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ORIGINAL RESEARCH

# Evaluation of Health Resource Efficiency and Its Influencing Factors in Ethnic Minority Areas of Guangxi: Data from 2010 to 2022

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**Objective:** Measuring the efficiency of health resources is one of the tools for determining how resources are utilized. Considering the necessity of assessing health resource efficiency, this study aims to evaluate the efficiency of health resource allocation and its influencing factors in Guangxi, a minority region.

**Methods:** An input-oriented Data Envelopment Analysis (BCC-DEA) and the Malmquist index model were employed to analyze the static and intertemporal efficiency of health resource allocation in 14 cities in Guangxi from 2010 to 2022. Finally, a Tobit regression model was used to estimate the factors influencing health resource allocation efficiency.

**Results:** Since the implementation of the new healthcare reform in 2009, the quantity of health resources in Guangxi has increased substantially. The average annual growth rate of total factor productivity change for health resources from 2010 to 2022 was 4.6%. However, the overall efficiency of health resource allocation remained low at 0.675, falling short of DEA effectiveness, with notable disparities across cities. Tobit regression analysis indicated that per capita disposable income ($\beta = 0.252$, 95% CI = 0.000–0.505) and the proportion of healthcare expenditure ($\beta = 0.011$, 95% CI = 0.004–0.017) were positively associated with efficiency scores, while population density ($\beta = -0.001$, 95% CI = −0.0007 – −0.0002) was negatively associated. These findings were further validated through a two-stage bootstrap truncated regression.

**Conclusion:** The efficiency of health resource allocation in Guangxi remains in need of improvement due to issues such as insufficient technological innovation and an unscientific allocation of resource scale. It is recommended that relevant authorities increase investments in health funding and technological innovation, improve institutional mechanisms, and allocate health resources in a scientific and rational manner.

**Keywords:** health resources, efficiency, productivity, DEA-Tobit model

## Introduction

Health resources serve as the foundation for the advancement of health services, and their effective allocation not only impacts the health status of residents but also significantly contributes to the sustainable progress of medical and health services.[1] Efficiency is regarded as a primary objective in public health management and is one of the fundamental principles promoted by the World Health Organization. Currently, many developing countries face challenges related to low efficiency in resource management,[2] making the rational allocation of health resources an increasingly relevant global issue.[3] The "Healthy China 2030" Outline Plan suggests that by 2030, China's healthcare system will be more comprehensive, the development of the healthcare sector will be more coordinated, healthy lifestyles will be widely adopted, and the quality and security of healthcare services will continue to improve. Improving health resource efficiency is one of the core measures to achieve these goals, as it enhances the accessibility, equity, and sustainability of health services. This study directly responds to the policy call by providing empirical evidence on efficiency gaps and identifying areas for optimization, particularly in underdeveloped ethnic minority regions such as Guangxi. The rational

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allocation and effective utilization of health resources are crucial prerequisites for enhancing public health and promoting health equity. Improving the efficiency of health resource allocation not only contributes to the accessibility and quality of healthcare services but also plays an important role in improving the standard of living and promoting economic growth. Since the implementation of the new medical reform in 2009, China has seen a general increase in health resource inputs. Between 2010 and 2022, there was a significant rise in the number of health institutions, hospital beds, and health technical personnel, with increases of 10.24%, 103.65%, and 98.37%, respectively. However, despite the growing quantity of health resources in China, the efficiency of their allocation remains low. In particular, in the western minority region of Guangxi, recent studies have shown that the efficiency of health resource allocation is significantly lower than that of other western provinces, such as Sichuan and the Ningxia Hui Autonomous Region.[4]

The Guangxi Zhuang Autonomous Region (20°54′-26°20′ N, 104°26′-112°04′ E) is located in the western part of China. It is one of the five major ethnic minority autonomous regions in China and the only coastal minority autonomous region in the western part of the country. As an important hub of the Maritime Silk Road, it holds a unique position in the strategy of Western China's development and the nation's overall opening-up. According to the Seventh National Census, Guangxi has a population of 50.13 million, making it the most populous ethnic minority province in China. The region's terrain is complex, with mountainous areas accounting for 70.8% of its landscape, posing significant transportation challenges. It is also generally regarded as an economically underdeveloped region,[5] with a GDP of 2.63 trillion yuan in 2022, ranking 19th nationwide. Its per capita GDP is only 52,164 yuan, ranking third from the bottom in the country. In recent years, Guangxi has been focused on building health institutions to meet the health needs of its residents. While there has been significant change in the total amount of health resources in Guangxi, little is known about the efficiency of health resources within the region and its variations.

To gain a more comprehensive understanding of, and enhance, the efficiency of health resource allocation in the region, it is essential to employ rigorous quantitative methods. At the same time, recent studies have highlighted the importance of integrating efficiency evaluation with modern information technologies — such as smart healthcare systems, the Internet of Things, and artificial intelligence — to strengthen the resilience and adaptability of healthcare systems.[6–10] DEA provides a valuable approach for assessing the efficiency of health resource allocation in this context. It is particularly suitable for underdeveloped or ethnically diverse regions such as Guangxi, as it can accommodate multiple inputs and outputs without requiring a predefined production function. This flexibility is especially beneficial in heterogeneous settings where healthcare systems face diverse constraints in terms of geography, infrastructure, and population needs. In recent years, several studies have measured and analyzed healthcare efficiency from different perspectives. First, studies at the national level primarily focus on evaluating the efficiency of different countries. For example, Aydin et al[11] assessed the efficiency of healthcare services in the Organization for Economic Co-operation and Development (OECD) countries, while Top et al[12] measured the efficiency of healthcare systems in 36 African nations. Second, some scholars have investigated efficiency at the regional level within a single country. For instance, Mazon evaluated the technical efficiency of municipalities in Santa Catarina, Brazil, in terms of public health expenditure and its relationship with health management.[13] Similarly, Ngobeni assessed and compared the technical efficiency of healthcare delivery across the nine provinces of South Africa.[14] Additionally, several studies have examined the efficiency of different types of hospitals. For example, researchers have compared the efficiency of teaching and non-teaching hospitals in the United States,[15] while in Iran's southwest region, studies have analyzed the efficiency of general hospitals, specialized hospitals, and multi-specialty hospitals.[16] Similar analyses have been conducted in Saudi Arabia, comparing general hospitals, specialized hospitals, and primary healthcare centers.[17] In the case of China, Gong et al evaluated the overall and two-stage efficiency of provincial healthcare systems,[18] while Du examined the relationship between healthcare quality and efficiency across the national, eastern, central, and western regions.[19] Jing et al[20] analyzed efficiency differences between public and private hospitals in Beijing. Following China's healthcare system reforms, government agencies and scholars have paid significant attention to efficiency at the national level,[18] in developed regions,[21] and within primary healthcare services.[22] However, relatively less focus has been given to the efficiency of healthcare services in underdeveloped ethnic minority regions.

The selection of appropriate input and output indicators is crucial for meaningful analysis.[23] Most researchers choose input indicators for hospital performance evaluation based on labor and capital inputs.[18,19,24–27] The number of health institutions and hospital beds is commonly used to represent capital input.[18,19,25] For labor-related variables, health workers,[18,26] health technical workers,[19,25] physicians,[12,24] and nurses[12,24,27] are frequently considered as types of labor input. Regarding output indicators, they are generally categorized into expected and undesirable outputs. Due to data availability constraints, most studies focus on expected indicators in their analyses. Outpatient or emergency visits,[18,19,25–27] inpatient admissions or discharges,[18,19,25,27] bed turnover rate,[23,28] and medical revenue[25,29] are commonly regarded as expected outputs. In contrast, infection incidence, the number of infectious disease cases, and patient or population mortality rates[24,30] are considered undesirable outputs.

Overall, researchers have provided valuable insights into the selection of input and output indicators. However, there are still several shortcomings. First, the frequent combination of absolute and relative figures in their analyses is prevalent. For instance, numerous studies simultaneously use the bed turnover rate and the number of visits as input indicators, which is not justifiable. Second, many researchers, while focusing on the input and output efficiency of health resources, have failed to consider the influencing factors. Consequently, we have made improvements based on these studies. In the context of minority regions, this study employs the BCC-DEA model and the Malmquist index model to conduct both static and dynamic analyses of the efficiency of health resource allocation in Guangxi from 2010 to 2022. By combining the Tobit regression model, we explore the factors influencing its productivity, analyze the problems and their causes, and offer rational suggestions to provide a reference for the scientific formulation of health development plans.

# Materials and Methods

## Data Envelopment Analysis

This study employs the Data Envelopment Analysis (DEA) approach to evaluate the efficiency of resource allocation. DEA is a technique introduced by researchers like Charnes and Cooper in 1978, designed to assess the relative efficiency of Decision Making Units (DMUs) that utilize multiple inputs and outputs. Subsequently, after years of adjustments and improvements, various model types have been developed, including the CCR model and the BCC model. The difference between the two lies in the assumption that the CCR model assumes constant returns to scale (CRS), while the BCC model is suitable for variable returns to scale (VRS) situations.[31] This study employs the BCC-DEA model under variable returns to scale (VRS) and adopts an input-oriented approach. The rationale for this choice is as follows:

In this study, we adopt an input-oriented BCC-DEA model to evaluate the efficiency of health resource allocation. This choice is particularly relevant for underdeveloped or ethnically diverse regions such as Guangxi, where resource scarcity and input constraints are more critical than output expandability. First, in many healthcare systems in economically disadvantaged regions, inputs such as medical personnel, equipment, and infrastructure are limited, making input reduction and resource optimization key priorities for local governments. Second, output levels (eg, outpatient visits, bed utilization) are often influenced by external factors—such as population health needs or migration—that are harder to control in the short term. Thus, focusing on minimizing input waste provides a more stable and actionable efficiency assessment framework.

Additionally, we apply the BCC model under variable returns to scale (VRS), which is more suitable for capturing efficiency in regions with diverse healthcare system sizes and institutional capacities. Unlike the CCR model, which assumes constant returns to scale, the BCC model accommodates scale inefficiencies that are common in fragmented or unevenly developed healthcare settings. This flexibility enables us to distinguish between pure technical efficiency and scale efficiency, thereby offering more nuanced policy insights for both input management and system scaling.

The BCC-DEA model allows for the decomposition of the overall efficiency score of decision-making units into scale efficiency (SE) and pure technical efficiency (PTE) when variable returns to scale are present. The relationship among these components can be expressed as: Overall Efficiency = Pure Technical Efficiency × Scale Efficiency. In this research process, various cities of Guangxi are selected as actual decision-making units (DMUs). Assuming there are $n$ decision-making units, where $j = 1, 2, \ldots, n$, each decision-making unit has a types of input and b types of output. That is, the input quantity $X_j = (X_{1j}, X_{2j}, \ldots, X_{aj})^T$ and the output quantity $Y_j = (Y_{1j}, Y_{2j}, \ldots, Y_{bj})^T$, where $X_{ij}$ represents the input quantity of the $j$-th decision-making unit for the $i$-th input indicator, and $Y_{rj}$ represents the output quantity of the $j$-th decision-making unit for the $r$-th output indicator. The formulas are given as follows:

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$$(\text{BCC})\begin{cases} \min\theta \\ \sum_{j=1}^{n} X_{pj}\lambda_j + S^- = \theta X_0 \\ \sum_{j=1}^{n} Y_{qj}\lambda_j - S^+ = Y_0 \\ \lambda_j \geq 0, S^+ \geq 0, S^- \geq 0, j = 1, 2, \ldots, n \\ \mathrm{S}^+ \geq 0, \mathrm{S}^- \geq 0 \end{cases}$$

In the above expression, θ represents the efficiency value of DMU*j*, λ*j* denotes the weight of the decision-making unit, X*j* represents the input quantity of the *j*-th decision-making unit, Y*j* represents the output quantity of the *j*-th decision-making unit, n is the number of decision-making units, $S^+$ and $S^-$ represent the slack variables for inputs and outputs, respectively. Therefore, when evaluating the effectiveness of decision-making unit DMU*j*, corresponding results can be obtained based on the optimal solution values of the model.

(1) If θ=1, and $S^+$ and $S^-$ are both 0, it indicates that DMU*j* is in a DEA efficient state;

(2) If θ=1, and $S^+$ and $S^-$ are not both 0, it indicates that DMU*j* is in a DEA weakly efficient state;

(3) If θ<1, and $S^+$ and $S^-$ are not both 0, it indicates that DMU*j* is in a non-DEA efficient state.

To examine the robustness of the efficiency estimates, we further re-estimated the DEA scores using an output-oriented BCC model and a constant-returns-to-scale (CCR) model. The results were compared to those from the original input-oriented BCC model to assess the consistency across model specifications.

## Bootstrap and Statistical Inference

To assess the statistical precision of the DEA efficiency estimates, we employed a bias-corrected and accelerated (BCa) bootstrap approach with 2,000 resamples. This method corrects for bias and skewness in the sampling distribution, providing confidence intervals around the efficiency scores of each DMU.

Additionally, we applied the Kruskal–Wallis rank sum test to evaluate whether efficiency scores differed significantly among the 14 cities. This non-parametric test is suitable for comparing multiple independent samples when the normality assumption is not guaranteed.

## Serial Correlation Test in Panel DEA

To assess whether time-dependent structures in the data could bias the estimation of the Malmquist productivity index, we performed a serial correlation test following the bootstrap-based approach proposed by Simar and Wilson (2007). This test examines whether DEA efficiency scores in period *t* are statistically dependent on those in period *t*–1. The test was conducted using 2,000 bootstrap replications.

## Malmquist Index Model

Traditional DEA models primarily facilitate static assessments of resource allocation efficiency using cross-sectional data. However, this study spans a longer time frame, necessitating consideration of temporal variations. The Malmquist index provides a means to evaluate changes in efficiency over a specified period, reflecting the performance of decision-making units.[32] Consequently, we implemented the Malmquist Productivity Index (MPI) method to analyze panel data and illustrate dynamic shifts in efficiency. The MPI, also known as Total Factor Productivity Changes (TFPCH), is derived from the distance function and can be represented by the following mathematical equations:

$$\mathrm{MPI}_I^t = \frac{E_I^t\left(x^{t+1}, y^{t+1}\right)}{E_I^t\left(x^t, y^t\right)}, MPI_I^{t+1} = \frac{E_I^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E_I^{t+1}\left(x^t, y^t\right)}$$

To thoroughly understand the technical level during both periods, we took into account the geometric mean:

$$MPI_I^G = \left(MPI_I^t MPI_I^{t+1}\right)^{\frac{1}{2}} = \left[\frac{E_I^t\left(x^{t+1}, y^{t+1}\right)}{E_I^t\left(x^t, y^t\right)} \times \frac{E_I^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E_I^{t+1}\left(x^t, y^t\right)}\right]^{\frac{1}{2}}$$

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The productivity function can be categorized into input-oriented efficiency change (EFFCH) and technical change (TECHCH). Additionally, efficiency change can be further broken down into scale efficiency change (SECH) and pure efficiency change(PECH).

$$MPI_I^G = (EFFCH_I) \times \left(TECHCH_I^G\right) = \frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \times [\frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \times \frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^t, y^t)}]^{\frac{1}{2}}$$

$$SECH = [\frac{E_{vrs}^{t+1}\left(x^{t+1}, y^{t+1}\right)/E_{crs}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E_{vrs}^{t+1}(x^t, y^t)/E_{crs}^{t+1}(x^t, y^t)} \times \frac{E_{vrs}^{t}\left(x^{t+1}, y^{t+1}\right)/E_{crs}^{t}\left(x^{t+1}, y^{t+1}\right)}{E_{vrs}^{t}(x^t, y^t)/E_{crs}^{t}(x^t, y^t)}]^{\frac{1}{2}}$$

$$PECH = \frac{E_{vrs}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E_{crs}^{t+1}(x^t, y^t)}$$

## Tobit Regression

Given that the overall efficiency value is a restricted dependent variable and is categorized into different stages, we employed the Tobit regression model to mitigate biases associated with the least squares regression method. Introduced in 1958, Tobit regression utilizes the maximum likelihood approach to randomly select n groups of samples for estimating maximum probabilities.[33] In our analysis, we treated the overall efficiency value from the DEA model as the dependent variable, while the influencing factors were designated as independent variables. The Tobit models are as follows:

$$Y_i = \beta_0 + \sum_{n=1}^{n} (\beta_i X_i + \mu, i = \ 1,\ 2, \ldots, \ \mathrm{n})$$

where $Yi^*$ represents the dependent variable, $Xi$ denotes the explanatory variable, and $\beta i$ is the coefficient associated with the explanatory variable, where, $i$ = 1, 2, …, n.

To ensure model validity, we reported diagnostic statistics including the log-likelihood, pseudo-$R^2$, and conducted a likelihood-ratio test for heteroskedasticity. The left-truncation point was set at 0 to reflect the lower bound of DEA efficiency scores. However, to address the potential limitations of the Tobit model—particularly issues related to endogeneity and bias from censoring at the boundaries—we further adopted a two-stage bootstrap truncated regression approach, following Simar and Wilson (2007). This method corrects for bias and provides consistent estimators of the relationship between efficiency scores and their determinants. The first stage involves estimating DEA efficiency scores, while the second stage applies truncated regression with bias-corrected bootstrap confidence intervals based on 2,000 replications. This approach allows for more robust inference and minimizes the risk of misleading conclusions due to serial dependence or data truncation.

## Data Resources and Regional Division

Demographic, economic, and geographic data were gathered from the Guangxi Statistical Yearbook for the years 2011 to 2023. Information regarding health resources was extracted from the Guangxi Health Statistics Yearbook covering the same period. It is important to mention that the data presented in each year's edition of the yearbook reflects figures from the preceding year. Guangxi province consists of 14 cities, According to the geographical position and the level of the GDP per capita, all the 14 cities were divided into three groups: Northern, Middle and Southern regions. The Northern region included Liuzhou, Guilin, Hechi, Baise. The Middle region included Hezhou, Wuzhou, Laibin, Guigang, Yulin. The Southern region included Nanning, Chongzuo, Qinzhou, Beihai, Fangchenggang.

Data analysis: Statistical analyses were conducted using STATA 18 and SPSS 24 software. All tests were performed at a 5% significance level ($p < 0.05$).

As the study relied on secondary data, there was no need for direct involvement from patients or the public.

## Input and Output Variables

The efficiency indicators were chosen based on the literature previously reviewed[18,19,25–27] and to ensure the credibility of the results (the total of input and output indicators should not exceed the total value of the DMU).[11] While the bed turnover rate is commonly used in China, some studies have noted the inappropriate mixing of absolute and relative figures,[23] leading this research to exclude that indicator. Additionally, since DEA focuses on efficiency, this study does not incorporate quality metrics such as mortality and cure rates. For input indicators, we selected health technical personnel, the number of medical institutions, and actual beds to represent human resources and capital. As for output indicators, we chose the total number of visits and discharges to capture both outpatient and inpatient services (Table 1).

To ensure that the selected input and output variables are theoretically sound and statistically valid, we conducted a Pearson correlation analysis and a principal component analysis (PCA). Table S1 presents Pearson correlation coefficients among the five variables, all of which are statistically significant at the 1% level. Furthermore, the PCA was conducted to explore the internal structure of the variables and avoid redundancy. The Kaiser-Meyer-Olkin (KMO) measure was 0.826, and Bartlett's Test of Sphericity was significant ($\chi^2 = 1412.20$, $p < 0.001$), indicating sampling adequacy (Table S2). As shown in Table S3, the first principal component explained 86.15% of the total variance, with all five variables loading highly on this component (Table S4). These results confirm that the variables share common structure and are appropriate for inclusion in a unified DEA model.

## Explanatory Variables Affecting Efficiency

The literature indicates that the factors influencing the efficiency of health resource allocation can be categorized into four main aspects: economic, demographic, social, and policy-related factors.[3,34–37] Economic factors primarily include regional economic development levels, per capita disposable income, the degree of healthcare marketization, etc. Demographic factors mainly encompass population size and structure, urban-rural distribution, the scale of the floating population, etc. Social factors involve education levels, healthcare service demand, medical technology levels, etc. Policy-related factors include government health policies, health insurance systems, the proportion of health expenditure, etc.

After reviewing the literature, we identified candidate variables based on data availability. Subsequently, two rounds of expert consultations were conducted to discuss which explanatory variables should be selected from the candidate variables. Economic factors were represented by per capita GDP (measured as real per capita GDP to reflect the level of economic development, calculated as the ratio of the actual GDP of each city to its population, adjusted using the base-year CPI) and residents' income levels (measured as the annual per capita disposable income in different regions). Second, population factors were captured by population density (measured as the number of people per square kilometer of land area) and urbanization rate (measured as the percentage of the urban population relative to the total population). Third, social factors were reflected in education level (measured as the proportion of primary and secondary school graduates in the total population) and the proportion of health technical workers (measured as the ratio of health technical workers to total health personnel). Finally, policy factors were represented by the number of people enrolled in basic medical insurance and the proportion of government health expenditures in total fiscal spending. Statistical descriptions of these variables are presented in Table 1.

# Results

## Descriptive Analysis

Table 2 shows that from 2010 to 2018, the total number of visits and beds in Guangxi Province exhibited an upward trend year by year. The number of institutions increased annually from 2010 to 2017, dropped sharply from 2018 to 2020, and then increased slowly from 2021 to 2022. The number of health technical personnel increased year by year from 2013 to 2022, with a notable decrease from 2011 to 2012. The number of discharges from hospitals increased annually from 2010 to 2022, but deviated from this trend in 2021.

**Table 1** Summary Statistics of the Variables

| Type | Variable | Unit | Mean | Min | Max |
|---|---|---|---|---|---|
| Input | Number of health technical personnel | Person | 21,232.47 | 3,879.00 | 89,952.00 |
| | Number of beds | Quantity | 16,576.51 | 2,351.00 | 63,252.00 |
| | Number of institutions | Quantity | 2,134.35 | 107.00 | 5,441.00 |
| Output | Total number of visits | Per 10,000 | 760.88 | 119.65 | 2,699.50 |
| | Number of discharges | Per 10,000 | 41.77 | 5.59 | 198.81 |
| Influencing Factor | Population density(pd) | person/sq.km | 244.01 | 98.40 | 487.17 |
| | Education level(el) | % | 3.46 | 1.96 | 4.73 |
| | Urbanization rate(ur) | % | 50.73 | 36.27 | 78.58 |
| | Proportion of health technical workers(pht) | % | 75.45 | 56.01 | 84.60 |
| | Government health expenditure(pgeh) | % | 11.54 | 6.46 | 15.31 |
| | PGDP | Yuan | 44,830.33 | 17,841.00 | 91,505.00 |
| | Residents' income levels(ril) | Yuan | 23,179.88 | 12,033.00 | 34,110.00 |
| | Number of participants in basic medical insurance(npbmi) | Person | 2,942,916.00 | 302,592.00 | 7,470,694.00 |

**Table 2** Descriptive Statistics of Inputs and Outputs

| Year | Items | Input | | | Output | |
|---|---|---|---|---|---|---|
| | | $I_1$ | $I_2$ | $I_3$ | $O_1$ | $O_2$ |
| 2010 | Mean | 1,292 | 10,295.286 | 16,604.643 | 432.758 | 20.878 |
| | Max | 3,073 | 28,184 | 37,873 | 1,341.202 | 54.575 |
| | Min | 232 | 2,351 | 4,388 | 119.647 | 5.585 |
| 2011 | Mean | 1,616 | 10,860.929 | 14,244.429 | 460.356 | 23.275 |
| | Max | 4,409 | 28,821 | 40,696 | 1,445.907 | 63.58 |
| | Min | 124 | 2,573 | 3,879 | 128.777 | 6.392 |
| 2012 | Mean | 1,953.929 | 12,017.429 | 15,698.929 | 515.467 | 27.696 |
| | Max | 5,372 | 31,945 | 44,891 | 1,582.427 | 73.205 |
| | Min | 122 | 2,811 | 4,259 | 142.286 | 7.339 |
| 2013 | Mean | 2,005.071 | 13,152.786 | 17,186.214 | 553.717 | 31.322 |
| | Max | 5,441 | 34,052 | 49,567 | 1,675.727 | 79.918 |
| | Min | 123 | 3,164 | 4,625 | 150.268 | 8.611 |
| 2014 | Mean | 2,091.357 | 14,425.929 | 18,472.714 | 594.405 | 34.138 |
| | Max | 5,256 | 37,362 | 53,486 | 1,796.083 | 87.574 |
| | Min | 123 | 3,719 | 5,141 | 144.23 | 9.918 |
| 2015 | Mean | 2,095.143 | 15,320.357 | 19,618.786 | 621.613 | 35.678 |
| | Max | 5,311 | 41,055 | 57,403 | 1,862.734 | 94.406 |
| | Min | 107 | 3,955 | 5,282 | 154.835 | 10.019 |
| 2016 | Mean | 2,252.571 | 16,050.714 | 20,704.643 | 663.52 | 37.876 |
| | Max | 5,250 | 43,093 | 61,224 | 2,011.134 | 101.78 |
| | Min | 214 | 3,928 | 5,593 | 176.824 | 9.671 |
| 2017 | Mean | 2,429.429 | 17,193.786 | 21,808.286 | 703.3 | 40.683 |
| | Max | 5,042 | 47,101 | 65,544 | 2,125.471 | 108.538 |
| | Min | 670 | 3,907 | 5,772 | 197.349 | 9.806 |
| 2018 | Mean | 2,410.143 | 18,281.429 | 22,921.857 | 727.355 | 43.192 |
| | Max | 4,887 | 50,676 | 69,125 | 2,222.53 | 115.18 |
| | Min | 684 | 4,033 | 5,976 | 196.6 | 12.516 |
| 2019 | Mean | 2,280.286 | 19,519.143 | 24,384.143 | 1,050.35 | 54.573 |
| | Max | 4,830 | 54,347 | 74,625 | 2,350.006 | 160.411 |
| | Min | 552 | 4,182 | 6,280 | 347.22 | 16.483 |

(*Continued*)

**Table 2** (Continued).

| Year | Items | Input | | | Output | |
|---|---|---|---|---|---|---|
| | | $I_1$ | $I_2$ | $I_3$ | $O_1$ | $O_2$ |
| 2020 | Mean | 2,419.714 | 21,179.571 | 26,587.143 | 1,085.9 | 60.219 |
| | Max | 4,969 | 56,751 | 80,141 | 2,322 | 164.61 |
| | Min | 661 | 4,735 | 6,620 | 344.5 | 13.889 |
| 2021 | Mean | 2,436.571 | 22,788.929 | 28,134.643 | 1,214.119 | 53.905 |
| | Max | 4,960 | 60,576 | 85,462 | 4,277.22 | 132.18 |
| | Min | 673 | 4,899 | 6,938 | 393.11 | 13.175 |
| 2022 | Mean | 2,464.286 | 24,408.286 | 29,655.643 | 1,544.219 | 79.526 |
| | Max | 5,091 | 63,252 | 89,952 | 2,699.5 | 198.81 |
| | Min | 648 | 5,420 | 7,380 | 431.519 | 14.44 |

**Notes**: I1: Institutions; I2: Beds;I3: Health technical personnel; O1: Total number of visits; O2: Number of discharges.

## The Efficiency of Health Resource Allocation in Guangxi

This study employs the BCC-DEA model to measure the efficiency of health resource allocation in 14 cities in Guangxi from 2010 to 2022 (Table 3). The average overall efficiency score of the sample is 0.675, which does not meet DEA effectiveness, indicating that these regions still have varying degrees of room for improvement. From a temporal perspective, the overall efficiency score shows an upward trend from 2010 to 2022, increasing from 0.558 in 2010 to 0.879 in 2022. From a regional perspective, the average overall efficiency scores across different cities range from 0.530 to 0.789, with Qinzhou having the highest score (0.789). The cities that need the most improvement in resource allocation efficiency are Wuzhou (0.530), Yulin (0.590), and Hezhou (0.604).

Overall efficiency can be decomposed into technical efficiency and scale efficiency. From the perspective of the pure technical efficiency index, the average pure technical efficiency of health resources across Guangxi's cities was 0.646 in 2010 and increased to 0.912 in 2022, reflecting a rise of 0.265 over time. From a regional perspective, the number of regions achieving DEA effectiveness in pure technical efficiency is lower than that in scale efficiency. Regarding the scale efficiency index, the average scale efficiency of health resources across Guangxi's cities was 0.879 in 2010 and increased to 0.962 in 2022, consistently exceeding the average pure technical

**Table 3** Efficiency Values of the 14 Regions in Guangxi in 2010–2022

| Regions | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Nanning | 0.533 | 0.609 | 0.652 | 0.664 | 0.687 | 0.685 | 0.633 | 0.622 | 0.616 | 0.803 | 0.791 | 0.601 | 0.868 | 0.674 |
| Liuzhou | 0.522 | 0.544 | 0.601 | 0.631 | 0.640 | 0.625 | 0.644 | 0.695 | 0.728 | 0.735 | 0.940 | 0.738 | 1.000 | 0.696 |
| Guilin | 0.543 | 0.569 | 0.573 | 0.584 | 0.609 | 0.606 | 0.616 | 0.652 | 0.681 | 0.700 | 0.686 | 0.663 | 0.856 | 0.641 |
| Wuzhou | 0.503 | 0.510 | 0.569 | 0.619 | 0.621 | 0.588 | 0.605 | 0.635 | 0.622 | 0.701 | 0.878 | 0.610 | 0.871 | 0.641 |
| Beihai | 0.456 | 0.472 | 0.485 | 0.536 | 0.496 | 0.468 | 0.475 | 0.522 | 0.504 | 0.640 | 0.712 | 0.452 | 0.673 | 0.530 |
| Qinzhou | 0.773 | 0.813 | 0.923 | 1.000 | 0.827 | 1.000 | 0.831 | 0.523 | 0.523 | 0.937 | 0.552 | 0.555 | 1.000 | 0.789 |
| Guigang | 0.683 | 0.565 | 0.593 | 0.605 | 0.663 | 0.648 | 0.649 | 0.648 | 0.654 | 1.000 | 0.907 | 0.551 | 0.921 | 0.699 |
| Yulin | 0.462 | 0.500 | 0.566 | 0.569 | 0.573 | 0.553 | 0.570 | 0.563 | 0.571 | 0.610 | 0.580 | 0.549 | 1.000 | 0.590 |
| Baise | 0.586 | 0.589 | 0.689 | 0.687 | 0.708 | 0.724 | 0.678 | 0.679 | 0.650 | 0.823 | 0.982 | 0.879 | 0.864 | 0.734 |
| Hezhou | 0.432 | 0.561 | 0.558 | 0.539 | 0.564 | 0.614 | 0.647 | 0.636 | 0.628 | 0.597 | 0.553 | 0.584 | 0.937 | 0.604 |
| Hechi | 0.651 | 0.720 | 0.573 | 0.624 | 0.646 | 0.669 | 0.681 | 0.670 | 0.662 | 0.624 | 0.641 | 0.662 | 1.000 | 0.679 |
| Laibin | 0.448 | 0.752 | 0.832 | 0.912 | 0.879 | 0.807 | 0.854 | 0.526 | 0.544 | 0.751 | 0.859 | 0.893 | 0.913 | 0.767 |
| Chongzuo | 0.585 | 0.594 | 0.737 | 0.627 | 0.632 | 0.601 | 0.613 | 0.615 | 0.623 | 0.952 | 0.827 | 0.760 | 0.691 | 0.681 |
| Fangchenggang | 0.640 | 0.609 | 0.698 | 0.674 | 0.674 | 0.647 | 0.625 | 0.632 | 0.783 | 1.000 | 0.761 | 1.000 | 0.707 | 0.727 |
| Mean | 0.558 | 0.600 | 0.646 | 0.662 | 0.659 | 0.660 | 0.651 | 0.616 | 0.628 | 0.777 | 0.762 | 0.678 | 0.879 | 0.675 |

efficiency of health resources. From a regional perspective, the scale efficiency values of all cities remain below 1 (Tables S5 and S6).

Table S7, most cities operated under increasing returns to scale (IRS) throughout the study period, while very few reached constant returns to scale (CRS). This pattern indicates that the majority of decision-making units had not yet attained their optimal operational scale. To test the robustness of the efficiency scores, we estimated alternative models using output-oriented BCC and input-oriented CCR assumptions. The results remained identical across all models (Table S8), indicating strong consistency and confirming the reliability of the original input-oriented findings.

## Bootstrap Confidence Intervals and Inter-City Comparisons

Table S9 presents the bias-corrected and accelerated (BCa) bootstrap confidence intervals for the DEA efficiency scores of each city. The results show moderate variation in the lower and upper bounds across cities, suggesting differences in score reliability. To further test the significance of inter-city differences, we conducted a Kruskal–Wallis rank sum test. The test yielded a significant result ($\chi^2 = 56.521$, df = 13, $p < 0.001$), indicating that efficiency levels vary significantly among the 14 cities (Table S10).

## The Input-Output Optimization Plan for the Allocation of Regional Health Resource

In the BCC model, we also assessed the projected values for the input and output indicators of the inefficient regions (Table 4). To enhance the efficiency of health resource allocation, these regions should either reduce their inputs or boost their outputs.

**Table 4** Variation of Inputs and Outputs Needed to Be Adjusted in 2022

| Regions | | $O_1$ | $O_2$ | $I_1$ | $I_2$ | $I_3$ |
|---|---|---|---|---|---|---|
| Nanning | Actual value | 2,699.50 | 198.81 | 5,091.00 | 63,252.00 | 89,952.00 |
| | Projection value | 4,580.22 | 198.81 | 5,091.00 | 64,320.31 | 82,738.36 |
| | Insufficient or redundancy value | 1,880.72 | 0.00 | 0.00 | −1,068.31 | −7,213.64 |
| | Insufficient or redundant rate (%) | 69.70 | 0.00 | 0.00 | −1.69 | −8.02 |
| Guilin | Actual value | 2,429.44 | 100.57 | 4,895.00 | 29,764.00 | 43,628.00 |
| | Projection value | 2,429.44 | 105.45 | 2,516.59 | 29,764.00 | 39,346.81 |
| | Insufficient or redundancy value | 0.00 | 4.88 | −2,378.41 | 0.00 | −4,281.20 |
| | Insufficient or redundant rate (%) | 0.00 | 4.86 | −48.59 | 0.00 | −9.81 |
| Wuzhou | Actual value | 1,554.22 | 59.76 | 1,707.00 | 19,145.00 | 23,424.00 |
| | Projection value | 1,554.22 | 66.22 | 1,707.00 | 18,585.49 | 23,424.00 |
| | Insufficient or redundancy value | 0.00 | 6.46 | 0.00 | −559.51 | 0.00 |
| | Insufficient or redundant rate (%) | 0.00 | 10.81 | 0.00 | −2.92 | 0.00 |
| Beihai | Actual value | 828.92 | 26.78 | 1,075.00 | 10,819.00 | 14,300.00 |
| | Projection value | 828.92 | 35.98 | 904.66 | 10,819.00 | 14,258.04 |
| | Insufficient or redundancy value | 0.00 | 9.20 | −170.34 | 0.00 | −41.96 |
| | Insufficient or redundant rate (%) | 0.00 | 34.33 | −15.85 | 0.00 | −0.29 |
| Fangchenggang | Actual value | 431.52 | 14.44 | 648.00 | 5,420.00 | 7,380.00 |
| | Projection value | 431.52 | 18.73 | 455.78 | 5,420.00 | 7,153.70 |
| | Insufficient or redundancy value | 0.00 | 4.29 | −192.22 | 0.00 | −226.30 |
| | Insufficient or redundant rate (%) | 0.00 | 29.72 | −29.66 | 0.00 | −3.07 |
| Laibin | Actual value | 1,022.10 | 47.37 | 1,443.00 | 15,034.00 | 15,596.00 |
| | Projection value | 1,022.10 | 47.37 | 1,443.00 | 14,399.34 | 15,596.00 |
| | Insufficient or redundancy value | 0.00 | 0.00 | 0.00 | −634.66 | 0.00 |
| | Insufficient or redundant rate (%) | 0.00 | 0.00 | 0.00 | −4.22 | 0.00 |
| Chongzuo | Actual value | 767.95 | 28.93 | 1,212.00 | 11,225.00 | 14,445.00 |
| | Projection value | 767.95 | 32.81 | 1,069.00 | 11,225.00 | 14,445.00 |
| | Insufficient or redundancy value | 0.00 | 3.88 | −143.00 | 0.00 | 0.00 |
| | Insufficient or redundant rate (%) | 0.00 | 13.40 | −11.80 | 0.00 | 0.00 |

**Notes**: Positive number represents insufficient rate, negative number represents redundancy rate.

Since the study covers a long time span, the latest data from 2022 is used as an example. For instance, the input-output projection analysis for Nanning reveals that to achieve a more optimal allocation of resources, the region could decrease its average health personnel count by 7,213.64 and the average number of beds by 1,068.31, while maintaining current output levels. Alternatively, Nanning could aim to increase outpatient and emergency visits by 1,880.72 without altering its present input levels.

## Serial Correlation Test for Panel DEA

Prior to Malmquist index estimation, we conducted a serial correlation test to assess whether time-dependent bias might affect the efficiency scores. Specifically, the Simar–Wilson (2007) bootstrap-based approach was applied using 2,000 replications to test the lag-1 correlation of DEA scores. As shown in Table S11, the test revealed no statistically significant serial correlation (mean lag-1 correlation = 0.256, p = 0.1284), suggesting that the use of the conventional Malmquist index is appropriate.

## The Productivity of Health Resource Allocation in Guangxi

The MPI of annual means was utilized to analyze productivity changes from 2010 to 2022, as presented in Table 5. The geometric mean of TFPCH stood at 1.046, signifying a 4.6% increase in the productivity of health resource allocation in Guangxi Province over the period from 2010 to 2022. Further delving into the reasons behind this increase, it was primarily attributed to a 4.2% rise in TECHCH. As for EFFCH, it exhibited a modest 0.4% growth, which was solely due to a corresponding 0.4% increase in PECH (Pure Efficiency Change, referring to changes in the efficiency of resource utilization without changes in technology). The year with the highest TFPCH was 2018–2019 (1.137), and the year with the lowest TFPCH was 2016–2017 (0.918).

Similarly, as shown in Figure 1, the TFPCH rate exhibits two peaks and one trough. The peaks occurred during 2018–2019 and 2021–2022, while the trough was observed during 2016–2017. The TECHCH index exhibited substantial variation, especially declines in 2015–2017 and 2020–2021, suggesting that stagnation or regression in technological advancement had a more pronounced effect on productivity dynamics. Figure 2 depicts the annual average value of the Malmquist index for 14 cities from 2010 to 2022. Among these cities, only Qinzhou has a TFPCH less than 1, while Yulin boasts the highest total factor productivity rate of 1.081. However, the EFFCH value of 5 cities fell below 1, and the PECH and SECH values of 4 cities were also less than 1.

**Table 5** Malmquist Index Analysis of Regional Health Resource Efficiency

| Year | EFFCH | TECHCH | PECH | SECH | TFPCH |
|---|---|---|---|---|---|
| 2010–2011 | 1.064 | 1.092 | 1.051 | 1.013 | 1.162 |
| 2011–2012 | 0.968 | 1.080 | 0.977 | 0.991 | 1.046 |
| 2012–2013 | 1.035 | 0.978 | 1.017 | 1.018 | 1.013 |
| 2013–2014 | 1.004 | 0.991 | 1.011 | 0.993 | 0.995 |
| 2014–2015 | 0.997 | 1.017 | 1.001 | 0.996 | 1.015 |
| 2015–2016 | 1.020 | 0.942 | 1.014 | 1.006 | 0.960 |
| 2016–2017 | 0.978 | 0.938 | 0.982 | 0.996 | 0.918 |
| 2017–2018 | 0.989 | 1.016 | 0.981 | 1.008 | 1.004 |
| 2018–2019 | 0.912 | 1.508 | 0.936 | 0.974 | 1.375 |
| 2019–2020 | 0.949 | 1.000 | 0.973 | 0.975 | 0.949 |
| 2020–2021 | 0.963 | 0.989 | 0.956 | 1.007 | 0.952 |
| 2021–2022 | 1.197 | 1.053 | 1.063 | 1.029 | 1.261 |
| Mean | 1.004 | 1.042 | 1.004 | 1.000 | 1.046 |

**Abbreviations**: EFFCH, technical efficiency change; TECHCH, technical progress index change; PECH, pure technical efficiency change; SECH, scale efficiency change; TFPCH, total factor productivity change.

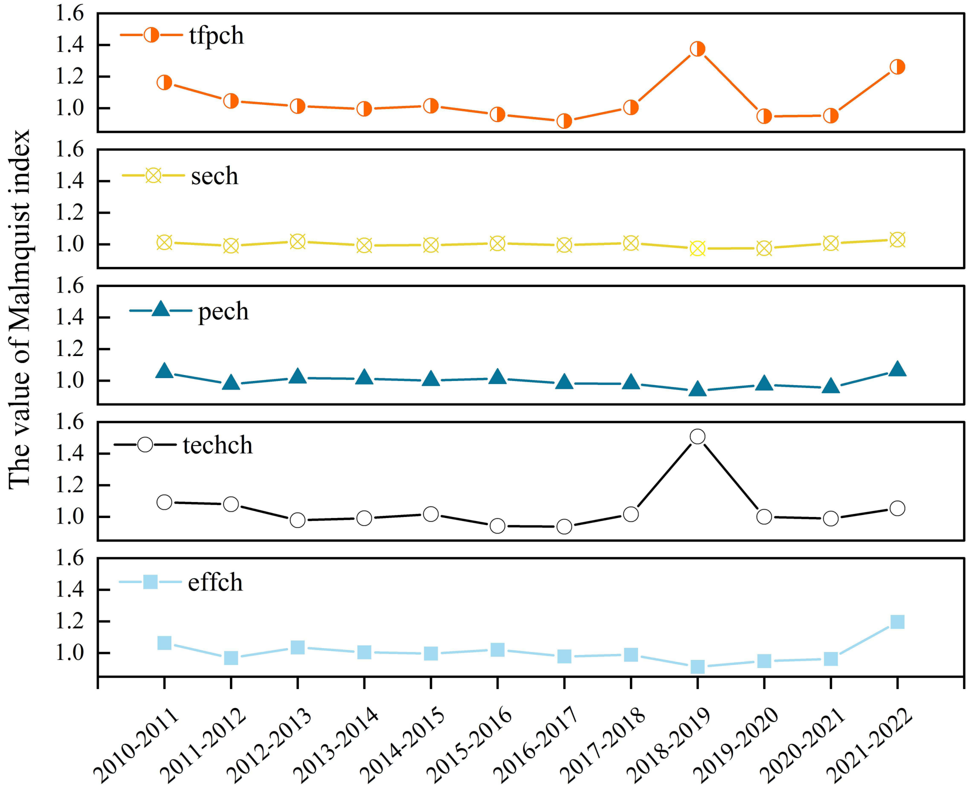


**Figure 1** Interannual analysis of regional health resource efficiency.

## Tobit Analysis of Health Resource Allocation

The Tobit regression results indicate that residents' income levels (β = 0.252, 95% CI = 0.000–0.505) and education levels (β = 5.538, 95% CI = 0.764–10.312) are positively associated with efficiency, both significant at the 5% level. In addition, population density (β = –0.0005, 95% CI = –0.0007 – –0.0002) and the proportion of government health expenditure (β = 0.011, 95% CI = 0.0039–0.0173) show statistically significant associations at the 1% level, with population density negatively and health expenditure positively influencing efficiency (Table 6).

However, to address potential biases arising from the bounded nature of DEA efficiency scores and the possible endogeneity of explanatory variables, a two-stage bootstrap truncated regression was also conducted, as shown in Tables S12 and S13. Results from this more robust method confirmed the significance of residents' income level, population density, and the proportion of government health expenditure, while the previously significant effect of education level was no longer statistically supported. This discrepancy highlights the importance of using bias-corrected methods to ensure the reliability of inferences drawn from efficiency analyses. All other variables were not significantly associated with the efficiency of health resource allocation in both the Tobit and the two-stage bootstrap truncated regression models ($p > 0.05$).

# Discussion

In general, due to the increase of population and the increase of demand for health services, the allocation of health resources in Guangxi is also increasing year by year. In response to the WHO's requirement that everyone have access to basic health services, China has carried out a number of comprehensive healthcare reforms since 2009, including enhancing the efficiency of health resource allocation to increase people's access to health services. This study calculated the effective allocation of health resources in Guangxi minority provinces from 2010 to 2022, which can explain the effect of the health system reform started in 2009 to a certain extent, and also provide some suggestions for future health system reform. Furthermore, Guangxi is located in the west, which is the province with the largest population of the five major ethnic minority areas in China, so it is representative to choose Guangxi as the sample for analysis.

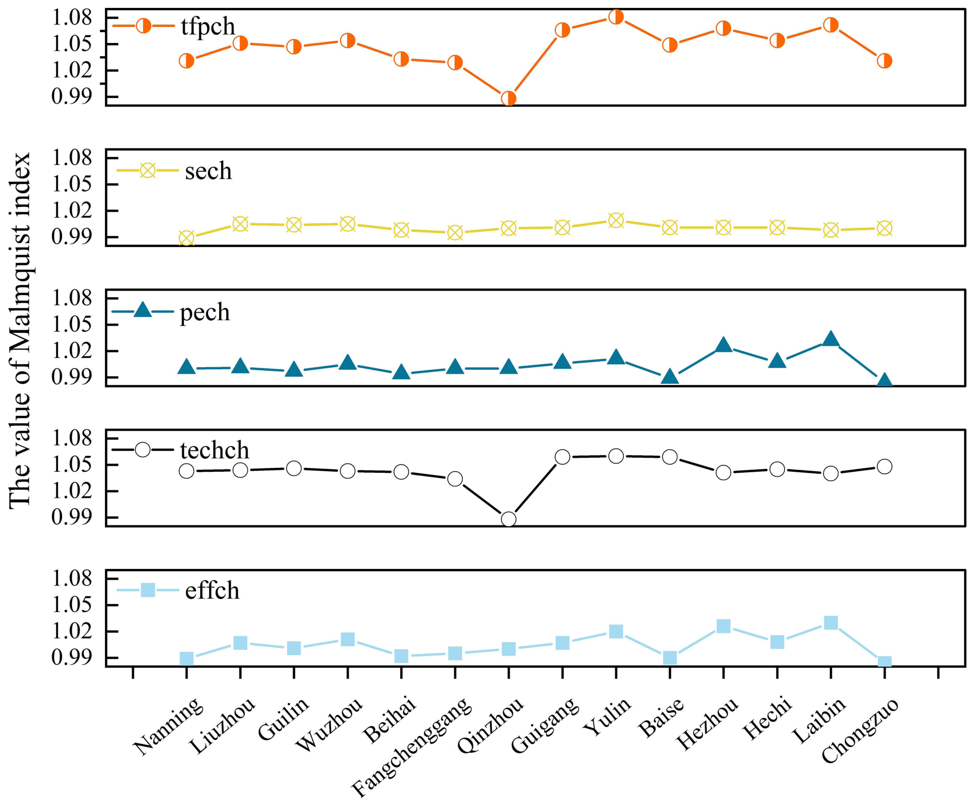


**Figure 2** Analysis on the efficiency of regional health resources at the city level.

A well-functioning health service system is often characterized by its high efficiency. Based on the Malmquist index, the average total factor productivity change (TFPCH) for health resource allocation efficiency in Guangxi from 2010 to 2022 exceeded 1, suggesting a positive trend in productivity. The TFPCH can be decomposed into two main components: technical efficiency change (EFFCH) and technological change (TECHCH). Furthermore, EFFCH can be further divided into pure technical efficiency change (PECH) and scale efficiency change (SECH). As illustrated in Figure 1, the increase in TFPCH observed in this study is attributed to improvements in both EFFCH and TECHCH, as both indicators

**Table 6** Tobit Regression Analysis of the Allocation Efficiency of Health Resources (N=112)

| Variable | Coefficient | Std. err | t | P>\|t\| | [95% conf. interval] |
|---|---|---|---|---|---|
| ln_pgdpi | −0.0868 | 0.0623 | −1.39 | 0.167 | −0.2104 ~ 0.0368 |
| ln_ril | 0.2524 | 0.1271 | 1.99 | 0.050** | 0.0005 ~ 0.5045 |
| pd | −0.0005 | 0.0001 | −3.90 | 0.000*** | −0.0007 ~ −0.0002 |
| ur | 0.0016 | 0.0022 | 0.74 | 0.459 | −0.0027 ~ 0.0059 |
| ln_npbmii | −0.0233 | 0.0182 | −1.28 | 0.203 | −0.0595 ~ 0.0128 |
| pgeh | 0.0106 | 0.0033 | 3.14 | 0.002*** | 0.0039 ~ 0.0173 |
| el | 5.5382 | 2.4073 | 2.30 | 0.023** | 0.7643 ~ 10.3120 |
| phtx | 0.2065 | 0.3303 | 0.62 | 0.533 | −0.4486 ~ 0.8615 |
| Constant | −0.8856 | 0.8129 | −1.09 | 0.278 | −2.4976 ~ 0.7264 |
| Log-likelihood | 61.2152 | | | | |
| *LR* - $\chi^2$ | 49.34 | | | | |
| *Prob* > $\chi^2$ | 0.000 | | | | |

**Note**: ln: Natural logarithm; ** $p < 0.01$, *** $p < 0.001$. The Tobit model is left-censored at 0, reflecting the bounded nature of DEA efficiency scores (0–1). Log-likelihood = 61.2152; LR $\chi^2$ = 49.34 ($p < 0.001$). Pseudo $R^2$ = 0.251. The LR test for heteroskedasticity was conducted, with $\chi^2$ = 6.72, p = 0.567.

remained above 1 during the study period. This suggests progress not only in the management and organization of health resources but also in the technological capabilities of the healthcare system in Guangxi. The findings highlight the urgency of enhancing technological advancement and innovation within the health sector.[38] Research has shown that such improvements may be linked to factors such as the education level of healthcare professionals and the utilization of medical services.[39] Additionally, Our study shows that the growth in EFFCH is primarily driven by gains in PECH. In contrast, SECH emerges as a limiting factor, indicating that the scale of operation in some regions may not be optimal. Therefore, to further improve the efficiency of health resource allocation and support the sustainable development of health services, Guangxi and its municipalities should prioritize technological innovation and optimize scale efficiency. Strengthening the service capacity of primary healthcare institutions, fostering collaboration across different levels of medical facilities, and improving training and incentive mechanisms for healthcare personnel are essential steps in this direction.[40]

The DEA efficiency analysis results indicate that the average efficiency score of health resource allocation in Guangxi from 2010 to 2022 was 0.675. This score exceeds that of Bratislava (0.564), Saudi Arabia (0.624), and Turkmenistan (0.639),[41] as well as Australia (0.588) and Denmark (0.629).[42] However, it remains lower than that of Spain (1.016), Taiwan, China (0.973), and Changsha, China (1.000).[43] Furthermore, when benchmarked against domestic minority or less-developed provinces using similar DEA approaches, Guangxi's average efficiency score (0.675) is comparable to Inner Mongolia (0.690)[4] and Qinghai (0.708),[44] but higher than Xinjiang (0.590).[4] These comparisons suggest that Guangxi's performance is not uniquely low, but rather reflects a broader pattern of resource allocation challenges faced by western and ethnic minority regions in China. This pattern is also consistent with findings from rural regions in other middle-income countries, such as Brazil, South Africa, and Indonesia, where geographic disparities and infrastructure constraints have similarly hindered efficient resource allocation.[45–47] These parallels further reinforce the relevance of Guangxi's experience to global health system reform discussions in resource-constrained settings. Notably, in 2022, only 28.57% of regions in Guangxi achieved high efficiency in health resource allocation, while more than 70% were found to be relatively inefficient. This underlines the structural and regional disparities that continue to hinder the optimal utilization and spatial distribution of health resources in the region. Improvements are needed in the efficiency of resource utilization and the rational planning of regional health resource distribution.[48] In remote areas, residents may have limited access to high-quality healthcare services, leading to deteriorating health conditions and increased medical demand. At the same time, some resources may be underutilized, resulting in wasted or misallocated medical resources. From the decomposition of overall efficiency, it is evident that pure technical efficiency has not reached an optimal level. This may be due to the misallocation of health human resources, preventing the full utilization of technical capabilities, as well as the irrational distribution of medical equipment, resulting in low utilization rates.[49] Scale efficiency in health resource allocation reflects whether resource supply is at an optimal scale. Our study indicates that scale efficiency is also below 1, which could be attributed to several factors. First, in some regions, the size of medical institutions may be either too large or too small, leading to a mismatch between the supply of health resources and actual demand. Second, there is an excessive reliance on large hospitals, while the service capacity of primary healthcare institutions remains insufficiently developed. This imbalance results in a significant patient influx into large hospitals, while primary institutions remain underutilized. Finally, disparities in economic development across Guangxi contribute to inefficiencies in resource allocation. High-quality medical resources are often concentrated in economically developed cities, whereas underdeveloped regions suffer from inadequate healthcare infrastructure and service capacity, ultimately reducing the overall efficiency of health resource allocation. These findings are consistent with the conclusions of Zheng D's study.[50] Although the scale efficiency scores were, on average, higher than the pure technical efficiency scores, the dominance of IRS among DMUs suggests that scale inefficiency remains a persistent and structural issue in the regional healthcare system. The analysis of predicted input-output values indicates that relatively low efficiency in health resource allocation is primarily observed in economically disadvantaged areas of Guangxi, such as Beihai and Chongzuo, which may be related to local economic development. The analysis of predicted output indicators reveals significant potential for improvement in both the total number of visits and the number of discharges, with the latter showing particularly substantial room for enhancement. Before the government decides to reduce health resources or expand health services to improve allocation efficiency, further investigation into the factors influencing health resource allocation efficiency is crucial.[43]

Studies have suggested that health resources in economically disadvantaged areas may be better utilized, potentially improving efficiency.[41] The Tobit regression results of this study indicate that per capita GDP does not have a significant impact on health resource allocation efficiency. This finding is consistent with the study by Zhong K et al, who attributed it to the guiding role of government policies and the implementation of healthcare reform, which have helped narrow the regional disparities in health resource allocation.[36] Therefore, the impact of regional economic levels on resource allocation efficiency appears to be relatively limited. However, our results show that per capita disposable income has a positive effect on resource allocation efficiency, which aligns with the findings of Gong J.[3] Residents' purchasing power directly affects healthcare demand and utilization. Individuals with higher disposable income are more likely to seek regular medical care and health check-ups, thereby increasing the utilization of health resources. Additionally, they tend to have greater health awareness and are more willing to invest in their well-being. However, our study indicates that the urbanization rate does not have a significant impact on the efficiency of health resource allocation, possibly due to mismatches between the supply and demand of medical resources and insufficient policy support. This finding is consistent with the study by Liang B.[34] In contrast, population density exhibits a negative effect on resource allocation efficiency. Several factors may contribute to this result. First, excessive healthcare demand in densely populated areas can lead to medical facilities operating beyond capacity, prolonged patient waiting times, and overworked healthcare professionals, ultimately reducing resource utilization efficiency.[51] Second, in high-density regions, health resources are often concentrated in major cities or large hospitals, while primary healthcare institutions remain underutilized, leading to inefficiencies in resource allocation.[52] Additionally, some densely populated areas may suffer from inadequate planning of medical institutions, resulting in redundant construction or suboptimal distribution of resources, further weakening overall allocation efficiency. This finding is supported by the research of El Husseiny[53] and Ahmed et al.[41]

Moreover, it is noteworthy that while previous studies have generally suggested that health technical personnel influence the efficiency of health resource allocation,[54] our study reached the opposite conclusion. Several factors may explain this discrepancy. First, in some impoverished areas, an increase in medical personnel does not necessarily lead to improved resource utilization efficiency, particularly in cases where infrastructure is underdeveloped, medical equipment is insufficient, or the hierarchical medical system is not well-established.[55] Second, if a significant portion of health personnel are assigned to administrative roles or inefficient departments, a higher proportion of medical staff may not result in a substantial efficiency improvement.[56] Similarly, our study found that the number of people enrolled in medical insurance does not have a significant impact on the efficiency of health resource allocation. Possible explanations include the fact that despite high insurance coverage, inefficiencies such as excessive medical treatment, redundant examinations, overprescription of medications, and the misuse of medical resources may still exist.[57] Additionally, in China, many insured residents tend to seek treatment at tertiary hospitals rather than primary healthcare institutions, leading to underutilization of community-level medical resources while overburdening large hospitals. As a result, the overall efficiency of health resource allocation remains unimproved. While education level showed a positive coefficient in the baseline model, its effect did not remain significant in robustness checks and should therefore be interpreted with caution. This suggests that the relationship between education and resource efficiency may be more complex or mediated by other factors not captured in the current model. By contrast, the proportion of government health expenditure was found to have a consistently significant and positive impact on efficiency. Increased public spending—particularly when directed toward primary care, public health infrastructure, and preventive services—can improve the spatial distribution of medical resources,[58] alleviate the financial burden on patients, and reduce delays in care. These improvements help prevent disease progression, promote early intervention, and ultimately enhance the effectiveness and equity of resource allocation across regions. This reinforces the view that improving health resource efficiency requires not only optimizing quantity, but also addressing structural, institutional, and behavioral factors. By applying the two-stage bootstrap truncated regression, we mitigated potential endogeneity stemming from factors such as income and health investment, while controlling for other relevant variables. The regression results (Tables S12 and S13) confirmed that per capita disposable income and public health expenditure are significant positive contributors to healthcare efficiency in Guangxi, whereas population density exerts a significant negative effect. These findings support the robustness of our model and align with the study's objective to uncover reliable efficiency determinants. Notably, the bias-corrected confidence intervals reinforce the stability of the estimates, enhancing the reliability of policy recommendations derived from our results.

## Limitations

There are several limitations in this study. First, the output indicators mainly reflect service volume due to data availability, while quality-related metrics such as patient satisfaction or clinical outcomes were not included. Second, while Tobit regression is appropriate for censored data, it identifies associations rather than causal relationships. Moreover, the regression analysis may be subject to omitted variable bias due to unobserved factors not included in the model, which could influence the estimated effects. Future studies should consider incorporating quality-adjusted indicators, applying causal inference methods, and including a broader set of explanatory variables to enhance robustness.

## Conclusion

This study is based on the latest officially published data and examines the allocation of health resources as well as the provision of health services in ethnic minority areas of Guangxi. It conducts both cross-sectional and longitudinal analyses to assess the static and dynamic efficiency of health resource allocation across different regions and explores the factors influencing allocation efficiency. The main findings of this study are as follows: First, the Malmquist index indicates an overall upward trend in the TFPCH in Guangxi from 2010 to 2022, although significant differences exist among cities within the region. Second, the overall efficiency of health resource allocation in Guangxi during 2010–2022 remained relatively low, primarily due to deficiencies in technical efficiency and scale efficiency. Third, factors positively influencing the overall efficiency of health resource allocation include per capita disposable income and the proportion of healthcare expenditure, while population density exhibits a negative impact. The effect of education level was not consistently significant across robustness checks and should be interpreted with caution.

This finding has policy implications not only for Guangxi but also for other ethnic minority regions and economically disadvantaged areas in China facing challenges in health resource integration. The empirical results of this study highlight three key policy recommendations. First, the government should further advance comprehensive healthcare reforms to enhance the efficiency of health services across cities. Second, in implementing healthcare reforms, policymakers should pay closer attention to regional economic conditions and health resource levels, tailoring policies to the specific needs of different areas. For instance, in regions with stronger economic development and relatively abundant health resources, efforts should focus on improving internal management efficiency within the healthcare system, optimizing institutional operations, and maximizing resource utilization. DEA results suggest that cities like Nanning could increase outpatient visits by nearly 70% without additional inputs, indicating substantial room for efficiency gains through better internal coordination. Conversely, in regions with weaker economic foundations and limited medical resources, short-term priorities should include expanding the total supply of healthcare resources to enhance service accessibility, particularly in remote and underserved areas. However, DEA results also reveal that some less-developed areas, such as Beihai and Fangchenggang, exhibit structurally inefficient resource allocation. For example, these cities could reduce redundant beds by 15–30% without compromising service delivery. This indicates that even in resource-constrained settings, dual strategies—both increasing investment and optimizing existing resource structures—are necessary to improve system performance. These quantified targets offer actionable guidance for local governments to reallocate resources more effectively. Moreover, the empirical evidence helps to explain how the identified socio-economic factors influence efficiency. Higher income levels likely enhance health-seeking behavior and awareness, promoting more effective use of services and encouraging system responsiveness. In contrast, high population density may strain infrastructure, leading to congestion and lower service quality. The observed output slack in relatively resource-rich regions like Nanning also points to managerial or institutional bottlenecks, reinforcing the need for internal reform and digital innovations such as smart hospital systems and performance-based management. These mechanisms demonstrate how resource efficiency is not only a function of quantity, but also of how well inputs are organized and managed. Third, maintaining stable economic growth is a fundamental prerequisite for ensuring sustained public health investment. It is also essential to further increase the proportion of healthcare expenditure within total government spending to reduce the financial burden of medical care. Additionally, optimizing the spatial distribution of health resources and strengthening public health education are crucial for enhancing health literacy and promoting overall well-being.

## Data Sharing Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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## Disclosure

The authors declare no conflicts of interest in this work.

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