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Research on the construction of labor education evaluation system based on the data envelopment analysis method

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Abstract Currently, there are obvious regional differences in the allocation of labor education resources, and the efficiency evaluation method is relatively single and lacks a systematic and scientific evaluation system, which makes it difficult to accurately reflect the effectiveness of the implementation of labor education, and restricts the balanced development of labor education and the overall efficiency improvement. This study constructed a labor education evaluation system based on the data envelopment analysis method, and analyzed the efficiency of labor education resource allocation and its influencing factors by selecting 259 relevant data across the country as samples from 2018-2024, using the DEA-BCC model and Malmquist index. The results show that: the mean value of the national labor education resource allocation efficiency in 2018-2024 is 1.083, indicating that the overall efficiency is effective but at a low level; regional differences are significant, with the highest efficiency in the western region (mean 1.353), followed by the central region (mean 1.001), and the lowest in the eastern region (mean 0.849); the efficiency of the allocation of labor education resources in each region has stability and persistence. Effective regions accounted for 58.1% of the total, showing that most regions still have room for improvement. Malmquist index analysis showed that total factor productivity improved in most regions, and the technical progress index improved rapidly after 2021. The analysis of influencing factors found that the number of regional schools, the number of international cooperative research dispatches and the efficiency of labor education are significantly positively correlated, and the proportion of illiterate population is significantly negatively correlated. This study provides theoretical support and practical reference for optimizing the allocation of labor education resources and improving the evaluation system.

Index Terms labor education, data envelopment analysis, resource allocation efficiency, Malmquist index, regional differences, influence factors

I. Introduction

Under the guidance of "double first-class" construction and "five education" talent cultivation concept, labor education has become an important part of talent cultivation in colleges and universities [1]. The Opinions on Comprehensively Strengthening Labor Education in Universities and Primary Schools in the New Era points out that labor education should be integrated into the whole process of talent cultivation and run through the teaching of various disciplines and specialties, so that students can learn to create, enhance the concept of labor, cultivate the spirit of labor, cultivate the habit of labor, and improve the labor literacy on the basis of the mastery of basic labor skills [2], [3]. Colleges and universities are the main position of labor education, which has an irreplaceable role in cultivating high-quality talents [4]. In recent years, many colleges and universities, in accordance with the national decision-making and deployment, have actively carried out the reform and exploration of labor education, and constructed a scientific and feasible labor education system to serve the national reform of higher education and the strategy of strengthening the country [5]. Although some positive progress has been made, labor education in the overall education and teaching is too weak and diluted, the content of education formality and fragmentation, the concept of education and the development of the times out of touch with the requirements of a number of problems can not be ignored [6], [7]. For this reason, according to the objectives and specific tasks of labor education reform, it is particularly important to build a labor education evaluation system that meets the requirements of the new era and reasonably guides the development of labor education in colleges and universities [8].

At this stage, domestic and foreign scholars have fewer relevant research results for the evaluation system of labor education, and the overall is still in the exploratory stage [9]. Combing through the research literature on the evaluation of labor education, some scholars have explored the necessity of constructing the evaluation system of labor education, but have not constructed a substantial evaluation system [10]. For example, Wang, J and Sun, B.

[11] pointed out that the main purpose of the construction of the labor education evaluation system is to solve the three main dilemmas of "difficulty in development", "difficulty in education" and "difficulty in evaluation" of labor education in colleges and universities, and indirectly enable students to understand and improve their own labor literacy. Ying, Z [12] in the analysis of the current situation of the evaluation system of labor education teaching in colleges and universities found that there are problems such as strong subjectivity and single evaluation index, which is difficult to comprehensively and objectively reflect the students' labor literacy and practical ability and other problems. And among the evaluation systems that have been constructed, Hu, S and Lv, Y [13] constructed four indicators of labor education in colleges and universities by using CIPP model and entropy weight method, which to a certain extent contributed to the construction of a strong educational country and the cultivation of talents. Wu, S [14] and others used multi-perspective research methods such as questionnaire survey, econometric analysis, and Delphi method to comprehensively measure students' labor literacy from four dimensions: labor concept, habit and quality, knowledge and skill, and emotion and attitude. In terms of methodological innovation, Xu, G and Zhang, W [15] proposed the construction and evaluation method of labor education curriculum evaluation system based on multimodal model, and the results show that the method performs well on various evaluation indexes, and the evaluation has a certain degree of validity.

From the analysis of the current research results, most of the research mainly focuses on higher vocational colleges and universities and primary and secondary schools to carry out the evaluation research related to labor education, and constructs the evaluation index system with different focuses [16]. The subject of evaluation is either individual students or labor education courses, focusing on empirical analysis and applied research at a single level or in a single discipline, and evaluating more of the stage results and educational outcomes. And less systematic and comprehensive research is carried out from the macro overall level of labor education carried out in colleges and universities [17]-[19]. Comprehensive evaluation of the educational process involving the activities of the subject of education, the lack of scientific and effective evaluation of the process of individual development and the lack of research on the comprehensiveness, standardization and systematicity of the content of the evaluation is still lacking.

As an important part of the national education system, labor education plays an irreplaceable role in cultivating students' labor consciousness, innovative spirit and practical ability. In recent years, China has attached great importance to the development of labor education, incorporating it into the national education system and continuously improving the relevant systems and standards at the policy level. However, due to factors such as unbalanced economic development and uneven distribution of educational resources in various regions, labor education still faces problems such as inefficient allocation of resources and unbalanced regional development in the process of implementation. How to scientifically evaluate the resource allocation efficiency of labor education, explore its influencing factors, and then put forward optimization strategies has become an important issue to be solved in the current education field. Scholars at home and abroad have mainly focused on the study of educational resource allocation efficiency in terms of evaluation of resource input and output efficiency, analysis of influencing factors and study of optimization strategies. In terms of research methods, Data Envelopment Analysis (DEA) has been widely used in the field of educational efficiency evaluation due to its advantages of not needing to pre-set the form of production function and being able to deal with multiple inputs and multiple outputs. Although existing research has made some progress in the evaluation of educational resource allocation efficiency, systematic research in the specific field of labor education is still insufficient, especially the lack of a comprehensive evaluation system based on the DEA method, as well as an in-depth exploration of regional differences in the efficiency of resource allocation in labor education and the factors that influence it. Based on this, this study constructs an evaluation system of labor education based on the DEA method, comprehensively evaluates the efficiency of labor education resource allocation, analyzes regional differences and their influencing factors, and provides theoretical support and practical references for optimizing the allocation of labor education resources. This study mainly adopts the following ideas: first, through literature combing, it constructs the evaluation index system of labor education resource allocation efficiency, including input indicators (teachers, finance, infrastructure) and output indicators (quantity, quality). Secondly, based on the panel data of 31 regions in China from 2018 to 2024, the input-oriented super-efficient DEA-BCC model is applied to evaluate the static efficiency of labor education resource allocation, and analyze the regional differences and time evolution trend. Then, the dynamic efficiency of labor education resource allocation is analyzed by DEA-Malmquist index to identify the main sources of total factor productivity changes. Finally, the proportion of illiterate population, the number of regional schools, the urbanization rate, the level of residents' income and the index of foreign exchange are selected as explanatory variables, and the Tobit model is used to analyze the influencing factors of the efficiency of the allocation of labor education resources, and targeted optimization suggestions are put forward based on the results of the study. This study evaluates the efficiency of labor education resource allocation from both static and dynamic dimensions, and explores the causes of regional differences through the analysis of influencing factors, providing theoretical basis and methodological support for the construction of a scientific and reasonable evaluation system of labor education.

II. Construction of an evaluation model for labor education

II. A. Definition of decision-making units

The first step in the DEA model for labor education evaluation chosen in this paper is to define the decision-making unit (DMU), which needs to be defined by considering the following factors:

(1) Homogeneity. The selected decision-making units should have similar characteristics and functions to ensure comparability among them. When evaluating labor education, enterprises in the same industry or with similar business models should be selected as decision units.

(2) Dynamism. When conducting dynamic evaluation, changes in decision-making units over time need to be considered. This may involve the addition of new decision-making units, the withdrawal of the original decision-making units, and changes in the input and output data of the decision-making units in different time periods.

(3) Moderation. The number of decision units should be kept moderate. Too few decision-making units may lead to a lack of representative evaluation results, while too many decision-making units may increase the computational complexity. In practical applications, it is necessary to determine the appropriate number of decision units according to the specific situation and needs [20].

II. B. DEA model

DEA is one of the commonly used methods in the field of labor education evaluation, which evaluates the performance of similar decision-making units (DMUs) by comparing their relative efficiencies. Specifically, DEA weights and sums the input and output indicators of each DMU to find the optimal combination of weights that maximizes the efficiency value of each DMU. In the DEA model, the efficiency value is equal to the sum of weighted outputs divided by the sum of weighted inputs. When the efficiency value is equal to 1, it means that the DMU is at the optimal efficiency boundary. When the efficiency value is less than 1, it indicates that the DMU is below the optimal level of efficiency [21]. The DEA model includes the CCR model and the BCC model. The CCR model is the model for the state of constant returns to scale and the BCC model is the model for the state of variable returns to scale.

(1) CCR model

CCR model is the basic model of DEA method, which is a nonparametric method based on linear programming to assess the relative efficiency of production decision units. CCR model assumes that the production process has constant scale reward, that is, the proportionality between input and output is constant.

In the CCR model, the comprehensive efficiency consists of two parts: technical efficiency and scale efficiency. Technical efficiency reflects the ability of a decision unit to maximize output for a given input. Scale efficiency reflects the production efficiency of a decision unit at its current scale. When the combined efficiency of a decision unit is equal to 1, it means that the decision unit is efficient in its production process. When the combined efficiency is less than one, it indicates that the decision unit has an efficiency loss in the production process.

Suppose there are n decision units, each with m input indicators and s output indicators. For the j th decision unit $(j=1,2,\cdots,n)$, its input indicator vector is $X_j=(X_{1j},X_{2j},\cdots,X_{mj})$ and its output indicator vector is $Y_j=(y_{1j},y_{2j},\cdots,y_{sj})$. Then, for a particular decision unit $i(i=1,2,\cdots,n)$, the CCR model can be used to calculate its combined efficiency by solving the following linear programming problem:

$$h_i=\frac{u^t y_i}{v^t x_i}=\frac{\sum_{s=1}^{k}u_s y_{si}}{\sum_{t=1}^{m}v_t x_{ti}},i=1,2,\cdots,n \tag{1}$$

Translating this into a linear problem yields:

$$\begin{aligned}&\min\theta\\&s.t.\sum\nolimits_{i=1}^{n}\lambda_i X_i-s^-=\theta x_0\\&\sum\nolimits_{i=1}^{n}\lambda_i X_i-s^+=y_0\\&\lambda_i\geq 0,s^+\geq 0,s^-\geq 0,i=1,2,\cdots n\end{aligned} \tag{2}$$

where U_s and V_j are the weights of the output and input indicators.

(2) BCC model

BCC model is an extended model of DEA method, different from CCR model, BCC model assumes that the production process has variable scale payoffs, i.e. the proportional relationship between input and output is variable. Under this assumption, the BCC model is mainly used to calculate the pure technical efficiency of a decision unit, excluding the effect of scale efficiency on the comprehensive efficiency.

Pure technical efficiency reflects the ability of a decision unit to maximize its output for a given input, independent of the scale of production. When the pure technical efficiency of a decision unit is equal to 1, it means that the decision unit is efficient in the production process. When the pure technical efficiency is less than one, it means that the decision unit has a loss of technical efficiency in the production process.

The mathematical expression form of the BCC model is similar to that of the CCR model, with the difference that the BCC model adds a constraint: $\sum_{i=1}^{n}\lambda_i = 1$. The details are as follows:

$$\begin{aligned}
&\min \theta \\
&s.t. \sum_{i=1}^{n}\lambda_i X_i - s^- = \theta x_0 \\
&\sum_{i=1}^{n}\lambda_i X_i - s^+ = y_0, \sum_{i=1}^{n}\lambda_i = 1 \\
&\lambda_i \geq 0, s^+ \geq 0, s^- \geq 0, i = 1,2,\cdots n
\end{aligned} \tag{3}$$

where U_s and V_j are the weights of the output and input metrics.

II. C.Introduction to the Malmquist Index

The Malmquist exponential analysis model is used to measure productivity changes and is commonly used to analyze productivity between two points in time. The model consists of two components: technical efficiency change and technical progress. Technical efficiency change measures the change in productivity between production units and technical progress measures the change in the level of technology. By comparing the Malmquist index between two points in time, it is possible to understand whether the productivity change stems from technical efficiency change or technical progress. The specific formula is:

$$\begin{aligned}
&M_i(x^{t+1}, y^{t+1}; x^t, y^t) = [D_i^t(x^{t+1}, y^{t+1}) / D_i^t(x^t, y^t)] \\
&*[D_i^{t+1}(x^{t+1}, y^{t+1}) / D_i^{t+1}(x^t, y^t)]^{1/2}
\end{aligned} \tag{4}$$

where $D_i^t(x^{t+1}, y^{t+1})$ denotes the distance function for the $(t+1)$ period in which the i th school is referenced to the production possibilities frontier of the t th year, and $D_i^t(x^t, y^t)$ denotes the distance function for the i th school in the current period referenced to the production possibilities frontier of the t th year [22]. The distance function is the inverse of the efficiency, so the inverse of $D_i^t(x^{t+1}, y^{t+1})$ can be obtained by linear programming of Eq:

$$\begin{aligned}
&\left[D_i^t\left(x^{t+1}, y^{t+1}\right)\right] - 1 = \min \theta^i \\
&s.t. Y_i^{t+1} \leq \sum_i z_i^t Y_i^t \\
&\sum_i z_i^t X_i^t \leq \theta^i X_i^{t+1} \\
&z_i^t \geq 0
\end{aligned} \tag{5}$$

Changes in the Malmquist productivity index can be decomposed into technical efficiency change (TEC) and technical change (TC). TEC is the index of relative efficiency change between period t and period $t+1$ under the condition of constant returns to scale and free disposal of factors, which is mainly due to efficiency improvement brought about by management and institutional reforms, etc., and is given by formula (6). TC is mainly the result of technological innovations and technological introduction, which can shift the production possibility boundary outward, and is given by formula (7).

$$TEC(x^{t+1}, y^{t+1}; x^t, y^t) = D_i^t(x^{t+1}, y^{t+1}) / D_i^t(x^t, y^t) \tag{6}$$

$$\begin{aligned}
&TC(x^{t+1}, y^{t+1}; x^t, y^t) = [D_i^t(x^{t+1}, y^{t+1}) / D_i^{t+1}(x^{t+1}, y^{t+1}) \\
&*D_i^t(x^t, y^t) / D_i^{t+1}(x^t, y^t)]^{1/2}
\end{aligned} \tag{7}$$

For the Malmquist index model, the focus of parameter analysis usually includes the following aspects:

(1) Total Factor Productivity (TFP): detects changes in the ratio between output and input, which visualizes the level of technological progress. If TFP is greater than 1, it indicates technological progress and productivity improvement. Conversely, it indicates technological regression and productivity decline.

(2) Pure technical efficiency (EFF): Used to measure the level of efficiency in utilizing input resources. If EFF is greater than 1, it means that the efficiency of resource utilization has improved. Conversely, it indicates a decline in efficiency.

(3) Mode of Operational Efficiency (MOE): mainly assesses the efficiency of output at a given scale of production, i.e., the extent to which economies of scale are utilized. When MOE is greater than 1, it indicates that there are economies of scale at the current scale. Conversely, it indicates the existence of scale diseconomies.

(4) Pure technical efficiency (PTE): embodied in the scale efficiency adjusted potential output efficiency level. If PTE is greater than 1, it indicates an increase in efficiency in terms of potential output. Conversely, it indicates a decrease in efficiency [23].

By analyzing these parameters, it is possible to have a comprehensive understanding of the technical progress, the efficiency change status and the economy of scale, so as to provide a reference basis for decision makers to improve the production method and enhance the production efficiency.

III. Efficiency measurement and data collection

When measuring the relative efficiency of the research object, the DEA model usually analyzes the outputs and inputs of the decision-making unit of the research object and makes reasonable decisions on the basis of comparative analysis. In analyzing the process of educational resource allocation, the evaluation index system is constructed from both input and output. The evaluation index system of labor education resource allocation is shown in Table 1. On the one hand, relevant indicators are mainly selected from the three directions of teachers, finance and infrastructure to measure the input of labor education resources. Teachers mainly include the number of teachers specialized in labor education, the number of dual-teacher teachers, the number of education managers and the number of teaching and administrative staff, which can reflect the staff structure of labor education more comprehensively. At the financial level, three indicators are chosen to reflect the level of financial investment in labor education, including the average per capita public financial budget for education, the investment in labor education infrastructure and the value of the assets of labor education teaching equipments. At the infrastructural level, two indicators are selected, namely, the floor area of school buildings and the area of labor education practice sites, which can reflect the overall situation of fixed assets. On the other hand, the output of labor education is measured in terms of quantity and quality. Due to the limitation of data availability, the quantity and quality of labor education are mainly reflected by the cumulative number of trainees graduated, the average number of students attending senior high school per 100,000 population, the number of graduates obtaining vocational qualification certificates, and the degree of satisfaction with labor education.

Table 1: Labor education resource allocation evaluation index system

Primary indicator	Secondary indicator	Tertiary index	Unit
Labor education input	Faculty	The number of special teachers of labor education (A1)	Person
		The number of teachers is the number of teachers. (A2)	Person
		The number of staff workers (A3)	Person
		Number of administrators (A4)	Person
	Finance	Public budget education business fee (A5)	Yuan
		Funding for the education infrastructure (A6)	Yuan
		Labor education teaching equipment assets (A7)	Yuan
	Infrastructure	Building area (A8)	m^2
		Labor education practice area (A9)	m^2
Labor education output	Quantity	The number of students in the labor and education period (B1)	Person
		The average number of schools in high school is (B2)	Person
	Mass	The number of graduates with skills certificate (B3)	Person
		Labor education satisfaction (B4)	%

This paper mainly selects 259 relevant data of China from 2018-2024 as the analysis sample to evaluate the efficiency of labor education resource allocation. The data are mainly derived from the measured data of China Education Statistical Yearbook, National Education Expenditure Implementation Statistics, China Labor

Marketization Index Compilation, and Wind database, and the data are analyzed by MaxDEA and MATLAB software. For the missing data, the interpolation method was used to fill in. The school sample statistics are shown in Table 2.

Table 2: School sample statistics

Subordinate region	Ordinary public school	Private school	Demonstration/double school	Total
East	50	29	26	105
Middle	43	25	20	88
West	30	20	16	66
Total	123	74	62	259

IV. Evaluation analysis of labor education

IV. A. Analysis of Resource Allocation Efficiency in Labor Education

The efficiency problem of labor education resource allocation mainly includes two parts: the static efficiency of resource allocation and the dynamic efficiency of total factor productivity. First of all, this paper measures the resource allocation efficiency of labor education based on the panel data of 31 regions in China in 2018-2024, using the input-oriented super-efficient DEA-BCC model, and the evaluation results of the resource allocation efficiency of labor education in each region are shown in Table 3. The 31 regions are divided into the following three categories: firstly, perennial ineffective regions. The number of times that the resource allocation efficiency of labor education in this category is ineffective is at least six times, including 12 regions such as Beijing, Shanxi, Inner Mongolia, Liaoning, Jilin, Shanghai, Jiangsu, Zhejiang, Shandong, Hubei, Hunan and Chongqing, with a larger proportion accounted for in the east. Second, ineffective and effective fluctuations in the region. The number of ineffective times of resource allocation efficiency of labor education in this type of region is 3 to 5 times, including 9 regions such as Tianjin, Hebei, Fujian, Jiangxi, Guangdong, Hainan, Shaanxi, Gansu and Xinjiang, with a larger proportion accounted for by the east. Specifically, the characteristics of the resource allocation efficiency of labor education are as follows: as a whole, the average value of the resource allocation efficiency of labor education in the country in 2018-2024 is 1.083, indicating that the resource allocation of labor education is effective, but the effectiveness is at a low level. At the same time, for the time series, the resource allocation efficiency of labor education shows a trend of first decreasing, then increasing, and then decreasing. From a regional perspective, there are obvious regional gaps in the resource allocation efficiency of labor education. According to the mean value sequence of labor education resource allocation efficiency, it can be seen that the top three regions are Tibet, Anhui and Ningxia, with efficiencies of 4.530, 1.373 and 1.297, while the bottom three regions are Shandong, Beijing and Shanghai, with efficiencies of 0.687, 0.634 and 0.615, indicating that there are large differences in the resource allocation efficiency of each region's labor education, which constrains the balanced development between regions and the improvement of overall efficiency. In addition, from the perspective of regional distribution, 18 regions are in an effective state, indicating that the resource allocation efficiency of labor education in most regions needs to be improved. From the perspective of time, the resource allocation efficiency of labor education in each region has stability and continuity as a whole, such as Shanghai's resource allocation efficiency of labor education is in an ineffective state from 2018 to 2024, and the degree of change is small, all converging to the mean value of 0.86.

This section continues to explore regional differences in the efficiency of labor education resource allocation. The regions are categorized into East, Central, and West according to the division criteria of the National Bureau of Statistics. The resource allocation efficiency of labor education in each region is shown in Figure 1. According to the chart, the efficiency of resource allocation for labor education in various regions is arranged in descending order as follows: West > Central > East. Specifically, the efficiency of resource allocation for labor education in the West is the highest, with an average of 1.353, followed by the Central region with an average of 1.001, while the East has the lowest efficiency, with an average of 0.849. There is still a certain gap from relative efficiency, and it is lower than the national average. In addition, from the perspective of the dynamic evolution trend, the difference in resource allocation efficiency of labor education between regions has shown a narrowing trend in recent years, and the difference between regions has become smaller year by year. It is worth noting that the resource allocation efficiency of labor education in central China fluctuates up and down around 1 in 2018-2024, indicating that central China is switching between ineffective and effective, which needs to be further controlled and optimized.

Table 3: Resource allocation efficiency evaluation results

Region	2018	2019	2020	2021	2022	2023	2024	Mean	Ranking
Beijing	0.943	0.765	0.578	0.519	0.558	0.55	0.525	0.634	30
Tianjin	0.733	0.728	0.739	0.838	1.23	1.204	1.158	0.947	17
Hebei	1.107	1.149	0.839	0.726	0.821	0.886	0.915	0.920	18
Shanxi	0.934	0.934	0.916	0.79	0.752	0.825	0.866	0.860	24
Inner Mongolia	0.837	0.718	0.74	0.757	0.839	0.795	0.802	0.784	27
Liaoning	0.731	0.84	0.865	0.851	0.913	0.97	0.949	0.874	23
Jilin	0.842	0.906	0.877	0.741	0.706	0.871	0.847	0.827	25
Heilongjiang	0.976	1.026	1.101	0.868	1.118	1.165	1.142	1.057	9
Shanghai	0.56	0.61	0.6	0.585	0.632	0.649	0.67	0.615	31
Jiangsu	0.889	0.865	0.695	0.691	0.687	0.698	0.75	0.754	28
Zhejiang	0.93	0.883	0.811	0.752	0.846	1.015	0.962	0.886	22
Anhui	1.342	1.151	1.34	1.342	1.399	1.46	1.576	1.373	2
Fujian	1.078	1.1	0.997	0.86	0.938	0.989	0.994	0.994	15
Jiangxi	0.974	1.087	1.193	0.948	0.948	1.081	1.065	1.042	12
Shandong	0.745	0.707	0.695	0.619	0.631	0.654	0.761	0.687	29
Henan	0.999	1.301	1.295	1.159	1.179	1.181	1.002	1.159	6
Hupei	1.131	0.939	0.673	0.607	0.72	0.746	0.714	0.790	26
Hunan	0.905	0.951	0.959	0.847	0.9	0.919	0.917	0.914	19
Guangdong	1.106	1.066	0.875	0.835	0.832	0.842	0.818	0.911	20
Guangxi	1.296	1.064	1.047	1.024	1.03	1.025	1.133	1.088	7
Hainan	0.964	0.965	0.906	0.95	0.966	1.17	1.087	1.001	14
Chongqing	0.949	1.007	0.919	0.795	0.824	0.876	0.895	0.895	21
Sichuan	1.447	1	1	1	1	1	1	1.064	8
Guizhou	0.858	1.056	1.154	1.382	1.567	1.654	1.407	1.297	4
Yunnan	1.231	1.041	0.994	0.922	1.012	0.997	1.084	1.040	13
Tibet	5.403	3.959	4.266	4.878	4.808	4.397	3.999	4.530	1
Shaanxi	0.935	1.132	1.033	0.995	1.091	1.108	1.007	1.043	11
Kansu	1.168	0.971	1.052	1.103	1.134	0.926	0.964	1.045	10
Qinghai	1.281	1.333	1.352	1.178	1.292	1.281	1.252	1.281	5
Ningxia	1.141	1.531	1.175	1.388	1.334	1.125	1.387	1.297	3
Xinjiang	0.733	0.785	1.069	0.863	1.062	1.165	1.139	0.974	16
Mean	1.134	1.083	1.057	1.026	1.089	1.104	1.090	1.083	

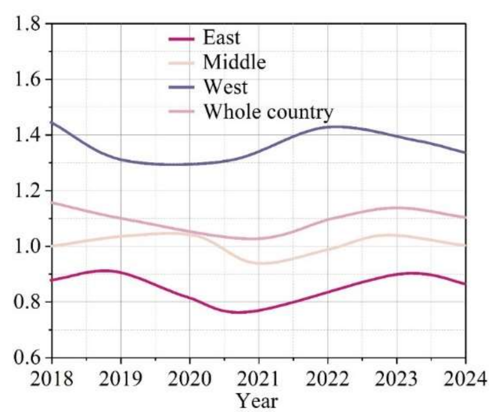


Figure 1: Resource allocation efficiency of education in districts

IV. B. DEA-Malmquist Index Analysis

This section organizes the DEA-Malmquist index of each region for two adjacent years from 2018-2024, and the distribution of DEA-Malmquist index in each region is shown in Figure 2. As can be seen from the figure, in terms of total factor productivity change, except for Tibet, which is obviously lower than 1, the vast majority of regions have total factor productivity greater than 1, indicating that the input-output efficiency of higher education in the vast majority of regions is improving, and that the total factor productivity growth of Liaoning, Shaanxi, Hubei, and Heilongjiang even exceeds 50% in individual years. In terms of scale efficiency change, Ningxia, Qinghai and Tibet have the largest changes, while regions such as Beijing and Guangdong, which have a higher level of economic development, are very stable in terms of scale efficiency change (stable improvement in scale efficiency). In terms of pure technical efficiency improvement, in addition to Beijing, Guangdong, Shandong, Hubei, Shandong, Shanghai and Zhejiang, Jiangsu and Tibet are also very stable in terms of pure technical improvement, which is generally characterized by pure technical efficiency improvement. In terms of comprehensive technical efficiency change, Beijing, Guangdong, Hubei, Shandong, Shanghai and Zhejiang are stable, while other regions have different degrees of fluctuation (affected by the combination of pure technical efficiency change and scale efficiency change). In terms of improvement in technological progress, the vast majority of regions have a technological improvement index greater than 1, except for Tibet, which has regressed significantly. Overall, for total factor productivity improvement, the Tibet region has a large gap with other regions due to a variety of reasons, including geography, climate and population. The Pearl River Delta and Yangtze River Delta regions have higher improvement efficiency (Guangdong, Zhejiang, Shanghai, Jiangsu) compared to neighboring regions.

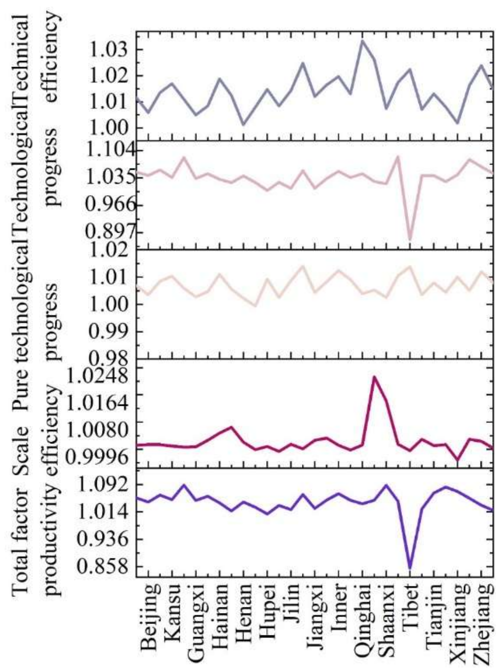
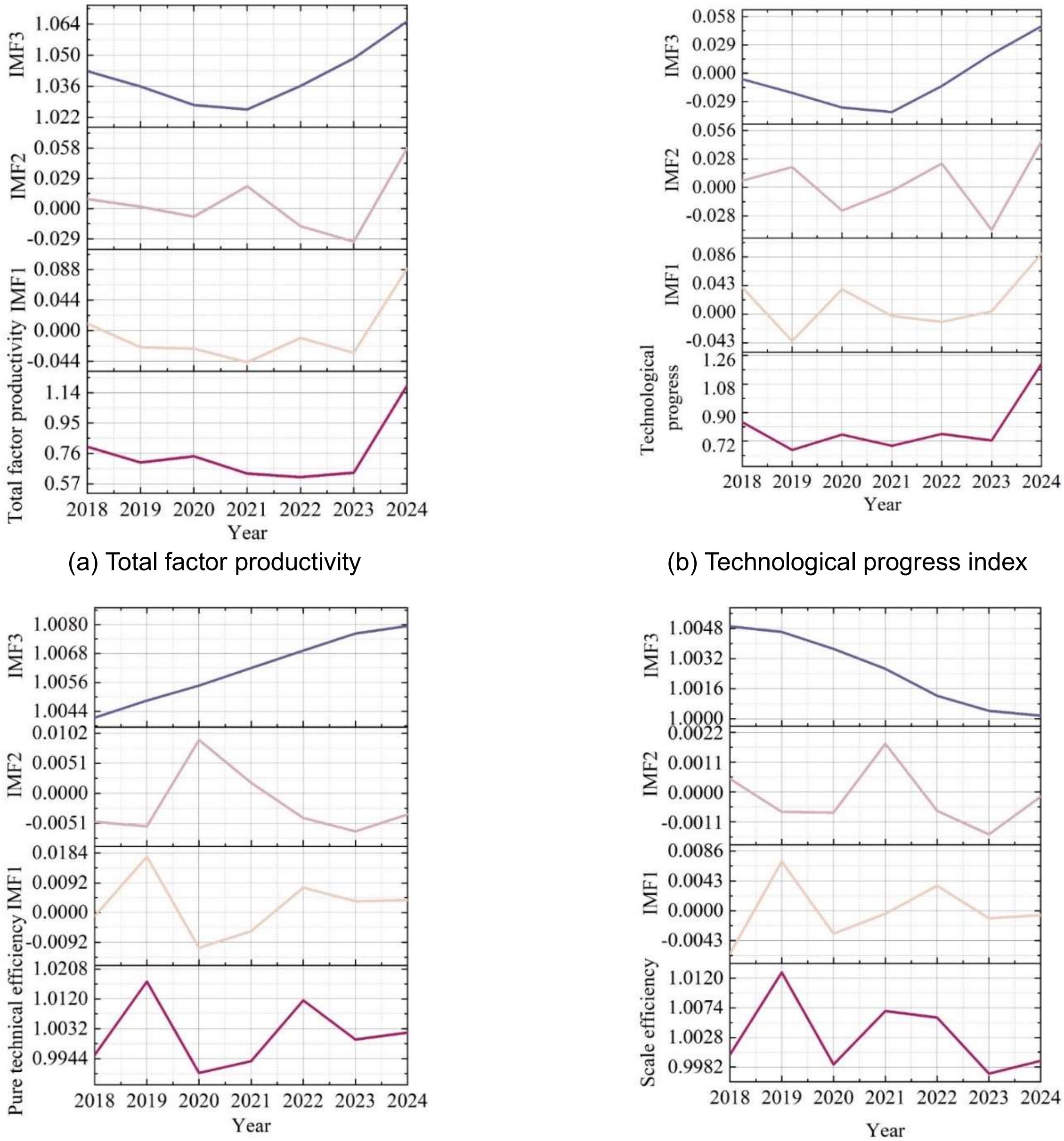


Figure 2: Distribution of DEA-Malmquist index in various regions

In order to analyze the trend of labor education input-output performance, EMD is further used to decompose the comprehensive DEA-Malmquist index (total factor productivity, technical progress index, pure technical efficiency index and scale efficiency index), and the results of EMD decomposition of the comprehensive DEA-Malmquist index are shown in Fig. 3 (Figs. a~d are total factor productivity, technical progress index, pure technical efficiency index and scale efficiency index). From the figure, it can be seen that the long-term trend of each DEA-Malmquist number shows the third component (IMF3). Among them, the long-term trends of the total factor productivity index and the technical progress index remain consistent, being the lowest point reached around 2021, with the difference that the factor productivity index is constant greater than 1 in the long-term trend, indicating that total factor productivity has been growing in the long-term trend, while the technical progress index is slightly less than 1 around 2021, indicating that there is a short-lived technological efficiency regression, and that, after a teething period, the technical progress index has risen rapidly again since 2021, which is perfectly consistent with the second growth curve theory. The long-term trend of the Technical Efficiency Index is constantly greater than 1 and the growth rate is getting faster and faster, indicating that technology is iterating at an accelerated rate. The long-term trend of the scale efficiency index is gradually decreasing and approaching 1, indicating that although the scale efficiency is growing in the long-term trend, the growth rate is slowing down, and individual regions have already seen the situation of decreasing scale efficiency, which also confirms the conclusion from the side.



(a) Total factor productivity (b) Technological progress index

(c) Pure technology efficiency index (d) Scale efficiency index

Figure 3: EMD decomposition results of the integrated DEA-Malmquist index

IV. C. Analysis of factors affecting labor education

IV. C. 1) Selection of indicators of impact factors

In this section, the influencing factors of labor education will be further explored based on the results of DEA measurement. In this study, the education of regional population, the level of higher education, the level of urbanization, the living standard of residents and the level of foreign exchange of colleges and universities are taken as the influencing factors of labor education, and the proportion of illiterate population in the population of 15 years old and above, the number of regional schools, the rate of urbanization, the per capita disposable income of urban residents, and the number of dispatches of international cooperative research are finally selected according to the accessibility, objectivity and measurability of data, number of papers exchanged in international academic conferences as explanatory variables, and the indicators of labor education investment efficiency influencing factors are shown in Table 4. At the same time, this paper deflated indicators such as urban residents' per capita disposable income using CPI consumer price index with 2018 as the base period. The study uses Stata 17.0 software to carry out fixed-effects ols, random-effects ols, mixed Tobit and random-effects Tobit estimation, respectively, according to the results of the Stata run, it can be seen that the use of the four models is significant at the level of 0.001, and the use of the random Tobit model to test the level of significance of 0.000, which indicates that the data are suitable for the use of the random effects of the Tobit model for testing.

Table 4: Factors of efficiency of labor education investment

Primary indicator	Measure indicator	Serial number
The population of the region is exposed to education	The population of illiterate people is at least 15 years old and above (%)	x_1
Regional education	Number of regional schools	x_2
Level of urbanization	Urbanization rate (%)	x_3
Living standard	Per capita disposable income (yuan)	x_4
Foreign exchange level	International cooperation research dispatch (number of people)	x_5
	The number of papers in the international academic conference (article)	x_6

IV. C. 2) Analysis of Impact Factor Results

The Tobit test of the factors influencing labor education is shown in Table 5 (***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively). The results show that the proportion of illiterate population in the population aged 15 and above passes the significance test at the 0.05 confidence level, and is negatively correlated with labor education, indicating that regional illiteracy rate has a certain impediment to the improvement of labor education. Therefore, in order to improve labor education, it is necessary to improve the overall education level of the region. The number of regional schools passes the significance test at the 0.01 confidence level, and the regression coefficient shows a positive correlation between the two, indicating that the number of regional schools can reflect the development level of regional labor education to a certain extent. The disposable income of urban residents passes the significance test at the confidence level of 0.1, and there is a positive correlation with labor education. The number of international cooperation and research dispatches passes the significance test at the confidence level of 0.05 and is positively correlated with labor education, indicating that foreign exchange and cooperation can significantly improve labor education. In addition, there is not enough evidence to show that the urbanization rate, the number of papers exchanged in international academic conferences and labor education have a significant correlation.

Table 5: Tobit test of the factors of labor education

Interpretation variable	Regression coefficient	Standard error	z value	p value
The population of illiterate people is at least 15 years old and above (%)	-0.0006522	0.0028561	-2.26	0.026**
Number of regional schools	0.0047250	0.0006005	8.05	0.000***
Urbanization rate (%)	-0.0015699	0.0025036	-0.63	0.536
Per capita disposable income (yuan)	0.1032613	0.0629855	1.69	0.095*
International cooperation research dispatch (number of people)	0.0001169	0.0000542	2.19	0.036**
The number of papers in the international academic conference (article)	0.0000001	0.0000155	0.01	0.996
_cons	-0.3126592	0.5531695	-0.58	0.562

V. Conclusion

The research on the construction of labor education evaluation system based on the data envelopment analysis method draws the following conclusions:

The average value of the national labor education resource allocation efficiency in 2018-2024 is 1.083, indicating that the whole is in the state of effective but low level of efficiency, and it shows the trend of change of decreasing, then increasing and then decreasing.

There are significant differences in the efficiency of labor education resource allocation between regions, with the highest efficiency in the western region, followed by the central region and the lowest in the eastern region, forming an inconsistent trend with the level of economic development. The top three regions are Tibet, Anhui and Ningxia, with efficiencies of 4.530, 1.373 and 1.297 respectively; the bottom three regions are Shandong, Beijing and Shanghai, with efficiencies of 0.687, 0.634 and 0.615 respectively.

Malmquist index analysis shows that, except for Tibet, the vast majority of regions have a total factor productivity greater than 1, the technological progress index is rapidly increasing after 2021, and the scale efficiency index is converging to 1, indicating a slowdown in the growth rate of scale efficiency.

The analysis of influencing factors shows that the number of regional schools and the number of international cooperative research dispatches have a significant positive effect on labor education efficiency, the proportion of illiterate population has a significant negative effect, while the urbanization rate and the number of papers exchanged at international academic conferences have no significant effect.

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