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Original Paper

Research on the Evaluation and Enhancement Countermeasure for the Supply Efficiency of Community Healthcare Services in China

Gulireba Maimaiti & Kun Chen
School of Politics and Public Administration, Xinjiang University, China

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Abstract
As the global population ages, the demand for community medical healthcare services increases. China exemplifies this trend. However, researches has primarily focused on large hospitals, neglecting community hospitals that cater to the basic medical needs of the elderly. This paper addresses this gap by developing a non-discretionary variable DEA model, which accounts for external constraints and uncontrollable factors in community healthcare services, enhancing the accuracy and objectivity of efficiency evaluations. Additionally, a Tobit model is employed to deeply analyze factors affecting efficiency, uncovering their interconnections. The study reveals: (1) Non-discretionary variable DEA-based efficiency analysis indicates significant regional disparities in the supply efficiency of community healthcare services across Chinese provinces. This suggests that supply efficiency is influenced not only by internal management quality but also by the external environment and policy direction. (2) The analysis of influencing factors reveals that population density and per capita GDP significantly positively impact supply efficiency, whereas the urbanization rate's impact is negligible. The proportion of the population aged 65 and older negatively affects supply efficiency, while the proportion of the population aged 0-14 and the percentage of children under 5 with moderate to severe malnutrition positively influence it.

Keywords
Community Healthcare Services, Supply Efficiency, Non-discretionary Variable DEA Model, Tobit

1. Introduction

According to the Declaration of Alma Ata (1978), primary healthcare aims to provide universally accessible basic health services to individuals and families within communities. China's primary healthcare system caters to the basic clinical and public health needs of one-fifth of the world's population (Li et al., 2017). The World Health Organization's data indicates that primary healthcare in China is delivered by professionals such as general practitioners, public health nurses, and community pharmacists. By 2019, 90% of Chinese families could reach the nearest primary healthcare facility within 15 minutes. The "Statistical Bulletin on the Development of Health and Wellness in China 2022" reports that by the end of 2022, there were 36,000 community healthcare service centers (stations), an increase of 288 from the previous year; the number of personnel in these centers increased by 34,000, a 5.0% growth; and the number of medical treatments provided was 830 million. However, improvements are needed in the quality of primary healthcare services in China, particularly in diagnosis, treatment, and chronic disease management in primary medical institutions. Despite significant efforts and achievements since 2009, China's primary healthcare system requires further strengthening (Li et al., 2020). Enhancing the efficiency of primary healthcare services is crucial. As an integral part of primary healthcare, community healthcare services require objective evaluation of their supply situation and identification of constraints to improve the primary healthcare system and service efficiency.

Many scholars have conducted in-depth research in primary healthcare, focusing mainly on the overall efficiency of primary healthcare institutions and specific regional issues (Liu et al., 2018; Leng et al., 2019; Su et al., 2023; Zhao et al., 2023; Zhou et al., 2023; Mei et al., 2023; Zeng et al., 2024). However, less attention has been given to community healthcare services across various regions, and the impact of non-discretionary variables on efficiency evaluation is often overlooked. Comprehensive studies of community healthcare services are essential, given their key role in the primary healthcare system.

This study evaluates the supply efficiency of community healthcare services in various regions of China, fully considering non-discretionary variables. It aims to provide a comprehensive and in-depth analysis of community healthcare services, reflecting their current state in China, and offering scientific decision-making support for policymakers. The study also aims to address previous research shortcomings, optimize community healthcare service supply, and enhance the construction of a more robust community healthcare service system to better meet public healthcare needs.

The paper is structured as follows: Section 2 reviews the literature on primary healthcare evaluation; Section 3 discusses research methods and indicator selection; Section 4 presents empirical analysis, including model construction for efficiency measurement and factor analysis; Section 5 concludes with a summary of findings, their theoretical and practical implications, limitations, and future research directions.

2. Literature Review

The efficiency of primary healthcare has consistently been a prominent topic in academic research. Early literature predominantly focused on the efficiency of primary healthcare services in developed countries, including Portugal (Amado et al., 2009; Gouveia et al., 2016), Canada (Milliken et al., 2011), the United States (Valdmanis et al., 2015), Spain (Cordero Ferrera et al., 2014; Campos et al., 2016), and Greece (Mitropoulos et al., 2016).

Over time, research perspectives have broadened to encompass other global regions, with a particular focus on China in recent years. Studies have been conducted by various researchers (Li et al., 2017; Liu et al., 2018; Leng et al., 2019; Li et al., 2020; Su et al., 2023; Zhao et al., 2023; Zhou et al., 2023; Mei et al., 2023; Zeng et al., 2024). Additionally, primary healthcare research has extended to countries such as Australia (Lewis et al., 2022; Khatri & Assefa, 2023) and Brazil (Capeletti et al., 2024).

In evaluating primary healthcare, the DEA method has been extensively utilized. Early studies often employed basic DEA models like the CCR and BCC models for efficiency evaluation. For example, Amado et al. (2009) used the DEA model to assess the efficiency of primary healthcare centers in Portugal, highlighting regional disparities in service accessibility, technical efficiency, and quality. Milliken et al. (2011) combined the DEA model with the Ordinary Least Squares (OLS) regression method to evaluate the efficiency of four primary care service delivery models in Ontario, Canada, revealing that community health centers were the least efficient. Valdmanis et al. (2015) applied the DEA model to assess the capacity of 67 county health departments in Florida, USA, to provide diagnostic and primary care services, suggesting that resources could be better allocated to traditional public health services. Gouveia et al. (2016) used the DEA model to evaluate the efficiency of medical services in 12 primary healthcare centers in Portugal, identifying opportunities for improvement in resource allocation and service provision. Campos et al. (2016) studied the efficiency of public resource use in Spain's healthcare systems using the DEA model, identifying three distinct efficiency levels among the autonomous communities.

As research has advanced, scholars have adopted more sophisticated DEA models. Cordero Ferrera et al. (2014) employed a four-stage DEA model to evaluate the efficiency of primary healthcare centers in Spain's Extremadura region, emphasizing the importance of considering service quality and sociodemographic characteristics. Mitropoulos et al. (2016) used a two-stage bootstrap DEA model to assess the production and economic efficiency of primary healthcare centers in Greece, suggesting that centers could improve by optimizing resource use and management strategies. Liu et al. (2018) applied the Bootstrap-DEA model to assess the technical efficiency of community healthcare service centers in Wuhan, China, proposing policy recommendations for resource allocation and capacity building. Leng et al. (2019) combined the DEA model, Malmquist index, and Tobit model to study the impact of China's 2009 health reform policy on the intangible service efficiency of primary medical institutions, finding that technological progress was the main driver of efficiency growth. Su et al. (2023) used an improved three-stage DEA model to assess the efficiency of primary healthcare institutions in China, noting a downward trend from 2012 to 2020 and significant regional differences. Zhao et al. (2023) analyzed the efficiency of primary healthcare services in China using the super SBM model, Malmquist index, and Tobit model, identifying financial support and social medical insurance policies as key determinants. Zhou et al. (2023) used the DEA model and Malmquist index to study the service efficiency of primary medical institutions in China, suggesting that urban institutions need to reduce resource waste and increase supply, while rural institutions can improve efficiency through technological transformation. Mei et al. (2023) used the super-efficiency DEA model and Malmquist index to study the service efficiency and spatial correlation of primary healthcare institutions in China, finding a general upward trend in efficiency but significant geographical disparities. Zeng et al. (2024) evaluated the efficiency of the primary healthcare system in a southwestern Chinese municipality post-health reform using the DEA model, SBM model, and Malmquist index, suggesting that horizontal integration reforms and strategic financial investments could improve efficiency. Capeletti et al. (2024) used DEA and quality-adjusted Malmquist indices to evaluate the efficiency and productivity development of primary healthcare services in Brazil's Santa Catarina state, noting a decline in overall productivity but improvements in service quality.

In summary, despite numerous studies on primary healthcare efficiency, there is ample scope for further research. This includes the application of sophisticated models that account for uncontrollable factors, environmental influences, regional disparities, technological advancements, and the impact on efficiency. It also involves considering non-economic aspects of service benefits. This paper, focusing on community healthcare service centers across China, employs a non-discretionary variable DEA model and Tobit model to assess the efficiency of community healthcare service provision, and delves into the factors influencing it.

3. Methodology and Selection of Indicators

3.1 Methodology

3.1.1 Non-discretionary Variable DEA Model

Data Envelopment Analysis (DEA) model was first introduced by Charnes et al. in 1978 as a tool for evaluating the relative efficiency of decision-making units (DMUs), particularly suitable for situations that require the simultaneous consideration of multiple inputs and outputs. Banker and Morey, in 1986, were the pioneers in proposing a DEA model that addresses non-discretionary variables. The non-discretionary variable DEA is a special type of efficiency assessment model that takes into account input or output variables that are not directly controlled by the DMUs.

However, traditional DEA models may have the issue of underestimating efficiency (Wei et al., 2011). Traditional DEA models are typically based on the strong assumption of free disposability, disregarding non-discretionary variables to simplify calculations and avoid subjective factors. In contrast to traditional DEA models, Bi et al. (2008) in the non-discretionary variable DEA model, categorize all input factors into two types: discretionary variables and non-discretionary variables. Discretionary variables are those that DMUs can control, while non-discretionary variables refer to variables that are fixed due to external factors, policy regulations, or other non-managerial factors.

In real life, many organizations or enterprises may not be able to fully control certain inputs or outputs, such as environmental factors, policy restrictions, and unpredictable market changes. The existence of these non-discretionary variables may lead to incorrect assessments of the efficiency of DMUs. Currently, the non-discretionary variable DEA model is widely applied in various fields, including medical services, to evaluate the operational efficiency of hospitals or clinics, taking into account policy changes and unpredictable patient flows.

Considering that in community healthcare services, the number of medical treatments and hospital admissions are influenced by a variety of factors, such as patient flow, demand for medical services, allocation of medical resources, capacity for medical services, and patient preferences, these factors are difficult to predict in advance and are therefore considered non-discretionary variables. In light of this, this paper introduces the non-discretionary variable DEA model to conduct the research.

$$
\begin{aligned}
&min && \theta - \varepsilon\left(\sum_{i\in D} s_i^- + \sum_{r=1}^{s} s_r^+\right)\\
&\text{subject to} && \theta x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^-, i \in D\\
& && x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^-, i \in ND\\
& && y_{ro} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+, r = 1, \dots, s
\end{aligned}
\quad (1)
$$

All variables are constrained to be positive, wherei $\in$ D indicates a free-disposal variable;i $\in$ ND indicates a non-free-disposal variable, suggesting that this input is exogenously fixed and is difficult to change based on the existing free management model.

3.1.2 Tobit Model

The Tobit regression model was proposed by Tobin (1958). The Tobit model effectively addresses the issue of truncation in the dependent variable, used to study dependent variables that meet certain constraints, thereby providing more accurate and consistent parameter estimates. Since the efficiency values assessed by the DEA model in this paper are between 0 and 1, showing characteristics of data truncation, the ordinary least squares method (OLS) would not provide unbiased and consistent estimates (Yang et al., 2018). Therefore, this paper uses the Tobit model for regression analysis, and the model is as follows:

$$
\begin{cases}
y_i = x_i\beta + \varepsilon_i\\
0 \le x_i\beta + \varepsilon_i \le 1\\
\varepsilon_i \sim (0, \sigma^2), i = 1,2, \dots
\end{cases}
\quad (2)
$$

Where, y_i denotes the explanatory variables, reflecting the efficiency of community healthcare service provision; x_i denotes the explanatory variables, representing the influencing factors; β denotes the regression parameters, representing the quantitative impact on the supply efficiency; ε_i denotes the random error term, which contains the random disturbance term that the model fails to explain.

3.2 Non-discretionary Variable DEA Model and Influence Factors

3.2.1 Non-discretionary Variable DEA Model and Selection of Input-Output Indicators

In the first phase of this paper, the non-discretionary variable DEA method will be utilized, based on input-output indicators, to make the evaluation of the supply efficiency of community healthcare services more comprehensive and refined. In line with the research questions of this paper and by referring to relevant literature in recent years, the following indicators have been selected as input-output indicators in the non-discretionary variable DEA model (see Table 1).

In previous studies on health care, the input indicators generally include financial, human, and material resources (Murray & Frenk, 2008; Yu, 2021). Specifically, financial input mainly consists of total health expenditure and the total expenditure of medical and health institutions; human resource input primarily involves health personnel, including licensed (assistant) physicians, registered nurses, pharmacists, technicians, and other health professionals; material input mainly includes the number of institutions and the number of beds. Therefore, this paper selects the number of institutions, the number of beds, the number of health personnel, and the total expenditure of medical and health institutions as input indicators.

Based on previous studies (Liu et al., 2018; Yan et al., 2021; Hou et al., 2022; Su et al., 2023), considering the representativeness and availability of the selected variables, this paper chooses the number of medical treatments, the number of hospital admissions, and the bed occupancy rate as output indicators. Among them, the number of medical treatments and hospital admissions are regarded as non-discretionary variables, reflecting the external constraints and uncontrollable factors in the process of community healthcare service provision.

The research object selected in this paper is the supply efficiency of community medical and health services in China, and the first stage requires the selection of input-output indicators, and the relevant data mainly come from the China Health and Health Statistics Yearbook, and it is difficult to collect the missing data of Tibet, Hong Kong, Macao and Taiwan, so this paper selects the data of community medical and health services of 30 provinces (autonomous regions and municipalities directly under the central government) of China, except for Tibet, Hong Kong, Macao and Taiwan, for the period of 2011-2020, and the data of community medical and health services in China are mainly obtained from the China Health and Health Statistics Yearbook. Therefore, this paper selects data related to community healthcare in 30 Chinese provinces (autonomous regions and municipalities directly under the central government) except Tibet and Hong Kong, Macao and Taiwan from 2011 to 2020. In the second stage, we need to select data on the indicators of influencing factors, and the relevant data mainly come from the China Statistical Yearbook and the China Health Statistics Yearbook.

Table 1. Input and Output Indicators

Type	Subcategory	Indicators
input	material input	number of institutions
		number of beds

	human resource input	number of health personnel
	financial input	total expenditure of medical and health institutions
	non-discretionary	number of medical treatments
output	variables	number of hospital admissions
	direct output	bed occupancy rate

3.2.2 Selection of Indicators and Influence Factors

In general, the supply efficiency of community healthcare services is influenced by various factors, such as the economy, population, and environment. Representative influencing factors include the level of economic development, population density, urbanization level, the percentage of the population aged 65 and older, the percentage of the population aged 0-14, and the percentage of children under 5 years of age with moderate to severe malnutrition. This paper takes the supply efficiency of community healthcare services as the dependent variable and uses a panel Tobit model based on maximum likelihood estimation, with each influencing factor as an independent variable. The Tobit model in this paper is as follows:

(1) Level of economic development. In theory, the level of economic development is the primary factor that constrains the supply of basic medical healthcare resources in a region (Jin et al., 2021). Residents in economically developed areas often have higher demands for medical healthcare services, hence, more healthcare resources are invested in these developed areas (Ao et al., 2021; Chen et al., 2021; Su et al., 2023). As the level of economic development increases, so do the living standards and health awareness of the residents, leading to a corresponding increase in their demand for medical healthcare services. This growth in demand will drive an increase in the supply investment of the community healthcare industry. Therefore, this paper selects per capita GDP as a measure of the level of economic development.

(2) Population Density. The scale of population density may have different impacts on the efficiency of government public service supply (Chen & Zhang, 2008). The higher the population density, the more pronounced the economies of scale in government healthcare expenditure, and the overall efficiency may be higher (Zhou et al., 2023). This paper predicts a positive relationship between the population density of each region and the efficiency of community healthcare service supply. Therefore, the population density selected in this paper is measured by the ratio of the total population to the area of the region.

(3) Urbanization level. In areas with higher levels of urbanization, medical resources continue to increase (Cheng & Yang, 2015). Regions with higher urbanization levels typically have richer economic resources, more comprehensive infrastructure, denser medical service networks, and more advanced medical technology and professional personnel. These factors collectively promote the effective supply of community medical and health services and the improvement of residents' health levels. Therefore, this paper selects the urbanization rate as a measure of the level of urbanization.

(4) The percentage of the population aged 65 and older. Many studies (Alatawi et al., 2020; Chen et al., 2022; Su et al., 2023) have indicated that the percentage of the population aged 65 and older has a certain impact on the efficiency of community healthcare service supply. The elderly often require more medical care and chronic disease management, necessitating that the community healthcare system provide corresponding services to meet this demand. Furthermore, the increase in the elderly population poses challenges to the allocation of medical resources, and community healthcare services need to make corresponding adjustments in terms of staffing, equipment updates, and financial investment. Therefore, this paper selects the percentage of the population aged 65 and older as one of the influencing factors of the efficiency of community medical healthcare service supply.

(5) The percentage of the population aged 0-14. This age group of people has a direct impact on the allocation and supply efficiency of community healthcare resources. According to data from 2020, the number of children aged 0-14 in China reached 253.38 million, accounting for 17.95% of the total population, an increase of 1.35 percentage points compared to 2010. The supply of community healthcare services needs to take into account the characteristics of this population structure and allocate resources reasonably to meet the medical healthcare needs of this age group. Therefore, this paper selects the percentage of the population aged 0-14 as one of the influencing factors of the efficiency of community healthcare service supply.

(6) The Percentage of children under 5 years of age with moderate to severe malnutrition . In China, the nutritional status of children under the age of 5 years old is gradually improving, but they still face issues such as malnutrition, obesity, and deficiencies in micronutrients, with significant disparities existing between urban and rural areas as well as different regions. When the proportion of malnourished children is high, the demand for community medical healthcare services increases. The supply of community healthcare services needs to be tailored to the characteristics of malnourished children, providing personalized and diversified medical services to meet their special needs. Therefore, this paper selects the percentage of children under 5 years of age with moderate to severe malnutrition as one of the influencing factors of the efficiency of community healthcare service supply.

4. Empirical Analysis

4.1 The Non-discretionary Variable DEA Model Efficiency Analysis

Based on input-output indicators, a non-discretionary variable DEA model was constructed to measure the supply efficiency of community healthcare services in 30 provinces (autonomous regions, municipalities directly under the Central Government) of China, as shown in Tables 2 and 3.

Looking at the data from different provinces, we can observe significant differences in the supply efficiency of community healthcare services across various regions. For instance, areas such as Shanghai, Jiangsu, Guangdong, and Chongqing have shown efficiency close to or reaching 1.00 in most years, indicating a very high level of service efficiency. In contrast, regions like Anhui, Fujian, and Jiangxi have an average efficiency between 0.5 and 1, which implies that the supply efficiency in these areas has not yet reached its optimal level and there is room for improvement. Comparatively, provinces such as Hebei, Shanxi, and Inner Mongolia have lower efficiency, which may suggest that there are certain deficiencies in the supply of healthcare services in these regions.

Looking at the time series from 2011 to 2020, the supply efficiency of different provinces shows varying trends. Some provinces have been able to maintain high efficiency consistently, indicating that they have been effectively managing and utilizing resources over the long term. Other provinces, although showing high efficiency in some years, have experienced fluctuations or declines in efficiency in other years, necessitating further optimization of resource allocation and enhancement of service capabilities.

When examining the regions of East, Central, West, and Northeast China, the average efficiency in the Eastern region remained above 0.80 from 2011 to 2019, showing relative stability at a high level. However, in 2020, the efficiency dropped to 0.69, a change likely directly related to the outbreak of a public health emergency and its impact on the health care system. The average efficiency in the Central region increased from 0.61 in 2011 to 0.67 in 2019, indicating an improvement in efficiency over this period. But in 2020, the efficiency fell to 0.52, possibly due to the significant impact of the public health emergency, leading to a decrease in service efficiency. The Western region's average efficiency has generally shown a downward trend, which may reflect the difficulties faced by the Western region in the supply of healthcare services. The Northeast region's average efficiency gradually declined from 0.43 in 2011 to 0.36 in 2020, which may indicate that the Northeast region faces more severe challenges in the supply of healthcare services.

Overall, from 2011 to 2020, the average supply efficiency of community healthcare services across the nation gradually decreased from 0.73 to 0.58. This indicates that, despite some regions experiencing improvements in efficiency, there is still a need for overall enhancement in the supply efficiency of community healthcare services on a national scale.

Table 2. The Non-discretionary Variable DEA Model Efficiency Analysis

Region	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Bei Jing	0.65	0.65	0.71	0.73	0.75	0.80	0.84	0.88	0.94	0.76
Tian Jin	0.85	0.90	0.92	0.92	0.90	0.83	0.92	0.93	0.95	0.81
He Bei	0.49	0.50	0.54	0.50	0.49	0.47	0.46	0.44	0.43	0.35
Shan Xi	0.49	0.47	0.43	0.39	0.37	0.38	0.38	0.38	0.34	0.29
Nei Meng Gu	0.64	0.55	0.49	0.41	0.44	0.45	0.44	0.39	0.32	0.32
Liao Ning	0.45	0.48	0.54	0.54	0.50	0.47	0.48	0.42	0.39	0.31
Ji Lin	0.42	0.44	0.42	0.44	0.38	0.40	0.42	0.43	0.55	0.50
Hei Long Jiang	0.44	0.35	0.35	0.39	0.38	0.39	0.42	0.36	0.35	0.28
Shang Hai	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.94	1.00	0.72

Jiang Su	1.00	0.98	0.99	0.98	0.95	0.91	1.00	1.00	1.00	0.77
Zhe Jiang	1.00	0.97	0.93	0.91	0.92	0.91	0.89	0.90	1.00	0.79
An Hui	0.66	0.67	0.70	0.65	0.64	0.63	0.66	0.62	0.51	0.58
Fu Jian	0.89	0.83	0.79	0.76	0.78	0.76	0.71	0.72	0.77	0.74
Jiang Xi	0.51	0.48	0.51	0.48	0.50	0.47	0.54	0.51	1.00	0.43
Shan Dong	0.54	0.53	0.54	0.53	0.52	0.54	0.55	0.52	0.45	0.48
He Nan	0.51	0.55	0.59	0.59	0.59	0.55	0.55	0.54	0.52	0.49
Hu Bei	0.86	1.00	0.97	1.00	0.90	0.96	0.83	0.72	0.66	0.50
Hu Nan	0.62	0.57	0.86	0.87	0.85	0.82	0.94	0.97	1.00	0.80
Guang Dong	1.00	0.98	1.00	1.00	1.00	0.97	1.00	1.00	0.92	0.83
Guang Xi	0.70	0.78	0.85	0.90	0.93	0.90	0.84	0.85	0.90	0.82
Hai Nan	1.00	1.00	1.00	0.99	0.95	0.87	0.83	0.72	0.68	0.60
Chong Qing	0.96	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.95
Si Chuan	0.66	0.76	0.75	0.73	0.71	0.71	0.78	0.79	0.82	0.78
Gui Zhou	1.00	0.85	0.87	0.81	0.98	0.82	0.66	0.64	0.69	0.51
Yun Nan	0.75	0.81	0.76	0.71	0.72	0.71	0.65	0.63	0.57	0.55
Shan Xi	0.50	0.49	0.50	0.49	0.45	0.48	0.53	0.52	0.44	0.35
Gan Su	0.67	0.65	0.53	0.55	0.53	0.52	0.50	0.45	0.44	0.40
Qing Hai	1.00	1.00	0.85	0.83	0.80	0.77	0.70	0.62	0.62	0.59
Ning Xia	1.00	1.00	1.00	0.99	0.96	0.92	0.82	0.80	0.80	0.81
Xin Jiang	0.58	0.62	0.56	0.54	0.53	0.48	0.49	0.46	0.44	0.33
Average	0.73	0.73	0.73	0.72	0.71	0.70	0.69	0.67	0.68	0.58

Table 3. Annual Changes in Average Efficiency by Region

Region	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Eastern Region	0.84	0.83	0.84	0.83	0.82	0.81	0.82	0.80	0.81	0.69
Central Region	0.61	0.62	0.68	0.66	0.64	0.63	0.65	0.63	0.67	0.52
Western Region	0.77	0.77	0.74	0.72	0.73	0.71	0.67	0.65	0.64	0.58
Northeastern Region	0.43	0.42	0.44	0.46	0.42	0.42	0.44	0.40	0.43	0.36

4.2 Analysis of Influencing Factors

This paper employs Stata 17.0 software, taking the efficiency of community healthcare service supply as the dependent variable, and using population density, per capita GDP, urbanization rate, percentage of the population aged 65 and older, percentage of the population aged 0-14, and percentage of children under 5 years of age with moderate to severe malnutrition as independent variables. A panel Tobit model is utilized for regression analysis. The results of the regression are presented in Table 2. The specific analysis of each influencing factor is as follows:

Population density has a significant positive impact on the efficiency of community healthcare service supply. This indicates that in densely populated areas, due to increased demand, more resources and attention are allocated to community medical healthcare services, thereby improving service efficiency. Secondly, a higher population density may bring economies of scale, allowing medical healthcare service providers to offer services at a lower per-unit cost, as fixed costs can be spread over a larger number of service users. Additionally, densely populated areas are usually able to attract more medical professionals because these areas may offer more job opportunities and better living conditions, thereby enhancing the professionalism and quality of medical services.

Per capita GDP has a significant positive impact on the efficiency of community healthcare service supply. An increase in per capita GDP typically means that residents have more disposable income, and the government has greater fiscal space to increase investment in community healthcare services. Secondly, regions with higher economic levels are more likely to invest in medical technology research and development, adopting advanced medical equipment and treatment methods to improve the efficiency and effectiveness of medical services. Additionally, economic growth can provide financial support for the construction and improvement of medical and health infrastructure, including the modernization and upgrading of hardware facilities at community health service centers (stations).

The urbanization rate has an insignificant positive impact on the efficiency of community healthcare service supply. Urbanization leads to an increase in population density, which may increase the demand for medical and health services. However, this increase in demand does not necessarily translate immediately into an increase in service supply. Although the population growth and economic potential brought by urbanization are conducive to increasing investment in community medical and health services, the actual improvement in service supply requires timely policy response, rational allocation of resources, and gradual improvement of infrastructure.

The percentage of the population aged 65 and older has an insignificant negative impact on the efficiency of community healthcare service supply. This is mainly because the increase in medical healthcare service supply often lags behind the pace of population aging, making it difficult for the supply to meet the rapidly growing demand in the short term. The allocation of community healthcare resources may be uneven among different types of services, resulting in insufficient attention and supply for the specific needs of the elderly population. In an aging society, the proportion of chronic disease patients is relatively high, which increases the pressure on community healthcare services in terms of prevention, treatment, and management of chronic diseases.

The percentage of the population aged 0-14 has a significant positive impact on the efficiency of community medical and health service supply. This indicates that as the proportion of this age group increases, so does the demand for community medical healthcare services. This is primarily because children aged 0-14 are in a stage of growth and development, with a relatively high demand for services such as preventive vaccinations, health check-ups, and disease treatment. The increase in demand, coupled with the provision of specialized services, along with policy and financial support, collectively contribute to improving the efficiency of community healthcare service supply, ensuring that children can receive efficient and professional medical services.

The percentage of children under 5 years of age with moderate to severe has a significant positive impact on the efficiency of community medical and health service supply. This suggests that as the proportion of this age group increases, the supply of community healthcare services may become more efficient. community healthcare services may strengthen the training and staffing of professionals, improve monitoring and intervention measures for children's nutritional status, and enhance their ability to diagnose and treat malnutrition in children. This improvement in professional skills not only increases the effectiveness of treatment but also reduces unnecessary medical resource waste through more accurate diagnosis and treatment, thereby further improving the efficiency of service supply.

Table 4. Influencing Factors Tobit Regression Results

Variable	Coef.	St. Err.	P-value
Population density	0.0001073	0.0000327	0.001***
Per capita GDP	0.0000032	0.0000011	0.004**
Urbanization rate	0.0011559	0.0029502	0.695
Percentage of the population aged 65 and older	-0.0071326	0.0075913	0.347
Percentage of the population aged 0–14	0.0089017	0.0044723	0.047*
Percentage of children under 5 years of age with moderate to severe malnutrition	0.0568632	0.0188	0.002***

Note. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively

5. Conclusion

5.1 Main Findings and Conclusions

This paper conducts a comprehensive assessment of the supply efficiency of community healthcare services in 30 provinces (autonomous regions, municipalities directly under the Central Government) of China by constructing a non-discretionary variable DEA model, and deeply analyzes the key factors affecting supply efficiency using the DEA-Tobit method.

The main research findings are as follows: (1) Through in-depth analysis using the non-discretionary variable DEA model, the study found significant regional differences in the supply efficiency of community healthcare services among various provinces in China. The eastern regions generally exhibit higher service efficiency; although there is still a gap compared to the eastern regions, the central regions have seen an improvement in service efficiency; while the northeastern and western regions face the challenge of lower efficiency. The study emphasizes that these differences not only reflect the direct impact of internal management on efficiency but also highlight the importance of the external environment and policy changes on the supply efficiency of community health services. The uncertainty of non-discretionary variables such as the number of medical treatments and hospital admissions further indicates that supply efficiency is not only constrained by the quality of internal management but is also greatly influenced by the external environment and policy orientation.

The analysis of influencing factors revealed that population density and per capita GDP have a significant positive impact on the supply efficiency of community healthcare services, indicating that densely populated and economically developed areas are more likely to provide efficient healthcare services. The insignificant impact of the urbanization rate may be related to the lag in the supply of healthcare services during the urbanization process. The negative impact of the percentage of the population aged 65 and older on supply efficiency suggests the need to pay attention to the special medical needs of the elderly population. The significant positive impact of the percentage of the population aged 0-14 and the percentage of children under 5 years of age with moderate to severe malnutrition indicates that the increased demand for healthcare services for the child population contributes to improving supply efficiency.

Thus, we can draw the following conclusions: (1) To address the disparities in efficiency between regions, the government needs to formulate and implement a series of differentiated policies, including increasing targeted investments in areas with lower efficiency such as the West and Northeast, implementing talent training and introduction programs, promoting medical technology innovation, and establishing regional coordination mechanisms to narrow the regional gap. (2) Faced with the challenge of an aging population, it is necessary to optimize the allocation of resources for the diagnosis and treatment of geriatric diseases, promote the signing of family doctor services to achieve personalized healthcare management, simplify the medical process, and establish a comprehensive elderly care service network. (3) In response to the issue of children moderate to severe malnutrition under 5 years old, strengthen early nutritional intervention, establish a child nutrition monitoring system, provide targeted nutritional supplements and health education services, especially for children from low-income and vulnerable groups; at the same time, encourage community healthcare institutions to carry out assessments of children's nutritional status and personalized guidance to promote the healthy growth of children. (4) By introducing modern management concepts and technologies, optimize service processes to improve the supply efficiency of community healthcare services.

5.2 Theoretical and Practical Implications

This paper evaluates the supply efficiency of community healthcare services using non-discretionary variable DEA model, enhancing the accuracy of efficiency assessment and offering a new perspective for efficiency evaluation that considers the impact of external factors. This approach has enriched the theoretical framework for evaluating the supply efficiency of community healthcare services. By conducting a comprehensive assessment of the supply efficiency of community healthcare services in 30 provinces (autonomous regions, municipalities directly under the Central Government) of China, the study reveals efficiency disparities among different regions, providing an empirical basis for policy-making.

5.3 Limitations and Future Research

This paper provides a new theoretical perspective and methodological support for the evaluation of the supply efficiency of community healthcare services by employing non-discretionary variable DEA model. Despite this, due to the lag in the updating of research data, there are certain limitations in terms of timeliness. Future research should aim to overcome this challenge to enhance the real-time relevance of the research findings.

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