [14, 15]. The specific situation of the technical efficiency of the cultural industry in various provinces and cities in China from 2004 to 2018 is shown in Table 5.

As can be seen from Table 6, the average technical efficiency of Chongqing's cultural industry from 2004 to 2018 was 1.163, which means that the technical efficiency of its cultural industry increased by 16.3% on average, ranking first. In addition, only the average technical efficiency in Qinghai is lower than 1. Specifically, Chongqing is the only region where the technological efficiency of the cultural industry has increased by more than 10%; Guangdong, Fujian, Beijing, Ningxia, Sichuan, and Shanghai increased by more than 5%; the growth rate of other regions, except Qingdao overseas is between 1% and 5%. From the calculation results, it can be seen from the calculation results that there is a large gap between the technical efficiency of the cultural industry in Qinghai and other regions [16].

(3) Efficiency of Technological Progress in Cultural Industry. The average value of the technological progress efficiency of the cultural industry in each year shows that the technical efficiency of the cultural industry has exceeded 1 in 9 observation periods, while China's cultural technological progress efficiency has exceeded 1 in only 5 periods, such as 2005-2006, 2006-2007, 2011-2012, 2012-2013, and 2014-2015. This shows that the application of science and technology and the adoption of new technologies in the cultural industry still needs to be strengthened. The specific calculation results are shown in Table 7.

As can be seen from Table 8, the average technological progress efficiency of Beijing's cultural industry from 2004 to 2018 was 1.064, indicating that its technological progress efficiency of the cultural industry increased by an average of 6.5%, ranking first. In addition, technological progress in Fujian, Gansu, and Xinjiang increased by 2.8%, 1.9%, and 0.6% respectively. The efficiency of technological progress in other regions did not exceed 1.

4.2. The Impact of Artificial Intelligence on the Efficiency of Cultural Industry. This paper takes 30 provinces, municipalities, municipalities directly under the central government, and autonomous regions in China (excluding Tibet due to incomplete data acquisition) as the research sample, takes 2005–2018 as the research interval, and uses the Malmquist index to measure the efficiency of the cultural industry. On this basis, verify the impact of the AI level on the efficiency of the cultural industry. The measurement tool used is Statal 5.0.

4.2.1. Selection of Index Variables

(1) Core Explanatory Variables. The research object of this paper is the influence mechanism of artificial intelligence on the efficiency of the cultural industry. Therefore, this chapter selects the development level of artificial intelligence as the

Table 1: Efficiency measurement indicators of the cultural industry.

Input index	Number of employees in cultural market operation institutions
	Operating costs of cultural market operating institutions
Output index	Operating income of cultural market institutions

Table 2: Efficiency of cultural industry in various provinces and cities in China from 2004 to 2018.

Region	04-05	05-06	06-07	07-08	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
Beijing	0.963	1.254	1.716	0.341	0.816	0.845	0.812	1.442	1.576	1.161	0.972	0.394	1.001	0.730
Tianjin	0.263	1.261	1.612	0.664	1.032	0.861	1.033	0.932	0.947	0.919	1.414	2.251	0.997	1.013
Hebei	1.053	1.093	1.392	0.353	1.057	0.373	0.325	1.113	1.031	0.997	0.892	1.013	0.911	1.131
Shanxi	0.333	1.141	1.282	0.326	0.873	0.394	1.152	0.739	2.734	0.361	0.872	0.918	1.055	1.039
Inner Mongolia	1.061	1.044	1.861	0.311	1.142	0.982	0.332	0.995	0.952	0.906	0.973	0.967	0.941	0.891
Liaoning	0.639	1.723	3.084	1.351	0.212	0.892	0.959	1.102	1.019	0.931	0.879	0.726	1.139	1.191
Jilin	1.211	1.051	1.051	0.990	1.109	0.967	0.866	1.075	1.026	0.975	0.966	1.047	1.141	0.935
Heilongjiang	1.317	0.919	1.535	0.713	1.091	0.937	0.949	1.099	0.961	0.996	0.903	0.943	1.053	0.874
Shanghai	1.056	1.180	1.735	1.049	0.969	0.915	1.036	1.144	0.558	1.002	1.314	0.331	1.453	0.118
Jiangsu	0.999	1.026	1.391	0.901	0.996	0.911	0.336	1.131	0.919	1.013	1.027	0.922	0.951	0.970
Zhejiang	0.911	1.099	1.414	0.729	0.973	0.943	0.784	1.153	0.902	0.969	1.105	0.954	1.141	0.861
Anhui	1.043	0.979	5.784	0.253	0.946	1.165	0.637	1.057	0.348	1.013	1.136	0.923	0.391	0.996
Fujian	1.087	1.060	2.201	0.978	0.721	0.971	0.911	1.139	0.335	2.794	0.887	0.822	1.062	0.956
Jiangxi	1.102	1.011	1.436	0.354	1.098	0.937	0.937	0.868	1.201	0.997	0.917	0.841	1.071	0.901
Shandong	1.131	1.094	1.522	1.019	0.612	1.112	0.849	1.058	0.821	1.132	0.919	0.961	0.973	0.832
Henan	0.893	1.428	1.245	0.961	1.037	0.816	0.852	1.216	1.009	0.893	1.012	0.840	1.031	1.046
Hubei	1.229	0.946	1.413	0.935	0.943	0.965	0.818	1.127	0.938	1.187	0.811	0.737	1.001	0.962
Hunan	1.006	1.101	1.999	0.876	0.906	0.914	1.011	1.071	0.955	1.187	0.732	0.971	1.011	0.971
Guangdong	1.036	0.990	1.323	1.115	0.724	1.047	1.463	1.066	0.533	1.040	1.203	1.464	1.906	0.651
Guangxi	0.997	0.939	1.491	0.929	0.987	0.931	0.875	1.151	0.961	0.995	1.061	0.932	1.058	0.986
Hunan	1.084	0.992	1.907	0.725	0.876	1.036	0.921	1.025	1.597	0.614	0.381	1.146	1.038	0.810
Chongqing	2.321	1.462	1.741	0.893	0.825	0.957	0.901	1.049	0.972	1.041	1.706	1.186	0.437	1.031
Sichuan	1.582	1.131	1.899	0.941	0.751	0.836	1.012	0.991	0.784	1.025	0.944	0.119	0.763	1.432
Guizhou	1.013	1.129	1.245	0.977	0.904	1.011	0.682	1.431	0.915	1.064	0.968	0.871	1.115	0.663
Yunnan	1.017	0.778	2.421	0.641	1.121	0.919	0.737	1.251	1.026	1.036	0.917	1.001	1.025	1.022
Shaanxi	1.032	0.931	1.498	0.832	1.051	0.968	0.791	1.337	0.351	1.041	0.876	1.245	0.871	1.119
Gansu	1.101	1.131	1.214	1.003	1.142	0.393	0.356	1.186	0.899	0.901	0.645	0.532	1.586	1.053
Qinghai	1.021	1.087	1.458	0.582	0.879	0.871	0.791	1.069	0.918	0.829	0.884	1.033	1.110	0.919
Ningxia	1.191	1.093	1.116	0.910	1.089	1.010	0.874	1.223	1.002	1.491	0.664	0.858	1.009	0.991
Xinjiang	0.304	1.023	1.470	1.001	0.324	1.190	0.835	1.002	1.037	1.230	0.513	1.293	1.001	0.926

core explanatory variable of the empirical model. Based on the definition of the concept of artificial intelligence in Chapter 2, because artificial intelligence can affect the efficiency of cultural industry at the technical and institutional levels and it also has mutual influence at the technical and institutional levels, it cannot be completely analyzed independently. Therefore, a comprehensive, comprehensive, systematic, and representative index system is needed to reflect the development level of artificial intelligence. The indicators of the basic level of artificial intelligence mainly reflect the development level of the whole society's technical facilities, policy guidance, and other institutional levels; the indicators at the technical level mainly reflect the development level of talents and other technical levels; and the indicators at the application level comprehensively reflect the development level of artificial intelligence technology and system level.

Based on the initial formation of three primary indicators of the artificial intelligence foundation layer, technology layer and application layer, it is expanded into nine secondary indicators [17]. Including electricity consumption, total telecommunications business, the proportion of fixed asset investment in information, computer, and software industry in the total social fixed asset investment, the number of scientific and technological institutions of large and medium-sized industrial enterprises, the total number of R&D personnel at that time, the number of graduates of higher education institutions, the number of patent authorizations, the total output value of the high-tech industry, the turnover of technical contracts, etc. Finally, the principal component analysis method is used to measure the development level of artificial intelligence. The data in the above secondary indicators are mainly from the statistical database of the China economic network and the China Statistical Yearbook. The specific index system is shown in Table 9.

This paper uses principal component analysis to determine the weight of the above indicators, as shown in Table 10.

After comprehensive calculation, the comprehensive evaluation value of the development level of artificial intelligence is finally obtained. Figure 2 shows the overall trend of the average development level of AI in various regions of China from 2005 to 2018. It can be seen that the overall

Table 3: Average efficiency of cultural industries in various provinces and cities in China from 2004 to 2018.

Region	Numerical value	Ranking
Beijing	1.122	1
Chongqing	1.111	2
Fujian	1.083	3
Gansu	1.065	4
Xinjiang	1.047	5
Sichuan	1.043	6
Shanghai	1.041	7
Guangdong	1.038	8
Jilin	1.025	9
Hunan	1.023	10
Ningxia	1.018	11
Guangxi	1.017	12
Yunnan	1.011	13
Henan	1.011	14
Hebei	1.009	15
Jiangxi	1.004	16
Heilongjiang	1.003	17
Inner Mongolia	1.003	18
Shaanxi	1.002	19
Jiangsu	1.002	20
Hubei	0.996	21
Tianjin	0.996	22
Hainan	0.995	23
Anhui	0.994	24
Zhejiang	0.986	25
Guizhou	0.984	26
Liaoning	0.981	27
Shandong	0.974	28
Shanxi	0.966	29
Qinghai	0.947	30

Table 4: Efficiency of the cultural industry from 2004 to 2018.

	Technical efficiency (effch)	Efficiency of technological progress (techch)	Pure technical efficiency (pech)	Scale efficiency (sech)	Total factor productivity of cultural industry (tfpch)
2004-2005	1.634	0.633	1.423	1.141	1.031
2005-2006	0.891	1.228	0.884	1.008	1.093
2006-2007	0.502	3.223	0.575	0.884	1.625
2007-2008	1.271	0.663	1.276	1.004	0.847
2008-2009	1.793	0.496	1.636	1.100	0.895
2009-2010	0.975	0.964	0.961	1.015	0.944
2010-2011	1.077	0.828	1.051	1.025	0.886
2011-2012	1.050	1.049	1.046	1.005	1.101
2012-2013	0.530	1.859	0.793	0.666	0.986
2013-2014	1.478	0.730	1.131	1.307	1.076
2014-2015	0.626	1.565	0.627	0.999	0.984
2015-2016	1.289	0.751	1.236	1.043	0.968
2016-2017	1.407	0.734	1.372	1.025	1.037
2017-2018	1.020	0.932	1.030	0.990	0.952

development level of AI in China showed an upward trend from 2005 to 2018.

(2) Control Variables. For the control variables, four factors, including economic development level, human capital, cultural system factors, and market cultural demand, are taken as the control variables, as shown in Table 11.

First, the cultural industry is an industry that comes into being when the overall social and economic level of China has developed to a certain extent. Spiritual and cultural needs will appear only after meeting the general material needs of life. Therefore, the development of the cultural industry cannot be separated from the impact of the level of economic development. Based on this, this paper selects per

Table 5: Technical efficiency of cultural industry in various provinces and cities in China from 2004 to 2018.

Region	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Beijing	1.516	1.013	0.479	1.123	2.191	0.901	0.990	1.378	1.174	0.794	1.322	0.797	0.961	0.737
Tianjin	0.653	1.065	0.534	1.239	1.753	0.396	1.122	0.935	0.513	1.323	0.795	2.422	0.922	1.034
Hebei	1.543	0.371	0.412	1.412	2.220	0.913	1.009	1.097	0.524	1.357	0.661	1.399	1.326	1.131
Shanxi	1.533	0.917	0.385	1.053	2.147	0.912	1.444	0.766	1.324	0.614	0.631	1.243	1.397	1.057
Inner Mongolia	1.582	0.847	0.525	1.212	2.511	1.000	1.000	1.000	0.439	1.528	0.634	1.314	1.271	0.913
Liaoning	0.923	1.376	1.000	1.000	0.791	0.935	1.201	1.061	0.538	1.298	0.614	0.986	1.741	1.303
Jilin	1.331	0.837	0.289	1.711	2.125	0.982	1.122	0.994	0.531	1.336	0.676	1.423	1.511	1.000
Heilongjiang	1.871	0.727	0.471	1.123	1.031	0.969	1.202	1.065	0.511	1.241	0.704	1.282	1.326	0.956
Shanghai	1.035	1.000	0.847	1.113	1.000	1.000	1.000	1.000	0.435	1.531	0.731	1.051	1.933	0.931
Zhejiang	1.112	0.933	0.566	1.224	1.549	1.001	0.931	1.093	0.422	1.779	0.591	1.297	1.711	0.928
Anhui	1.475	0.831	1.637	0.492	1.721	1.13	0.817	0.999	0.411	1.635	0.763	1.255	1.271	1.062
Fujian	1.816	0.875	0.607	1.331	1.129	1.056	1.003	1.064	0.393	2.980	0.815	1.117	1.629	1.046
Jiangxi	1.772	0.822	0.412	1.526	1.056	0.971	1.156	0.864	0.623	1.374	0.671	1.142	1.586	0.961
Shandong	1.173	0.811	0.541	1.333	1.110	0.903	1.051	1.031	0.416	1.645	0.738	1.312	1.287	0.874
Henan	1.153	1.192	0.373	1.416	0.702	0.335	1.097	1.122	0.531	1.217	0.737	1.141	1.467	1.065
Hubei	1.843	0.755	0.720	1.479	1.356	0.971	1.063	1.053	0.476	1.963	0.504	1.137	1.462	1.043
Hunan	1.463	0.894	0.602	1.075	1.931	0.935	1.243	1.057	0.481	1.651	0.467	1.321	1.501	1.057
Guangdong	1.977	0.831	0.393	1.743	1.432	1.033	1491	1.000	0.438	1.241	0.633	1.313	1.603	0.836
Guangxi	1.530	0.787	0.433	1.474	1.973	0.941	1.099	1.105	0.503	1.411	0.726	1.335	1.469	1.032
Hainan	1.721	0.804	0.579	1.233	1.699	1.057	1.150	0.973	1.252	0.691	0.513	1.557	1.541	0.374
Chongqing	5.132	1.218	0.467	1.758	1.459	0.971	1.165	0.962	0.473	1.736	0.982	1.604	0.705	1.105
Sichuan	1.945	0.913	0.573	1.049	1.325	0.374	1.232	0.901	0.496	1.711	0.599	1.163	1.153	1.559
Guizhou	1.781	0.912	0.842	1.866	1.671	1.024	0.832	1.401	0.459	1.722	0.612	1.133	1.616	0.716
Yunnan	1.407	0.633	0.721	0.839	0.795	0.969	0.921	1.205	0.544	1.471	0.577	1.372	1.434	1.057
Shaanxi	1.699	0.764	0.396	1.534	1.391	1.006	0.993	1.216	0.436	1.519	0.576	1.359	1.235	1.193
Gansu	1.675	0.910	0.371	1.437	2.512	0.921	1.037	1.131	0.456	2.124	0.474	0.724	2.244	1.087
Qinghai	1.000	1.000	0.751	0.404	3.301	0.967	0.918	1.126	0.477	1.297	0.572	1.405	1.528	1.019
Ningxia	0.803	0.861	0.835	1.726	1.942	1.034	1.144	1.119	0.524	1.951	0.496	1.166	1.359	1.007
Xinjiang	1.314	0.821	0.866	1.525	1.792	1.237	1.146	0.913	0.523	0.408	0.878	1.757	1.504	1.000

Table 6: Average value of the technical efficiency of the cultural industry in various provinces and cities in China from 2004 to 2018.

Region	Numerical value	Ranking
Chongqing	1.162	1
Guangdong	1.060	2
Fujian	1.054	3
Beijing	1.053	4
Ningxia	1.052	5
Sichuan	1.051	6
Shanghai	1.050	7
Hainan	1.048	8
Zhejiang	1.048	9
Jilin	1.046	10
Gansu	1.044	11
Guangxi	1.043	12
Xinjiang	1.042	13
Jiangsu	1.038	14
Hunan	1.033	15
Yunnan	1.031	16
Inner Mongolia	1.031	17
Shaanxi	1.029	18
Henan	1.025	19
Hubei	1.025	20
Guizhou	1.024	21
Anhui	1.021	22
Heilongjiang	1.020	23
Shandong	1.018	24
Shanxi	1.013	25
Liaoning	1.011	26

Table 7: Technological progress of cultural industry in various provinces and cities in China from 2004 to 2018.

Region	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Beijing	0.638	1.238	3.584	0.749	0.372	0.936	0.824	1.046	1.342	1.462	2.248	0.894	1.042	0.928
Tianjin	0.402	1.184	3.021	0.536	0.589	0.963	0.966	0.998	1.829	0.748	1.779	0.929	1.081	0.935
Hebei	0.683	1.257	3.397	0.603	0.476	0.958	0.818	1.014	1.967	0.735	1.356	0.736	0.687	0.957
Shanxi	0.527	1.247	3.331	0.785	0.406	0.983	0.798	1.031	2.065	0.588	1.383	0.736	0.755	0.982
Inner Mongolia	0.671	1.233	3.546	0.672	0.455	0.988	0.831	0.995	1.954	0.593	1.534	0.736	0.741	0.975
Liaoning	0.689	1.256	3.084	1.352	0.268	0.954	0.798	1.038	1.893	0.716	1.432	0.736	0.657	0.914
Jilin	0.662	1.255	3.476	0.579	0.522	0.984	0.772	1.082	1.906	0.704	1.429	0.736	0.755	0.985
Heilongjiang	0.704	1.263	3.218	0.635	0.537	0.967	0.793	1.031	1.181	0.803	1.284	0.736	0.798	0.914
Shanghai	0.519	1.181	2.049	0.889	0.969	0.915	1.036	1.144	1.282	0.652	1.799	0.792	0.752	0.876
Jiangsu	0.569	1.191	3.012	0.574	0.631	0.939	0.859	1.015	2.099	0.568	1.788	0.736	0.658	0.907
Zhejiang	0.467	1.179	2.493	0.595	0.631	0.936	0.841	1.061	2.137	0.545	1.871	0.736	0.667	0.927
An Zheng	0.707	1.259	3.533	0.514	0.552	0.987	0.722	1.058	2.062	0.604	1.555	0.736	0.701	0.938
Fujian	0.598	1.211	3.626	0.535	0.638	0.921	0.893	1.071	2.097	0.937	2.139	0.736	0.652	0.923
Jiangxi	0.623	1.239	3.626	0.538	0.534	0.986	0.811	1.005	1.991	0.726	1.368	0.736	0.679	0.938
Shandong	0.637	1.242	2.805	0.586	0.551	0.974	0.808	1.027	1.974	0.688	1.321	0.736	0.755	0.952
Henan	0.775	1.198	3.337	0.678	0.471	0.977	0.777	1.065	1.906	0.728	1.361	0.736	1.524	0.982
Hubei	0.667	1.254	3.439	0.632	0.508	0.987	0.769	1.071	1.969	0.604	1.606	0.736	0.691	0.922
Hunan	0.685	1.232	3.318	0.815	0.469	0.978	0.813	1.013	2.011	0.719	1.567	0.736	0.673	0.917
Guangdong	0.556	1.193	3.381	0.641	0.505	0.967	0.977	1.066	1.149	0.648	1.921	0.808	1.189	0.733
Guangxi	0.652	1.256	3.406	0.631	0.491	0.987	0.796	1.012	1.454	1.644	1.241	1.234	1.257	1.045
Hainan	0.583	1.234	3.295	0.565	0.515	0.982	0.783	1.053	1.266	0.877	1.699	0.736	0.674	0.917
Chongqing	0.544	1.201	3.728	0.511	0.565	0.985	0.779	1.092	2.055	0.612	1.737	0.739	0.621	0.932
Sichuan	0.813	1.121	3.313	0.896	0.414	0.956	0.821	1.092	2.016	0.631	1.577	0.736	0.662	0.918
Guizhou	0.608	1.224	3.656	0.524	0.541	0.986	0.817	1.021	2.015	0.618	1.583	0.736	0.692	0.926
Yunnan	0.723	1.229	3.356	0.762	0.401	0.948	0.821	1.038	1.886	0.705	1.572	0.736	0.715	0.966
Shaanxi	0.637	1.217	3.789	0.525	0.565	0.962	0.796	1.099	1.955	0.655	1.534	0.736	0.704	0.934
Gansu	0.657	1.257	3.302	0.702	0.455	0.975	0.787	1.047	1.972	1.366	1.362	0.736	0.707	0.974
Qinghai	1.021	1.087	1.944	1.442	0.266	0.907	0.862	0.949	1.925	0.638	1.545	0.736	0.727	0.971
Ningxia	0.594	1.269	3.335	0.522	0.561	0.977	0.764	1.093	1.911	0.764	1.338	0.736	0.742	0.985
Xinjiang	0.612	1.246	3.411	0.659	0.46	0.962	0.772	1.077	1.982	1.424	1.354	0.736	0.666	0.926

Table 8: Average value of the technological progress of the cultural industry in various provinces and cities in China from 2004 to 2018.

Region	Numerical value	Ranking
Beijing	1.064	1
Fujian	1.027	2
Gansu	1.018	3
Xinjiang	1.005	4
Tianjin	0.996	5
Shanghai	0.993	6
Sichuan	0.992	7
Hunan	0.990	8
Henan	0.984	9
Heilongjiang	0.983	10
Yunnan	0.981	11
Jilin	0.980	12
Guangdong	0.976	13
Guangxi	0.975	14
Shaanxi	0.973	15
Inner Mongolia	0.972	16
Anhui	0.972	17
Hubei	0.971	18
Liaoning	0.970	19
Ningxia	0.968	20
Hebei	0.967	21
Jiangsu	0.964	22
Qinghai	0.964	23
Jiangxi	0.963	24
Guizhou	0.962	25
Chongqing	0.957	26
Shandong	0.957	27
Shanxi	0.953	28
Hainan	0.950	29
Zhejiang	0.940	30

Table 9: Selection of AI development level indicators.

Target	Primary index	Secondary indicators
Development level of artificial intelligence	Foundation layer	Power consumption
		Total telecommunication business
		Proportion of fixed asset investment in information, computer and software industry in the whole society
	Technical level	Number of scientific and technological institutions of large and medium-sized industrial enterprises
		R&d personnel at that time
		Number of graduates from higher education institutions
	Application layer	Number of patents authorized
		Total output value of high-tech industry
		Turnover of technology contract

Table 10: Index weight of artificial intelligence development level.

Index	Weight
Power consumption	0.04
Total telecommunication business	0.11
Proportion of fixed asset investment in information, computer and software industry in the whole society	0.08
Number of scientific and technological institutions of large and medium-sized industrial enterprises	0.14
R&d personnel at that time	0.15
Number of graduates from higher education institutions	0.01
Number of patents authorized	0.16
Total output value of high-tech industry	0.15
Turnover of technology contract	0.11

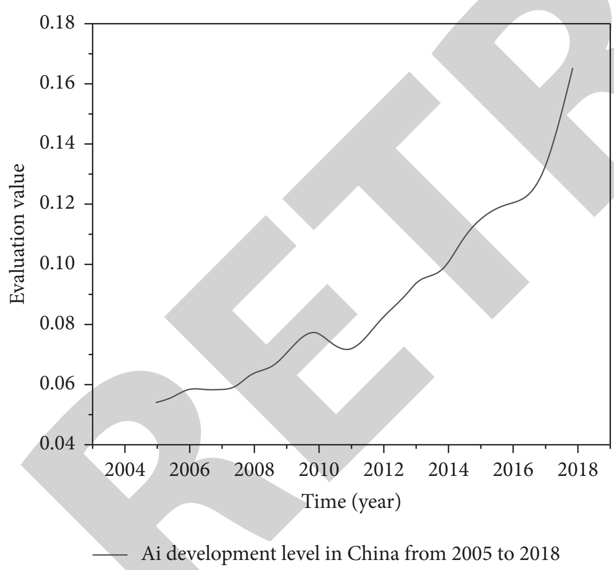

Figure 2: Development level of artificial intelligence in China from 2005 to 2018.

capita GDP as an indicator to measure the level of economic development. Second, human capital, as the human resource input of the efficiency of the cultural industry, is inseparable from the efficiency of the cultural industry. Theoretically, the higher the quality of human capital, the more obvious the role of human capital in improving the efficiency of the cultural industry. Therefore, this paper selects the proportion of high school and above in the total employment of society as the index to evaluate the quality of human resources. Third, national support can promote the development of the cultural industry, so this paper selects cultural broadcasting fees as the measurement index of national financial investment. Fourth, the market's cultural demand is the internal condition for the emergence and development of the cultural market. Under the influence of the market supply and demand mechanism, it can promote the innovation and development of enterprises in the cultural industry. Therefore, this paper selects the per capita consumption expenditure on education, culture, and entertainment as the index to measure the demand for cultural consumption [18].

4.2.2. Model Setting. In order to further verify the above analysis, we need to analyze the impact of artificial intelligence on the efficiency of the cultural industry from an empirical perspective and test the impact of artificial intelligence on the production efficiency of the cultural industry through the panel data model. The reasons for choosing panel data analysis include the following three aspects. First, the use of panel data models can increase the degree of freedom of samples and the amount of information, so as to reduce the gap between insufficient data supply and information demand in the efficiency model of the cultural industry. Second, this model can reflect the inter provincial gap in cultural industry and the regional differences in the impact of artificial intelligence on cultural industry in eastern, central, and western China. Thirdly, after Hausmann test and LM test of random utility model and fixed utility model, this paper believes that the OLS regression model is the most efficient;. At the same time, the

Table 11: Selection of control variables.

Other influencing factors	Specific measurement indicators	Control variable representation
Economic development level	Per capita GDP	Per capita GDP
Human capital	Proportion of high school and above in the number of employees	Human resource quality (human)
Cultural broadcasting expenses	Special financial expenditure for culture (ce)	Cultural system factors
Per capita consumption expenditure on education, culture and entertainment	Cultural consumption (yt)	Market cultural needs

Hausmann test results of ordinary least squares (OLS) and two-stage least squares estimation (2SLS) show that there may be endogenous explanatory variables in the model, and the instrumental variable method needs to be used. The specific construction model is as follows:

$$tfp_{it} = c + aai_{it} + \beta C + \mu_{it}, \tag{12}$$

where, i and t represent the region and year respectively; TFP is the explained variable, which indicates the efficiency of the cultural industry; a_i is the core explanatory variable, representing the development level of artificial intelligence; C are other factors that affect the total factor productivity of the cultural industry, and the per capita GDP (GDP), human resource quality (human), cultural consumption (YT), and special cultural fiscal expenditure (CE) are selected as control variables; α, β are parameters to be estimated; and μ is random disturbance term. In the model, a represents the influence coefficient of the development level of artificial intelligence on the total factor productivity of the cultural industry, which is the core result of this paper.

4.2.3. Empirical Results and Robustness Test. In order to explore the impact of artificial intelligence on the efficiency of the cultural industry, this paper will carry out OLS regression, 2SLS regression, limited information maximum likelihood (LIML), two-step optimal GMM, and iterative GMM, respectively. Firstly, OLS is used as the reference term for the model. As the Hausmann test results show that there may be endogenous problems in the model, the 2SLS model is used to add tool variables to solve the endogenous problems. However, there may be weak instrumental variables, and LIML is more insensitive to weak instrumental variables. For the sake of robustness, LIML is again used for regression analysis of the model [19]. At the same time, because the impression of some other unobservable factors will inevitably lead to heteroscedasticity and other problems, this paper uses the optimal GMM and iterative GMM models to control and reduce the heteroscedasticity and weak instrumental variables in the model.

(1) Regression Results. The empirical results of the impact of AI on the efficiency of the cultural industry are shown in Table 12. Column (1) shows the OLS regression results with control variables. The AI coefficient of the explanatory variable is significantly positive, indicating that the AI development level has a positive impact on the efficiency of the cultural industry. Column (2) is the 2SLS regression result. After solving some possible endogenous problems, the AI coefficient of the explanatory variable is still significantly positive. Column (3) is the regression result estimated by LIML, and the AI coefficient of the explanatory variable is significantly positive, indicating that this result has certain robustness. Column (4) is the regression result using two-step GMM estimation, and the AI coefficient of the explanatory variable is significantly positive. Column (5) is the regression result estimated by iterative GMM, and the AI coefficient of the explanatory variable is also significantly positive.

The empirical results of the impact of AI on the technical efficiency of the cultural industry are shown in Table 13. Column (1) shows the OLS regression results with control variables. The AI coefficient of the explanatory variable is significantly positive, but it does not pass the significance test. Column (2) is the 2SLS regression result. After solving some possible endogenous problems, the AI coefficient of the explanatory variable is positive and fails to pass the significance test. Column (3) is the regression result estimated by LIML. The AI coefficient of the explanatory variable is positive, and it still fails to pass the significance test. Column (4) is the regression result estimated by two-step GMM, and the AI coefficient of the explanatory variable is positive. Column (5) is the regression result estimated by iterative GMM, and the AI coefficient of the explanatory variable is also positive.

The empirical results of the impact of AI on the efficiency of technological progress in the cultural industry are shown in Table 14. Column (1) shows the OLS regression results with the control variable added. The AI coefficient of the explanatory variable is positive, indicating that the AI development level has a positive impact on the technological progress of the cultural industry. Column (2) is the 2SLS regression result. After solving some possible endogenous problems, the AI coefficient of the explanatory variable is significantly positive. Column (3) is the regression result estimated by LIML. The explanatory variable AI coefficient is significantly positive, indicating that this result is robust. Column (4) is the regression result using two-step GMM estimation, and the AI coefficient of the explanatory variable is significantly positive. Column (5) is the regression result estimated by iterative GMM, and the AI coefficient of the explanatory variable is also significantly positive [20].

(2) Result Analysis. From the above regression results, we can see that the coefficient of the impact of AI development level on the efficiency of cultural industry and the efficiency of technological progress is significantly positive. This means

Table 12: Impact of artificial intelligence on the efficiency of the cultural industry.

Variable	(1) OLS1	(2) 2SLS1	(3) LIML1	(4) GMM1	(5) IGMM1
Ai	0.7588**	0.7558*	0.7561*	0.8182**	0.8201**
	(1.9673)	(1.8724)	(1.8688)	(2.0339)	(2.0385)
Gdp	−6.03*E* − 06**	−5.68*E* − 06**	−5.69*E* − 06**	−5.62*E* − 06**	−5.62*E* − 06**
	(−2.0373)	(−1.8665)	(−1.8655)	(−1.8412)	(−2.0750)
human	−0.0022	−0.0004	−0.0004	0.0004	0.0004
	(−0.5552)	(−0.1033)	(−0.1035)	(0.0855)	(0.0886)
yt	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.6421)	(0.2961)	(0.2960)	(0.0478)	(0.0434)
ce	0.0000	−0.0001	−0.0001	−0.0002	−0.0002
	(0.0441)	(−0.1173)	(−0.1172)	(−0.2380)	(−0.2397)
N	420	390	390	390	390
F inspection, *P* value	0.0558	—	—	—	—
Chi square test, *P* value	—	0.0961	0.0965	0.0677	0.0672

Table 13: Impact of artificial intelligence on the technical efficiency of the cultural industry.

Variable	(1) OLS2	(2) 2SLS2	(3) LIML2	(4) GMM2	(5) IGMM2
ai	0.9439*	0.2642	0.2711	0.1079	0.0971
	(1.8068)	(0.5156)	(0.5264)	(0.2123)	(0.1912)
gdp	−4.45*E* − 06**	−0.00000157	−0.0000016	−0.0000035	−0.00000173
	(−1.3988)	(−0.4999)	(−0.5077)	(−0.1121)	(−0.0554)
human	0.0025	0.0065*	0.0065*	0.0074*	0.0076**
	(0.5814)	(1.7075)	(1.7056)	(1.9521)	(2.0030)
yt	−0.0002***	−0.0002***	−0.0002***	−0.0002***	−0.0002***
	(−4.6401)	(−5.2234)	(−5.2241)	(−5.2508)	(−5.2673)
ce	0.0005	0.0013	0.0013	0.0013	0.0013
	(0.5136)	(1.4521)	(1.4488)	(1.4545)	(1.4202)
N	420	390	390	390	390
F inspection, *P* value	0.0001	—	—	—	—
Chi square test, *P* value	—	0.0001	0.0001	0.0001	0.0001

Table 14: Impact of artificial intelligence on technological progress efficiency of cultural industry.

Variable	(1) OLS3	(2) 2SLS3	(3) LML3	(4) GMM3	(5) IGMM3
ai	0.9224	1.7330**	1.7330**	1.7571**	1.7571*
	(1.4341)	(2.2278)	(2.2277)	(2.2695)	(2.2694)
gdp	−0.00000459	−7.76*E* − 06*	−7.76*E* − 06*	−7.92*E* − 06*	−7.92*E* − 06*
	(−1.2075)	(−1.7854)	(−1.7854)	(−1.8349)	(−1.8350)
human	−0.0114**	−0.0134**	−0.0134**	−0.0135**	−0.0135**
	(−1.9871)	(−2.1809)	(−2.1809)	(−2.1956)	(−2.1956)
yt	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(5.2204)	(4.9067)	(4.9067)	(4.9035)	(4.9034)
ce	−0.0026**	−0.0036***	−0.0036***	−0.0036***	−0.0036***
	(−2.0554)	(−2.7237)	(−2.7237)	(−2.7141)	(−2.7140)
N	420	390	390	390	390
F inspection, *P* value	0.0001	—	—	—	—
Chi square test, *P* value	—	0.0001	0.0001	0.0001	0.0001

that the positive impact of AI on the cultural industry is mainly through promoting the technological progress of the cultural industry, so as to promote the efficiency of the cultural industry.

First, in terms of the efficiency of the cultural industry, the impact of artificial intelligence on the efficiency of the cultural industry is estimated to be 0.8200 under the iterative GMM model. Because the cultural industry is a technology intensive industry, the production of its products depends on technological creativity. The positive impact of artificial intelligence on the efficiency of the cultural industry shows that artificial intelligence can effectively promote the innovative development of the cultural industry. This result is consistent with the theoretical analysis above. Artificial intelligence can indeed break the current situation of path dependence in the cultural industry and promote the path creation of the cultural industry.

Second, from the perspective of technical efficiency, the regression result is not significant. From the perspective of objective conditions, the reason for this result may be that the government's public data has time constraints, so the length of data acquisition is limited, and it does not fully show the evolution process of artificial intelligence and cultural industry efficiency. Combined with the previous theoretical analysis, AI failed to promote the path creation of technology in the cultural industry. On the one hand, government policies have a great impact on the technical efficiency of the cultural industry. Although at the national level, China has issued many relevant policies on the integration of science, technology, and culture, there is a certain time lag in the cultural industry policies on digital technologies such as artificial intelligence at the local government level.

Third, in terms of the efficiency of technological progress, the impact of AI on the efficiency of technological progress of the cultural industry is estimated to be 1.7571 under the iterative GMM model, which is much larger than the impact coefficient of AI on the efficiency i the cultural industry. This shows that at this stage, the impact of artificial intelligence on the cultural industry is mainly through providing technical support to the cultural industry and providing new technology application in its production and operation process, so as to improve the efficiency of technological progress of the cultural industry and then promote the efficiency of the cultural industry. Combined with the above theoretical analysis, specifically speaking, at this stage, artificial intelligence can promote the cultural industry to realize the creation of a technological path, but the impact of artificial intelligence on the cultural industry is still relatively simple, mainly through technological breakthroughs and innovation, bring emerging technologies into the cultural industry, and realize the breakthrough technological path creation of the cultural industry, so as to promote the technological progress efficiency of the cultural industry. The quality of talents has a significant negative impact on the efficiency of technological progress in the cultural industry, that is, when the quality of talents continues to improve, it fails to promote the efficiency of technological progress in the cultural industry, which is consistent with the above analysis results of professional and technical talents and compound talents in the cultural market. At this stage, the impact of artificial intelligence on the efficiency of the cultural industry is restricted by the lack of compound talents. The situation of the gradual path creation formed by the integration of artificial intelligence and cultural industry technology has not been fully apparent.

Based on the analysis of the above results, the path creation process of artificial intelligence to promote the cultural industry first needs to experience the process of technology path creation such as the generation of new technologies and technology spillovers. With the continuous development of technological breakthroughs, product innovation, the formation of industrial formats, and other aspects, institutional path creation will occur synchronously. At this stage, the cultural industry has initially completed the process of technological path creation, but institutional path creation has not been fully realized.

5. Conclusion

When constructing the theoretical framework of cultural industry goodwill value evaluation, this paper divides the influencing factors of goodwill value evaluation into three levels: input layer network structure, hidden layer network structure, and output layer network structure according to the hierarchy theory and the characteristics of cultural industry goodwill value. Then the wavelet neural network method is used to analyze, and the superposition of the three-layer network structure is realized. The hierarchical network structure can more objectively reflect the hierarchical relationship between the index systems, which can be used as the theoretical basis for building the evaluation index system and model.

This paper uses the value chain theory to construct the cultural industry's goodwill value evaluation index system. When constructing the cultural industry goodwill value evaluation index system, according to the value chain theory, combined with the characteristics of the cultural industry, through the analysis of the constituent elements that affect the cultural industry goodwill value evaluation, the primary evaluation index system is determined; then, combining the questionnaire method and the wavelet neural network method, the preliminarily determined evaluation indicators are screened layer by layer, some special indicators are eliminated, and the index system of cultural industry goodwill value evaluation is constructed, which solves the disadvantage of subjectivity in the selection of indicators to a certain extent.

By constructing the efficiency index system of cultural industry, this paper uses the DEA-Malmquist index method to measure the efficiency of the cultural industry, the efficiency of technological progress of the cultural industry, and the technological efficiency of the cultural industry. By constructing the index system of the development level of artificial intelligence, the development level of artificial intelligence in China is measured by principal component analysis. At the same time, OLS regression and 2SLS regression are used to test the impact of artificial intelligence on the efficiency of the cultural industry, and LIML, two-step optimal GMM, and iterative GMM are used to test the stability of the results. The results show that first, AI can promote the efficiency of the cultural industry and promote the innovative development of the cultural industry. Second, limited by imperfect national policies, the shortage of compound talents and the incomplete market competition pattern, the impact of AI on the technical efficiency of the cultural industry is not significant. Third, at this stage, the role of artificial intelligence in promoting the efficiency of the cultural industry is mainly to provide technical support for the cultural industry and provide emerging technical support in its production and operation, so as to promote the technological progress of the cultural industry and promote the improvement of the efficiency of the cultural industry.

Data Availability

The labeled data set used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

This work was supported by Quzhou College of Technology.

References

[1] M. S. Jalaee, A. Ghaseminejad, S. A. Jalaee, N. Amani Zarin, and R. Derakhshani, "A novel hybrid artificial intelligence approach to the future of global coal consumption using whale optimization algorithm and adaptive neuro-fuzzy inference system," *Energies*, vol. 15, no. 7, pp. 2578–2581, 2022.

[2] E. C. Rivera, J. J. Swerdlow, R. L. Summerscales et al., "Data-driven modeling of smartphone-based electrochemiluminescence sensor data using artificial intelligence," *Sensors*, vol. 20, no. 3, pp. 625–630, 2020.

[3] Z. Yu, X. Z. Shi, X. Chen et al., "Artificial intelligence model for studying unconfined compressive performance of fiber-reinforced cemented paste backfill," *Transactions of Nonferrous Metals Society of China*, vol. 31, no. 4, pp. 1087–1102, 2021.

[4] Z. Czako, G. Sebestyen, and A. Hangan, "Automaticai - a hybrid approach for automatic artificial intelligence algorithm selection and hyperparameter tuning," *Expert Systems with Applications*, vol. 182, no. 16, pp. 115225–115230, 2021.

[5] F. Saeik, M. Avgeris, D. Spatharakis et al., "Task offloading in edge and cloud computing: a survey on mathematical, artificial intelligence and control theory solutions," *Computer Networks*, vol. 195, no. 3, pp. 108177–108182, 2021.

[6] L. Ma, "An immersive context teaching method for college English based on artificial intelligence and machine learning in virtual reality technology," *Mobile Information Systems*, vol. 2021, no. 2, pp. 1–7, 2021.

[7] S. Yoo and N. Kang, "Explainable artificial intelligence for manufacturing cost estimation and machining feature visualization," *Expert Systems with Applications*, vol. 183, no. 7, pp. 115430–115435, 2021.

[8] T. Li, J. Yang, and D. Cui, "Artificial-intelligence-based algorithms in multi-access edge computing for the performance optimization control of a benchmark microgrid," *Physical Communication*, vol. 44, no. 3, pp. 101240–101245, 2021.

[9] N. Park, K. Jang, S. Cho, and J. Choi, "Use of offensive language in human-artificial intelligence chatbot interaction: the effects of ethical ideology, social competence, and perceived human-likeness," *Computers in Human Behavior*, vol. 121, no. 3, pp. 106795–106799, 2021.

[10] C. Wang, T. S. Teo, and M. Janssen, "Public and private value creation using artificial intelligence: an empirical study of ai voice robot users in Chinese public sector," *International Journal of Information Management*, vol. 61, no. 4, pp. 102401–102406, 2021.

[11] Q. Demlehner, D. Schoemer, and S. Laumer, "How can artificial intelligence enhance car manufacturing? a delphi study-based identification and assessment of general use cases," *International Journal of Information Management*, vol. 58, no. 2, pp. 102317–102321, 2021.

[12] C. Li and J. Cui, "Intelligent sports training system based on artificial intelligence and big data," *Mobile Information Systems*, vol. 2021, no. 1, pp. 1–11, 2021.

[13] M. You, S. Li, D. Li, and S. Xu, "Applications of artificial intelligence for coal mine gas risk assessment," *Safety Science*, vol. 143, no. 2, pp. 105420–105425, 2021.

[14] A. Khatua, A. Khatua, X. Chi, and E. Cambria, "Artificial intelligence, social media and supply chain management: the way forward," *Electronics*, vol. 10, no. 19, pp. 2348–2351, 2021.

[15] A. Sharma and R. Kumar, "A Framework for Pre-computated Multi- Constrained Quickest QoS Path Algorithm," *FUTURISTIC TRENDS IN COMPUTING TECHNOLOGIES*, vol. 9, pp. 3–6, 2017.

[16] M. S. Pradeep Raj, P. Manimegalai, P. Ajay, and J. Amose, "Lipid data acquisition for devices treatment of coronary diseases health stuff on the internet of medical things," *Journal of Physics: Conference Series*, vol. 1900, no. 1, Article ID 012038, 2021.

[17] X. L. Zhao, X. Liu, J. Liu, J. Chen, S. Fu, and F. Zhong, "The effect of ionization energy and hydrogen weight fraction on the non-thermal plasma vocs removal efficiency," *Journal of Physics D Applied Physics*, vol. 52, no. 14, 2019.

[18] R. Huang and X. Yang, "Analysis and research hotspots of ceramic materials in textile application," *Journal of Ceramic Processing Research*, vol. 23, no. 3, pp. 312–319, 2022.

[19] C. Liu, M. Lin, H. L. Rauf, and S. S. Shareef, "Parameter simulation of multidimensional urban landscape design based on nonlinear theory," *Nonlinear Engineering*, vol. 10, no. 1, pp. 583–591, 2021.

[20] W. J. Chang, L. B. Chen, C. Y. Sie, and C. H. Yang, "An artificial intelligence edge computing-based assistive system for visually impaired pedestrian safety at zebra crossings," *IEEE Transactions on Consumer Electronics*, vol. 67, no. 1, pp. 3–11, 2021.