Evaluation of Educational Resource Efficiency Based on the Data Envelopment Analysis Model and Malmquist Index

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Abstract

This article aimed to apply the DEA-BCC model and the DEA-Malmquist index to evaluate the efficiency of educational resource allocation in provincial universities. Secondary data were obtained from 40 provincial colleges and universities in Sichuan Province from 2017 to 2022. Factors such as human, physical, and financial capital were used as input indicators, while educational outcomes, scientific research, and social services served as output indicators. The DEA-BCC model shows that the average value of comprehensive technical efficiency was 0.911, with an average pure technical efficiency of 0.978 and an average scale efficiency of 0.929, indicating scale efficiency as a constraining factor. According to the DEA-Malmquist index model results, the total factor productivity has an average value of 0.707. This suggests a 29.30% decrease in efficiency over these 6 years. The average value of the technical efficiency index is 0.985, which decreases by 0.074. The average value of the technological progress efficiency index was 0.718, indicating that the sample of provincial universities did not experience high technological progress efficiency. Technological regression during this period primarily influenced the changes in total factor productivity. The research findings indicate technical efficiency issues in utilizing educational resources at provincial universities. The results of this study are anticipated to offer valuable insights and benefits to key stakeholders in the education sector. By presenting a robust tool for assessing the efficiency of educational resource allocation, the study underscores the critical role of technical and scale efficiencies in enhancing effectiveness. Through a comprehensive analysis of educational resource inputs and outputs, this paper identifies the key factors influencing efficiency, providing invaluable data support to decision-makers and managers in the education sector.

Keywords: provincial university; efficiency; educational resources; DEA–BCC model; DEA–Malmquist index

Introduction

Despite increasing interest in educational efficiency, there remains a notable gap in understanding the factors affecting resource allocation at the provincial level. This study aims to bridge this gap by applying the DEA–BCC model and DEA–Malmquist index method to evaluate and improve the efficiency of educational resource allocation.

The DEA–BCC model and DEA–Malmquist index are essential for this analysis as they provide comprehensive approaches for evaluating and enhancing resource efficiency. The DEA–BCC model assesses the technical efficiency of resource utilization, with a particular emphasis on scale efficiency as a limiting factor. Conversely, the DEA–Malmquist index offers insights into changes in total factor productivity over time, emphasizing variations in efficiency and technological progress (Chen et al., 2023). These methods are precious for identifying inefficiencies and areas for improvement, thereby facilitating the development of targeted strategies for optimizing resource allocation.

The allocation of educational resources is pivotal for enhancing the efficiency and effectiveness of provincial universities (Fadda et al.,2022). As these institutions navigate the evolving educational landscape and strive to meet the growing demands of students and society, optimizing resource management becomes essential for their operational success and long–term viability (He, 2022).

Previous studies measured the effectiveness of university educational resources based on three dimensions and six indicators: human capital, physical capital (Kamarudin et al., 2023), and financial capital as input indicators (Egorov & Serebrennikov, 2023; Haddad et al., 2021). Additionally, three dimensions and five indicators–educational outcomes, scientific research, and social services–were used as output indicators (Lepori et al., 2013). The emphasis on scale efficiency in the DEA–BCC model and the focus on productivity change in the DEA–Malmquist index provide a nuanced understanding of resource use and its impacts.

Focusing on 40 provincial universities in Sichuan Province from 2017 to 2022, this research seeks to offer actionable insights for enhancing resource management and addressing inefficiencies. Wei and Jun (2022) proposed deepening the reform of resource allocation methods and improving resource allocation efficiency. The results are expected to contribute to policymakers, university administrators, and educational planners by providing practical recommendations for improving resource allocation. By addressing inefficiencies and optimizing resource management, this research aims to support the development of a more effective and sustainable university education system.

Objective of study

1. To apply the DEA-BCC model to statistically evaluate the efficiency of educational resource allocation in provincial universities.
2. To utilize the DEA-Malmquist index to dynamically assess the efficiency of educational resource allocation in provincial universities.
3. To explore whether pure technical change is the key factor restricting the improvement of the total factor productivity of provincial universities.

Literature Review

Recent research on the efficiency of educational resource allocation in higher education has advanced significantly. Notable studies include Agasisti and Dal (2006), who investigated the impact of financial capital on university performance; Li (2020), who examined the application of DEA models in educational settings; and Duan (2019), who assessed the role of technological advancements on educational outcomes. These studies have provided valuable insights into various dimensions of educational efficiency. However, notable gaps still need to be addressed, particularly in the comprehensive evaluation of educational resource efficiency within provincial universities. Bornmann et al. (2023) concentrated on financial resources but needed to account for the interplay between human and physical capital, which could influence overall efficiency. Cui et al. (2019) applied DEA methods but needed to explore dynamic changes in efficiency over time, thus limiting the generalizability of the findings. Lee (2016) focused on technological advancements but did not address the impact of scale efficiency on overall productivity. This study identifies a critical knowledge gap: the need for an integrated analysis of static and dynamic factors affecting educational resource efficiency. Current literature needs a thorough examination of how scale efficiency and technological progress impact the overall productivity of provincial universities. To address this gap, this study will apply the DEA-BCC model and DEA-Malmquist index method to understand educational resource allocation efficiency better.

Theoretical Foundations

This section includes the core theories and models for assessing educational resource efficiency. Chen (2023) provided insights into the impact of financial capital on educational performance, while Xiong (2022) introduced DEA models for efficiency measurement. These foundational theories lay the groundwork for understanding how various inputs influence educational outcomes.

Quantitative Methods

Quantitative methods such as DEA, multiple linear regression, and principal component analysis are widely employed in measuring educational efficiency (Wohlrabe et al., 2019). Wang (2020) utilized DEA to evaluate the input-output efficiency of educational resources, comparing regional efficiency differences. Zhou and Tian (2020) used DEA models to assess educational resource allocation efficiency, revealing variations based on university type, region, and disciplinary area. Jin and Wang (2019) applied DEA to analyze input-output efficiency in Chinese universities, while Li and Qian (2020) used meta-frontier analysis to study the efficiency of educational resource allocation in China. These studies demonstrate that DEA methods are prevalent in public-domain research but emphasize the need for a well-established input-output indicator system to measure resource efficiency accurately.

Dynamic efficiency evaluation

The DEA-Malmquist index is an effective tool for analyzing changes in total factor productivity over time. Agasisti et al. (2019) demonstrated the use of the Malmquist index in tracking efficiency changes, offering valuable insights into technological progress and efficiency variations. Nevertheless, its application to provincial universities remains relatively underexplored.

Factors influencing efficiency

Factors affecting university efficiency include financial funds, student demand, disciplinary structure, Institutional level, University region, and performance. Ding et al. (2023) and Olari (2022) highlighted the influence of financial support and student needs on resource allocation. However, these studies often overlook the effects of technological progress and scale efficiency on overall productivity (Holmlund et al., 2010). The demand and characteristics of different fields may lead to uneven resource distribution, and the size of an institution also impacts resource allocation (Munoz, 2016). Regional economic levels and development disparities contribute to variations in higher education resource allocation (Alizadeh et al., 2020).

Contextual applications

Wei and Jun (2022) underscored the importance of quantifying efficiency within specific regional or institutional contexts, suggesting region-specific strategies for improving resource allocation. This study will focus on provincial universities in Sichuan, utilizing these insights to provide targeted recommendations for enhancing resource utilization. While existing literature offers valuable insights into various aspects of educational resource efficiency, there is a need for a comprehensive approach that integrates both static and dynamic measurements. This study aims to address this gap by applying the DEA-BCC model and DEA-Malmquist index method to provide a more thorough analysis of resource allocation efficiency in provincial universities.

Conceptual Framework

This framework comprehensively evaluates university resource utilization by considering input factors (human capital, physical capital, financial capital) and output factors (including educational outcomes, scientific research, and social services) from an input-output perspective. The DEA-BCC model is used to calculate technical efficiency under variable returns to scale, while the DEA-Malmquist index monitors dynamic efficiency changes. This dual approach allows for both static analysis of current efficiency and dynamic tracking of efficiency evolution. Consequently, the framework provides a scientific basis for optimizing resource allocation and improving university performance. The research framework is illustrated in Figure 1.

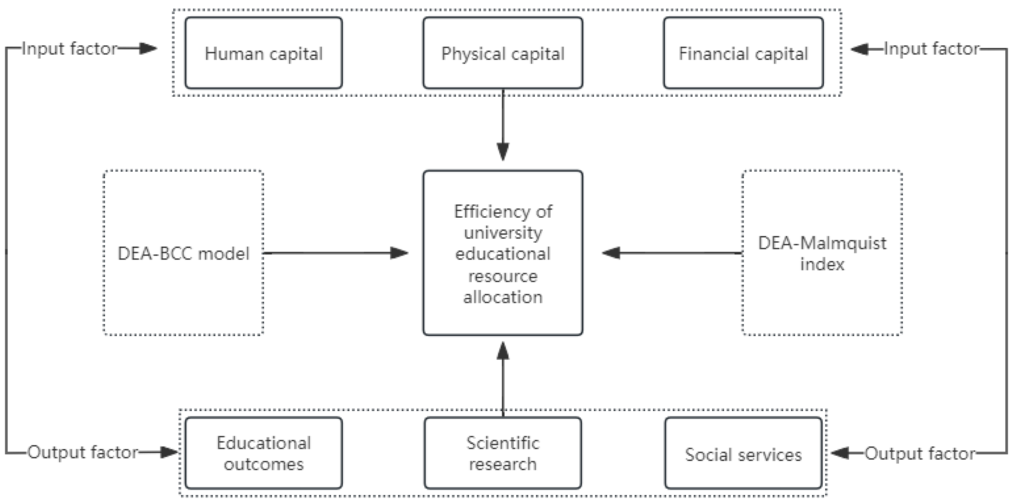

Figure 1 Conceptual framework

Research Methodology

The study focuses on universities in Sichuan Province, China, specifically those directly managed by provincial education authorities. Two hundred forty data samples were collected from 40 provincial universities in Sichuan. The research period spans from 2017 to 2022. This section discusses using DEA models to measure and analyze the efficiency of educational resources and identify factors influencing their efficiency by using DEAP 2.1 software for analysis.

1. Introducing the DEA model

This study applies DEA to measure the educational resource allocation efficiency and total factor productivity changes in provincial universities.

1.1 Introducing the DEA-BCC model

In economics, it is a formula used to study production efficiency issues. It is commonly expressed using the ratio of inputs and outputs as follows:

E (efficiency) = O (output) / I (input)

The DEA method is also based on the ratio of inputs and outputs to calculate efficiency values and construct a frontier curve. Then, the distance between each decision-making unit and the frontier curve is computed, resulting in the relative efficiency values of each decision-making unit. This study assumes there are decision-making units (DMUs) of n to be evaluated. Each DMU has m resource inputs and p outcome outputs. The efficiency evaluation index h for the s-th DMU is then the ratio of its weighted inputs to its weighted outputs, which can be expressed as follows:

$$h_s = \frac{u_1 y_{1j} + u_2 y_{2j} + \dots + u_p y_{ps}}{v_1 x_{1j} + v_2 x_{2j} + \dots + v_m x_{ms}} = \frac{\sum_{r=1}^{p} u_r y_{rs}}{\sum_{i=1}^{m} v_i x_{ms}}, s = 1, 2 \dots, n$$

$$v \geq 0; u \geq 0 \quad (1)$$

where:

h_s	=	Efficiency evaluation index of the n-th decision-making unit.
$y_{(r=123\cdots p)}$	=	Outcome outputs.
$x_{(i=123\cdots m)}$	=	Resource inputs.
$s_{(j=123\cdots n)}$	=	Decision-making units.
$v_{(i=123\cdots m)}$	=	Represents a measurement weight for inputs.
$u_{(r=123\cdots p)}$	=	Represents a measurement weight for outputs.
y_{rs}	=	The r-th output quantity of the s-th decision-making unit.
x_{ms}	=	The m-th input quantity of the s-th decision-making unit.

A constraint must be imposed on this efficiency value, limiting all DMUs to having an efficiency value within the range of 0 and 1 when using the weights above. This can be represented as:

$$\frac{\sum_{r=1}^{p} u_r y_{rs}}{\sum_{i=1}^{m} v_i x_{ms}} \leq 1 \qquad (2)$$

where:

y_{rs}	=	The r–th output quantity of the s–th decision–making unit.
x_{ms}	=	The m–th input quantity of the s–th decision–making unit.

DEA–BCC model: In 1984, Banker, Charnes, and Cooper proposed a DEA model for estimating scale efficiency, which was later known as the BCC model. The BCC model is based on variable returns to scale (VRS) and calculates pure technical efficiency by excluding the influence of scale on efficiency rankings. This means that the BCC model focuses solely on measuring the technical efficiency of decision–making units without considering the impact of scale. The input–oriented BCC model is as follows:

$$\begin{aligned}
&\max \sum_{r=1}^{p} \mu_r y_{rs} - \mu_0 \\
&s.t. \sum_{r=1}^{p} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \\
&\sum_{j=1}^{n} v_i x_{is} = 1 \\
&v \geq 0; \mu \geq 0; \mu_0 \; free \\
&i = 1,2,\ldots m; r = 1,2,\ldots p; j = 1,2,\ldots n
\end{aligned} \qquad (3)$$

where:

y_{rs}	=	The r–th output quantity of the s–th decision–making unit.
x_{is}	=	The i–th input quantity of the s–th decision–making unit.
y_{rj}	=	The r–th output quantity of the j–th decision–making unit.
x_{ij}	=	The i–th input quantity of the j–th decision–making unit.
s.t.	=	Subject to indicating the guiding part of the constraint conditions.
$v_{(i=123\cdots m)}$	=	Represents a measurement weight for inputs.
$\mu_{(r=123\cdots p)}$	=	Represents a measurement weight for outputs.

1.2 Introducing the DEA-Malmquist model

In this study, the adjacent cross-reference Malmquist index is employed to measure the overall efficiency changes of decision-making units between two consecutive periods. It is the most widely used Malmquist index and was first introduced by Färe et al. in 1992. The Malmquist index from period t to t+1 is represented as:

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \sqrt{\frac{E^t(x^{t+1}, y^{t+1})E^{t+1}(x^{t+1}, y^{t+1})}{E^t(x^t, y^t)E^{t+1}(x^t, y^t)}} \tag{4}$$

In the formula above, $E^t\ (x^t y^t)$ and $E^t\ (x^{t+1} y^{t+1})$ A represents technological efficiency values for two different periods. The relationship between the Malmquist index, technical efficiency change, and technological progress change can be expressed using the Malmquist index decomposition transformation as follows:

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{E^{t+1}(x^{t+1}, y^{t+1})}{E^t(x^t, y^t)} \sqrt{\frac{E^t(x^t, y^t)E^t(x^{t+1}, y^{t+1})}{E^{t+1}(x^t, y^t)E^{t+1}(x^{t+1}, y^{t+1})}} \tag{5}$$

Based on the expansion and transformation of the above formula, it can be observed that the Malmquist index by using DEAP 2.1 software, which represents total factor productivity, is equal to the product of technical efficiency change and technological progress change. Technical efficiency changes can be further decomposed into the product of scale and pure technical efficiency changes. The simplified representation is as follows:

$$M_0\ (x_{t+1}, y_{t+1}, x_t, y_t) = Tfpch = Tech \times (Sech \times Pech) = Tech \times Effch \tag{6}$$

where:

Tfpch	=	Total factor productivity.
Tech	=	Pure technical change.
Sech	=	Scale efficiency.
Pech	=	Pure technical efficiency.
Effch	=	Technical efficiency.

2. Variable selection and data sources

One of the most crucial aspects of the DEA evaluation model is the selection of input-output indicators and samples, as they significantly impact the final evaluation results. This study employed a comprehensive and concise system of input-output indicators. The details are shown in Table 1.

Table 1. Input-output evaluation index system of resource allocation in provincial universities.

Indicators	Secondary Indicators	Tertiary Indicators
Inputs	Human capital	1 Teaching and research staff
		2 Other faculty and staff
	Physical capital	3 Total fixed assets
		4 Books (in ten thousand volumes)
		5 Total building area
	Financial capital	6 Expenditure on educational affairs and operational expenses
Outputs	Educational outcomes	7 Number of full-time students
	Scientific research	8 Number of patents
		9 Number of published papers
	Social services	10 Number of adult education students and other students
		11 Income from technology transfer and operations in the current year

The measurements involved six input and five output indicators

3. Data sources

This study selected 40 provincial universities in mainland Sichuan. The period for studying the efficiency of educational resource allocation is from 2017 to 2022. The data originated primarily from sources such as the Sichuan Provincial Budget and Final Accounts Open Platform (Department of Financial Management, 2022), the China Education Statistics Yearbook (Department of Financial Affairs, 2022), the Sichuan Education Statistics Yearbook (China Ministry of Education Quality Assessment Center, 2022), the financial analysis report of the Sichuan Provincial Education Department's universities (Department of Education and Science, 2022), compilation instructions for the final accounts, and other relevant local yearbooks and official websites.

Results

1. Results of the variables

Table 2 highlights significant diversity among 40 provincial universities in Sichuan, China. Teaching and research staff range from 93 to 2,310 persons, and other staff range from 51 to 1,151 persons, averaging 181.096 persons. Total fixed assets range from 1,749.230 to 324,830.060 ten thousand yuan, and book volumes average 149.080 ten thousand volumes, ranging from 6.600 to 377.530 ten thousand volumes. Building areas vary from 4,415.000 to 1,284,329.000 sq.m, averaging 440,454.788 sq.m. Educational and operational expenses range from 3,853.210 to 207,817.030 ten thousand yuan, with an average of 57,002.463 ten thousand yuan. Full-time students range from 1,659 to 69,449 persons, averaging 19,509.750 persons. Patents range from 101 to 1,022, averaging 119.600. Published papers range from 101 to 1,306, averaging 146.504. Adult and other students range from 121 to 95,613 persons, averaging 1,992.971 persons. Income from technology transfer ranges from 100 to 41,772.700 ten thousand yuan, averaging 1,290.954 ten thousand yuan.

Kurtosis and skewness show that the variables exhibit positive skewness, indicating a rightward shift in the data distribution. Most kurtosis values were relatively high, suggesting a heavy tail in the data distribution.

2. Results of the comprehensive technical efficiency evaluation of educational resource allocation in provincial universities

Table 3 presents the DEA-BCC model calculation results, with details provided below. The average value for comprehensive technical efficiency was 0.911, with the highest value recorded in 2018 at 0.985 and the lowest in 2019 at 0.866. The average value for pure technical efficiency was 0.978, with the highest value in 2018 at 0.988 and the lowest value in 2017 at 0.957. The average value for scale efficiency was 0.929, with the highest value in 2018 at 0.997 and the lowest in 2019 at 0.879. There were relatively small differences in the variation each year.

Regarding the effective numbers for each efficiency indicator, pure technical efficiency had the highest average value of 0.978, scale efficiency of 0.929, and comprehensive technical efficiency of 0.911. Figure 2 shows that the consistent technical efficiency over the years indicates effective resource utilization. In contrast, the fluctuations in comprehensive and scale efficiency move in the same direction, with a significant decline in 2019 followed by a recovery, suggesting that scale efficiency is relatively low.

Table 2. Descriptive statistics of variables.

Variables	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Input variables						
Teaching and research staff (person)	93.000	2,310.000	894.863	567.079	1.241	0.622
Other faculty and staff (person)	51.000	1,151.000	181.096	156.823	3.878	20.826
Total fixed assets (ten thousand ¥)	1,749.230	324,830.060	102,640.738	69,822.899	1.498	1.672
Books (ten thousand volumes)	6.600	377.530	149.080	84.050	1.063	0.371
Total building area (sq.m)	4,415.000	1,284,329.000	440,454.788	300,060.924	1.508	1.887
Expenditure on educational affairs and operational expenses (ten thousand ¥)	3,853.210	207,817.030	57,002.463	45,533.514	1.818	2.802
Output variables						
Number of full-time students	1,659.000	69,449.000	19,509.750	12,273.415	1.567	2.203
Number of patents	101.000	1,022.000	119.600	68.134	11.899	176.156
Number of published papers	101.000	1,306.000	146.504	127.409	8.443	78.949
Number of adult education students and other students	121.000	95,613.000	1,992.971	7,217.514	11.81	177.074
Income from technology transfer and operations in the current year (ten thousand ¥)	100.000	41,772.700	1,290.954	4,235.373	7.658	71.178

Table 3. DEA-BCC model calculation results table for provincial universities from 2017 to 2022.

Year	Comprehensive Technical Efficiency		Pure Technical Efficiency		Scale Efficiency	
	Mean	Significant figures	Mean	Significant figures	Mean	Significant figures
2017	0.935	25	0.957	26	0.975	27
2018	0.985	33	0.988	34	0.997	34
2019	0.866	13	0.983	29	0.879	13
2020	0.872	16	0.984	26	0.884	17
2021	0.930	23	0.981	29	0.945	24
2022	0.879	20	0.977	31	0.896	20
Mean	**0.911**	**21.667**	**0.978**	**29.167**	**0.929**	**22.500**

Note: Significant figures refer to the number of efficiency values equal to one.

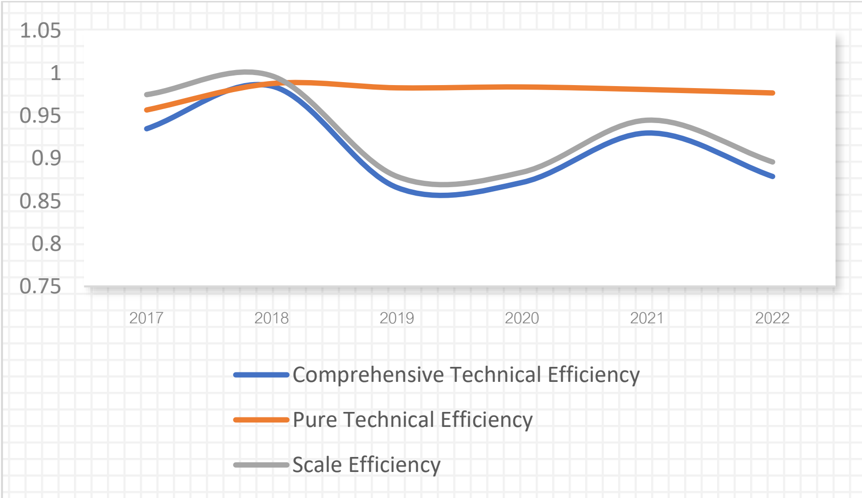

Figure 2. Trends in the DEA-BCC model calculation results of provincial universities from 2017 to 2022

3. Results of total factor productivity and pure technical change evaluation of educational resource allocation in provincial universities

Table 4 presents the results from the Malmquist index model, revealing a decline in the total factor productivity index for 40 provincial universities from 2017 to 2022, with an average value of 0.707, reflecting a 29.30% reduction in efficiency over these six years. A decomposition of the results indicates that the average value of the technical efficiency index was 0.985, corresponding to a 7.4% decrease. Additionally, the average value of the technological progress efficiency index was 0.718, showing significant fluctuations throughout the period. He suggests that the sample universities did not demonstrate high technological progress efficiency, with variations in total factor productivity primarily driven by technological regression. As shown in Figure 3, the overall trend in changes in total factor productivity closely mirrors that of pure technical change, indicating that total factor productivity is predominantly influenced by pure technical change. The main reason for the decline during 2021-2022 was the pandemic, which led to a decrease in the number of students. Additionally, the reduced budget for educational resources contributed to the decline in various indicators.

Table 4. DEA-Malmquist index calculation results for provincial universities in China from 2017 to 2022.

Year	Efficiency Value				
	Pure Technical Change	Scale Efficiency	Pure Technical Efficiency	Technical Efficiency	Total Factor Productivity
2017-2018	0.111	1.024	1.034	1.059	0.118
2018-2019	0.652	0.875	0.995	0.871	0.568
2019-2020	0.976	1.003	1.001	1.004	0.980
2020-2021	2.827	1.074	0.996	1.07	3.024
2021-2022	0.955	0.939	0.996	0.935	0.893
Mean	**0.718**	**0.981**	**1.004**	**0.985**	**0.707**

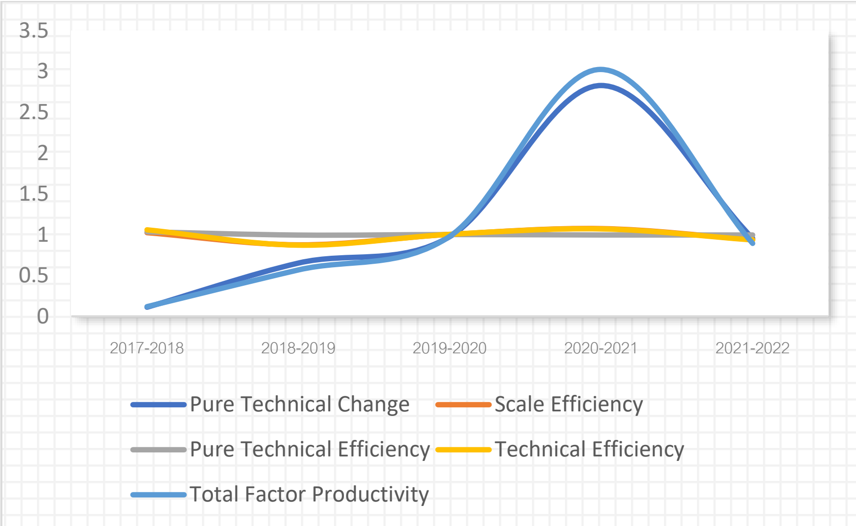

Figure 3. Trends in the Malmquist index of provincial universities 2017-2022

Discussion

1. Comprehensive technical efficiency evaluation of educational resource allocation in provincial universities

The first objective of this study is to statistically evaluate the efficiency of educational resource allocation in provincial universities using the DEA-BCC model. Results indicate that the comprehensive technical efficiency of provincial universities from 2017 to 2022 is low, with minimal annual changes. More than half of the provincial universities face significant efficiency issues, primarily due to low-scale efficiency. This result aligns with Marginson (2011), who highlighted that scale efficiency is essential for improving the comprehensive technical efficiency of universities. In contrast, Welch and Pavel (2017) posit that technical efficiency is the key determinant of comprehensive technical efficiency. Therefore, provincial universities must prioritize resource integration, sharing, and more optimized and rational allocation of educational resources to address these inefficiencies.

2. Total factor productivity evaluation of educational resource allocation in provincial universities

The second objective is to dynamically evaluate the efficiency of educational resource allocation in provincial universities using the DEA-Malmquist index. Analysis of data from 2017 to 2022 reveals that the total factor productivity of provincial universities is low, indicating ongoing challenges in educational resource management. This trend is attributed to two primary factors: a decline in technical efficiency, reflecting the universities' failure to fully utilize educational resources at the current technological level, and a lag in technological progress, indicating insufficient innovation and improvement in resource allocation and usage. To effectively enhance total factor productivity, it is essential to optimize resource allocation and implement fair regulatory measures to ensure resource utilization performance. This result aligns with the findings of Ngobeni et al. (2023), who argue that balancing efficiency, fairness, and benefits is crucial for enhancing the total factor productivity of educational resource allocation in provincial universities.

3. Pure technical change as a key factor in improving total factor productivity

The third objective is to explore whether pure technological change is a key factor restricting the improvement of total factor productivity in provincial universities. The results confirm that pure technological change is indeed a critical factor affecting total factor productivity. Underutilization of educational resources significantly contributes to inefficiencies in the higher education system. The results align with Labanino et al. (2022), who argue that promoting new technologies and methods through regional experience exchange can enhance total factor productivity. Conversely, Altbach (2015) contends that pure technological change has a lesser impact on total factor productivity compared to scale efficiency. In summary, improving total factor productivity requires strategic resource allocation, technological progress, and effective human resource development.

New Knowledge

New findings on the efficiency of university educational resource allocation have been discovered through the application of the DEA–BCC model and the DEA–Malmquist index. The results indicate that pure technical change is a key factor in improving total factor productivity. Specifically, the average comprehensive technical efficiency value of 0.911 is negatively impacted by a relatively low average scale efficiency of 0.929. Additionally, the average total factor productivity, which stands at 0.707, is constrained by a lower average value for pure technical change of 0.718. These insights provide valuable references for enhancing the efficiency of educational resource allocation in universities, as illustrated in the following diagram:

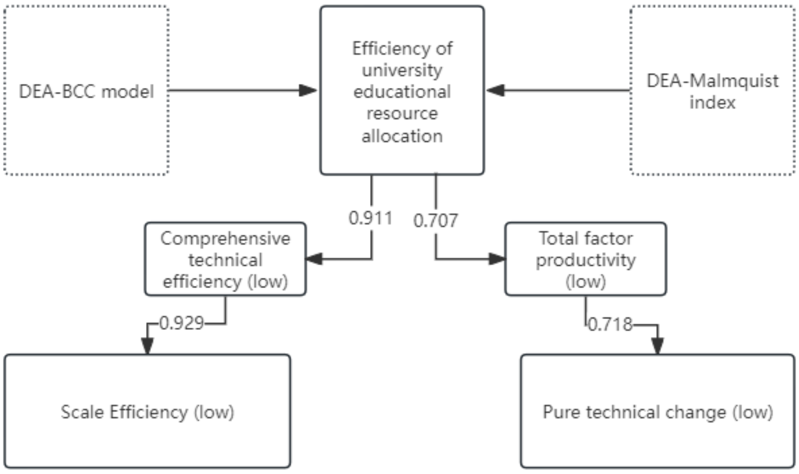

Figure 4. Research results analysis diagram

Conclusions

The study found that the comprehensive technical efficiency of provincial universities is low, with scale efficiency being the main factor restricting their development. The Malmquist index results indicate that from 2017 to 2022, the total factor productivity of provincial universities declined, and the average technical progress efficiency index was low. These changes were primarily influenced by technological regression. Therefore, provincial universities should prioritize enhancing scale efficiency and pure technical change to improve comprehensive technical efficiency and total factor productivity. Addressing technological regression is crucial for overcoming current limitations. These measures are essential for optimizing the utilization of educational resources and advancing overall institutional development.

Recommendations and limitations

Recommendations:

Technological improvement: Universities should promote the adoption of new technologies and methods to improve the technological utilization of educational resources.

1. Regional cooperation and experience sharing: It is recommended that provincial universities enhance cooperation and share best practices in educational resource allocation.

2. Human resource training: Accelerate the training of academic human resources to enhance the capacity of university personnel to utilize educational resources effectively.

3. Scientific resource allocation: Policymakers and university administrators should focus on the scientific allocation of resources to ensure fairness and effectiveness in their management strategies.

Limitations and future research:

The study acknowledges several limitations and provides directions for future research:

1. Limitations in indicator selection: The study recognizes certain limitations related to the level of detail in selecting input and output indicators. Future research should refine the selection of these indicators to ensure more accurate assessments of resource allocation efficiency.

2. Weight arrangement: The arrangement of weights for each indicator requires further exploration. Investigating optimal weight arrangements will help accurately reflect the relative importance of different indicators.

3. Method combination: Future research should investigate practical ways of combining Data Envelopment Analysis (DEA) methods with other research approaches. Integrating DEA with other methodologies can promote a more comprehensive and accurate understanding of the factors influencing the efficiency of educational resource allocation in provincial universities.

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