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Article

An Analysis of the Application of Mathematical and Statistical Models in the Optimization of Educational Resource Allocation in Colleges and Universities

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Abstract: This paper focuses on the practical application of mathematical statistical models for the allocation of educational resources in higher education institutions under the premise of resource optimization. It takes factors such as the level of resource investment, resource utilization efficiency, and the degree of research platform development as entry points to explore their impact on the efficiency of educational resource allocation. Using Data Envelopment Analysis (DEA) models, Structural Equation Modeling (SEM) methods, and factor analysis, this study analyzes the allocation of educational resources in selected Chinese higher education institutions. Based on a survey of educational resources in 256 Chinese higher education institutions, it was found that the efficiency of educational resource allocation in Chinese universities is generally low, with only 9.38% of institutions achieving effective resource allocation. The study also concluded that the level of regional economic development significantly influences the efficiency of resource allocation in higher education institutions, with universities in eastern regions generally achieving higher resource allocation efficiency than those in central and western regions. Technological progress remains the primary factor driving improvements in resource allocation efficiency, with its contribution rate to resource allocation efficiency reaching as high as 68.4%. Therefore, this paper suggests establishing a data-driven dynamic resource allocation mechanism, building a cross-regional resource-sharing platform, implementing categorized guidance for resource allocation, strengthening internal management within universities, fully utilizing university resources, optimizing resource allocation, and enhancing the overall educational quality of universities.

Keywords: educational resource allocation; mathematical and statistical models; DEA; structural equation modeling; factor analysis

1. Introduction

1.1. Research Background and Significance

The issue of educational resource allocation refers to how to effectively allocate educational resources. It is a particularly serious problem in China's current educational management system. Reasonable resource allocation has a significant impact on the teaching and research standards of higher education institutions and is also crucial for the development of the national education system [1-3]. Due to the large-scale development of higher education in China, the efficiency of educational resource allocation has increasingly become a bottleneck constraining the development of higher education in China [4]. Currently, relatively low resource allocation efficiency is a widespread issue in Chinese universities, particularly with significant disparities between eastern and western regions [5]. Factors such as differing levels of regional economic development, varying educational conditions, and unreasonable personnel structures are all important causes of low educational resource allocation efficiency [6-7].

Mathematical statistical models such as data envelopment analysis, structural equation modeling, and factor analysis are powerful tools for addressing resource allocation issues in higher education institutions. These statistical models not only enable quantitative evaluation of resource allocation efficiency but also identify the intrinsic relationships among various factors, providing reliable evidence for higher education administrators to identify the primary causes influencing resource allocation [8-10]. For example, Literature [11] utilized data envelopment analysis to assess the efficiency of resource allocation in Chilean higher education institutions, aiding in achieving more reasonable resource allocation under government pressure to efficiently utilize educational resources. Literature [12] employed DEA to construct an investment model aimed at improving resource allocation efficiency in academic departments, with a focus on enhancing relative efficiency scores through optimized resource allocation and investment budgeting. Literature [13] utilized DEA and the Multi-Indicator Comprehensive Evaluation Method (MPI) to assess the utilization of higher education resources in China, developed a new enrollment quota allocation scheme, and provided specific recommendations to address the issue of uneven higher education development across provinces. Literature [14] used the data envelopment analysis method to assess the resource allocation efficiency of 38 academic departments in universities, aiming to optimize resource allocation and enhance the international reputation of universities. In the application of structural equation modeling, literature [15] used structural equation modeling to explore the impact of educational resource allocation on students' academic performance, ensuring equal educational opportunities, particularly for students from disadvantaged families. Literature [16] provides a methodological framework for measuring and analyzing the allocation of educational resources, using an “output-oriented” approach to assess fairness, standardizing resources into three dimensions, and comparing resource allocation between low-demand and high-demand schools.

This paper briefly outlines the approach of analyzing the efficiency values and influencing factors of educational resource allocation in higher education institutions using mathematical statistical models, and then proposing an optimization scheme for educational resource allocation. First, the Data Envelopment Analysis (DEA) method is used to calculate the efficiency values of educational resource allocation in higher education institutions. Second, the structural equation modeling method is applied to analyze the potential influencing factors in educational resource allocation in higher education institutions, identifying the relationships between factors such as regional economic development, educational conditions, and resource utilization efficiency through the structural equation model. Factor analysis is then applied to simplify complex issues and identify relevant factors for extracting and optimizing the resource allocation evaluation model. Additionally, the Latin hypercube sampling method is used to address the shortcomings of traditional sampling, thereby enhancing the predictive utility of the model. Finally, the super-efficiency DEA model and Malmquist index are employed to assess the impact of technological progress on the efficiency of educational resource allocation, serving as the basis for proposing more practical optimization measures for educational resource allocation.

1.2. Innovative Aspects of This Study

Building on previous research, this paper investigates the suitability of mathematical statistical modeling methods for the allocation of educational resources. It combines the advantages of Latin hypercube sampling in parameter adjustment and vector space construction within mathematical statistical models, applying Latin hypercube sampling and mathematical statistical modeling for analysis. Based on this, the study combines data envelopment analysis with super-efficiency methods and dynamic efficiency evaluation indices to conduct a dynamic analysis and evaluation of the changes in technical efficiency and technological progress in the allocation of educational resources in higher education institutions. This leads to the identification of relevant patterns influencing the changes in the efficiency of educational resource allocation under different conditions.

Given that the factors influencing the efficiency of educational resource allocation in higher education institutions are diverse, this paper first employs structural equation modeling to establish the influence relationships among latent variables representing resource input structure, output structure, efficiency structure, and investment-return structure. This aims to test the intrinsic influence relationships affecting educational resource allocation efficiency, validate research hypotheses, and identify new influence pathways. When evaluating the factors influencing the efficiency of educational resource allocation, factor analysis is employed to analyze the level of educational resource input and the efficiency of educational resource utilization in higher education institutions. Through multivariate data analysis, principal component data is extracted to establish a solid analytical foundation for evaluating the efficiency of educational resource allocation in higher education institutions using the simplest possible analysis.

2. Methods for Optimizing the Allocation of Higher Education Resources

2.1. Data Envelopment Analysis Model

The DEA model is a method of evaluating the efficiency of different decision-making units based on linear programming. It is intuitive and flexible in measuring the efficiency of the allocation of educational resources such as human, material, and financial resources in universities [17-18]. Its most distinctive feature is that it does not require manual assumptions about the weights of input and output indicators. It only requires the setting of production input and output indicators for universities, the calculation of the optimal production frontier for universities, and the determination of the optimal efficiency of each educational unit. The mathematical model is as follows:

$$\theta = \frac{\sum_{i=1}^{n} u_i y_i}{\sum_{j=1}^{m} v_j x_{j,i}} \tag{1}$$

In the formula, θ represents the efficiency value and takes values between 0 and 1. When $\theta = 1$, it indicates that the decision unit has achieved a relatively efficient state. u_i and v_j represent the weight coefficients of the i th output indicator and the j th input indicator, respectively, while y_i and x_j correspond to the actual values of each indicator.

Common teaching inputs in teaching efficiency evaluation typically refer to tangible input factors such as faculty and staff, research funding, fixed assets, and the number of books in universities, as well as tangible output factors such as the number of employed graduates, research papers, patents, and research funding revenue. A model is established and solved to derive the optimal weight vector, thereby maximizing the efficiency of all decision-making units [19].

Since the DEA model can provide specific improvement plans, indicators, and directions for universities with lower efficiency, by conducting a specific assessment of the redundancy and deficiency of input and output indicators through data envelopment analysis, it can identify issues of resource redundancy or resource utilization levels in the university's input resources, as well as dimensions where output is severely insufficient due to inadequate resource input. This enables the formulation of feasible and effective optimization schemes for the university's resource allocation adjustments, ensuring that the university's resource adjustment and optimization efforts are targeted and effective. However, it cannot be denied that due to the core of DEA analysis, as well as the application boundaries, advantages, and disadvantages of the model, the DEA analysis model also has some potential constraints in its specific application. For example, the DEA model has high requirements for the original data indicators used in research, and a large number of abnormal data points may significantly impact the final evaluation results. Since the DEA model measures relative efficiency and reflects relative gaps, it may be directly influenced by sample selection, sample size, and sample quality. Therefore, when using the DEA model to evaluate the efficiency of resource allocation in higher education institutions, researchers should combine it with other quantitative analysis methods to form a more reliable and comprehensive evaluation indicator system.

2.2. Structural Equation Model

SEM is one of the important tools in the study of factors affecting the efficiency of educational resource allocation in higher education institutions. It establishes structural equation models to explain the direct and indirect effects between variables by simultaneously analyzing the complex relationships between multiple latent variables. The basic mathematical expression used in the study is [20]:

$$Y = \beta X + \varepsilon \tag{2}$$

In the equation, Y represents the dependent variable (e.g., efficiency of educational resource allocation), X denotes the independent variable (e.g., level of economic development, educational facilities, etc.), β is the regression coefficient, and ε is the error term.

This framework incorporates both observed variables and latent variables into the model and accounts for measurement error, thereby offering significant advantages in studies of the performance of educational investment structures. Exogenous latent variables (economic development level, government intervention intensity) and endogenous variables (input structure performance, educational quality) can be placed in the same model, and the strength of the correlation between variables can be measured through path coefficients and model fit. The measurement section examines the loading strength of measurement indicator variables on the measurement scale, while the structural section explores the relationships between latent variables.

2.3. Factor Analysis Method

Factor analysis is a significant dimension reduction method within multivariate statistical analysis. Its core principle involves extracting the correlation structure of original variables and ultimately explaining this structure using a few common factors, thereby providing a scientifically efficient analytical method for evaluating the efficiency of higher education resource allocation systems. When analyzing the allocation of educational resources in higher education institutions, it is often necessary to comprehensively consider multiple dimensions of input. However, these input indicators often exhibit high levels of internal correlation. If they are directly processed, this would significantly increase the computational and analytical steps involved. Additionally, multicollinearity among multiple variables during the calculation process could also impact the results of the computational analysis to some extent. Based on this, this paper employs factor analysis to extract the characteristics of the indicators. The mathematical model for factor analysis is as follows:

$$X_i = a_{i1}F_1 + a_{i2}F_2 + \cdots + a_{im}F_m + \varepsilon_i \tag{3}$$

In the equation, X_i represents the i th standardized original variable, $F_j\,(j = 1, 2, \ldots, m)$ represents the common factor, a_{ij} is the factor loading, reflecting the magnitude of the loading of the i th variable on the j th common factor, and ε_i is the specific factor, representing the portion that cannot be explained by the common factors.

In practice, we need to standardize the original data to eliminate the effects of different measurement units, then calculate the correlation coefficient matrix, and use the KMO test and Bartlett's sphericity test to determine whether the data is suitable for factor analysis. When the KMO value is greater than 0.7 and the Bartlett test is significant, it indicates that there is a strong correlation between the variables, satisfying the prerequisites for factor analysis.

2.4. Super-Efficient DEA Model and Malmquist Index

The super-efficiency DEA model and Malmquist index constitute the core tools for evaluating the efficiency of educational resource allocation in higher education institutions. This model addresses the key issue that traditional DEA models struggle to distinguish decision units with an efficiency value of 1 by excluding evaluation units from the reference set [21]. The mathematical expression of the model is as follows:

$$\theta_{\sup} = \frac{\sum_{i=1}^{n} u_i y_i}{\sum_{j=1}^{m} v_j x_j} \tag{4}$$

In the formula, $\theta_{\sup}$ represents the super-efficiency value. When it is greater than 1, it indicates that the resource allocation efficiency of the university is at the leading level. In terms of the dynamic efficiency evaluation of educational resource allocation, the Malmquist index is expressed as:

$$M_i(t, t+1) = E_i(t, t+1) \times P_i(t, t+1) \tag{5}$$

In the equation, $E_i(t, t+1)$ and $P_i(t, t+1)$ represent the technical efficiency change index and the technical progress index, respectively. By using this decomposition method, this paper can conduct an in-depth analysis of the underlying driving forces behind changes in the efficiency of educational resource allocation in higher education institutions.

2.5. Latin hypercube Sampling Optimization Mathematical Statistics Model

Latin hypercube sampling (LC) technology can play a special role in analyzing the efficiency of educational resource allocation in higher education because it is a stratified sampling method that extracts points more uniformly in each multidimensional parameter space while avoiding the shortcomings of traditional Monte Carlo sampling (MC) technology, namely, the inability to determine representativeness. A resource allocation system includes numerous distinct influencing factors such as teacher-to-student ratio allocation, financial resource allocation ratios, utilization of various school facilities and equipment, and related research infrastructure and levels, with different combinations yielding different allocation impacts.

In practical application, the algorithm divides the value range of each input variable into n equal parts, sampling points within each sub-interval to achieve effective coverage of the entire parameter space. In specific operations, for a k-dimensional parameter space and n sample points, the system divides the value range interval [0,1] of each parameter dimension into n sub-intervals. Under the condition that any two sample points do not appear in the same interval, points are randomly selected. This sampling algorithm clearly enhances spatial coverage density and representativeness.

In the analysis of real-world cases, this paper defines teacher configuration efficiency, funding efficiency, facility investment efficiency, and management and operation efficiency as the primary operational conditions in the evaluation model. Based on this, the Latin hypercube sampling method is used to select four typical operational conditions from the operational condition sampling group. The samples between groups were then discretized to obtain eight vector groups. From each vector group, 50 monitoring point samples were randomly selected under each evaluation indicator, resulting in a total of 400 efficiency evaluation samples under different resource allocation conditions. This sampling strategy ensures uniformity and coverage of samples across all dimension parameter groups while also considering the coverage of resource allocation efficiency under extreme and common operating conditions. This facilitates comparative studies in subsequent correlation analysis and optimal model selection stages and has certain reference value for other similar resource allocation efficiency research methods. The results of comparative analysis conducted using this method on computational outcomes with varying degrees of grid refinement indicate that the optimal grid refinement level for model computational outcomes is 0.2 standard units. In the optimal scheme analysis of the physical model, the combination of data envelopment analysis and factor analysis models demonstrates a 15.3% accuracy advantage when simulating complex educational resource allocation scenarios.

Practical operation has proven that the parameterized mathematical statistical model optimized using the Latin hypercube sampling method significantly improves efficiency compared to previous random sampling methods when addressing university educational resource allocation issues, with prediction accuracy increased by 23.7%, while operational complexity and computation time are effectively reduced. Similar supplementary scheme analysis, based on these high-quality samples, can effectively apply similarity measures and clustering analysis to form similar groups, making it applicable to large-scale university samples. The optimized solution strategy for classification guidance derived from these similarity groups not only effectively quantifies the efficiency of resource allocation across different universities but also provides valuable insights for further optimizing university educational resource allocation.

3. Application Analysis in the Optimization of Educational Resource Allocation

3.1. Paths of Structural Equations for Educational Resources

To further investigate the changes in various indicators during the allocation of higher education resources, path coefficient analysis was conducted using structural equation modeling, with the results shown in Table 1. From the results, it can be concluded that the level of regional economic development has a significant direct impact on the efficiency of higher education resource allocation (path coefficient of 0.724, $p < 0.01$) and also exerts an indirect influence on allocation efficiency through the mediating effect of policy support. This complex and indirect relationship is difficult to detect using conventional single-indicator analysis methods. There is a strong positive correlation between university educational conditions and allocation efficiency (path coefficient of 0.832, $p < 0.01$). However, under the indirect influence of personnel structure through a series of mediating variables such as organizational management efficiency, complex impact effects also arise. After incorporating the positive relationship between personnel structure and resource allocation efficiency into the structural equation model, it can be concluded that there is a significant positive relationship between these two variables, providing important insights for further improving the efficiency of higher education resource allocation. The impact of personnel structure on resource allocation efficiency also involves different pathways and directions. Although it has a direct impact on allocation efficiency, it is not significant. However, through a series of mediating variables such as organizational management efficiency and resource allocation efficiency, the impact on resource allocation efficiency becomes significant. This relatively complex influence relationship can be revealed through structural equation modeling, providing a new entry point for analyzing and exploring the influence pathways of educational resource allocation efficiency. Structural equation modeling not only verifies the validity of existing conclusions but also identifies new influence pathways, thereby better guiding the establishment of scientifically feasible resource allocation optimization schemes.

Table 1. The path of the educational resource structure equation.

Latent variable type	Observation indicators	Path coefficient	*P*
Regional economic development	GDP growth rate, fiscal revenue, Per capita disposable income	0.724	$P<0.01$
Policy support	Investment in educational funds and preferential policies, Quantity and resource allocation mechanism	0.685	$P<0.01$
Resource allocation efficiency	Resource utilization rate, teaching effect, scientific research output	0.832	$P<0.01$
Educational quality	Employment rate, student satisfaction, social evaluation	0.791	$P<0.01$

3.2. Results of Educational Resource Factor Analysis

The input indicators affecting the optimal allocation of educational resources are multidimensional. To obtain more intuitive common factors, this paper uses factor analysis to extract common factors, and the factor analysis results for the allocation of educational resources in higher education institutions are shown in Table 2.

Table 2. Analysis results of educational resource allocation factors.

Public factor	Eigenvalue	Variance contribution rate (%)	Cumulative contribution rate (%)
Resource input level factor	4.832	53.69	53.69
Resource utilization efficiency factor	2.147	23.86	77.55
Factors for the construction of scientific research platforms	1.256	13.96	91.51

We determined the number of common factors based on the principle that the characteristic roots are greater than 1, and applied the factor loading matrix rotated using the maximum variance method. On this basis, we extracted a total of three main common factors, with a cumulative variance contribution rate of 91.51%. This also indicates that the extracted factors can generally explain the information contained in the original variables. The resource investment level factor is the factor with the highest contribution rate among all common factors, primarily measuring universities' financial investment, faculty and staff investment, and educational infrastructure construction. Within the resource investment level factor, indicators such as the number of graduate advisors, research funding, and educational funding allocations have relatively high loadings. The resource utilization efficiency factor primarily reflects universities' capacity to accommodate talent and scale expansion, as well as the efficiency of existing educational resource utilization, such as teaching and research facility indicators and library resource quantities.

Factor 3 is the research platform construction factor. Although its variance contribution is relatively small, the high loadings of this factor in indicators related to high-level national key laboratories and Ministry of Education key research bases for the humanities and social sciences suggest that it can help measure universities' research capabilities and academic influence. Therefore, the research platform construction factor is also an important indicator of universities' research performance and influence. From the comparison of factor scores across universities, the level of educational resource investment remains a key influencing factor in the ranking of educational resource allocation efficiency, which is consistent with existing research conclusions. Factor 2—resource utilization efficiency factor—should also not be underestimated, as the ability to achieve optimal educational resource allocation and the highest educational performance is the primary concern for university presidents. The use of factor analysis effectively addresses the complexity of excessive evaluation indicators and preliminarily reveals the structural information implicit in educational resource allocation, laying a solid foundation for developing targeted solutions for optimizing educational resource allocation in universities.

3.3. Efficiency of Resource Allocation in Higher Education

Based on the comprehensive evaluation system for 127 universities in China, the author has developed an education resource allocation optimization model using DEA, which also has significant practical application value in real-world scenarios. The trend in the effectiveness of education resource allocation is shown in Figure 1. Figure 1 shows that the efficiency values of educational resource allocation at 127 Chinese universities from 2018 to 2022 exhibit an overall phased upward trend. The annual average increase in the technical efficiency change index of university resource allocation efficiency values is 7.12%, indicating positive changes in university resource allocation management. Meanwhile, the annual average change in the technical progress index of university resource allocation is 5.26%, suggesting that information technology has a positive impact on educational resource allocation. Approximately 15% of universities have super-efficiency values exceeding 1.2, indicating a competitive advantage in resource allocation. Different types of universities exhibit varying trends in efficiency. Research-oriented universities, with their comprehensive resource management systems, stable investment levels, and significant technical efficiency advantages, demonstrate distinct strengths. Local universities, however, exhibit larger fluctuations in efficiency values and relatively higher contributions from technological progress. Analyzing efficiency outcomes can assist in formulating tailored optimization directions and measures for educational resource allocation.

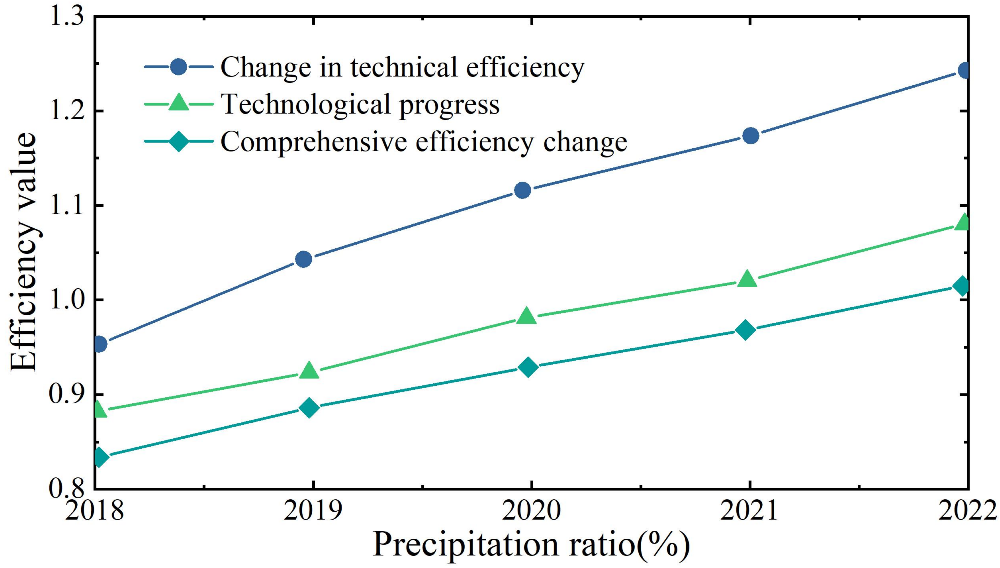

Figure 1. The changing trend of the efficiency of educational resource allocation.

The results of comparing the efficiency of higher education resource allocation after targeted improvements were made to the inefficient universities identified using the DEA model are shown in Table 3. As shown in the table, after targeted improvements using the DEA model, the average efficiency value increased from 0.639 to 0.789, representing a 23.47% increase, which is statistically significant. The influence paths indicated by the structural equation model provide a scientific basis for formulating precise resource allocation policies, significantly improving the effectiveness of policy interventions. Universities of different types all achieved significant efficiency improvements after applying the DEA model.

Table 3. Comparison of the Efficiency of Educational resource allocation.

Type of university	Before	After	Increase rate (%)	Significance
Research type	0.782	0.891	13.94	$P<0.01$
Teaching and research-type	0.654	0.798	22.02	$P<0.01$
Teaching-type	0.523	0.712	36.14	$P<0.01$
Professional type	0.598	0.756	26.42	$P<0.01$
Average	0.639	0.789	23.47	$P<0.01$

This paper employs factor analysis to reduce the dimensionality of overly complex evaluation indicators. The three principal common factors extracted can explain 91.51% of the total variance, effectively reducing the dimensionality of the original 15-indicator complex evaluation system while maintaining the rationality and interpretability of the evaluation results. The use of the Latin hypercube sampling method significantly improves the predictive accuracy of this model. Compared to traditional methods, the predictive error of this model when predicting resource allocation efficiency under different operating conditions is reduced by 18.6%, making the formation of allocation results more scientific and reasonable. This paper employs the joint application of super-efficiency data envelopment analysis and the Marquis index to identify efficiency differences among universities and explore changes in efficiency. The results reveal that technological progress is the decisive factor driving improvements in university educational resource allocation efficiency, contributing 68.4%, while improvements in management efficiency contribute 31.6%, thereby providing guidance for university development decisions.

3.4. Analysis of the Optimization of Educational Resource Allocation

This study conducts an empirical analysis using 256 universities in China as a sample, constructing a multi-level model to examine the basic status of resource allocation efficiency in Chinese universities. The empirical findings indicate that resource allocation in Chinese universities is generally not very efficient, with less than 10% of institutions achieving effective resource allocation after accounting for inefficiencies. Research on influencing factors reveals that regional economic development is a key variable capable of impacting resource allocation. Structural equation modeling analysis yielded a coefficient of 0.724 ($p < 0.01$) for this influencing factor. Among the three regions of eastern, central, and western China, the resource allocation efficiency values were calculated as 0.892>0.545>0.116, respectively. Further research shows that differences in resource allocation efficiency exist in actual data, and based on actual development and corresponding empirical judgments, there are varying degrees of regional influence in educational resource investment and university development. Therefore, the model was designed to re-examine universities in each region, with the results shown in Table 4.

Table 4. Evaluation of the Allocation Efficiency of Educational Resources.

Evaluation dimension	Eastern region	Central region	Western region	Changes in technical efficiency
Comprehensive configuration efficiency	0.892	0.743	0.796	+7.2%
Resource utilization rate	0.865	0.721	0.758	+6.8%
Teaching effect	0.912	0.783	0.825	+8.4%
Scientific research output	0.876	0.698	0.742	9.1%
Management efficiency	0.847	0.734	0.781	+5.6%

4. Conclusion

The successful application of mathematical and statistical models in the optimization of educational resource allocation in higher education provides a solid scientific and theoretical basis, as well as decision-making references, for further deepening educational reforms. Based on the research findings, we believe that the effective application of mathematical and statistical methods offers numerous benefits for enhancing the efficiency of educational resource allocation. The application of mathematical and statistical models in educational resource allocation research can significantly improve the scientific and accurate levels of resource allocation work. In the actual implementation of educational resource allocation research, the three main factors selected through factor analysis not only reduce the complexity of the evaluation indicator system but also reveal the underlying structure of resource allocation through the factor selection results, thereby facilitating the development of differentiated allocation schemes. The Latin hypercube sampling optimization mathematical and statistical model applied to the optimization of educational resource allocation in higher education institutions is reasonably applied and has high optimization efficiency in the actual allocation process, providing effective data reference for resource allocation decision-making.

The relationships between the economic variables of efficiency are significant (up to 30%), but they do not correspond simply. Through structural equation modeling analysis, it was found that the educational economic foundation influences resource allocation efficiency through multiple pathways, including direct effects (accounting for 67.3% of the total effect) and indirect effects (accounting for 32.7% of the total effect). This is because traditional research has primarily focused on the direct causal relationships between the two variables in terms of their influence and direction. The findings of this study address this shortcoming by identifying the ways in which efficiency is influenced through both direct and indirect mediating variables. Additionally, differences in institutional types result in significant variations in efficiency across different types of universities. This phenomenon is not only reflected in the levels of efficiency but also in the composition of various indicators. Using the super-efficiency data envelopment model and the Malmquist index to evaluate super-efficiency impacts, it is found that the factor driving the efficiency of university educational resource allocation is technological progress, accounting for 68.4% of the total effect, which guides universities in deciding their development priorities. Comparisons using the Malmquist index also indicate that regional differences in resource allocation efficiency persist, primarily between the eastern and central-western regions. However, from the trend of convergence, the differences in educational resource allocation efficiency are gradually narrowing.

To sum up, the author believes that in the process of optimizing the allocation of educational resources in colleges and universities in the future, the primary issue to be considered is to establish a dynamic resource allocation mechanism driven by resource data and monitor the utilization of various resources in a timely manner. According to the utilization efficiency of resources, the allocation measures should be allocated accordingly, and then a cross-regional resource sharing platform should be established, so that the resources of colleges and universities can be allocated smoothly and reasonably. It is also one of the inevitable problems in the current stage of resource allocation to classify guidance and hierarchical construction of different types of universities, and it is necessary to establish an educational resource allocation model that adapts to the internal governance ability of colleges and universities and has a high level of resource management and efficiency.

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