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Research Article

Research on the Efficiency of "Dual-Chain" Integration of Talent Chain and Industrial Chain of Vocational Education Based on Big Data Technology

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Since China has implemented the policy of "dual-chain" integration of vocational education, the level of vocational education in China has been developed rapidly. In order to study the current efficiency of dual-chain integration of vocational education in China, taking 31 Chinese provinces and cities as examples, the DEA-BPNN calculation model is used to calculate the efficiency of Chinese vocational education from 2010 to 2019, and the results of the study show that although the development of vocational education in China has achieved certain results, the crude development mode, which is mainly based on the increase of investment, has not been fundamentally changed.

1. Introduction

Vigorous development of vocational education and cultivation of a stable industrial workforce are of great practical significance in improving the employability of low- and middle-income groups and in eradicating poverty with precision. Since the beginning of this century, especially the 12th Five-Year Plan of China, the government of China (GOC) has introduced a series of policies to increase financial support for vocational education. The national education funding has increased from 1,956.18 billion yuan in 2010 to 5,017.81 billion yuan in 2019, an increase of more than 2.5 times in 10 years, maintaining an average annual increase of 17.5%. With the strong support of financial resources, vocational education nationwide has trained an average of 11,242,900 students per year during 2010–2019, as shown in Figure 1, and vocational education in China has gradually stepped into a healthy and benign development track.

The integration of talent chain and industry chain is the prerequisite foundation for the benign development of China's economy and society. In December 2017, the Opinions of the General Office of the State Council on Deepening the Integration of Industry and Education clearly required for the first time to "deepen the integration of industry and education and promote the organic connection between education chain, talent chain, industry chain, and innovation chain." This is an urgent requirement for promoting structural reform on the supply side of human resources and is of great significance for comprehensively improving the quality of education, expanding employment and entrepreneurship, promoting economic transformation and upgrading, and cultivating new dynamic energy for economic development under the new situation [1].

Industrial chain is an important concept in industrial economics, and its basic connotation is that "enterprises in the same industry or in different industries, with products as the object, based on specialized division of labor, with input-output as the link, value-added as the guide, to meet user demand as the goal, according to the specific collaboration relationship and spatial and temporal layout to form a dynamic chain organization associated with the top and bottom [2]." Industrial chain is divided into vertical supply

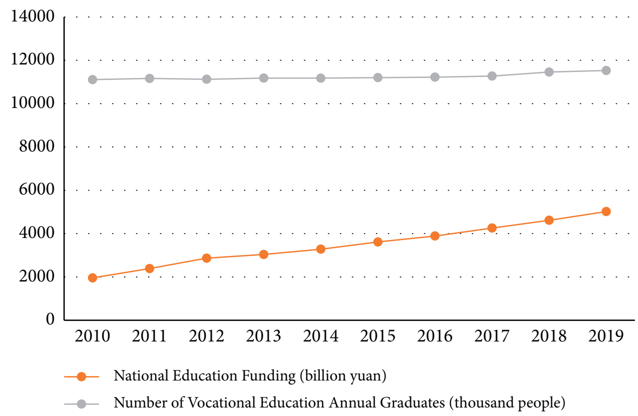

Figure 1: Education funding and number of vocational education graduates from 2010 to 2019 in China.

and demand chain and horizontal collaboration chain. Vertical relationship is the main structure of the industry chain, and some people divide this vertical division of labor into the upstream, middle, and downstream relationship of the industry; horizontal collaborative relationship is the industry supporting issue that we often mention [3]. The industrial chain describes the process of value-added activities within and between enterprises for the production of products and services for final transactions. Talent chain refers to a series of skilled talents trained by vocational education from upstream to downstream of the industry chain, including low-range, mid-range, high-range, and different levels of talents required by the market [4]. In vocational education, industrial chain and talent chain have inner consistency and correspondence. The talent chain includes both the series of talent training from middle level to senior level to professional graduate students and also the same level of talent chain in the horizontal to form a training series that is compatible with the industrial chain [5].

The formation and development of the industrial chain will directly determine the scale, structure, and future development direction of the talent chain. The industrial chain fundamentally determines the size of the talent chain and its internal structure which includes the type structure, ability structure, and education structure of the talent chain. The size of talent gathering between different regions is essentially determined by the scale of industry, and the size of talent is fundamentally determined by the competitiveness of the regional industrial chain, the proportion of advanced industries, and the income level. At the same time, the industrial chain also determines the structure of the talent chain, which includes the structure of education, ability, and talent type.

Talent chain provides effective support for the operation of the industrial chain. First, in addition to research, development, and management talents, technical talents also play a key role in supporting industrial development, which is an important premise for the effective operation of the industrial chain. Secondly, the talent chain is the key support to promote the innovation development of the industrial chain. The key to the innovation development of the industrial chain lies in the innovation development of each enterprise in the industrial chain, and all kinds of innovation activities in the enterprise need the active participation of relevant personnel.

From the integrating of talent chain and industrial chain, it is of great value to reexamine the essential connotation and construction path of vocational education, which can not only clarify the key role played by vocational education in the integrating process of talent chain and industrial chain but also examine the development path of vocational education with the basic perspective of "dual-chain" integration. The integration of "dual chain" has played a positive role in the development of vocational education in China, but how effective is the integration of "dual chain" and how to optimize the system of "dual chain" in the future are the issues that need to be studied behind the vigorous development of vocational education.

At present, no scholars in China have studied and measured the efficiency of "dual-chain" integration in vocational education, but the research related to the efficiency of vocational education has formed a certain basis, such as Zhang analyzed the industrial characteristics and industrial processes of higher vocational education, established a higher vocational education input-output table, and built a dynamic input-output model of higher vocational education by combining the Fahrenheit macroeconomic mathematical model [6]. Hongqin designed three output indicators and five input indicators to analyze the input-output performance of higher vocational institutions in China by using DEA analysis method on the first batch of national model higher vocational institutions in China, which provides some reference for the optimal resource allocation of higher vocational institutions [7]. Meixiang proposed a three-tier vocational education efficiency evaluation index system based on the characteristics of vocational education and input and output elements [8]. Hui and Yunan initially selected 12 input indicators and 11 output indicators and established a PCA-DEA two-step evaluation model can better empirically analyze the school performance of higher vocational institutions in 30 provinces in China. It is found that the overall efficiency of higher education institutions in 30 provinces in China shows a distribution of high in the east and low in the middle, and "high input-low output-low efficiency" is common [9]. From these studies, it can be seen that the current measurement of vocational education efficiency is mostly conducted by constructing DEA models, and the studies are mostly focused on measuring the efficiency of vocational education inputs and outputs, but there is basically no research on the efficiency of "dual-chain" integration.

At the early stage of Internet development, a large amount of data storage was regarded as a burden due to the capacity and function of storage devices and other limitations, but with the continuous updating of technology, people have changed their original misconceptions about data, and with the development of the times, scholars have deepened their knowledge and understanding of big data, and the concept of big data has been developed nonstop. Based on the essential attributes, big data were summarized to four distinctive characteristics, namely, volume, variety, velocity, and value. These characteristics clearly distinguish big data from traditional data. From the perspective of resources, big data is a new factor of production, a fundamental and strategic resource, and an important productivity, as important as natural resources and human resources. From a technological perspective, big data were described as "a new generation of technologies and architectures that enable effective value extraction from diverse and massive data through rapid acquisition, discovery, and analysis." From an integrative perspective, Boyd and Crawford view big data as a cultural, technological, and academic phenomenon based on an analysis of the interaction of technology, analytics, and perceptions [10]. The current application of big data is mostly through further mining of data and analyzing and organizing the results generated according to data correlation, which in turn generates judgments and predictions on the future development trends of things. It has a strong reference value because such predictions are reasonable predictions based on scientific data.

China's information technology service revenue increased more than six-fold from 653 billion yuan in 2010 to 4358 billion yuan in 2019, as shown in Figure 2. Information technology has facilitated the development of various industries, and the advantages of big data technology and its wide application also point out a new direction for vocational education in the information era. In order to effectively carry out vocational education in the new normal of education and strengthen the functions and effects of vocational education work, traditional vocational education methods have to be constantly updated with the progress of technology and adjust their ideas to meet the new development needs. As the frontier of cultivation, development, and inheritance of mainstream ideas, values, and culture in society, schools are the bridgeheads with the most active ideas, the most intensive knowledge, and the fullest use of network information technology. While the current steps of informatization and smart campus construction in domestic universities are accelerating, big data technology should be fully applied to the field of vocational education to enhance the accuracy and effectiveness of vocational education in talent training and better play the role of ideological bastion and nurturing function of school.

Therefore, based on big data technology, this study collects a large amount of data related to the measurement of "dual-chain" integration efficiency of industrial chain and talent chain of vocational education and calculates the input-output technical efficiency of vocational education in China from 2010 to 2019 with the help of DEA-BPNN efficiency calculation model to complete the study on the current "dual-chain" integration efficiency of vocational education in China.

2. Evaluation Index System of the Efficiency of the "Dual-Chain" Integration of Vocational Education

The establishment of a scientific and reasonable input-output efficiency evaluation index system is a prerequisite for an objective and accurate evaluation of the efficiency level of "dual-chain" integration of vocational education. The selection of the evaluation index system mainly follows the following principles: (a) scientific principle, according to the problem studied in this paper, the selection of indicators, data acquisition, and evaluation methods should follow the principle of scientificity; (b) uniformity principle, the selected index data should be used for comparative analysis, so the selection of indicators should be uniform and conform to the uniform caliber; and (c) easy-to-operate principle, the evaluation index system of vocational education "dual-chain" integration should be more convenient to use. Based on the existing research results and the "five-dimensional view of quality" in the annual report on the quality of vocational education personnel training, this paper has conducted a study on the quality of higher vocational education. Based on the existing research results, this paper optimizes and improves the evaluation index system of input-output efficiency of vocational education. The inputs of vocational education resources include human, material, and financial resources [11]: the comprehensive level of teachers' input and human resources utilization rate of vocational colleges and universities, which reflect the input of human resources; the basic conditions of vocational colleges and universities, which reflect the input of material resources; the income of school expenses and the level of annual per-student financial allocation, which reflect the input of financial resources. The output results of vocational education are usually transformed through intangible assets, including the output results of talent cultivation quality of vocational education, services provided to society, and teaching and research quality. Therefore, the evaluation index system of "dual-chain" integration efficiency of vocational education at three levels includes input indicators covering human, material, and financial resources and output indicators covering talent cultivation, scientific research, and social services [7–9]. The structure chart of the selected input-output efficiency evaluation index system is detailed in Table 1.

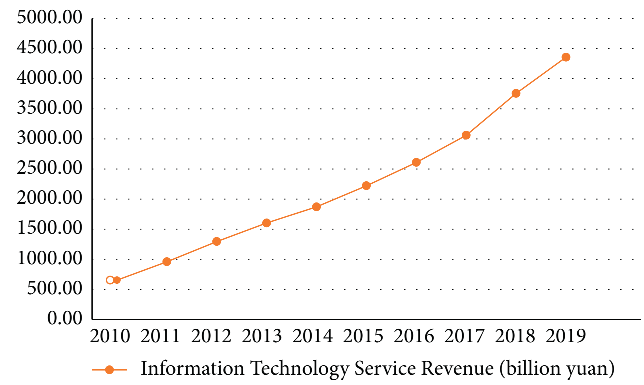

Figure 2: China information technology service revenue 2010 to 2019.

3. Evaluation Model of the Efficiency of the "Dual-Chain" Integration of Vocational Education

In this paper, a comprehensive evaluation analysis of vocational education input-output efficiency is conducted

Table 1: Evaluation index system of input-output efficiency of “dual-chain” integration in vocational education.

General objectives	First indicators	Secondary indicators	Tertiary indicators
Vocational education input-output efficiency evaluation indicators	Input indicators	Human resources	Student-teacher ratio A_{11}
			Proportion of full-time teachers with “dual-teacher” qualifications (%) A_{12}
			Percentage of senior titles (%) A_{13}
		Material resources	Teaching and research equipment per student (yuan/student) A_{21}
			Number of on-campus practical teaching workstations per student (pcs/student) A_{22}
			Value of on-campus practical teaching equipment provided by enterprises (yuan) A_{23}
		Financial resources	Annual per-pupil financial allocation level (yuan) A_{31}
			Income from school expenses (million yuan) A_{32}
	Output indicators	Talent cultivation	Number of graduates in the current year (person) B_{11}
			Graduate employment rate (%) B_{12}
			Dual certificate acquisition rate of graduates (%) B_{13}
			Proportion of self-employment (%) B_{14}
			Monthly income of graduates (yuan) B_{15}
		Scientific research	Horizontal technical service arrivals (million yuan) B_{21}
		Social services	Nonacademic training arrivals (million yuan) B_{31}
			Employer satisfaction (%) B_{32}

based on a combination of portfolio assignment and DEA. The DEA model requires that the number of decision units should be more than twice the sum of the input and output indicators. The total number of decision units in this paper is 31. In order to avoid the influence of DEA evaluation results, six secondary indicators are considered as input and output indicators. Although the optimal efficiency of the decision unit in DEA analysis is independent of the selected input and output indicators, the importance of each tertiary indicator to the same secondary indicator varies; therefore, this paper uses a combination of hierarchical analysis and entropy weighting method to assign weight to the tertiary indicators under each secondary indicator through the combination of subjective and objective weights so as to calculate the weighting of six groups of input and output indicators standardized data and then conduct DEA efficiency analysis.

3.1. Portfolio Empowerment. The weighted combination calculation is done for the three-level indicators under each second-level indicator, with m evaluation objects and k third-level indicators under a certain second-level indicator.

First, the subjective weights of each indicator are determined by hierarchical analysis. The specific steps are as follows:

① Establish a hierarchical structure model

② Construct the judgment matrix of the three-level indicators under the second-level indicators by using the proportional 9 scale method $C = \left\{c_{ij}\right\} (i, j = 1, 2, \ldots, k)$

③ Calculate the weight vector by (1) (the square root method is used in this paper) $P = [\alpha_1, \alpha_2, \ldots, \alpha_k]^T$

④ Consistency test by (2) and (3)

$$\alpha_j = \frac{\sqrt[k]{\prod_{i=1}^{k} C_{ij}}}{\sum_{j=1}^{k} \sqrt[k]{\prod_{i=1}^{k} C_{ij}}} (i, j = 1, 2, \ldots, k), \tag{1}$$

$$\lambda_{\max} = \frac{1}{k} \cdot \sum_{j=1}^{k} \frac{(CP)_j}{\alpha_j}, \tag{2}$$

$$CR = \frac{CI}{RI}, \tag{3}$$

where $CI = (\lambda_{\max} - k)/(k - 1)$ and RI is the average random consistency index. When $CR < 0.1$, the constructed contrast matrix is considered valid [12].

Next, the objective weights of each index were determined by the entropy weighting method. The specific steps are as follows:

① Calculate the standardization matrix C of the efficiency evaluation index data and adopt the improved normalization method to standardize the efficiency evaluation index data, and the specific formulae are (4) and (5)

② Calculate the contribution point l_{ij} of the $j -$th indicator in the efficiency evaluation of vocational education in the $i -$th province and city through (6)

③ Calculate the information entropy h_j of the $j -$th evaluation index through (7)

④ Calculate the entropy weight $\widetilde{P} = [\beta_1, \beta_2, \ldots, \beta_k]^T$ of the evaluation index by (8)

Positive indicator normalization formula:

$$x_{ij}' = \frac{m x_{ij}}{\sum_{i=1}^{n} x_{ij}}. \tag{4}$$

Inverse indicator normalization formula:

$$x_{ij}' = m\left[\frac{\max\limits_{1\le i\le m}\{x_{ij}\} - x_{ij}}{\sum_{i=1}^{m}\left(\max\limits_{1\le i\le m}\{x_{ij}\} - x_{ij}\right)}\right]. \tag{5}$$

$$l_{ij} = \frac{c_{ij}}{\sum_{i=1}^{m} c_{ij}}, \ (j = 1, 2, \ldots, k). \tag{6}$$

$$h_j = -\frac{1}{\ln k}\sum_{i=1}^{m} l_{ij} \ln l_{ij}, \ (j = 1, 2, \ldots, k). \tag{7}$$

$$\beta_j = \frac{1 - h_j}{k - \sum_{j=1}^{k} h_{ij}} \ (i, j = 1, 2, \ldots, m). \tag{8}$$

Finally, in order to comprehensively consider the differences in the importance of the tertiary evaluation indicators under each secondary evaluation index, and considering the advantages and shortcomings of each of the two methods, this paper adopts a combination of hierarchical analysis and entropy weight method to determine the weights $W = [\omega_1, \omega_2, \ldots, \omega_k]^T$ of the tertiary evaluation indicators under each secondary evaluation index by the following equation:

$$\omega_j = \sigma\alpha_j + (1 - \sigma)\beta_j, \ (j = 1, 2, \ldots, k), \tag{9}$$

where ω_j is the combination weight of the $j-$th indicator for its secondary indicators, α_j is the weight of the $j-$th indicator for its secondary indicators calculated by hierarchical analysis, β_j is the weight of the $j-$th indicator for its secondary indicators calculated by entropy weighting method, σ is the preference coefficient $(0 < \sigma < 1)$, and the preference coefficient chosen in this paper is $\sigma = 0.5$. [13].

3.2. Data Envelope Analysis. The DEA method is to use mathematical planning to build an evaluation model to evaluate the relative effectiveness of the production process among decision units with multiple inputs and multiple outputs. The CCR model and the BCC model are the two original DEA models, and they can be used jointly to evaluate whether the production process of a decision unit is technically efficient and scale efficient. Technically efficient means that the data of any one input and any one output of the decision unit do not need to be changed, and the inputs and outputs have reached the optimum with respect to other decision units. The so-called scale-effective means that the ratio of change (increase or decrease) in the output of the decision unit is equal to the ratio of change (increase or decrease) in the input, that is, in the optimal state of constant returns to scale. For the nontechnologically efficient decision units, the BCC model can calculate the target input-output data to achieve technical efficiency. For nontechnologically efficient decision units, the CCR model can measure whether the decision unit is in the increasing or decreasing returns to scale stage. The following is a brief description of the input-oriented CCR model and the BCC model and the related conclusions [14].

Suppose a system has n decision units DMU_j, $j = 1, 2, \ldots, n$. Each decision unit has m input indicators and s output indicators, and the input and output data are represented by m-dimensional vector x_j and s-dimensional vector y_j, respectively. The input-oriented BCC model evaluating the decision unit DMU_0 is obtained by the following equation:

$$\min\gamma,$$
$$\begin{cases} \sum_{j=1}^{n}\lambda_j x_j + s^- = \gamma x_0 \\ \sum_{j=1}^{n}\lambda_j x_j - s^+ = y_0 \\ \sum_{j=1}^{n}\lambda_j = 1 \\ \lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n) \ge 0, s^- \ge 0, s^+ \ge 0 \end{cases}, \tag{10}$$

where γ is called technical efficiency (vrste) and s^-, s^+ are called slack variables. Let the optimal solutions of the model be γ^0, s^{-0}, s^{+0}, then there are the following conclusions about technical effectiveness: (1) if $\gamma^0 = 1$, then the decision unit is weakly technically effective. At this point, if all optimal solutions again satisfy $s^{-0} = s^{+0} = 0$, then the decision unit technology is valid. (2) If $\gamma^0 < 1$, then the decision unit is nonweakly technically valid. When the decision unit is nontechnically valid, the input-output data can be adjusted to reach technical validity. The adjustment method is as follows: let x_0 and y_0 be the original input and output data of $DM\ U_0$, $\hat{x}$ and $\hat{y}$ be the adjusted target input and output data, and let $\hat{x} = r^0 x_0 - s^{-0}$ and $\hat{y} = y_0 + s^{+0}$. Then, $DM\ U_0$ achieves technical validity under the target input and output data while the other decision units keep the original input and output data unchanged. The input-oriented CCR model is obtained by the following equation:

$$\min\theta,$$
$$\begin{cases} \sum_{j=1}^{n}\lambda_j x_j + s^- = \theta x_0 \\ \sum_{j=1}^{n}\lambda_j x_j - s^+ = y_0 \\ \lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n) \ge 0, s^- \ge 0, s^+ \ge 0 \end{cases}, \tag{11}$$

where θ is called the overall efficiency (crste). When the decision unit is weakly technically efficient, the CCR model can be used to discern the returns to scale of the decision unit. Assume that θ^0, λ^0 is the unique optimal solution of the model, and if $\theta^0 = 1$, then the scale of the decision unit is effective. Otherwise, if $\sum_{j=1}^{n}\lambda_j^0/\theta^0 < 1$, then DMU_0 increasing returns to scale (irs), meaning that the decision unit is suitable to increase (reduce) inputs, expand (reduce) production scale; if $\sum_{j=1}^{n}\lambda_j^0/\theta^0 > 1$, then DMU_0 decreasing returns to scale (drs), meaning that the decision unit is not suitable to change the scale of production.

Using technical efficiency and overall efficiency, scale efficiency (scale) = overall efficiency (crste)/technical efficiency (vrste) is defined. From the above analysis, it is clear that if two of the three values of crste, vrste, and scale are 1, then the decision unit is both technically and scale efficient; if one value is less than 1, then the decision unit must be either nontechnically efficient or nonscale efficient.

The traditional DEA method cannot explain the dynamic changes in the efficiency of decision units and the Malmquist index solves the problem. For this reason, scholars have introduced the Malmquist index based on the traditional DEA model and applied it to the production frontier efficiency analysis method to measure productivity changes. The calculation of Malmquist efficiency index in this paper is shown in the following equations:

$$M x_i^{k_1}, y_i^{k_1}, x_i^{k_2}, y_i^{k_2} = \mathrm{PEC}_{\mathrm{RD}} \times \mathrm{SEC}_{\mathrm{RD}} \times \mathrm{TC}_{\mathrm{RD}}, \tag{12}$$

$$\mathrm{PEC}_{\mathrm{RD}} = \frac{E_v^{k_2} x_i^{k_2}, y_i^{k_2}}{E_v^{k_1} x_i^{k_1}, y_i^{k_1}}, \tag{13}$$

$$\mathrm{SEC}_{\mathrm{RD}} = \left[\frac{E_c^{k_1} x_i^{k_2}, y_i^{k_2} / E_v^{k_1} x_i^{k_2}, y_i^{k_2}}{E_c^{k_1} x_i^{k_1}, y_i^{k_1} / E_v^{k_1} x_i^{k_1}, y_i^{k_1}} \times \frac{E_c^{k_2} x_i^{k_2}, y_i^{k_2} / E_v^{k_2} x_i^{k_2}, y_i^{k_2}}{E_c^{k_2} x_i^{k_1}, y_i^{k_1} / E_v^{k_2} x_i^{k_1}, y_i^{k_1}}\right]^{1/2}, \tag{14}$$

$$\mathrm{TC}_{\mathrm{RD}} = \left[\frac{E_v^{k_1} x_i^{k_1}, y_i^{k_1}}{E_v^{k_2} x_i^{k_1}, y_i^{k_1}} \times \frac{E_v^{k_1} x_i^{k_2}, y_i^{k_2}}{E_v^{k_2} x_i^{k_2}, y_i^{k_2}}\right]^{1/2}. \tag{15}$$

In the formula, M is the Malmquist index. k_1, k_2 denote any two adjacent periods, E denotes the efficiency score, $x_i^{k_1}$ and $x_i^{k_2}$ denote any two adjacent periods of input quantity of the $i-$th decision unit, $y_i^{k_1}$ and $y_i^{k_2}$ denote any two adjacent periods of output quantity of the $i-$th decision unit, respectively. The subscripts c and v represent the constant scale returns and variable scale returns, respectively. Equations (13)–(15) are the decomposition result of the efficiency index trilateration.

According to the basic principle of Malmquist index to evaluate efficiency, if Malmquist index >1, it means that the efficiency level improves; if Malmquist <1, it means that the efficiency level decreases; if Malmquist = 1, it means that the efficiency level does not change. PEC represents pure technical efficiency change, greater than 1 means that the level of capital input technology use improves, and SEC represents the change of scale efficiency, greater than 1 indicates that the degree of rational allocation of input and output factors is improved compared with the optimal scale. TC represents technical change, which refers to intangible factors, which includes technological progress, organizational innovation, and so on that have an impact on output in addition to input factors. TC greater than 1 indicates the existence of potential technological progress and vice versa.

3.3. BP Neural Network. The calculation results obtained by the above DEA model reflect the efficiency index of the current DMU_i set, i.e., the efficiency index of the "dual-chain" integration of Chinese vocational education in a certain year. However, when we want to continue to evaluate the integration efficiency of other years, if we make the data of each year together to form a new DMU_i set, then the calculation results of the original year will need to be updated. If we treat the new year as a new DMU_i set alone, then the calculation results of the "dual-chain" integration efficiency of each year will not be comparability. To solve this problem, a backpropagation neural network (BPNN) model is introduced on the basis of DEA model, and a two-layer feedforward neural network with Sigmoid implicit neurons and linear output neurons is constructed and trained by Levenberg–Marquardt backpropagation algorithm based on the DEA calculation results.

Using the Sigmoid activation function for the implicit neuron input, mapping the variables into (0, 1), the Sigmoid function output image is close to the S-curve, the output is smooth and easy to derive, and its expression is shown in the following equation:

$$S(x) = \frac{1}{1 + e^{-ipu}}, \tag{16}$$

where $S(x)$ denotes the output value of Sigmoid function and ipu denotes the training sample index data.

The loss function is chosen as the mean square error function, and its expression is shown in the following equation:

$$LS = \frac{1}{m} \sum_{i=1}^{m} (z_i - \widehat{z}_i), \tag{17}$$

where LS denotes the loss function input value, and z_i and $\widehat{z}_i$ are the calculated and predicted values of the ith run line efficiency index, respectively. The training algorithm uses the Levenberg–Marquardt algorithm, which is the most widely used nonlinear least squares algorithm and usually has the fastest convergence speed relative to other backpropagation training algorithms. The structure of the two-layer feedforward BP neural network model based on DEA training sample data is shown in Figure 3, which can obtain the "dual-chain" integration efficiency values for the new year without affecting the integration efficiency calculation results for the past years.

4. Experimental Results

4.1. Data Preprocessing. In this paper, a comprehensive evaluation of the efficiency of "dual-chain" integration inputs and outputs in vocational education is conducted based on a combination of portfolio assignment and DEA. The DEA model requires that the number of decision units should be more than twice the sum of the input and output indicators. There are 16 decision units, and the data of decision units are limited, so we can only get three years of panel data of six higher education institutions, one decision unit for each year, and there are only 18 decision units in total. In order to

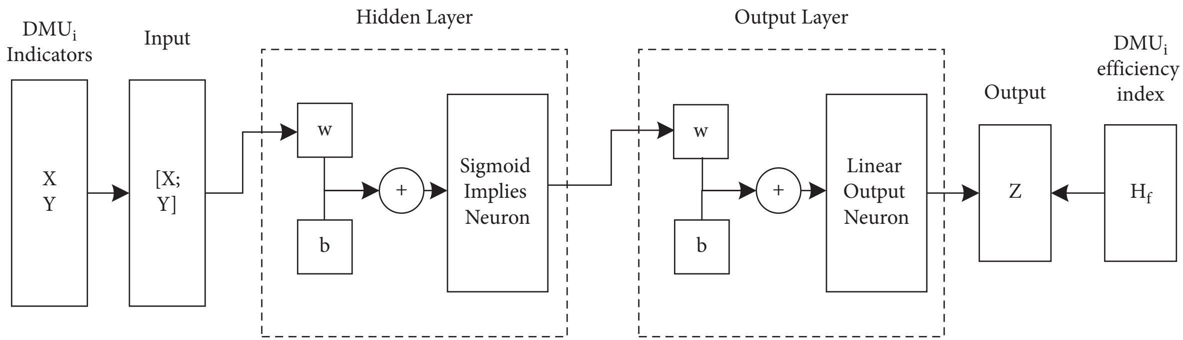

Figure 3: Schematic diagram of DEA-BPNN model.

avoid the influence of DEA evaluation results, six secondary indicators are considered as input and output indicators. Although the optimal efficiency of the decision unit in DEA analysis is independent of the selected input and output indexes' magnitudes, the importance of each tertiary index differs for the same secondary index. Therefore, this paper uses a combination of hierarchical analysis and entropy weighting method to assign weights to the tertiary indexes under each secondary index through the combination of subjective and objective weights so as to calculate the weighting of six groups of input and output indexes standardized data and then conduct DEA efficiency analysis.

The judgment matrix under each second-level indicator is obtained through expert interviews, and the AHP weights of the three-level indicators under each second-level indicator are calculated through Equations (1)–(3). All judgment matrices pass the consistency test, then the second-level indicators are grouped, and the three-level indicators are standardized, respectively. The entropy weights of the three-level indicators under each second-level indicator are calculated by Equations (4)–(8). Finally, the combination weights of the three-level indicators are calculated by (9). The results are shown in Table 2, and the original data are not listed due to space limitation.

4.2. Comprehensive Evaluation Based on DEA. This paper adopts the DEA-Malmquist index trichotomous method to study the efficiency of "dual-chain" integration of vocational education in China [15]. The 31 provinces in China are used as the decision-making unit, and the vocational education input and output variables are incorporated into the unified decision-making unit. Since the statistics of vocational education financial inputs have been available since 2009, the panel data of 31 provinces from 2010 to 2019 are selected as the samples in this paper, and the calculation results are shown in Table 3.

From the calculation results we can see that, in terms of technical efficiency, in 2019 among 31 provinces nationwide, vocational education inputs and outputs are at DEA efficiency level in 4 provinces, namely, Hebei, Sichuan, Shanghai, and Beijing, while the remaining 27 provinces are at DEA inefficiency. A total of 15 provinces have efficiency levels higher than the national average (0.785). The 4 provinces of Hainan, Ningxia, Qinghai, and Tibet have the lowest scores and the lowest efficiency levels.

In terms of pure technical efficiency, in 2019, in addition to 4 provinces of Hebei, Sichuan, Shanghai, and Beijing, there are 5 provinces of Guangxi, Henan, Heilongjiang, Guizhou, and Shanxi to achieve pure technical efficiency effective, indicating that the existing technical level and resource allocation of vocational education inputs in the above 9 provinces have reached the efficiency level. The remaining 22 provinces are in the invalid state of pure technical efficiency, indicating that their existing technology and resource allocation efficiency are not fully utilized.

From the perspective of scale efficiency, only Hebei, Shanghai, Beijing, Sichuan, and 4 provinces achieve scale efficiency effectively in 2019 and are in the state of constant scale payoff, indicating that the financial vocational education investment in 4 provinces has achieved the optimal scale. The remaining 27 provinces are at the inefficient level of scale efficiency. Among them, 12 provinces, including Guangxi, Shaanxi, and Henan, are in a state of decreasing scale payoff, which indicates that 12 provinces have overinvestment in vocational education. 14 provinces, including Yunnan, Heilongjiang, and Jilin, are in the state of increasing scale payoff, which indicates that 14 provinces have underinvestment in vocational education and need to continue to increase the scale of investment in vocational education.

In general, the efficiency of "dual-chain" integration in vocational education is higher in Hebei, Sichuan, Shanghai, Beijing, and other provinces, which means that these provinces and cities have done a good job in "dual-chain" integration in vocational education. The efficiency of "dual-chain" integration is lower in Hainan, Ningxia, Qinghai, Tibet, and other provinces and cities, which can learn from the policies of Beijing and Shanghai and take measures to improve the efficiency of "dual-chain" integration according to their actual situation.

Table 4 gives the dynamic changes of the Malmquist productivity index, technical efficiency index, and technical progress efficiency index in 31 provinces in China from 2010 to 2019. The results show that the average value of the Malmquist productivity index for vocational education inputs in China is 0.849 during the 10-year period, and productivity is declining with an average annual efficiency level of 16%. Further decomposition analysis shows that the main reason for the decline in the Malmquist productivity

Table 2: Input-output portfolio weights.

First indicators	Secondary indicators	Tertiary indicators	AHP weights	Entropy weighting	Portfolio weights
Input indicators	Human resources	A_{11}	0.5435	0.6927	0.6181
		A_{12}	0.2678	0.0863	0.1771
		A_{13}	0.1887	0.2210	0.2049
	Material resources	A_{21}	0.5630	0.1257	0.3444
		A_{22}	0.2192	0.0449	0.1321
		A_{23}	0.2178	0.8294	0.5236
	Financial resources	A_{31}	0.3100	0.1565	0.2333
		A_{32}	0.6900	0.8435	0.7668
Output indicators	Talent cultivation	B_{11}	0.3469	0.1952	0.2711
		B_{12}	0.1758	0.0010	0.0884
		B_{13}	0.3160	0.0245	0.1703
		B_{14}	0.0877	0.7633	0.4255
		B_{15}	0.0896	0.0160	0.0528
	Scientific research	B_{21}	1.0000	1.0000	1.0000
	Social services	B_{31}	0.7000	0.9653	0.8327
		B_{32}	0.3000	0.0347	0.1674

Table 3: Input-output efficiency of vocational education in 31 provinces nationwide in 2019.

Province	Technical efficiency	Pure technical efficiency	Scale efficiency	Payoffs for scale
Hebei	1.000	1.000	1.000	Unchanged
Sichuan	1.000	1.000	1.000	Unchanged
Shanghai	1.000	1.000	1.000	Incremental
Beijing	1.000	1.000	1.000	Unchanged
Guangxi	0.996	1.000	0.996	Decreasing
Shaanxi	0.983	0.994	0.989	Decreasing
Henan	0.976	1.000	0.976	Decreasing
Hunan	0.942	0.963	0.978	Decreasing
Yunnan	0.935	0.972	0.962	Increasing
Heilongjiang	0.865	1.000	0.865	Increasing
Zhejiang	0.847	0.876	0.967	Unchanged
Liaoning	0.842	0.872	0.966	Increasing
Anhui	0.835	0.872	0.958	Decreasing
Jilin	0.829	0.952	0.871	Incremental
Hubei	0.813	0.865	0.940	Increasing
Guizhou	0.809	1.000	0.809	Decreasing
Chongqing	0.768	0.790	0.972	Decreasing
Shandong	0.765	0.783	0.977	Decreasing
Jiangxi	0.763	0.812	0.940	Unchanged
Shanxi	0.752	1.000	0.752	Decreasing
Gansu	0.723	0.767	0.943	Decreasing
Tianjin	0.686	0.699	0.981	Decreasing
Jiangsu	0.672	0.689	0.975	Decreasing
Guangdong	0.672	0.693	0.970	Unchanged
Inner Mongolia	0.663	0.689	0.962	Increasing
Fujian	0.658	0.689	0.955	Increasing
Xinjiang	0.654	0.683	0.958	Increasing
Hainan	0.594	0.641	0.927	Decreasing
Ningxia	0.523	0.573	0.913	Decreasing
Qinghai	0.482	0.513	0.940	Unchanged
Tibet	0.294	0.380	0.774	Decreasing
Average value	0.785	0.831	0.942	

level of vocational education inputs in China from 2010 to 2019 is due to the decline in the efficiency of technical progress, which declined by 20.4% per year on average during the period. During the same period, the technical efficiency showed an efficiency improvement of 5.5% per year on average due to some improvement in both pure technical efficiency and scale efficiency. The improvement of technical efficiency enhances to some extent the declining trend of the Malmquist productivity index of vocational education inputs in China caused by the regression of technical progress efficiency. Thus, in the long run, the Malmquist productivity index of vocational education inputs

Table 4: Malmquist productivity index, technical efficiency change index, and technical progress index for 31 provinces, averaged over the years.

Year	Change in Malmquist index	Change in technical efficiency index	Change in technical progress index	Change in pure technical efficiency index	Scale efficiency change in index
2010–2011	0.651	1.222	0.538	1.127	1.096
2011–2012	0.829	1.025	0.814	1.034	0.998
2012–2013	0.737	1.188	0.624	1.124	1.063
2013–2014	0.796	1.006	0.785	1.030	0.970
2014–2015	0.934	0.992	0.949	0.985	1.015
2015–2016	0.992	1.018	0.984	1.000	1.028
2016–2017	0.831	1.002	0.821	1.018	0.974
2017–2018	0.959	1.036	0.927	1.022	1.019
2018–2019	0.912	1.051	0.865	1.004	1.044
Average values	0.849	1.060	0.812	1.038	1.023

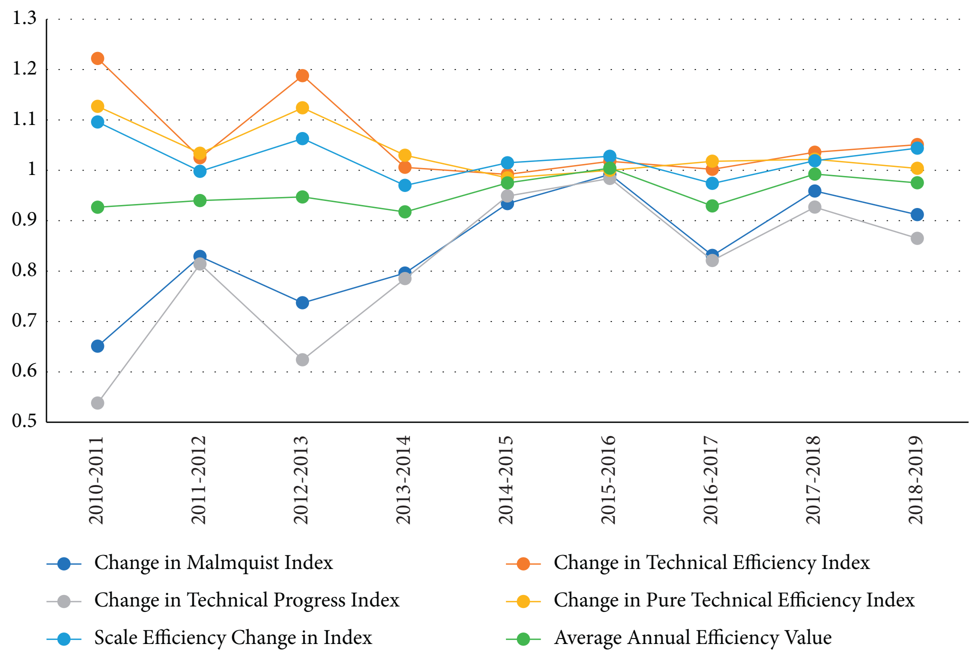

Figure 4: The annual changes in each index for 31 provinces.

in China keeps improving. The above results show that the level of technology use of vocational education investment in China has improved between 2010 and 2019, and the resource allocation efficiency of vocational education investment has been effectively improved, which indicates that the "dual-chain" integration policy is beginning to bear fruit in China. The deterioration of the efficiency of technological progress indicates that the current development of vocational education in China is characterized by roughness, and it is necessary to further deepen the policy of "dual-chain" integration of vocational education, improve the utilization rate of vocational education resources, and promote the healthy and efficient development of vocational education [16].

Figure 4 was drawn based on the calculation results in Table 4, and it reflects the annual changes in each index. From the changes of the Malmquist productivity index of vocational education inputs in China during 2010–2019, the Malmquist productivity index was less than 1 during the 10 years. The average annual efficiency value of 1.004 in 2015–2016 reached the highest value during the 10 years. From the change of the technical progress efficiency index, the technical progress efficiency of China's vocational education investment is in a negative state during 2010–2019, with an average annual efficiency level of 20.4%. The degree of technical progress efficiency regression is weakening since 2012 from the change of data in 10 years. It indicates that the effect of the national policy of "dual-chain" integration to adjust the structure of financial investment in vocational education, optimize the mode of vocational education training, and improve the quality of vocational education training is gradually emerging.

Because there are obvious regional differences in financial vocational education investment, this paper further divides 31 provinces into eastern, central, and western regions according to the administrative division of China, in order to understand the regional differences of the

Table 5: Regional average Malmquist productivity index, technical efficiency change index, and technical progress index, 2010–2019.

	Period	2010–2011	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018	2018–2019	Average value
Eastern region	Scale efficiency index	1.070	1.032	1.006	1.014	1.023	0.967	1.075	1.016	1.055	1.029
	Pure technology efficiency index	1.113	1.073	1.187	1.033	1.006	1.012	0.996	1.075	1.019	1.057
	Technological progress change index	0.535	0.814	0.660	0.768	0.958	1.007	0.816	0.922	0.879	0.818
	Technological efficiency change index	1.167	1.083	1.168	1.024	1.006	0.956	1.048	1.069	1.051	1.064
	Malmquist productivity index	0.630	0.890	0.777	0.795	0.973	0.976	0.863	0.994	0.933	0.870
Central region	Scale efficiency index	1.078	0.980	1.077	0.993	0.989	1.070	0.961	1.041	1.022	1.023
	Pure technology efficiency index	1.083	1.007	1.074	0.982	1.004	0.992	0.995	0.950	1.039	1.014
	Technological progress change index	0.530	0.809	0.594	0.812	0.938	0.962	0.835	0.942	0.876	0.811
	Technological efficiency change index	1.163	0.984	1.153	0.973	0.990	1.059	0.953	0.986	1.059	1.036
	Malmquist productivity index	0.625	0.807	0.695	0.800	0.939	1.030	0.801	0.940	0.939	0.842
Western region	Scale efficiency index	1.140	0.987	1.127	0.949	1.036	1.053	0.939	1.013	1.092	1.037
	Pure technology efficiency index	1.157	1.001	1.093	1.099	0.923	0.964	1.102	1.033	0.964	1.037
	Technological progress change index	0.519	0.801	0.602	0.800	0.927	0.952	0.845	0.913	0.849	0.801
	Technological efficiency change index	1.314	0.985	1.227	1.040	0.953	1.013	1.031	1.044	1.050	1.073
	Malmquist productivity index	0.698	0.799	0.752	0.843	0.892	0.974	0.881	0.963	0.902	0.856

Malmquist productivity index of vocational education investment in China from 2010 to 2019. From the results of Table 5, the Malmquist productivity index, technical efficiency index, and technical progress index of financial vocational education investment in the eastern, central, and western regions basically tend to change in the same direction and magnitude during the period of 2010–2019. Among them, the Malmquist productivity index has been increasing over time, indicating that its declining efficiency has been improving. In terms of the mean value, the Malmquist productivity index is highest in the western region, followed by the eastern and central regions. The technical efficiency index is higher in the east and west regions than in the central region. The technological progress change index is higher in the east than in the central and west regions. The scale efficiency index is higher overall in the west than in the east and central regions. The pure technical efficiency index in the eastern region is higher than that in the central and western regions. The above results show that the efficiency of "dual-chain" integration and student training quality of vocational education in the eastern region are higher than those in the central and western regions. With financial support at all levels, the scale of financial investment in vocational education in the western region has improved rapidly and the quality of student training has also improved to a certain extent. However, the crude development mode, which is mainly based on the increase of investment, has not been fundamentally changed. The integration of "dual chains" in vocational education in the western region is still in the initial development stage. Due to financial constraints, the development of vocational education in the central region, which is a large population area, lags behind that in the east and west regions as a whole.

4.3. Training and Evaluation of BP Neural Network. The calculation results of the first stage above are only applicable to the current year, and if the DEA method is used to continue to calculate the efficiency of subsequent years and expect them to be compared with the previous years, the calculation results will produce a certain degree of distortion. To address the above problems, the DEA-BPNN model is used, and MATLAB 2020b is applied, with the vocational education technical index data set of 31 provinces and cities from 2010 to 2019 as the BPNN input data set, and the DEA efficiency with preference order as the BPNN output target data, with the training set:validation set:test set ratio of 0.7 : 0.15 : 0.15, and the implied number of neurons is 10, the LM algorithm is chosen for training, and the computational results are obtained after the computer runs for 1.328 s. The results show that the absolute error of the training set, validation set, and test set is less than 5.2e-5 for more than 95% of the total number of objects, and the best performance of the validation set is achieved at the 138th training of BPNN, i.e., the validation set has the lowest mean square error, and the overall fitting effect is better; moreover, the regression R values of both the validation set and the test set are close to 1, indicating that the probability of overfitting is low. Compared with the DEA model, the DEA-BPNN model has no effect on the results of the stage analysis, and it can also compare different sample sets, so it is more suitable for the calculation of the efficiency of "dual-chain" integration of vocational education in multiple years and provinces and cities.

5. Conclusion

This paper uses the DEA-Malmquist index method to evaluate the efficiency of vocational education inputs in China from 2010 to 2019, constructs a DEA-BPNN model based on BP neural network, and draws the following conclusions.

(1) The results of DEA static analysis in 31 provinces show that the financial vocational education funding input and output in 27 provinces in China are in DEA ineffective state in 2019. The results of pure technical efficiency show that 9 provinces, such as Hebei and Shanxi, are in the pure technical efficiency effective in 2019, and the remaining 22 provinces are in the pure technical efficiency ineffective state. This indicates that after the implementation of the "dual-chain" integration policy in most provinces in China, the "dual-chain" integration effect has not been fully reflected, and the existing technology and resources have not been fully utilized, and further measures are needed to give full play to vocational education. It is necessary to take further measures to give full play to the advantages of "dual chain" and promote the improvement of vocational education training quality.

(2) Malmquist index and its decomposition show that during 2010–2019, the level of technology use of vocational education investment in China has been improved, and the efficiency of resource allocation in vocational education has been effectively improved. It indicates that the implementation of vocational education policy based on "dual-chain" integration has been effective in China. However, the deterioration of the efficiency of technological progress indicates that the development of vocational education in China is still characterized by a very rough and sloppy approach.

(3) The results of the subregional analysis show that the Malmquist productivity index and scale efficiency index in the western region are higher than those in the eastern and central regions. The technical efficiency, pure technical efficiency, and technical progress efficiency indices in the eastern region are higher than those in the central and western regions. The above results show that the efficiency of "dual-chain" integration of vocational education in the eastern region is significantly better than that in the central and western regions, but the crude development mode of increasing input as the main means has not been fundamentally changed. Due to financial constraints, the development of vocational

education in the western region, as a large population area, lags behind that in the eastern and central regions.

Based on this research result, the efficiency of "dual-chain" integration of vocational education in eastern, central, and western regions of China can be analyzed to find out the important factors affecting the efficiency of "dual-chain" integration and put forward corresponding policy suggestions according to the actual situation to promote the rapid and healthy development of vocational education quality.

Data Availability

The labelled data sets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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