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Research article

Regional healthcare resource allocation and decision-making: Evaluating the effectiveness of the three-stage super-efficiency DEA model

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A R T I C L E I N F O

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A B S T R A C T

This study addresses the challenge of achieving a more rational allocation of medical resources at the regional level, using Guangxi Province, China, as a case study. A three-stage super-efficiency Data Envelopment Analysis (DEA) model is employed to assess and analyze the effectiveness of resource allocation. The research methodology involves identifying input, output, and environmental variable indicators to construct a healthcare resource allocation index system. The indicator data are processed using Excel software. The three-stage super-efficiency DEA model is then applied to evaluate the healthcare system in Guangxi Province, focusing on Pure Technical Efficiency Change (PEC), Scale Efficiency Change (SEC), Efficiency Change (EC), Technological Change (TC), and Total Factor Productivity (TFP). Finally, the Malmquist index method is utilized to measure and dynamically analyze the efficiency of healthcare resource allocation. The study's results show that, from a static perspective, the average comprehensive efficiency is 1.067 before adjustment and 1.054 after adjustment, indicating relatively high overall efficiency in healthcare resource allocation in Guangxi Province. However, environmental factors and random errors have led to an overestimation of healthcare resource allocation efficiency, which the three-stage super-efficiency DEA model effectively corrects. Additionally, the average SEC and PEC values are 0.997 and 0.998, respectively, both below 1. This indicates that both scale efficiency and pure technical efficiency contribute to a decline in technical efficiency. Based on the results of the sensitivity analysis, the conclusions regarding the efficiency of healthcare resource allocation in Guangxi are deemed highly reliable. Despite the influence of uncertain factors, the model consistently provides stable and coherent assessment results in most scenarios. Therefore, special attention is needed to improve scale efficiency in healthcare resource allocation within the region, alongside enhancing management and technological capabilities in the healthcare sector. Overall, this study provides valuable reference and guidance for researchers and practitioners in related fields and offers scientific decision support for healthcare resource allocation.

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1. Introduction

In today's society, the allocation and efficient utilization of healthcare resources are crucial issues in ensuring public health [1]. To address the challenges related to efficiency and equity in healthcare resource allocation, many countries and regions are actively exploring and conducting research. In particular, the regional allocation of healthcare resources is often influenced by regional characteristics, levels of economic development, and policy decisions, all of which impact the quality and accessibility of healthcare services. To tackle this challenge, academia and policymakers have been seeking effective assessment and management tools [2–4]. The Data Envelopment Analysis (DEA) model, a method for evaluating and comparing the efficiency of multiple inputs and outputs, has been widely applied in healthcare resource management [5].

The three-stage super-efficiency DEA model has a wide range of applications. In the public service sector, this model can be used to assess the operational efficiency of institutions such as hospitals and schools, thereby assisting policymakers in optimizing resource allocation and enhancing service quality. In the manufacturing industry, the model is valuable for evaluating production line efficiency, identifying bottlenecks in the production process, and proposing improvement measures. In the financial services sector, it can assess the operational efficiency of financial institutions like banks and securities companies, providing decision support for risk management and business optimization. Moreover, with the ongoing advancements in globalization and information technology, the efficiency evaluation of complex systems, such as multinational corporations and transnational projects, has become increasingly critical. The three-stage super-efficiency DEA model, with its robust capability to handle multiple inputs and outputs, and its ability to account for external environmental factors while eliminating stochastic errors, offers innovative approaches and methodologies for evaluating the efficiency of these complex systems.

The innovative goal and contribution of this study lie in providing an overview of recent domestic research literature on the efficiency of healthcare resource allocation. Based on this, the following innovative contributions are proposed: (1) Theme and Issue: This study focuses on the efficiency of healthcare resource allocation, addressing fairness and quality issues arising from resource scarcity and unequal distribution. (2) Objective: This study aims to explore effective methods for enhancing the efficiency of healthcare

Table 1
Current status of research on resource allocation.

Author	Research Area	Research Method	Key Findings	Potential Gaps or Limitations
Krmac [6]	Port Efficiency Evaluation	DEA	DEA is an effective tool for assessing port performance	Limited to the port sector, not extended to other areas of resource allocation
Nong [7]	Vietnam Port Performance	Delphi Method, Kamet Principle, DEA	Factors such as capital, operational costs, and labor affect port performance	Lacks in-depth exploration of the impact of policy and management on efficiency
Su [8]	Healthcare Resource Allocation	Gini Coefficient, Theil Index, Three-Stage DEA	Resource allocation is influenced by multiple factors; the improved three-stage DEA effectively assesses efficiency	Integration between equity evaluation and efficiency assessment needs strengthening
Gong [9]	Healthcare Resource Allocation in Sichuan Province	Super-Efficiency Slack-Based Model, Malmquist Index	Proposes input-output optimization strategies	Limited to a specific region, lacks nationwide comparison
Wang [10]	Cultural and Creative Industry Resource Optimization	Neural Network Algorithm	Establishes a resource optimization recommendation model	Focused on a specific industry, not extended to other public sectors
Tang [11]	Energy Efficiency in China	Three-Stage DEA	Environmental regulations, economic development, and technological innovation impact energy efficiency	Lacks in-depth exploration of energy efficiency differences across regions
Shah [12]	Energy Efficiency in G7 Countries	DEA and others	Trade promotes energy efficiency, but R&D does not directly enhance efficiency	Does not consider energy efficiency comparisons with non-G7 countries
Shah [13]	Energy efficiency in South Asian countries	SBM-DEA, Malmquist index	Technological change (TC) is the main determinant.	The sample size is small and does not fully cover the global region.
Yasmeen [14]	Port Efficiency Evaluation	DEA	DEA is an effective tool for assessing port performance	Limited to the port sector, not extended to other areas of resource allocation
Shah [15]	Vietnam Port Performance	Delphi Method, Kamet Principle, DEA	Factors such as capital, operational costs, and labor affect port performance	Lacks in-depth exploration of the impact of policy and management on efficiency
Shah [16]	Healthcare Resource Allocation	Gini Coefficient, Theil Index, Three-Stage DEA	Resource allocation is influenced by multiple factors; the improved three-stage DEA effectively assesses efficiency	Integration between equity evaluation and efficiency assessment needs strengthening
Shah [17]	Healthcare Resource Allocation in Sichuan Province	Super-Efficiency Slack-Based Model, Malmquist Index	Proposes input-output optimization strategies	Limited to a specific region, lacks nationwide comparison
Shah [18]	Cultural and Creative Industry Resource Optimization	Neural Network Algorithm	Establishes a resource optimization recommendation model	Focused on a specific industry, not extended to other public sectors
Shah [19]	Energy Efficiency in China	Three-Stage DEA	Environmental regulations, economic development, and technological innovation impact energy efficiency	Lacks in-depth exploration of energy efficiency differences across regions

resource allocation to optimize the coverage and quality of medical services. (3) Innovation and Contribution: By integrating the super-efficiency DEA model with the three-stage DEA model, this study addresses the limitations of traditional DEA models in measuring the size of effective decision-making units (DMUs) and environmental factors, thereby improving the accuracy and precision of efficiency measurement. Additionally, the study employs the Malmquist Index method to conduct a dynamic analysis of healthcare resource allocation efficiency, uncovering trends in local and regional resource allocation efficiency. This provides more targeted references for policymakers.

1.1. Literature review

Table 1 summarizes the current research status in the field of resource allocation.

In the field of regional healthcare resource allocation and decision-making, many researchers are dedicated to exploring methods to improve efficiency and fairness. For example, Krmac and Mansouri Kaleibar (2023) focused on the DEA method for port efficiency assessment. They systematically reviewed 116 papers on port performance and found that DEA is an effective tool for assessing future port performance [6]. Similarly, Nong (2023) evaluated the performance of Vietnamese ports using a combination of the Delphi technique, Kamet principle, and DEA model. Factors such as capital, operating expenses, and labor significantly impacted port performance, with scale and management skills being the primary sources of port efficiency [7]. In the healthcare resource field, Su et al. (2022) used the Gini coefficient, Theil index, and healthcare resource density index to evaluate the fairness of resources, while also applying an improved three-stage DEA method to assess efficiency [8]. Furthermore, Gong et al. (2023) analyzed the allocation of health resources in Sichuan Province using a super-efficiency slack model and Malmquist index, proposing input-output optimization strategies. Their findings indicated that health resource allocation was influenced by various factors, including average annual income, population density, and education level [9]. Additionally, Wang et al. (2023) focused on resource optimization and decision-making in the cultural and creative industries, establishing a model for recommending and optimizing entrepreneurial projects in these industries using neural network algorithms [10]. Meanwhile, Tang et al. (2023) studied energy efficiency issues in China, measuring and analyzing the total factor energy efficiency of provincial and comprehensive economic zones using a new three-stage DEA model. They found that environmental regulations, economic development, and technological innovation significantly impact energy efficiency [11]. These studies demonstrate the attention given to resource allocation and decision-making across different fields, as well as the application of various methods, providing important references and insights for practice.

Research on energy efficiency, productivity, and related factors across various fields and contexts has been extensively explored by many scholars. Shah et al. (2022) focused on the Group of Seven (G7) countries, investigating the impact of trade, financial development, and government integrity on energy efficiency. Using methods such as DEA, they found that trade positively influenced energy efficiency. However, the study highlighted two critical points: first, while research and development (innovation) increased trade, it did not enhance energy efficiency; second, although governance promoted trade, it paid less attention to improving energy efficiency. The study also suggested that governments should establish clear links between policies and energy efficiency; otherwise, environmental cleanliness goals may not be achieved [12]. In a separate study, Shah et al. (2023) focused on South Asian countries, evaluating energy efficiency and productivity growth using the Slack-Based Measure DEA (SBM-DEA) and Malmquist productivity index methods. They identified TC as the primary driver of energy productivity growth, rather than inefficiency. During the study period, South Asian countries experienced varying degrees of decline in energy efficiency and productivity, attributed to factors such as low energy conversion efficiency and slow growth in input and output [13]. Yasmeen et al. (2023) examined the Organization for Economic Co-operation and Development (OECD) countries, exploring the impact of green technology, environmental taxes, and natural resources on energy efficiency. Using methods like the Malmquist–Luenberger index and super SBM-DEA, they found that environmental taxes and green technology were key factors in improving energy efficiency, productivity, and reducing energy intensity. The study also emphasized the importance of the "rule of law," noting its critical role in implementing green technology and tax reforms, encouraging industries to adhere to green principles and balance growth with environmental sustainability [14]. Shah et al. (2024) conducted research across developed and developing countries, utilizing methods such as SBM, meta-frontier analysis, and the Malmquist–Luenberger index to evaluate energy efficiency, technology gaps, and energy productivity changes in the Group of Twenty (G20) countries. Their findings indicated that the average energy efficiency in developed countries was higher than in developing countries, with developed nations also showing a greater technological gap, reflecting their advanced energy technology advantage. However, in terms of energy productivity, developed countries exhibited an overall increasing trend, while developing countries showed a declining trend, with decreasing technological efficiency identified as one of the main contributing factors [15].

Shah et al. (2023) examined the impact of renewable and non-renewable energy consumption and carbon emissions on energy efficiency and productivity changes in the Group of Twenty (G20) countries. They found that various factors, including renewable energy consumption, significantly influenced energy efficiency and productivity. Specifically, considering negative outputs (such as carbon emissions) improved the efficiency and productivity changes associated with renewable energy. Additionally, the study identified TC as a key determinant of energy productivity growth [16]. Shah et al. (2024) investigated the efficiency of forestry resources and their productivity changes in China. They employed methods such as DEA-SBM, meta-frontier analysis, and the Malmquist productivity index to assess the efficiency of forest resources, regional technological heterogeneity, and Total Factor Productivity (TFP) growth in Chinese provinces. Their findings indicated that while the overall efficiency of forestry resource utilization in China improved, TFP showed a downward trend, primarily due to insufficient technological innovation [17]. In another study, Shah et al. (2024) focused on the impact of climate change on agricultural production efficiency in China. Using methods such as the DEA Malmquist productivity index, they explored how climate factors affected changes in agricultural TFP across different regions. The results suggested that climate factors might lead to some degree of overestimation in the assessment of agricultural productivity in

China, with significant variations among regions [18]. Additionally, Shah et al. (2022) investigated the impact of China's energy policy transformation on energy efficiency. Utilizing methods like DEA-SBM, they evaluated the energy efficiency of Chinese provinces and found that while progress had been made in energy policy transition, further efforts were needed to address production technology issues [19]. In summary, these studies provide comprehensive insights into various aspects of energy efficiency and productivity, ranging from a global perspective to specific cases in China. They offer significant revelations and valuable insights for advancing our understanding of these issues.

1.2. Three-stage super-efficiency DEA model

Approaches for addressing the three-stage DEA model may be selected based on research objectives, data characteristics, and practical requirements. To overcome the limitations of traditional DEA models, the proposed three-stage DEA model enhances efficiency evaluation by sequentially eliminating the effects of environmental factors and random noise, resulting in more accurate efficiency values.

Stage 1: The initial efficiency assessment is performed using traditional DEA models, such as the BCC model, on the raw input-output data. The primary objective of this stage is to identify the initial efficiency values for each DMU and the input slack variables.

Stage 2: Regression analysis is conducted on the slack variables from Stage 1 using the Stochastic Frontier Analysis (SFA) method. This step aims to separate the influences of environmental factors, managerial inefficiencies, and random noise on the slack variables. Input variables are adjusted to ensure all DMUs operate under equivalent external conditions and stochastic effects.

Stage 3: The adjusted input data from Stage 2, along with the original output data, are reintroduced into the DEA model for a final efficiency assessment. The results of this stage reflect the true efficiency values after accounting for environmental factors and random noise.

Commonly utilized methods include.

(1) Traditional DEA Method: This conventional approach is frequently used to assess the relative efficiency of units. Within the three-stage DEA model, input and output indicators for each stage are quantified, and the DEA method is applied to evaluate the efficiency levels at each stage.
(2) Malmquist Index: The Malmquist index is a technique for evaluating productivity changes and can be used to assess Efficiency Changes (ECs) between different time points or entities. In the context of the three-stage DEA model, the Malmquist index helps analyze efficiency shifts at each stage and identify factors influencing these changes.
(3) DEA Window Analysis: This method combines DEA techniques with time-series analysis to examine dynamic ECs. Within the three-stage DEA model, DEA window analysis is used to monitor efficiency fluctuations at different time points and identify factors that shape these variations.
(4) Panel Data DEA Model: Designed for panel data that includes both time-series and cross-sectional data, the panel data DEA model allows for the simultaneous consideration of unit and time ECs. In the three-stage DEA model, the panel data DEA model can be employed to analyze the efficiency levels of various units over time and clarify factors affecting ECs.
(5) Nonlinear DEA Model: This model accounts for nonlinear relationships, providing a more accurate representation of complex relationships within the production process. Using the nonlinear DEA model within the three-stage DEA framework enables the modeling and analysis of complex EC relationships, thereby enhancing understanding of efficiency levels at each stage.

In the allocation of healthcare resources, efficiency evaluation is crucial. The three-stage super-efficiency DEA model offers a more precise assessment of the efficiency levels of healthcare institutions, providing a scientific basis for optimizing resource allocation. In the first stage, the traditional DEA model is employed to evaluate the initial efficiency of each healthcare institution, identifying those with high efficiency and those requiring improvement. To accurately assess the utilization efficiency of precision medicine resources, careful selection of input and output indicators is essential. Inputs should include costs associated with research and development of precision medicine technologies, procurement and maintenance of high-end medical equipment, and training and development of specialized personnel. Outputs should focus on the quality and quantity of precision medical services, such as the number of successfully implemented personalized treatment plans, significant improvements in patient health, and overall satisfaction with medical services. In the second stage, SFA regression is used to eliminate the effects of environmental factors and random noise, resulting in more objective and fair evaluation results. This stage requires a detailed analysis of factors impacting the efficiency of precision medicine resource utilization. These factors include, but are not limited to, regional economic development levels, uneven distribution of medical resources, and the extent of policy support, as well as internal factors such as random errors in technological operations and differences in sample quality. In the third stage, the efficiency of each healthcare institution is reassessed based on the adjusted input data, yielding more accurate efficiency values. This provides robust support for resource allocation decisions.

1.3. Fundamental DEA model

The DEA model is a widely used method for evaluating and measuring the efficiency of organizations, units, or individuals across multiple inputs and outputs. The DEA methodology holds significant importance in modern management and decision sciences, as reflected in several key aspects.

(1) Efficiency Assessment Tool: DEA is a non-parametric efficiency evaluation method that assesses the efficiency of various organizations or DMUs. By comparing multiple inputs with multiple outputs, DEA can identify which units achieve optimal performance with current resources and determine the extent to which other units can emulate them. This enables managers and decision-makers to identify potential areas for improvement, thereby enhancing resource utilization efficiency.
(2) Multi-Dimensional Comparisons: DEA allows for comparisons involving multiple inputs and outputs without requiring conversion into a single measurement unit. This capability for multi-dimensional comparisons makes DEA applicable in various fields, including production, healthcare, education, and finance, as it can capture the complexity and diversity of organizations or systems.
(3) Decision Support: The results of DEA provide crucial decision support for managers and decision-makers, helping them determine the best resource allocation strategies, formulate performance improvement plans, and evaluate organizational performance. Through DEA analysis, managers can pinpoint areas needing improvement and develop measures to enhance efficiency and performance.
(4) Reflecting Organizational Efficiency Levels: DEA not only assesses overall efficiency but also decomposes it into different dimensions, such as technical efficiency and scale efficiency. This decomposition provides a more comprehensive understanding of organizational efficiency levels and their influencing factors, helping managers identify specific areas for improvement and implement targeted management and optimization strategies.
(5) Wide Applicability: DEA methodology does not rely on specific economic theory assumptions, nor does it require assumptions about the normality or linearity of data. Therefore, it is applicable to various types of organizations and issues, whether in enterprises under market economic systems, public sectors, or non-profit organizations.

In summary, the importance of DEA methodology lies in its ability to provide managers and decision-makers with a powerful tool for evaluating and optimizing the efficiency of organizations or systems. This, in turn, enhances resource utilization efficiency, promotes performance improvement, and supports more effective decision-making.

This model can be classified into two primary types: input-oriented and output-oriented. The input-oriented DEA model aims to minimize inputs while achieving maximum output. This approach emphasizes optimizing resource utilization to achieve the highest output with the least input, operating within predefined input constraints. In contrast, the output-oriented DEA model focuses on maximizing outputs while maintaining specified input levels [20]. This model strives to achieve the best possible outcome by efficiently utilizing available resources to maintain fixed input levels. In DEA analysis, two commonly utilized variants are the Charnes, Cooper, and Rhodes (CCR) model and the Banker, Charnes, and Cooper (BCC) model. The CCR model assumes constant returns to scale, implying a fixed proportional relationship between inputs and outputs [21]. The standard formulation of the model is depicted in Equation (1):

$$\begin{cases} \min \theta \\ \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{ik}, i = 1, 2, \cdots, m \\ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{rk}, j = 1, 2, \cdots, n \\ \lambda_j, s_i^-, s_r^+ \geq 0, r = 1, 2, \cdots, p \end{cases} \tag{1}$$

Consider a scenario with n DMUs, where θ represents the comprehensive efficiency value, λ_j denotes the weight variable, s_i^- signifies the slack variable for input, s_r^+ denotes the slack variable for output, x_{ij} represents the i-th input of the j-th DMU, and y_{rj} represents the r-th output of the j-th DMUs, ensuring that both x_{ij} and y_{rj} are greater than or equal to zero. The BCC model, which allows for variable returns to scale, permits distinct proportional relationships in production [22]. The linear programming formulation of the BCC model is presented in Equation (2):

$$\begin{cases} \min \theta \\ \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{ik}, i = 1, 2, \cdots, m \\ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{rk}, r = 1, 2, \cdots, p \\ \sum_{j=1}^{n} \lambda_j = 1, j = 1, 2\cdots, n \\ \lambda_j, s_i^-, s_r^+ \geq 0 \end{cases} \tag{2}$$

If the above models yield an optimal solution, the following conclusions can be drawn: If $\theta < 1$, it indicates that the DMU is DEA inefficient. If $\theta = 1$, and both s^- and s^+ are equal to 0, it indicates that the DMU is DEA efficient. If $\theta = 1$, and either $s^- \neq 0$ or $s^+ \neq 0$, it indicates that the DMU is weakly DEA efficient.

1.4. Super-efficiency DEA model

Given the limitations of conventional BCC and CCR models, which are restricted to evaluating the relative efficiency or inefficiency of DMUs without providing a comprehensive comparison and ranking of all DMUs based on their efficiency values [23], this study introduces the super-efficiency DEA model to overcome these constraints. Unlike traditional DEA approaches that focus solely on relative efficiency among units, the super-efficiency method offers a distinct advantage: it can identify the most outstanding performers and provide more precise efficiency evaluations. The super-efficiency approach sets stricter evaluation criteria for units that achieve optimal efficiency levels, requiring other units to reach this pinnacle to be considered relatively efficient. These stringent criteria enhance the accuracy and reliability of efficiency assessments. Moreover, the super-efficiency method incorporates the concept of boundary efficiency, which corresponds to a unit's maximum efficiency level. This inclusion allows for a more accurate depiction of a unit's potential efficiency. By integrating boundary efficiency, the super-efficiency method provides a deeper evaluation of efficiency, helping units recognize and overcome potential obstacles to achieving optimal efficiency. The specific model for super-efficiency DEA is outlined in Equations (3) and (4):

$$\min \theta - \varepsilon \left(\sum_{t=1}^{m} s_i^- + \sum_{r=1}^{n} s_r^+ \right) \tag{3}$$

$$\begin{cases} \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{ik}, i = 1, 2, \cdots, m \\ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{rk}, r = 1, 2, \cdots, p \\ \lambda_j, s_i^-, s_r^+ \geq 0, j = 1, 2, \cdots, n \end{cases} \tag{4}$$

In Equations (3) and (4), θ represents the comprehensive efficiency value. When $\theta < 1$, it indicates DEA ineffectiveness; when $\theta \geq 1$, the decision unit is effective, with higher θ values indicating higher efficiency. x_{ij} denotes input variables, y_{rj} signifies output variables, and s_i^- and s_r^+ represent slack variables for inputs and outputs, respectively. λ_j stands for the weight variable.

The Three-Stage DEA model is a sophisticated and comprehensive methodology used to evaluate DMUs, specifically designed to

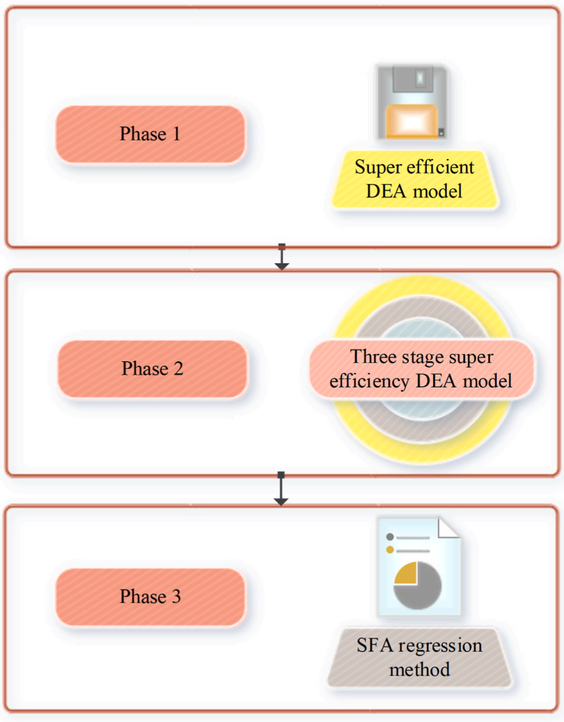

Fig. 1. Logic diagram of three-stage super-efficiency DEA model.

mitigate the influence of environmental factors and random disturbances. This approach involves dividing specific tasks and functions into three distinct stages [24]. In the initial stage, an appropriate DEA model is selected to gauge the efficiency of each DMU, with options including the BCC model and the CCR model. The careful selection of a suitable DEA model is crucial for accurately measuring the performance of individual DMUs. This requires thoughtful consideration of the DEA model most aligned with the research objectives and sample data. The second stage not only calculates efficiency values but also identifies the slack variables of input indicators for DMUs operating at optimal efficiency levels [25]. In the final stage, SFA regression is integrated, utilizing adjusted input data and original output data. The goal in this phase is to reapply the DEA approach to reassess the efficiency values of the DMUs, now incorporating the influence of environmental factors and random disturbances. This iterative process yields efficiency values that are more precise, robust, and practically significant. By mitigating the impacts of external environmental factors and random disturbances, the Three-Stage DEA model enhances the objectivity and reliability of the evaluation [26].

When employing the SFA model for regression, it bifurcates into two scenarios. In the first scenario, if an input-oriented DEA model is chosen initially, input slack variables are used as the dependent variables. Conversely, in the second scenario, if an output-oriented DEA model is selected, output slack variables serve as the dependent variables [27–29]. The formulations for each scenario are presented in Equation (5).

$$s_{ij} = f(Z_j; \beta_i) + v_{ij} + \mu_{ij}; i = 1, 2, \cdots, M; j = 1, 2, \cdots, N \tag{5}$$

In Equation (12), s_{ij} denotes the slack variable value associated with the i-th input of the j-th DMUs; Z_j represents the environmental variable; β_i signifies the coefficient corresponding to the environmental variable; v_{ij} represents the random interference term. It is assumed that v_{ij} follows a normal distribution $N\left(0, \sigma^2_{v_{ij}}\right)$, and μ_{ij} follows a truncated normal distribution $N^+\left(\mu_{ij}, \sigma^2_{\mu_{ij}}\right)$, where v_{ij} represents the managerial inefficiency term and is assumed to follow a normal distribution. Additionally, μ_{ij} follows another normal distribution. The terms v_{ij} and μ_{ij} are independent, indicating no correlation between them [30]. The schematic representation of the three-stage super-efficiency DEA model is depicted in Fig. 1.

1.5. Malmquist Exponential model

All the aforementioned DEA models are limited to static analyses of DMU efficiency within a single time period from a horizontal perspective. However, they exhibit limitations in their ability to dynamically analyze efficiency across various time periods [31,32]. Currently, the predominant method for studying dynamic efficiency within the DEA framework is the Malmquist index model. Let (x^t, y^t) and (x^{t+1}, y^{t+1}) represent the input-output vectors for periods t and $t+1$, respectively. $D^t(x^t, y^t)$ and $D^{t+1}(x^{t+1}, y^{t+1})$ denote the distance functions based on variable returns to scale for periods t and $t+1$. The Malmquist index from time t to $t+1$ can be expressed as Equations (6) and (7), reflecting the TC under variable returns to scale between the two periods:

$$M^t = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \tag{6}$$

$$M^{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^{t+1}, y^{t+1})} \tag{7}$$

To adopt a scientifically rigorous approach in selecting benchmarks, the evaluation of the Malmquist index for DMUs from period t to $t+1$ involves using the geometric mean of these two Malmquist indices, as expressed in Equation (8).

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \tag{8}$$

When the Malmquist index M exceeds 1, it indicates an improvement in efficiency. An index M equal to 1 signifies that efficiency has been maintained, while a value less than 1 implies a decrease in efficiency. By reconfiguring the aforementioned equation, the Malmquist index can be further decomposed into the product of TC and EC. This functional decomposition is illustrated in Equation (9):

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \tag{9}$$

The TC and EC in Equation (9) can be expressed as shown in Equations (10) and (11):

$$EC = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \tag{10}$$

$$TC = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \tag{11}$$

The variation in technical efficiency is represented by EC. An EC value exceeding 1 signifies that technical efficiency has contributed to an increase in productivity, resulting in a relative improvement in technical efficiency. When EC equals 1, technical efficiency does not contribute to productivity enhancement, and relative technical efficiency remains unchanged. An EC value below 1 indicates a significant deviation of the decision unit's production from the production frontier, leading to a decrease in relative technical efficiency. Technical Progress Change refers to the TC of the decision unit. A TC value exceeding 1 indicates that technological progress has contributed to increased productivity. A TC value equal to 1 suggests that technological progress has not contributed to productivity growth. Conversely, a TC value below 1 implies that technological progress has impeded productivity increases. Thus, the interrelations among the TFP index, EC, and TC are summarized in Equation (12):

$$\boldsymbol{TFP} = \boldsymbol{EC} \times \boldsymbol{TC} \tag{12}$$

Assuming variable returns to scale, the adjustment in technical efficiency for the decision unit can be further decomposed into Pure Technical Efficiency Change (PEC) and Scale Efficiency Change (SEC). The relationships are explained in Equation (13):

$$\boldsymbol{EC} = \boldsymbol{PEC} \times \boldsymbol{SEC} \tag{13}$$

The TFP index can ultimately be represented as shown in Equation (14):

$$\boldsymbol{TFP} = \boldsymbol{PEC} \times \boldsymbol{SEC} \times \boldsymbol{TC} \tag{14}$$

If the TFP index exceeds 1, it indicates an upward trajectory in the efficiency of healthcare resource allocation. Conversely, if it falls below 1, it suggests a declining trend. Indices such as the Technological Progress index, PEC index, and SEC index contribute positively to TFP when they exceed 1, thereby fostering an overall increase. Conversely, when these indices fall below 1, they contribute to a decrease in TFP.

1.6. Indicator system construction

Based on the principles of indicator selection, this study has determined the input indicators, output indicators, and environmental variable indicators. For input indicators, considering that healthcare expenditure encompasses not only healthcare facility construction, bed purchases, and medical staff salaries, a synthesis of scholars' opinions [33] and existing studies has been used. The selected input indicators include the number of healthcare facilities, the number of healthcare facility beds, healthcare expenditure,

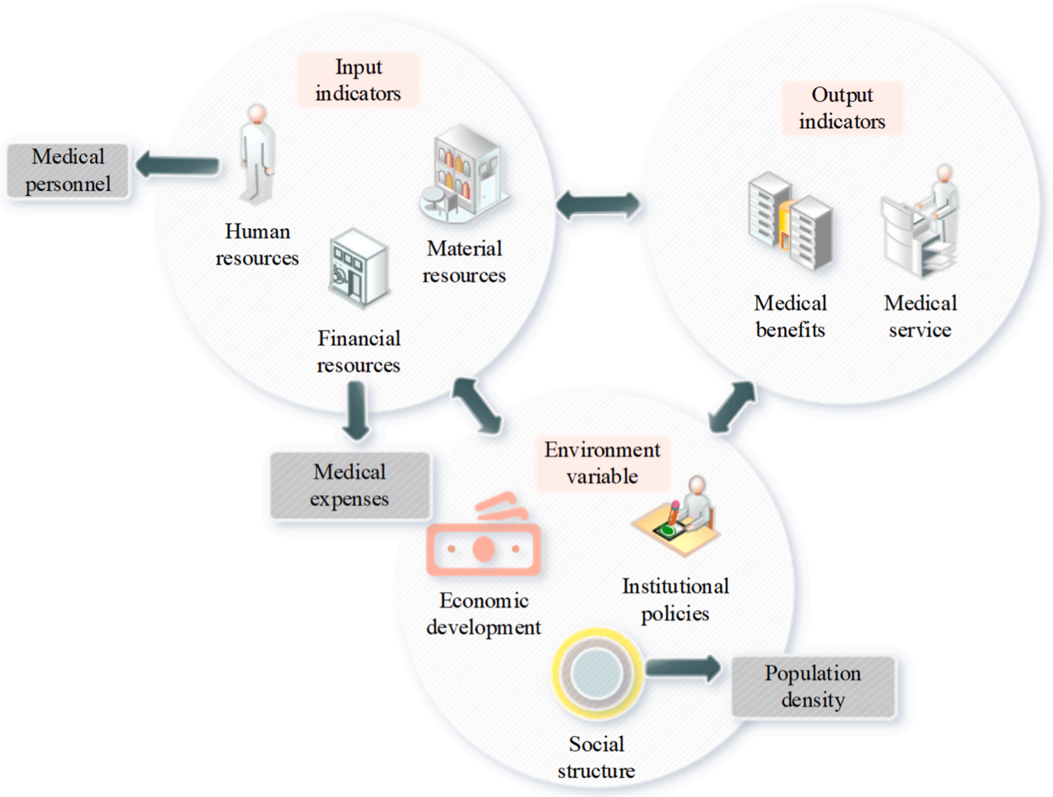

Fig. 2. Index system construction.

and the number of healthcare facility personnel. For output indicators, drawing from scholarly research [34], the AHP method is employed due to its effectiveness in addressing complex decision-making problems involving multiple objectives, criteria, factors, and levels. AHP combines qualitative and quantitative analysis by constructing a hierarchical structure that decomposes a complex decision problem into simpler components. Through pairwise comparisons and calculations, AHP derives the weights and priorities of various factors, thereby providing a scientific basis for decision-making. The strength of AHP lies in its ability to transform difficult-to-quantify qualitative judgments into actionable quantitative analysis, thus enhancing the scientific rigor, reliability, and feasibility of decisions.

However, this study recognizes that health indicators are influenced by multiple factors. Therefore, the selected output indicators include bed utilization rate, number of discharged patients, and bed turnover rate, aiming to evaluate efficiency from both medical benefits and healthcare service perspectives. The bed utilization rate represents the proportion of occupied bed days to the total available bed days on a daily basis. Economically, a notably low bed utilization rate often indicates diminished efficiency and increased costs for healthcare institutions. Hence, this metric is used as a representation of healthcare efficiency and is calculated as the total occupied bed days divided by the total available bed days. For assessing healthcare service, two indicators have been chosen: the number of discharged patients and bed turnover rate. Generally, under consistent conditions, a higher number of discharged patients and a faster bed turnover rate indicate superior healthcare services. The number of discharged patients includes individuals released after treatment, categorized as "cured," "improved," or "not cured." Bed turnover rate refers to the frequency of discharged patients per bed over a specified period and is calculated as the number of discharged patients divided by the average number of available beds. Regarding environmental variable indicators, this study draws on the research of Ahmed et al. (2020) [35] and, in conjunction with the current medical and health status in Guangxi Province, selects per capita Gross Domestic Product (GDP), population density, urbanization rate, and fiscal decentralization to investigate their impact on the efficiency of medical and health resource allocation. Per capita GDP serves as a metric for assessing living standards across various regions and is calculated as the total GDP divided by the resident population in each locality. Population density measures the concentration of residents per unit land area and is expressed as the resident population divided by the land area of each region. The urbanization rate quantifies the level of urban development across regions, represented by the urban population divided by the total population. Fiscal decentralization reflects the extent of regional government autonomy and control over financial matters, calculated as local fiscal revenue divided by local fiscal expenditure. By comprehensively examining these indicators, the study aims to provide a thorough evaluation of healthcare resource allocation efficiency and determine the influence of environmental factors on it. The schematic representation of the indicator system is depicted in Fig. 2.

The description of each indicator is shown in Table 2.

1.7. Experimental data design

This study uses Guangxi as a case example to explore regional healthcare resource allocation issues. The healthcare data from 2012 to 2019 are sourced from the Guangxi Statistical Yearbook, the Information Center of the Guangxi Provincial Health Committee, and the official websites of various municipal statistical bureaus. These data encompass input, output, and environmental variable indicators for healthcare resources across 16 cities in Guangxi Province during the specified timeframe. The data collection process involves extracting information from the aforementioned sources, followed by meticulous data entry and processing using Microsoft Excel. Stringent checks are conducted during the data entry phase to ensure accuracy and minimize discrepancies that could impact subsequent calculations. Efficiency values in the first and third stages are computed using MaxDEA software, while Frontier4.1 software plays a pivotal role in examining the influence of environmental factors on resource allocation efficiency during the second stage. The mathematical calculations for the SFA regression method are meticulously followed, with Excel used for implementing function formulas. To discern trends in TFP, the Malmquist index is employed, with DEAP2.1 software facilitating the processing of this metric.

This study employs a rigorous three-stage super-efficiency DEA model, adhering to the following detailed procedures:

Stage 1: Initial DEA Analysis.

Table 2
Description of each indicator.

Indicator Dimension	Index	Unit
Human Resources	Number of Healthcare Personnel	Persons
Financial Resources	Healthcare Expenditure	Billion CNY
Material Resources	Number of Healthcare Institution Beds	Beds
	Number of Healthcare Institutions	Units
Healthcare Benefits	Number of patients discharged	Persons
	Bed occupancy rate	%
Healthcare Services	bed turnover rate	Times
Economic Growth	GDP per capita	CNY
Policy System	fiscal decentralization	%
Social Structure	Population density	Persons/sq.km
	urbanization rate	%

(1) Model Selection: The BCC model is utilized for the initial DEA analysis due to its capability to handle variable returns to scale, which more accurately reflects the operational realities of healthcare institutions.
(2) Input and Output Variables Determination: Input variables include medical expenditures, the number of healthcare personnel, and the quantity of medical equipment, reflecting healthcare resource allocation. Output variables consist of medical service volume, patient satisfaction, and quality of care.
(3) Initial Efficiency Assessment: A sensitivity analysis of key variables in the data is conducted to assess the extent to which data fluctuations impact the model results, thereby evaluating the uncertainty of the findings. The BCC model assesses the initial efficiency of healthcare institutions, providing efficiency scores and slack variables for each institution.

Stage 2: SFA Regression Analysis.

(1) Selection of Environmental Variables: Through a literature review and expert consultation, environmental variables are selected, including regional economic development levels, population density, and policy support intensity [36].
(2) Regression Model Construction: The SFA method is employed to construct a regression model where slack variables from the first stage serve as the dependent variables and environmental variables as independent variables. This analysis isolates the impact of environmental factors on slack variables.
(3) Input Adjustment: Based on the SFA regression results, adjustments are made to the input variables to account for the influence of environmental factors on efficiency assessment.

Stage 3: Super-Efficiency DEA Analysis.

(1) Application of Adjusted Data: The adjusted input data from the second stage are used along with the original output data to reapply the DEA model. The super-efficiency DEA model is selected to allow for efficiency values greater than 1, offering a more comprehensive evaluation of healthcare institutions' efficiency levels. The Monte Carlo simulation method is employed to generate datasets through multiple random samplings and to execute a three-stage super-efficiency DEA model. This approach allows for the observation of the model's stability and variability, thereby quantifying the uncertainty inherent in the model.
(2) Result Interpretation: The results from this stage are thoroughly analyzed to determine the true efficiency levels of each healthcare institution and to understand the underlying factors contributing to these levels.

In the sensitivity analysis, reasonable ranges of variation for each key variable are established based on the fluctuations observed in actual data and expert judgment. For instance, the range for the number of healthcare personnel is set according to the standard deviation or coefficient of variation from historical data, while the level of policy subsidies as an environmental variable is adjusted to account for variations across different policy scenarios. These ranges are designed to encompass a variety of plausible situations, ensuring the comprehensiveness and accuracy of the sensitivity analysis. The three-stage super-efficiency DEA model is re-run under different values for each key variable. This involves adjusting the input data to reflect changes in the variables and recalculating critical indicators such as overall efficiency, pure technical efficiency, and scale efficiency. Multiple model runs provide output results across various scenarios.

2. Efficiency analysis of healthcare resource allocation in Guangxi Province

2.1. First-stage super-efficiency DEA static analysis

The *t*-test reveals that three environmental variables—regional GDP growth rate, population density, and policy support intensity—significantly impact the slack variables, with p-values of 0.01, 0.03, and 0.005, respectively. These variables are retained for

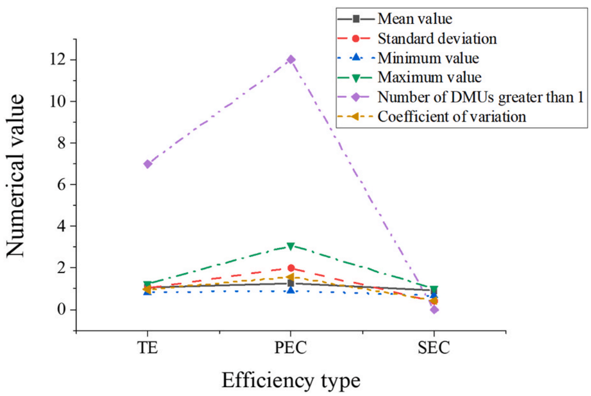

Fig. 3. Descriptive statistics of first-stage Super-Efficiency DEA values for prefecture-level cities in Guangxi Province.

subsequent input adjustments. In the SFA model, the impact of random error terms on slack variables, in addition to environmental variables, is also considered. The estimation results indicate that the variance of the random error term, σ^2, is 0.04, suggesting that random disturbances have a measurable but relatively minor effect on the efficiency assessment.

In the preliminary stage, MaxDEA software is used to calculate and statistically examine the comprehensive efficiency, PTE, and scale efficiency of healthcare resources in Guangxi Province from 2012 to 2022. This analysis relies exclusively on input and output data. The DMUs represent the number of cities with an efficiency indicator value exceeding 1. Descriptive statistical findings of the super-efficiency DEA values across different cities within Guangxi Province during this initial stage are depicted in Fig. 3.

During the current period, the mean comprehensive efficiency of prefecture-level cities in Guangxi Province is 1.067, with a standard deviation of 1.024, indicating considerable variation in efficiency across these cities. The lowest recorded comprehensive efficiency is 0.822, while the highest reaches 1.241. The coefficient of variation in efficiency is 0.961, reflecting the extent of variability among prefecture-level cities. The average PEC is 1.266, with a standard deviation of 1.988, suggesting significant disparities in PEC among cities. The lowest observed PEC is 0.908, and the highest is 3.077. Notably, twelve prefecture-level cities exhibit PEC values exceeding 1, indicating technological advantages in these regions. The coefficient of variation for PEC is 1.567, highlighting the diversity in technological levels across regions. The average SEC is 0.896, with a standard deviation of 0.392, indicating relatively smaller differences. The lowest SEC recorded is 0.655, while the highest is 0.996. Some regions show an SEC of 0, suggesting potential wastage in scale. The coefficient of variation for SEC is 0.436, illustrating the relative stability of scale efficiency. These statistical findings provide insights into the average levels, variations, and distribution of different efficiency aspects among prefecture-level cities in Guangxi Province. While there are substantial differences in comprehensive efficiency and PEC, SEC shows comparatively modest variation. These indicators offer valuable understanding of resource allocation and efficiency variations among different regions. Additionally, the observation that no city achieves an average scale efficiency above one over the nine years, with a minimum of only 0.654, underscores that scale efficiency is a crucial factor hindering overall technical efficiency improvement. In the upcoming "Fourteenth Five-Year Plan" period, Guangxi Province should prioritize adjusting the scale of investment in healthcare resources and optimizing the configuration of healthcare resources.

2.2. *Three-stage super-efficiency DEA static analysis*

To provide a comprehensive assessment of the competitive capacities of digital bilateral platforms influenced by artificial intelligence technology, this section presents the descriptive statistical results of the three-stage super-efficiency DEA values for prefecture-level cities in Guangxi Province, as illustrated in Fig. 4.

In the third stage, the mean comprehensive efficiency of prefecture-level cities in Guangxi Province is 1.054, with a notable standard deviation of 0.61, indicating substantial variability in efficiency across these cities. The efficiency values range from a minimum of 0.913 to a maximum of 1.474. Notably, six prefecture-level cities exhibit efficiency values exceeding 1, signifying performance above the regional average. The coefficient of variation for efficiency is 0.577, highlighting the degree of efficiency diversity among these cities. For PTE, the average for prefecture-level cities in Guangxi Province is 1.166, with a standard deviation of 0.922, reflecting significant disparities in PEC. Values range from a minimum of 0.963 to a maximum of 1.930, with twelve prefecture-level cities demonstrating PEC values exceeding 1, indicating technological advantages in these areas. The coefficient of variation for PEC is 0.791, emphasizing the extent of technological diversity among different regions. The average SEC for prefecture-level cities in Guangxi Province is 0.931, with a standard deviation of 0.331, indicating relatively minor differences in scale efficiency. SEC values range from a minimum of 0.751 to a maximum of 1.086, with two prefecture-level cities surpassing a scale efficiency of 1, while some areas show scale efficiency below 1, reflecting variations in scale. The coefficient of variation for scale efficiency is 0.355, suggesting relative stability in scale efficiency. These statistical findings provide a nuanced analysis of the three-stage super-efficiency DEA values for prefecture-level cities in Guangxi Province. They reveal the average levels, variability, and distribution of efficiency across regions, with significant disparities in comprehensive efficiency and PEC, while differences in scale efficiency are comparatively smaller.

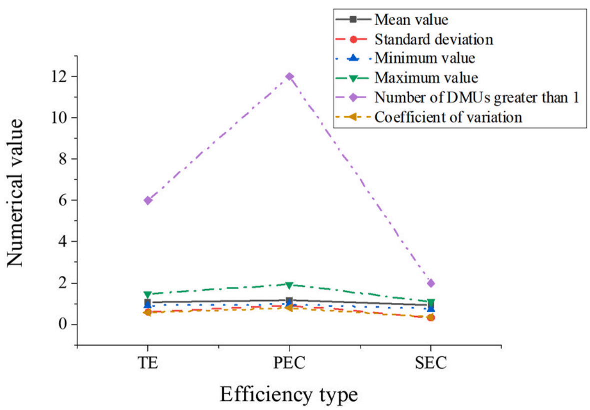

Fig. 4. Descriptive statistics of three-stage super-efficiency DEA values for prefecture-level cities in Guangxi Province.

A comprehensive analysis of Figs. 3 and 4 reveals that after accounting for the impact of environmental variables and random errors, the average overall efficiency decreased from 1.067 before adjustment to 1.054 after adjustment. This suggests that the overall efficiency of healthcare resource allocation in Guangxi is relatively high. However, it is important to recognize that the effectiveness of resource distribution in the region is influenced by environmental factors and random errors, indicating a disproportionate increase in efficiency. The 3S super-efficiency DEA model effectively addresses these impacts on resource allocation.

To assess the effect of model assumptions on the results, a sensitivity analysis was conducted. By altering the scale returns assumption of the DEA model from variable returns to scale to constant returns to scale, it was observed that the efficiency value of healthcare institution B decreased from 1.12 to 1.07. This demonstrates that variability in scale returns significantly impacts efficiency evaluation results, particularly when considering differences in healthcare institution sizes. Based on the comparison between model results and actual conditions, it is necessary to make continuous adjustments to model parameters and data processing methods, such as modifying the selection of environmental variables or changing data normalization techniques, to enhance the model's adaptability and accuracy.

2.3. Dynamic analysis of healthcare resource allocation efficiency in Guangxi Province

The Malmquist index methodology is employed to compute the comprehensive TFP index and its corresponding decomposition values across various time periods in Guangxi Province, spanning from 2012 to 2022. The unadjusted TFP index and its decomposition values for these discrete time intervals in Guangxi Province are visually illustrated in Fig. 5.

This study analyzes the EC across different time periods.

- From 2012 to 2013: The technical EC is 0.997, TC is 0.995, PEC is 1.009, SEC is 0.987, and the TFP index is 0.992. During this period, there is a slight decrease in overall technical efficiency, with technological progress being relatively slow. There is a slight improvement in PEC, a decrease in SEC, and a slight decline in the TFP index.
- From 2013 to 2014: The technical EC slightly improves to 0.999, TC reaches its peak at 1.029, PEC slightly improves to 1.002, SEC also improves to 0.998, and the TFP index significantly improves to 1.029, indicating an overall trend of efficiency enhancement.
- From 2014 to 2015: The technical EC further improves to 1.028, TC decreases to 0.948, PEC slightly improves to 1.016, SEC slightly improves to 1.012, and the TFP index slightly decreases to 0.975.
- From 2015 to 2016: The technical EC falls back to 0.997, TC remains stable at 0.996, PEC decreases to 0.990, SEC slightly improves to 1.007, and the TFP index remains stable at 0.992.
- From 2016 to 2017: The technical EC slightly improves to 1.003, TC slightly increases to 1.006, PEC increases to 1.004, SEC remains stable at 0.999, and the TFP index also improves to 1.010.
- From 2017 to 2018: The technical EC, TC, PEC, SEC, and TFP index all remain relatively stable during this period.
- From 2018 to 2019: The technical EC slightly decreases to 1.000, TC falls to 0.983, PEC remains stable at 1.001, SEC slightly improves to 0.999, and the TFP index also slightly decreases to 0.983.
- From 2019 to 2020: The PEC remains stable at 1.003, the SEC slightly increases to 1.003, and the TFP index decreases marginally to 0.992.
- From 2020 to 2021: PEC decreases to 0.997, SEC slightly increases to 1.004, and the TFP index decreases marginally to 0.986.
- From 2021 to 2022: The EC remains stable at 1.000, the TC increases to 1.002, PEC remains stable at 0.999, SEC increases to 1.008, and the TFP index decreases slightly to 0.996.

Fundamentally, the principal factor driving the decline in the TFP index in Guangxi Province is the regression in technological progress, with a relatively minor impact stemming from the reduction in technical efficiency. However, the combined SECs and PEC have collectively influenced the decline in technical efficiency. This underscores the imperative need for a comprehensive analysis and

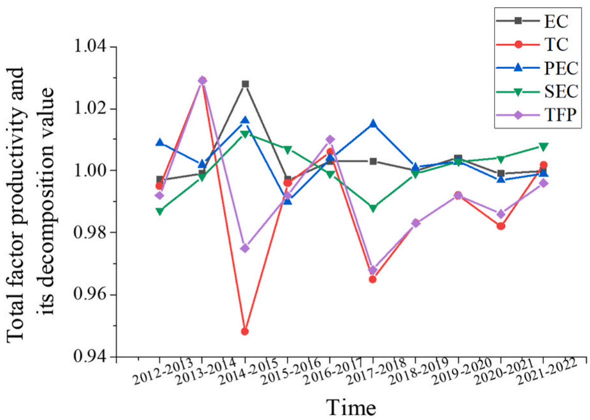

Fig. 5. Unadjusted TFP index and its decomposition values for different time intervals in Guangxi Province.

enhancements in efficiency aspects to foster future economic development and productivity growth in Guangxi Province. For a more nuanced perspective, Fig. 6 illustrates the adjusted TFP index alongside its decomposition values, revealing the intricate dynamics across different time intervals in Guangxi Province.

During the period from 2012 to 2019, the average TFP index in Guangxi Province declined from 0.968 to 0.962, indicating an overall decrease of 3.8 % in resource allocation efficiency. Remarkably, this reflects a 0.6 percentage point increase from the initially observed 3.2 % decrease before adjustment, highlighting a clear downward trend in the efficiency of medical and health resource allocation over the seven-year period. Following adjustment, the average EC improved, rising from 0.997 to 0.999. The initial reduction of 0.3 % decreased to a modest 0.1 %, reflecting a notable 0.2 percentage point improvement. This positive change can be attributed to slight advancements in both PEC and SEC post-adjustment, collectively enhancing technical efficiency. By mitigating the influence of external environmental variables and random error terms, the mean value of technological progress decreased from 0.972 pre-adjustment to 0.963. After adjustment, the mean values of SEC and PEC are 0.997 and 0.998, respectively, both below 1. This underscores the collaborative contribution of both scale efficiency and PEC to the reduction in technical efficiency. Consequently, it is evident that heightened attention is imperative for improving scale efficiency in medical and health resource allocation in the region. Substantive efforts are warranted to enhance management and technological capabilities within the medical and health sectors. After 2020, the TC continues to show an upward trajectory. The changes in the SEC are influenced by various factors such as global economic conditions and policy adjustments. The TFP index decreases slightly to 0.996 in 2022, primarily due to educational policies and changes in the labor market.

To validate the performance advantages of the method proposed in this study, it was compared with the Tobit regression model and the traditional DEA model, as detailed in Table 3. The Tobit regression model is generally used to analyze the relationship between efficiency values and environmental variables, rather than directly assessing the efficiency values themselves. Consequently, the three-stage DEA model offers a clear advantage in terms of direct efficiency assessment. Compared to the traditional DEA model, the three-stage super-efficiency DEA model, with its more complex settings and data processing steps, provides more detailed technical and scale efficiency decompositions.

3. Discussion

During the collection of data on the number of healthcare personnel in hospitals, instances of abnormally high or low values are identified. Further investigation reveals that these outliers could be attributed to data entry errors or inconsistencies in statistical criteria. Consequently, these anomalies are corrected, and relevant indicators are recalculated to ensure the accuracy of the model's input data. In assessing the efficiency of medical equipment allocation, data is sourced not only from hospital self-reports but also from government statistics and reports from third-party research institutions. A comparison of data from these various sources indicates that certain hospitals might have exaggerated or underestimated their reported figures. Therefore, a weighted averaging approach is employed to process this data, resulting in a more accurate depiction of medical equipment allocation.

The three-stage super-efficiency DEA model is re-run under various values for each key variable, and changes in critical indicators such as overall efficiency, pure technical efficiency, and scale efficiency are recorded. Analysis of these variations reveals that changes in the number of healthcare personnel have the most significant impact on the model's results, while variations in policy subsidies had a relatively minor effect. This finding suggests that, when formulating healthcare resource allocation strategies, priority should be given to increasing the number of healthcare personnel to enhance service efficiency.

Based on the results of the sensitivity analysis, the robustness of the three-stage super-efficiency DEA model can be assessed. In this study, the model demonstrates relatively stable output results when faced with reasonable variations in key variables, indicating strong robustness. However, it is also observed that under certain extreme scenarios (such as a significant reduction in the number of healthcare personnel or an abrupt cessation of policy subsidies), the model's results can undergo substantial changes. This highlights the need to be mindful of these potential risks in practical applications and to develop appropriate countermeasures. In conjunction with the findings from the sensitivity analysis, it can be concluded that the conclusions regarding the efficiency of healthcare resource

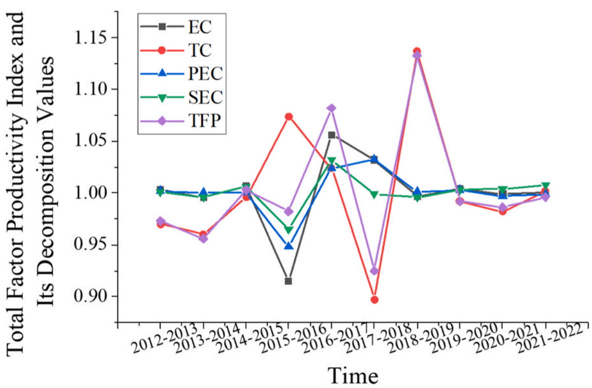

Fig. 6. Adjusted TFP index and its decomposition values for different time intervals in Guangxi Province.

Table 3
Average efficiency scores of different resource allocation models.

Year	Traditional DEA	Tobit Regression Model	Three-Stage Super-Efficiency DEA
2019	1.02	1.01	1.08
2020	1.01	1.00	1.07
2021	1.00	1.00	1.09
2022	1.01	1.01	1.07

allocation in Guangxi are highly reliable. Despite the influence of uncertain factors, the model consistently provided stable and coherent assessment results in most cases, thereby offering strong support for the formulation of healthcare resource allocation strategies.

In addressing the uncertainties within the three-stage super-efficiency DEA model, it is crucial to recognize that the complexity of healthcare resource allocation arises not only from data diversity but also from numerous unforeseen factors within the system's internal and external environments. To enhance the model's robustness and practical applicability, a decision is made to explore and integrate two key dimensions: uncertainty modeling methods in the risk assessment of digital process systems, and expert judgment and uncertainty handling strategies in socio-technical system analysis.

First, this study draws on advanced concepts from the risk assessment of digital process systems, integrating uncertainty modeling techniques into the three-stage super-efficiency DEA model. This process begins with a comprehensive identification of potential sources of uncertainty in the allocation of healthcare resources, which includes but is not limited to errors in data collection and processing, subjectivity in model parameter settings, and the potential impact of external environmental changes on resource allocation efficiency. Subsequently, theoretical tools such as probability theory and fuzzy mathematics are employed to quantify these sources of uncertainty, leading to the construction of a propagation model for uncertainty within the framework of the model. By simulating resource allocation scenarios under different conditions, the study evaluates the scope and degree of uncertainty's impact on model outputs, thereby providing a scientific basis for formulating more robust resource allocation strategies. Simultaneously, the importance of expert judgment in addressing complexity and uncertainty is recognized. Therefore, the active involvement of experts in the field of healthcare management is sought during the model construction and evaluation processes. Insights and experiences regarding factors affecting healthcare resource allocation efficiency are gathered and integrated through expert interviews and surveys. This invaluable expert knowledge not only provides essential references for setting model parameters but also enhances the interpretability of model outputs. Experts, leveraging their extensive industry backgrounds and practical experiences, are able to offer in-depth interpretations of the model conclusions, identify potential issues, and suggest avenues for improvement, thereby providing more intuitive and practical recommendations for healthcare decision-makers.

Gong et al. (2024) studied the efficiency of healthcare resource allocation in Hainan Province and found it to be generally poor and declining from 2016 to 2020, with significant regional disparities. Technological progress was identified as a key factor influencing efficiency, particularly in economically developed areas with large populations, which exhibited relatively higher efficiency. This finding has important implications for the development and high-quality construction of the healthcare industry in the Hainan Free Trade Port. The study proposed several measures.

(1) Rational Allocation of Resources: Based on factors such as population, geography, and demand, there should be a rational allocation of medical hardware and software resources. Advancing hierarchical diagnosis and treatment and promoting "Internet+" healthcare can help balance the expansion of high-quality medical resources, thereby improving efficiency.
(2) Cultivation of Healthcare Professionals: Hainan Province should expedite the introduction and training of healthcare professionals, focusing on enhancing healthcare technology, service quality, and staff competence to meet the growing medical demands [37].

In light of these recommendations, and to further enhance the efficiency of healthcare resource allocation in Guangxi Province as reflected in the conclusions of this study, the following policy recommendations are proposed.

(1) Strengthen Supervision and Elevate Management Standards: The Guangxi provincial government must ensure that investment growth is reasonable relative to outputs. Both the government and healthcare institutions should prioritize technological progress and service quality to ensure the high-quality development of healthcare services. In areas with lower technical efficiency, existing medical resources should be integrated and fully utilized, while enhancing the synergy and integration of healthcare service systems [38]. Additionally, institutional innovation should be encouraged to explore new service models, conduct scientific research, and enhance capabilities in utilizing network technologies. This includes optimizing disease prevention, diagnosis, and treatment schemes using big data and artificial intelligence technologies to provide more accurate, convenient, and personalized medical services. The introduction of new technologies and high-tech medical equipment should be promoted to elevate medical service levels. Regarding healthcare funding, the Guangxi provincial government should strengthen supervision, budget planning, clarify the flow of funds, ensure transparency in fund allocation, prevent fund loss, waste, and corruption, and enhance the efficiency of medical fund utilization. Professional third-party supervision and audit institutions could be introduced to strengthen budgetary auditing. Additionally, mobilizing social forces to establish a medical

fund information disclosure platform and setting up a hotline for public reporting and feedback on medical service information can broaden public supervision channels [39].

(2) Adjust Resource Inputs and Optimize Allocation Structures: The results indicate that the efficiency of healthcare resource allocation in Guangxi Province is largely constrained by scale efficiency. When formulating healthcare resource plans, the Guangxi provincial government should consider factors such as geographical accessibility, population distribution, and the economic and social development status of various regions. This approach should include existing distribution and utilization of healthcare resources to scientifically determine the scale of healthcare service development. Coordinating and arranging various types of healthcare resources, such as institutions, personnel, and beds, will enable residents across the province to access high-quality health services and alleviate the imbalance between the supply and demand of healthcare resources [40].

(3) Cultivate Medical Innovation Capabilities and Promote Technological Progress: According to the Malmquist index calculation results, the decrease in TFP in Guangxi Province after adjustment was mainly due to a decline in technological progress. Enhancing technological progress can improve overall efficiency. The government should focus on boosting innovation capabilities, promoting technological advancements, cultivating innovation, and improving the level of medical technology.

Establishing a scientific, efficient, and transparent healthcare management system is crucial for enhancing resource allocation efficiency. The Guangxi Provincial Government should strengthen oversight of healthcare institutions to ensure their operations comply with regulations and that service quality meets established standards. Additionally, a robust performance evaluation mechanism should be implemented, incorporating indicators such as resource allocation efficiency, service quality, and patient satisfaction. This mechanism can incentivize healthcare institutions to improve their management practices and service quality. The government should introduce a series of supportive policies to encourage healthcare institutions to enhance internal management and operational efficiency. For example, institutions that excel in technological innovation and service optimization could receive awards or subsidies. Special support policies should be developed for regions with limited medical resources to promote a more balanced distribution of healthcare services. Furthermore, the government should enhance policy guidance to support the implementation of a tiered healthcare system, alleviating the diagnostic and treatment pressure on large hospitals and improving the service capacity of primary healthcare institutions. Technological advancement is a key driver of healthcare sector development. The Guangxi Provincial Government should increase support for medical innovation, encouraging healthcare institutions and researchers to develop and apply new technologies and methods. Establishing dedicated funds and providing research platforms can significantly support medical innovation. Strengthening exchanges and cooperation with leading international medical institutions, as well as assimilating advanced international medical technologies and management practices, will enhance the overall level of healthcare in Guangxi.

Regarding the medical sector in China, this study proposes the following recommendations: The Chinese medical sector needs to strengthen medical research innovation, enhance medical technology development, and cultivate innovative medical talents. Firstly, the government can promote research innovation in the medical field through tax incentives, such as reducing personal income tax and lowering corporate income tax. These measures would encourage medical professionals and enterprises to invest in research [41]. Additionally, attracting world-class medical researchers, improving the assessment and incentive systems for medical research talents, and cultivating high-level medical research expertise can significantly stimulate innovation in medical research. Secondly, promoting the development of medical research bases and strengthening collaboration with top international medical and health institutions can facilitate the introduction of advanced medical technologies and management models, leading to innovations in medical technology [42]. Furthermore, new technologies such as artificial intelligence, big data, and cloud computing should be gradually integrated into the medical and health fields. Local governments should increase investment in these areas to foster technological progress in the medical sector. Finally, cultivating innovative medical talents is crucial. The government should promote cooperation between universities and hospitals, accelerate the training of professional and technical personnel to address manpower needs in key medical and health areas, and increase subsidies for talent recruitment policies. Enhancing the professional level of medical and health personnel is also essential [43]. Strengthening regional coordination and cooperation, conducting centralized training, improving the technical level of medical services, and regularly dispatching medical personnel to grassroots public health units are necessary to ensure the accessibility and quality of medical and health services.

The limitations identified in this investigation primarily manifest across several dimensions. Firstly, despite efforts to capture the complexities and diversity inherent in the healthcare domain through the adopted model system, the current model's design and implementation require simplifications due to the intricate nature of real-world circumstances. These simplifications may lead to the insufficient consideration of certain subtle yet crucial aspects, affecting the model's accuracy in simulating and representing real-world healthcare resource allocation scenarios. Secondly, research dependent on data inevitably faces constraints related to the quality and availability of data. The limitations encountered in data collection and preprocessing in this study may potentially impact the reliability and effectiveness of the final analytical outcomes. Particularly noteworthy is the challenge of comprehensively obtaining healthcare data, given its high sensitivity and the demand for completeness. Future refinements of this study could include, but are not limited to, the following.

(1) Augmenting the existing model framework by integrating additional dimensions and data elements, such as socio-economic indicators, the status of medical technological advancements, and shifts in healthcare service demand. This effort aims to develop a more comprehensive and detailed assessment system for evaluating healthcare resource allocation efficiency.

(2) Emphasizing fundamental elements of the healthcare domain and conducting thorough empirical investigations. This could include examining the role of technological innovation in enhancing the quality and efficiency of medical services, the impact of human resource management strategies on the operational efficiency of medical institutions, and the impact of resource

allocation policies on optimizing overall healthcare system efficiency. Expanding the scope of research locales and diversifying the range and number of research variables is also imperative. By encompassing diverse healthcare systems globally, scrutinizing various healthcare system models, and investigating a broader spectrum of related variables, richer and more universally applicable conclusions can be drawn. Consequently, this approach could provide more precise and robust theoretical foundations, as well as practical guidance, for the strategic allocation, refined management, and decision-making processes concerning healthcare resources on a global scale and across different regions.

(3) Expanding the scope of research locales and diversifying the range of research variables. By including diverse healthcare systems globally, examining various healthcare system instances, and exploring a broader spectrum of related variables, it is anticipated that more nuanced and universally applicable conclusions can be drawn. This approach could provide more precise and robust theoretical foundations and practical recommendations for the strategic allocation, refined management, and decision-making regarding healthcare resources on a global scale and across different regions.

In the manufacturing industry, the three-stage super-efficiency DEA model has been employed to assess production line efficiency. By eliminating the effects of external factors, such as market environment and fluctuations in raw material prices, as well as random errors, including equipment failures and operational mistakes, the model provides a more accurate reflection of the true efficiency of production lines. This approach offers robust support for production optimization and cost control. In the financial services industry, the model is also utilized to evaluate the operational efficiency of financial institutions, such as banks and securities firms. By accounting for the impact of external factors, including the macroeconomic environment and regulatory policies, as well as internal management and operational risks, the model helps financial institutions identify opportunities for efficiency improvements, optimize resource allocation, and enhance competitiveness.

4. Conclusion

This study explores regional healthcare resource allocation using a three-stage super-efficiency DEA model. By comparing its results with those obtained from other methods, it demonstrates that the three-stage super-efficiency DEA model not only assesses the technical efficiency of healthcare resources but also accounts for environmental factors and random disturbances, thereby enhancing the accuracy of the outcomes. Compared to traditional DEA models, the three-stage super-efficiency DEA model offers a more comprehensive evaluation of healthcare institution efficiency and produces more reliable results. Additionally, in comparison to the SFA method, the three-stage super-efficiency DEA model provides better interpretability. The results from analyzing healthcare resource allocation efficiency using the three-stage super-efficiency DEA model show an overall improvement in efficiency when considering environmental factors and random disturbances. This study preliminarily examines the impact of environmental factors and random disturbances on healthcare resource allocation efficiency. However, future research could further refine the types of these factors and their specific mechanisms of action. Conducting in-depth studies on both the long-term and short-term effects of various external factors—such as different policy environments, economic fluctuations, and natural disasters—on the efficiency of healthcare resource allocation would be beneficial.

CRediT authorship contribution statement

Ying Liu: Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Lanxian Mai:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Investigation, Funding acquisition, Formal analysis, Data curation. **Feng Huang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Investigation, Data curation, Conceptualization. **Zhiyu Zeng:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Data curation.

Data availability statements

All data generated or analyzed during this study are included in this published article [and its supplementary information files].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships thatcould have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References

[1] M. Yi, J. Peng, L. Zhang, Y. Zhang, Is the allocation of medical and health resources effective? Characteristic facts from regional heterogeneity in China, Int. J. Equity Health 19 (1) (2020) 1–21.
[2] F. Wu, W. Chen, L. Lin, X. Ren, Y. Qu, The Balanced allocation of medical and health resources in urban areas of China from the perspective of sustainable development: a case study of Nan Nanjing, Sustainability 14 (11) (2022) 6707.
[3] M.R. Tellez Cabrera, Health resource allocation among indigenous peoples from the right to health and health capability approaches: the case of P'urhépecha people, Global Publ. Health 17 (6) (2022) 986–1001.
[4] C. Lu, Z. Zhang, X. Lan, Impact of China's referral reform on the equity and spatial accessibility of healthcare resources: a case study of Beijing, Soc. Sci. Med. 235 (22) (2019) 112386.
[5] J.A. Marin-Garcia, J.P. Garcia-Sabater, A. Ruiz, J. Maheut, J.J. Garcia-Sabater, Operations Management at the service of health care management: example of a proposal for action research to plan and schedule health resources in scenarios derived from the COVID-19 outbreak, J. Ind. Eng. Manag. 13 (2) (2020) 213–227.
[6] E. Krmac, M. Mansouri Kaleibar, A comprehensive review of data envelopment analysis (DEA) methodology in port efficiency evaluation, Marit. Econ. Logist. 25 (4) (2023) 817–881.
[7] T.N.M. Nong, Performance efficiency assessment of Vietnamese ports: an application of Delphi with Kamet principles and DEA model, The Asian Journal of Shipping and Logistics 39 (1) (2023) 1–12.
[8] W. Su, L. Du, Y. Fan, P. Wang, Equity and efficiency of public hospitals' health resource allocation in Guangdong Province, China, Int. J. Equity Health 21 (1) (2022) 1–18.
[9] J. Gong, L. Shi, X. Wang, G. Sun, The efficiency of health resource allocation and its influencing factors: evidence from the Super-Efficiency slack based model-Tobit model, International Health 15 (3) (2023) 326–334.
[10] Z. Wang, Y. Deng, S. Zhou, Z. Wu, Achieving sustainable development goal 9: a study of enterprise resource optimization based on artificial intelligence algorithms, Resour. Pol. 80 (2023) 103212.
[11] Y. Tang, H. Ding, X. Shan, X. Wang, Application of the novel three-stage DEA model to evaluate total-factor energy efficiency: a case study based on 30 provinces and 8 comprehensive economic zones of China, Results in Engineering 20 (5) (2023) 101417.
[12] W.U.H. Shah, G. Hao, H. Yan, R. Yasmeen, I.U.H. Padda, A. Ullah, The impact of trade, financial development and government integrity on energy efficiency: an analysis from G7-Countries, Energy 255 (2022) 124507.
[13] W.U.H. Shah, G. Hao, H. Yan, R. Yasmeen, Y. Lu, Energy efficiency evaluation, changing trends and determinants of energy productivity growth across South Asian countries: SBM-DEA and Malmquist approach, Environ. Sci. Pollut. Control Ser. 30 (8) (2023) 19890–19906.
[14] R. Yasmeen, X. Zhang, R. Tao, W.U.H. Shah, The impact of green technology, environmental tax and natural resources on energy efficiency and productivity: perspective of OECD Rule of Law, Energy Rep. 9 (2023) 1308–1319.
[15] W.U.H. Shah, N. Zhu, G. Hao, H. Yan, R. Yasmeen, Energy efficiency evaluation, technology gap ratio, and determinants of energy productivity change in developed and developing G20 economies: DEA super-SBM and MLI approaches, Gondwana Res. 125 (2024) 70–81.
[16] W.U.H. Shah, G. Hao, H. Yan, N. Zhu, R. Yasmeen, G. Dincă, Role of renewable, non-renewable energy consumption and carbon emission in energy efficiency and productivity change: evidence from G20 economies, Geosci. Front. (2023) 101631.
[17] W.U.H. Shah, G. Hao, H. Yan, J. Shen, R. Yasmeen, Forestry resource efficiency, total factor productivity change, and regional technological heterogeneity in China, Forests 15 (1) (2024) 152.
[18] W.U.H. Shah, Y. Lu, J. Liu, A. Rehman, R. Yasmeen, The impact of climate change and production technology heterogeneity on China's agricultural total factor productivity and production efficiency, Sci. Total Environ. 907 (2024) 168027.
[19] W.U.H. Shah, G. Hao, H. Yan, R. Yasmeen, Y. Jie, The role of energy policy transition, regional energy efficiency, and technological advancement in the improvement of China's environmental quality, Energy Rep. 8 (2022) 9846–9857.
[20] H.L. Jeon, H. Lee, D. Yoon, Y. Lee, J.H. Kim, D. Jee, Burden of diabetic macular oedema in patients receiving antivascular endothelial growth factor therapy in South Korea: a healthcare resource use and cost analysis, BMJ Open 10 (12) (2020) e042484.
[21] R. Gropp, A. Guettler, V. Saadi, Public bank guarantees and allocative efficiency, J. Monetary Econ. 116 (20) (2020) 53–69.
[22] L. Simar, P.W. Wilson, Technical, allocative and overall efficiency: estimation and inference, Eur. J. Oper. Res. 282 (3) (2020) 1164–1176.
[23] T.P. Papalexopoulos, D. Bertsimas, I.G. Cohen, R.R. Goff, D.E. Stewart, N. Trichakis, Ethics-by-design: efficient, fair and inclusive resource allocation using machine learning, Journal of Law and the Biosciences 9 (1) (2022) lsac012.
[24] M. Du, Y. Zhao, T. Fang, L. Fan, M. Zhang, H. Huang, Evaluating the Inequality of medical resource allocation based on spatial and non-spatial accessibility: a case study of Wenzhou, China, Sustainability 14 (14) (2022) 8331.
[25] J. Wang, Z. Wang, Z.G. Zhang, F. Wang, Efficiency-quality trade-off in allocating resource to public healthcare systems, Int. J. Prod. Res. 60 (21) (2022) 6469–6490.
[26] R. Chandran, N. Gayathri, S. Rakeshkumar, Reliability aware medical resource allocation for health care Industrial Internet of Things (IIoT) using tabu search and alo algorithm, J. Med. Imaging Health Inform. 11 (12) (2021) 3090–3095.
[27] Y.G. Guo, Q. Yin, Y. Wang, J. Xu, L. Zhu, Efficiency and optimization of government service resource allocation in a cloud computing environment, J. Cloud Comput. 12 (1) (2023) 18.
[28] D. Olivia, C. Amrutha, A. Nayak, M. Balachandra, A. Saxena, Clinical severity level prediction based optimal medical resource allocation at mass casualty incident, IEEE Access 10 (2) (2022) 88970–88984.
[29] W. Su, Y. Hou, M. Huang, J. Xu, Q. Du, P. Wang, Evaluating the efficiency of primary health care institutions in China: an improved three-stage data envelopment analysis approach, BMC Health Serv. Res. 23 (1) (2023) 995.
[30] R. Gearhart, N. Michieka, A non-parametric investigation of supply side factors and healthcare efficiency in the US, J. Prod. Anal. 54 (1) (2020) 59–74.
[31] V. Ngobeni, M.C. Breitenbach, G.C. Aye, Technical efficiency of provincial public healthcare in South Africa, Cost Eff. Resour. Allocation 18 (1) (2020) 1–19.
[32] Y. Ma, T. Wang, H. Zheng, On fairness and efficiency in nonprofit operations: dynamic resource allocations, Prod. Oper. Manag. 32 (6) (2023) 1778–1792.
[33] J.W. März, S. Holm, M. Schlander, Resource allocation in the Covid-19 health crisis: are Covid-19 preventive measures consistent with the Rule of Rescue? Med. Healthc. Philos. 24 (4) (2021) 487–492.
[34] R. Ma, F. Meng, H. Du, Research on intelligent emergency resource allocation mechanism for public health emergencies: a case study on the prevention and control of COVID-19 in China, Systems 11 (6) (2023) 300.
[35] S.T. Ahmed, M. Sandhya, S. Sankar, TelMED: dynamic user clustering resource allocation technique for MooM datasets under optimizing telemedicine network, Wireless Pers. Commun. 112 (2) (2020) 1061–1077.
[36] E. Zarei, M. Yazdi, R. Moradi, et al., Expert Judgment and Uncertainty in Sociotechnical Systems analysis[M]//Safety Causation Analysis in Sociotechnical Systems: Advanced Models and Techniques, Springer Nature Switzerland, Cham, 2024, pp. 487–530.
[37] Y. Gong, D. Ma, W. Feng, Study on the allocation efficiency of medical and health resources in Hainan Province: based on the super-efficiency SBM—Malmquist model, PLoS One 19 (2) (2024) e0294774.

[38] Q. Hao, F. Xu, L. Chen, P. Hui, Y. Li, Hierarchical multi-agent model for reinforced medical resource allocation with imperfect information, ACM Transactions on Intelligent Systems and Technology 14 (1) (2022) 1–27.
[39] J. Wang, W. Jia, Resources allocation and utilization efficiency in China's healthcare sector, China Finance and Economic Review 10 (2) (2021) 88–109.
[40] M. Huang, D. Luo, Z. Wang, Y. Cao, H. Wang, F. Bi, et al., Equity and efficiency of maternal and child health resources allocation in Hunan Province, China, BMC Health Serv. Res. 20 (1) (2020) 1–10.
[41] L. Liu, W. Xu, Y. Su, X. Zhou, Evaluation of health resource allocation efficiency based on data envelopment analysis 2014–2018 in two dimensions of time-region, Discrete Dynam Nat. Soc. (2021) 1–10.
[42] G. Hao, Y. Ling, Evaluation on efficiency of medical and health service resource allocation in jiangsu province, Modern Hospital Management 20 (1) (2022) 1–4.
[43] Q. Li, J. Wei, F. Jiang, G. Zhou, R. Jiang, M. Chen, W. Hu, Equity and efficiency of health care resource allocation in Jiangsu Province, China, Int. J. Equity Health 19 (2020) 1–13.