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Measurement of Medical Equipment Input Efficiency: Evidence from Medical and Healthcare Institutions in Chongqing, China

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Abstract

In recent years, guided by policies, China's public health system has experienced rapid growth in inputs, particularly in medical equipment. From the Resource-Based View (RBV), organizations gain advantages through resources and capabilities, emphasizing not only key resources but also their utilization. Therefore, the critical issue is whether the investments are reasonable and effectively utilized, which relates to policy guidance and internal management. Previous studies often neglected medical equipment and mortality rates in capacity measurement due to data opacity and methodological limitations, resulting in biased outcomes. This study measures the capacity utilization (CU) of healthcare institutions in Chongqing, China from 2018 to 2021 using data envelopment analysis (DEA) and directional distance function (DDF). Findings reveal that the healthcare institutions in most districts of the city are underutilizing their capacity, even though their medical equipment remains relatively scarce. Furthermore, CU levels do not adequately reflect the advantages in economic conditions and medical resources. The results of Tobit regression analysis support the findings, highlighting managerial deficiencies within the public health sector.

Keywords

Data envelopment analysis; Capacity utilization; Medical and health institutions; Undesirable output; Medical equipment

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1. Introduction

Medical equipment is essential for health service, contributing significantly to disease prevention, diagnosis, treatment, and patient rehabilitation (World Health Organization, 2012). Its availability, accessibility, and effective use are crucial for achieving health system performance goals. Developing countries have long suffered from inadequate medical equipment due to limited funding and technology (World Health Organization, 2010). The issue has garnered global attention, leading to strategic goals proposed by the World Health Assembly in 2008 and 2009 aimed at enhancing technology transfer and improving access to health products (World Health Organization, 2012).

To address these challenges, China has promoted investment in medical equipment through various policies. For example, the 2015 guidance from the General Office of the State Council mandated financial support for public hospitals aligned with regional health planning. Furthermore, the 2020 notice emphasized continued investment in medical equipment. As a result, the decade from 2012 to 2021 saw a significant growth in medical equipment investment (see Fig. 1), with the number of units nearly tripling from 3.59 million to 10.49 million, indicating a robust annual growth exceeding 10% (Health Economics Statistical Yearbook, 20132022).

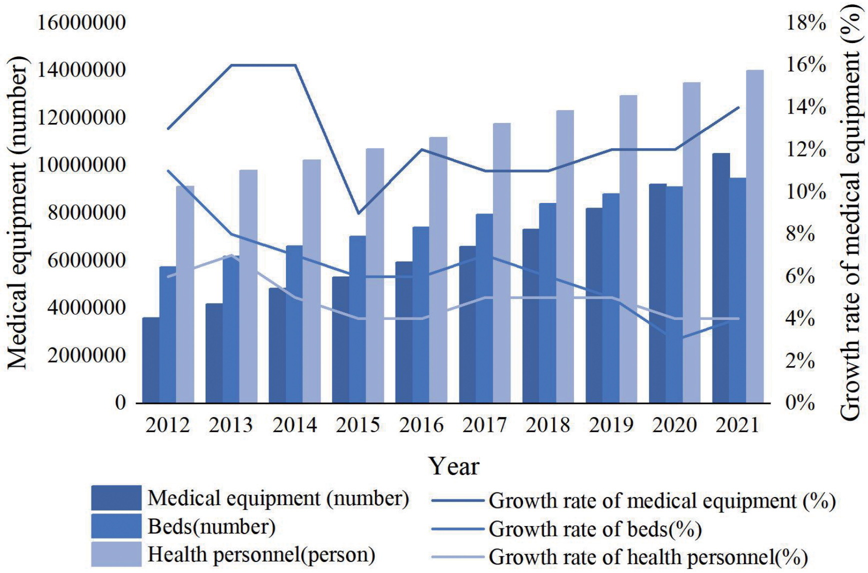

Fig. 1. Number of medical equipment, beds, and healthcare personnel in medical and health institutions in China from 2012 to 2021.

However, this rapid investment growth also brings challenges. From the Resource-Based View (RBV), medical equipment is a strategic resource that, when effectively managed, enhances service delivery and health outcomes. The value of these resources depends not only on their quantity but also their effective management and utilization. Improper utilization or overinvestment in medical equipment can lead to inefficiencies, overcapacity, and waste of valuable resources. Furthermore, the procurement and supply of medical equipment, involving substantial financial resources, prone to medical corruption. For instance, medical equipment procurement was the leading sector for corruption cases in China's public healthcare organizations between 2011 and 2018, accounting for approximately a quarter of the overall cases (Fu *et al.*, 2023). Thus, it can be witnessed that with the advancement of anti-corruption reforms in healthcare in

2023, policies have tightened regarding medical equipment investment, strengthening resource allocation management. For example, the Chinese Ministry of Finance issued guidelines requiring strict adherence to prescribed procedures for the allocation of equipment assets, prohibiting debt financing for the procurement of large medical equipment, and guiding public hospitals to allocate resources reasonably while controlling disorderly expansion and competition.

The article is grounded in the view that an organization's competitive advantage arises not merely from acquiring resources but also from their effective utilization. In healthcare, it is important to align medical equipment investment with institutional needs to maximize capacity. However, limited transparency in assessing equipment utilization has led to insufficient formal attention from policymakers (Simoens, 2009). This study addresses the gap by measuring capacity utilization (CU), using a data envelopment analysis (DEA) model based on the directional distance function (DDF), which incorporates mortality rate as an undesirable output to provide a comprehensive view of resource utilization.

By promoting transparency and accountability, this study emphasizes how innovation and development policies can maximize the value of medical resources. Chongqing Municipality, China, exemplifies the importance of aligning development policies with the goal of enhancing healthcare infrastructure and management capabilities. Based on data available, this study focuses on 38 districts' medical and healthcare institutions in this municipality, from 2018 to 2021, offering valuable insights into healthcare resource governance and management, with inspirations for other developing regions.

In summary, this research enriches the literature on CU measurement in healthcare by integrating mortality rates as undesirable outputs and framing medical equipment within the RBV framework. This approach underscores the importance of strategic resource management in improving healthcare outcomes, providing practical suggestions for governance and utilization of medical equipment in developing countries and informing effective policy interventions.

The rest of the paper is organized into five sections. Section 2 introduces the RBV analytic framework and reviews applied research on CU in the healthcare context. Section 3 describes the CU measurement method considering undesirable outputs, along with the input-output indicators and conceptual model for medical and healthcare institutions. Section 4 presents the empirical results, comparing traditional methods with the new approaches and analyzing regional differences in CU. This section also explores the role of external factors through Tobit regression analysis. Finally, section 5 concludes the study and provides related policy recommendations.

2. Theoretical Background

2.1. The role of policy and management: RBV perspective

From the Resource-Based View (RBV) (Wernerfelt, 1984), an organization's resources and capabilities are central to its strategies. Resources encompass assets, capabilities, organizational processes, attributes, information, and knowledge controlled by the organization. Capabilities refer to the organization's ability to effectively utilize these resources. In public management, identifying key resources within organizations is a focal point of current research. However, connecting these key resources with various aspects of public management—such as organizational performance and management stability—remains important yet underexplored (Porcher and Simon, 2016; Lee and Chen, 2022). In the healthcare sector, medical equipment is recognized as a vital resource. In China, the management principles for medical equipment are guided by policies issued by the central government, while procurement and usage are shaped by internal management practices within healthcare departments. The interaction between policy and management influences the investment and allocation of key resources, resulting in varying outcomes in resource utilization.

While pro-investment policies have increased investment in medical equipment, this upward trend has recently contracted due to anti-corruption reforms in healthcare. Overinvestment in equipment may complicate management, leading to inefficiency and creating opportunities for corruption in procurement and usage processes, particularly when healthcare institutions lack adequate management capabilities. A balanced investment, combined with effective management capabilities, may enable healthcare institutions to achieve a competitive advantage and operate more efficiently. Our analytical framework (see Fig. 2), grounded in RBV theory, emphasizes the interaction between resources and capabilities in the public sector. By analyzing capacity utilization, it reflects the performance outcomes resulting from this interaction.

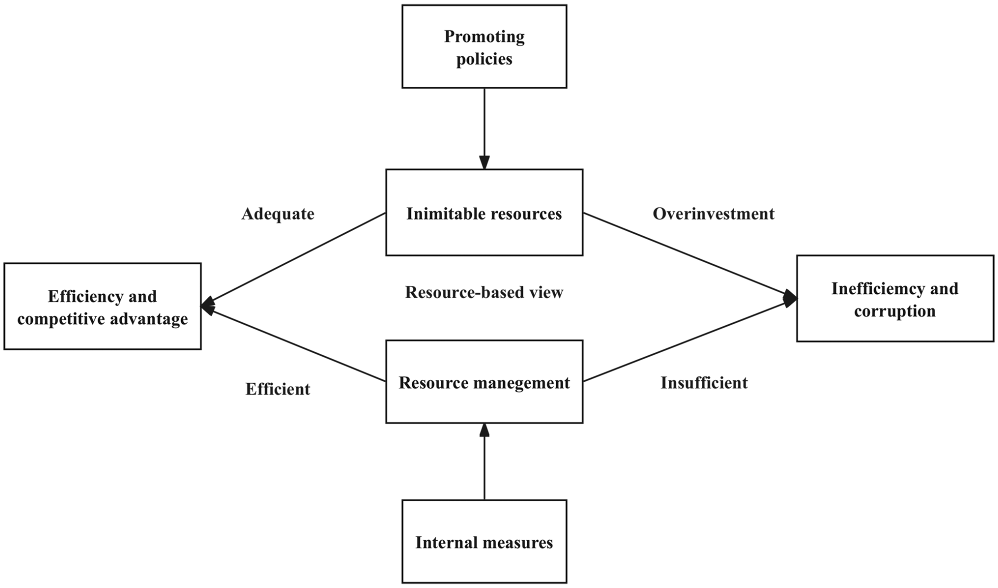

Fig. 2. RBV framework.

2.2. View on capacity and capacity utilization

Capacity is a key concept in economic literature. Johansen (1968) defined production capacity as "the maximum amount that can be produced per unit of time with existing plant and equipment, provided that the availability of variable factors of production is not restricted." The definition highlights that capacity is measured by the output of a production unit when all fixed inputs are fully utilized (Pascoe and Tingley, 2006). Capacity studies focus on the efficiency of managing limited resources to address fluctuations in healthcare service demand (Jack and Powers, 2009). To effectively handle these fluctuations, available capacity should ideally match or exceed demand. However, excess capacity can result in inefficiency in resource allocation, emphasizing the need for a balanced capacity management approach.

Capacity utilization is a concept related to the capacity level, serving as a metric for assessing resource use in production units. It is generally defined as the ratio of actual (observed) output to potential capacity for an industrial, commercial, or production entity over a specific period (Färe *et al.*, 2000; Nelson, 1989).

Potential capacity reflects the maximum potential output or service that a DMU can achieve, given its technology and fixed inputs, without constraints on variable inputs that can be adjusted in the short term (Färe *et al*., 1989a; Johansen, 1968).

However, CU measures based solely on actual (observed) output may be biased as they can mix the effects of overcapacity and technical inefficiency (Karagiannis, 2015). To address this, Färe *et al*. (1989a) introduced an inefficiency-corrected measure of CU that relies on the output level of technical efficiency rather than observed output. Coelli *et al*. (2002) further defined ray capacity output as the maximum increase for the observed output vector, representing the DMU's effective output. Thus, the ratio of effective output to the potential output is considered a more accurate measure of unbiased capacity utilization.

2.3. Capacity utilization in medical and healthcare

CU is a critical area of empirical research within the medical field. The predominant approach to measuring CU in healthcare systems involves constructing a production frontier using non-parametric methods. Färe *et al*. (1989b) pioneered this by creating production frontiers from observed input-output data to assess the optimal utilization of capacity and variable inputs in Michigan hospitals through DEA. The DEA-based methodology has since gained widespread adoption in healthcare research (Kuntz *et al*., 2007; Magnussen and Mobley, 1999; Valdmanis *et al*., 2015). Notably, Valdmanis *et al*. (2010) employed bootstrap DEA to evaluate the capacity of Florida's public health sector, while Arfa *et al*. (2016) utilized a dual non-parametric model with directional output distance functions to measure public hospitals' CU in Tunisia.

We review the input and output metrics used in previous CU studies within the healthcare system (see supplementary A). Inputs typically encompass the number of beds and staff, with some studies also considering related expenditures from a budgetary perspective. Smith-Daniels *et al*. (1988) emphasized the importance of medical equipment as a critical resource alongside labor in healthcare capacity management. However, due to a lack of transparent data, medical equipment is often overlooked in efficiency and capacity assessments (Karagiannis, 2015).

Many existing studies primarily focus on output indicators such as the number of surgeries or hospitalizations, often ignoring undesirable outputs like mortality rates. Given that healthcare organizations aim to treat illnesses and save lives, mortality is a crucial negative output. Researches have established a link between CU and mortality rates (Kerstens and Shen, 2021; Madsen *et al*., 2014). Neglecting this undesirable output can skew evaluations of hospital efficiency and productivity through DEA (Hu *et al*., 2012). Recent studies, including one by Song *et al*. (2023), have attempted to fill this gap by incorporating mortality as an undesirable output within hospital production techniques through two sub-technologies. They assessed the performance of Chinese public hospitals using machine learning for feature selection. The findings indicate that the accounting for mortality significantly affects long-run output-oriented plant CU of healthcare institutions.

3. DEA-based CU Measurement

DEA-based CU measurement adopts the short-term perspective, categorizing input indicators into fixed and variable inputs. It identifies the output potential of fixed inputs—such as land and facilities—defining capacity, while the difference between actual output and capacity represents capacity utilization.

Fixed inputs cannot be adjusted in quantity by the producer in the short run, whereas variable inputs like raw materials and fuel, can be modified more readily.

The measurement method consists of three steps (Cui *et al.*, 2023; Fukuyama *et al.*, 2021; Yang *et al.*, 2019a): (1) using the output-oriented DEA model to measure the effective output while imposing constraints on both fixed and variable inputs; (2) relaxing the constraints on variable inputs to construct a new output-oriented DEA model ; and (3) calculating the ratio of the effective output to the production capacity to derive the CU rate.

3.1. Capacity utilization in DEA

Assume there are J decision-making units (DMUs). Each DMU_j(j=1,2,...,J) can transfer inputs X to outputs Y. The inputs consist of variable inputs V and fixed inputs F, represented as $X_j=(F_j, V_j)$. The output-oriented DEA model, based on the assumption of variable returns to scale (VRS), is presented as follows:

$$Max\ \theta\ s.t.\left\{\sum_{j=1}^{J}\lambda_j X_j \le X_o, \sum_{j=1}^{J}\lambda_j Y_j \ge \theta Y_o, \sum_{j=1}^{J}\lambda_j = 1, \lambda_j \ge 0\ \forall j\right\} \tag{1}$$

where λ_j is the intensity variable, and θ stands for the proportion of output expansion and measures how much the output of DMU_o can theoretically be increased while keeping the current level of inputs constant. Effective output can be expressed as $\theta^* Y_o$. To solve for capacity, we relax the constraints on variable inputs (restricting only fixed inputs), leading to the new model:

$$Max\ \hat{\theta}\ s.t.\left\{\sum_{j=1}^{J}\lambda_j F_j \le F_o, \sum_{j=1}^{J}\lambda_j Y_j \ge \theta Y_o, \sum_{j=1}^{J}\lambda_j = 1, \lambda_j \ge 0\ \forall j\right\} \tag{2}$$

According to model (2), the capacity is $\hat{\theta}^* Y_o$. Based on the definition of effective output and capacity (Coelli *et al.*, 2002), the capacity utilization of DMU_o can be expressed as:

$$CU = \frac{\theta^* Y_o}{\hat{\theta}^* Y_o} = \frac{\theta^*}{\theta^*} \tag{3}$$

The value of CU ranges from 0 to 1. A CU value of 1 indicates that the capacity of the evaluated unit is fully utilized. Consequently, a higher value of CU reflects a greater degree of resource utilization.

3.2. CU with undesirable outputs

Building on the work of Yang *et al.* (2019a), this study introduces the concept of joint weak disposability (JWD) for undesirable outputs. It utilizes the directional distance function (DDF) to develop a new CU measurement model, thereby enhancing the traditional DEA-based approach.

Assume there are J DMUs. Each DMU_j(j=1,2,...,J) can transform variable inputs V and fixed inputs F into desirable outputs Y and undesirable outputs B. The production possibility set (PPS) for this scenario can be defined as:

$$T = \left\{(F,V,Y,B) \middle| (Y,B) \text{ is producible from } (F,V)\right\} \tag{4}$$

Y and B exhibit weak disposability, meaning that a reduction in undesirable outputs must be accompanied by a proportional decrease in desirable outputs. Building on the work of Yang *et al.* (2019a), Färe *et al.* (2006), and Färe and Grosskopf (2009), JWD can be characterized as:

$$\mathrm{JWD}_{YB}:(F_j,V_j,Y_j,B_j)\in T, 0\le \vartheta_j\le 1,\ \forall j \Rightarrow (F_j,V_j,\vartheta_j Y_j,\vartheta_j B_j)\in T \tag{5}$$

where F_j, V_j, Y_j, and B_j denote the observed values of each input and output indicator for the DMU_j, respectively. The abatement factors ϑ_j indicate the proportional change in both desirable and undesirable outputs, such that a reduction in undesirable outputs leads to a corresponding decrease in desirable outputs. Consistent with Yang *et al*. (2019a), we allow each decision unit to have distinct abatement factors. We define $\boldsymbol{\lambda}=(\lambda_1, \lambda_2, ..., \lambda_J)$ as a vector of intensity variables. This allows us to expand the PPS in Eq. (1) under the VRS assumption, leading to the following model:

$$T=\left\{(F,V,Y,B)\left|\begin{array}{l}\sum_{j=1}^{J}F_j\lambda_j\le F,\sum_{j=1}^{J}V_j\lambda_j\le V,\\ \sum_{j=1}^{J}\vartheta_j Y_j\lambda_j\ge Y,\sum_{j=1}^{J}\vartheta_j B_j\lambda_j=B,\\ \sum_{j=1}^{J}\lambda_j=1,\lambda\ge 0,0\le\vartheta_j\le 1\ \forall j\end{array}\right.\right\} \tag{6}$$

Let $\mathbf{g}=(g^Y, g^B)\ge 0$ represent the direction vector, indicating that the evaluated units in the PPS simultaneously increase desirable outputs while decreasing undesirable outputs in the direction of (g^Y, g^B). Thus, the (restricted) directional distance function of DMU_k can be expressed as follows:

$$\begin{aligned} D_0(F_k,V_k,Y_k,B_k;\mathbf{g}) &= \max\left\{\beta\left|\left(F_k,V_k,Y_k+\beta g^Y,B_k-\beta g^B\right)\in T\right.\right\}\\ &=\max\left\{\beta\left|\begin{array}{l}\sum_{j=1}^{J}F_j\lambda_j\le F_k,\sum_{j=1}^{J}V_j\lambda_j\le V_k,\\ \sum_{j=1}^{J}\vartheta_j Y_j\lambda_j\ge Y_k+\beta g^Y,\sum_{j=1}^{J}\vartheta_j B_j\lambda_j=B_k-\beta g^B,\\ \sum_{j=1}^{J}\lambda_j=1,\lambda\ge 0,0\le\vartheta_j\le 1\ \forall j,\beta \text{ free}\end{array}\right.\right\}\end{aligned} \tag{7}$$

Model (4) is a nonlinear model. By setting $\mu_j=\vartheta_j\lambda_j\ge 0$ and $v_j=(1-\vartheta_j)\lambda_j=\lambda_j-\mu_j$, we can derive $v_j\ge 0$, $\lambda_j=v_j+\mu_j\ge 0$ and $\sum_{j=1}^{J}\lambda_j=\sum_{j=1}^{J}(v_j+\mu_j)=1$. Consequently, model (4) can be reformulated as a (restricted) DDF in the following linear form:

$$\begin{aligned} D_0(F_k,V_k,Y_k,B_k;\mathbf{g}) &= \max\left\{\beta\left|\left(F_k,V_k,Y_k+\beta g^Y,B_k-\beta g^B\right)\in T\right.\right\}\\ &=\max\left\{\beta\left|\begin{array}{l}\sum_{j=1}^{J}F_j(v_j+\mu_j)\le F_k,\sum_{j=1}^{J}V_j(v_j+\mu_j)\le V_k,\\ \sum_{j=1}^{J}Y_j\mu_j\ge Y_k+\beta g^Y,\sum_{j=1}^{J}B_j\mu_j=B_k-\beta g^B,\\ \sum_{j=1}^{J}(v_j+\mu_j)=1,v_j+\mu_j\ge 0\ \forall j,\\ \sum_{j=1}^{J}\mu_j\le 1,\mu_j\ge 0\ \forall j,v_j\ge 0\ \forall j,\beta \text{ free}\end{array}\right.\right\}\end{aligned} \tag{8}$$

Next, we relax the constraints on variable inputs by introducing a set of scaling factors $\boldsymbol{\delta}=(\delta_1, \delta_2, ..., \delta_j)$, resulting in the unrestricted directional distance function as:

$$\hat{D}_0(F_k,V_k,Y_k,B_k;\mathbf{g})=\max\left\{\beta\left|\left(F_k,V_k,Y_k+\beta g^Y,B_k-\beta g^B\right)\in T\right.\right\}$$
$$=\max\left\{\beta\left|\begin{array}{l}\sum_{j=1}^{J}F_j(v_j+\mu_j)\le F_k,\sum_{j=1}^{J}V_j(v_j+\mu_j)\le\delta_k V_k,\\ \sum_{j=1}^{J}Y_j\mu_j\ge Y_k+\beta g^Y,\sum_{j=1}^{J}B_j\mu_j=B_k-\beta g^B,\\ \sum_{j=1}^{J}(v_j+\mu_j)=1,v_j+\mu_j\ge 0\ \forall j,\\ \sum_{j=1}^{J}\mu_j\le 1,\mu_j\ge 0\ \forall j,v_j\ge 0\ \forall j,\beta\text{ free}\end{array}\right.\right\} \tag{9}$$

The scaling factors indicate the degree to which variable inputs are adjusted when the evaluated DMU maximizes outputs. The introduction of these factors effectively weakens the constraints on variable inputs from the original model.

Since model (6) relaxes the constraints based on model (5), the solutions of both models must satisfy $\hat{D}_0^*(F_k,V_k,Y_k,B_k;\mathbf{g})\ge D^*{}_0(F_k,V_k,Y_k,B_k;\mathbf{g})$ for any $(F_k, V_k, Y_k, B_k)\in T$. Consequently, CU in its reduced form can be defined as follows:

$$CU_{diff}=\hat{D}_0^*(F_k,V_k,Y_k,B_k;\mathbf{g})-D^*{}_0(F_k,V_k,Y_k,B_k;\mathbf{g}) \tag{10}$$

Unlike the traditional ratio-based definition, this indicator utilizes the difference between two DDFs to offer a more nuanced assessment of the inefficiencies of the evaluated DMU. To more accurately reflect the resource utilization and facilitate comparisons of CU values across both two models, we refine CU with consideration for undesirable outputs as follows:

$$CU=1-CU_{diff} \tag{11}$$

The CU value ranges from 0 to 1, reflecting the level of resource utilization. Specifically, a CU of 1 indicates that the evaluated unit's capacity is fully utilized. In contrast, a CU of less than 1 may signify two types of overcapacities: (1) Absolute-overcapacity, where excess fixed inputs or insufficient variable inputs lead to overall overcapacity, and (2) Factor-specific excess capacity, indicating that some fixed inputs are overloaded alongside certain variable inputs.

With reference to the studies of Kirkley *et al*. (2002) and Yang *et al*. (2019a), we classify CU into three categories as follows:

Definition 1: When $CU^*=1$, the capacity of the DMU_o is considered fully utilized.

Definition 2: If $CU^*<1$ and all variable inputs meet the condition $\delta^*\ge 1$ simultaneously, the is classified as having absolute-overcapacity.

Definition 3: When $CU^*<1$ holds, but not all variable inputs satisfy the condition $\delta^*\ge 1$ simultaneously the DMU_o is classified as having factor-specific excess capacity.

Meanwhile, we can calculate the optimal values for the variable inputs:

$$V^*=\sum_{j=1}^{J}V_j(v_j^*+\mu_j^*) \tag{12}$$

where v^*_j and μ^*_j represent the optimal solution to model (6). In the case of factor-specific excess capacity, the specific excess inputs can be identified by examining the difference between the optimal and actual values of the variable inputs.

3.3. Variables and data sources

In China, medical and healthcare institutions—including hospitals, community medical institutions, and professional public health institutions are responsible for delivering medical and public health services (World Health Organization, 2015). This study evaluates these institutions across 38 districts in Chongqing. Although the choice of Chongqing was driven by data availability, it still ensures the robustness of representativeness of findings.

Chongqing, one of China's major municipalities, features a diverse range of healthcare settings that include both urban and rural areas. This diversity allows for a comprehensive analysis that reflects various challenges and practices relevant across the country. Furthermore, the healthcare policies in Chongqing align closely with national strategies, making our findings pertinent to other regions with similar governmental directives. The issues of resource allocation, management capabilities, and CU are prevalent in many developing areas of China, suggesting that insights from this study may extend applicable beyond Chongqing. Additionally, the results can serve as a benchmark for future research in other provinces, providing a foundation for comparative studies.

With a population of approximately 32.12 million, Chongqing ranks first among Chinese cities in size as of 2023. Its geographical diversity includes highly urbanized remote rural regions, providing insights into disparities in healthcare provision. Furthermore, the ongoing enhancements to its healthcare infrastructure, including 21,361 medical and healthcare institutions and over 240,000 beds as of 2021, make it the most extensive healthcare system among China's only four municipalities directly under the Central Government, surpassing the other three, namely Beijing, Shanghai, and Tianjin. These characteristics position Chongqing as an excellent case study for understanding broader trends in healthcare infrastructure development.

As mentioned above, we focus on personnel and beds as the primary inputs. The number of beds is treated as fixed inputs, consistent with existing literature (e.g., Färe *et al*., 1989b; Valdmanis *et al*., 2004; Arfa *et al*., 2016). The classification of healthcare personnel as a variable input remains debated; some argue that the numbers of professional staffs, such as pharmacists and registered nurses, are relatively stable (Song *et al*., 2023), while others assert that all healthcare staffs are variable inputs (Färe *et al*., 1989b; Karagiannis, 2015). For this analysis, we define healthcare personnel—including professional personnel, managers, and other employees—as a variable input. We also include medical equipment as a variable input indicator, measured by the total value of any single piece of medical equipment valued over 10,000 yuan.

Output indicators reflect the outpatient and inpatient functions of healthcare institutions, typically including hospitalization days and outpatient visits. In this study, we select inpatient numbers and outpatient visits as output indicators. The mortality rate serves as an undesirable output, calculated as per the methodology outlined by Song *et al*. (2023). Emergency deaths, deaths of discharged patients, and deaths in observation rooms constitute the mortality rate. Emergency deaths are defined as the number of deaths occurring in the emergency rooms divided by the number of emergency patients, and the other two concepts have similar definitions.

In summary, the input-output model developed in this study comprises one fixed input (beds), two variable inputs (medical equipment and health personnel), two good outputs (outpatient visits and inpatient), and one bad output (mortality rate) (see Fig. 3). The dataset is collected from the *Chongqing Health Economy Statistical Yearbooks* (2019—2022). To ensure comparability across years, we adjust all monetary variables to 2018 constant prices using the consumer price index (CPI). Table 1 provides descriptive statistics of the indicators.

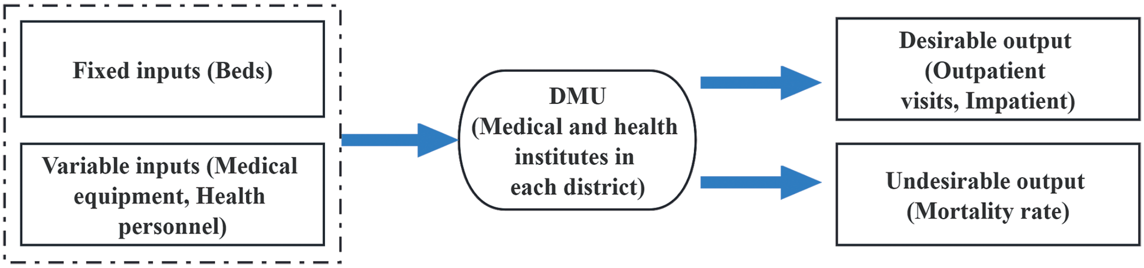

Fig. 3. A simple illustration of the indicator system.

Table 1
Descriptive statistics of medical and health institutions.

Variables		Year	Mean	SD	Min	Max
Variable inputs	Medical equipment	2018	63829.00	65520.22	12792.00	400857.00
		2019	69977.15	71545.63	8374.82	436241.96
		2020	79918.10	84717.62	14494.26	533717.14
		2021	89416.54	96758.51	18074.29	608252.75
	Health personnel	2018	7017.26	4673.88	1498.00	26751.00
		2019	7375.08	4985.91	1574.00	28787.00
		2020	7601.05	5013.23	1628.00	29250.00
		2021	7762.58	5255.17	1688.00	30587.00
Fixed input	Beds	2018	5666.63	2804.01	1176.00	14410.00
		2019	5965.76	2943.39	1140.00	15035.00
		2020	5992.97	2940.98	1209.00	16049.00
		2021	6127.26	2939.25	1302.00	16033.00
Desirable output	Outpatient visits	2018	413.25	265.25	129.94	1432.10
		2019	452.05	288.74	130.69	1614.64
		2020	434.55	258.11	123.19	1392.73
		2021	212.69	216.25	32.55	1272.90
	Impatient	2018	18.22	8.53	5.33	48.39
		2019	19.44	9.27	5.61	53.24
		2020	17.33	8.21	5.11	46.06
		2021	18.70	9.66	5.73	56.57
Undesirable output	Mortality rate	2018	0.42	0.29	0.12	1.34
		2019	0.45	0.34	0.10	1.50
		2020	0.51	0.42	0.12	2.09
		2021	0.58	0.46	0.10	2.09

The changes in average input and output indicators are shown in Fig. 4. Notably, the volume of medical equipment inputs surged between 2018 and 2021, with the value rising from 638,290 thousand yuan in 2018 to 894,165.4 thousand yuan in 2021, reflecting an average annual growth rate of 11.91%. Given the significant fluctuations, it is reasonable to classify medical equipment as a variable input. The number of health personnel also exhibited steady growth, with an annual growth rate of 3.43%. In contrast, the input of beds, remained relatively stable, showing an average annual growth rate of only 2.66%. Over the four years, the inpatient admissions remained stable, whereas outpatient visits experienced a significant decline after 2020. This decline may be attributed to adjustments in the outpatient policy and patients postponing routine healthcare following the outbreak of the Public Health Emergency of International Concern (PHIC) at the end of 2019 (Xiao *et al*., 2021). Additionally, the rising mortality rates indicate the adverse effects of the public health crisis on overall health outcomes.

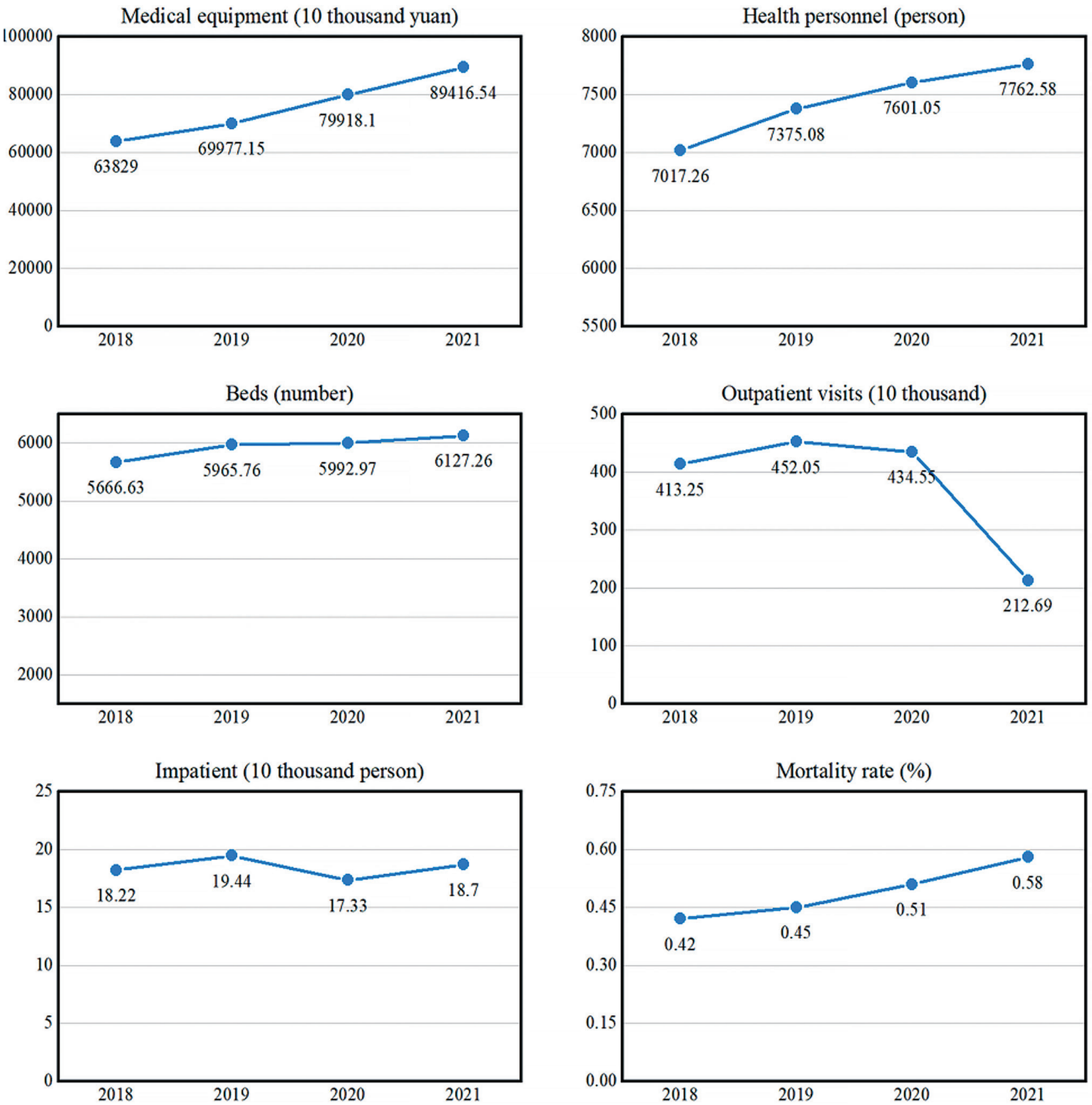

Fig. 4. Changes in mean values of input and output indicators.

4. Empirical Analysis

4.1. CU indicators and comparative analysis

This section mainly analyzes the CU of medical and healthcare institutions in Chongqing's districts, utilizing a model that incorporates undesirable outputs. In our empirical study, we denote the direction vector as $g=(g^Y, g^B)=(Y_0, B_0)$, with (Y_0, B_0) representing the output variable of the DMU_0. The results are presented in Table 2. Notably, eight districts achieved CU values of 1 consistently over the four years, indicating full CU. This consistent full utilization reflects effective management, supportive policies, market adaptability, and potential regional advantages. The average CU across 38 districts during this period is 0.9180, with more than half of the districts (23/38) exceeding this average, signaling commendable resource management practices in these areas. However, the average CU value dropped to 0.8637 in 2021, suggesting a potential gap in CU across districts and years. This observation warrants further exploration of the underlying causes and implications. Sections 4.3 will analyze the regional variations in CU. Fig. 5 illustrates the distribution of CU values over the years, reflecting that while CU values were relatively clustered in 2018, they exhibited greater dispersion by 2021. The widening variability suggests emerging disparities in resource allocation efficiency, likely influenced by changing healthcare demands, shifts in policy priorities, or differing resources across districts. Addressing these disparities is crucial for ensuring equitable access and optimizing resources utilization across all districts.

Table 2
CU indicators incorporating undesirable outputs from 2018 to 2021.

DMUs	CU indicator				Average	
	2018	2019	2020	2021	Value	Rank
Northeast						
DMU1	1.0000	1.0000	1.0000	0.8206	0.9552	18
DMU2	0.9889	0.9493	1.0000	0.9703	0.9771	14
DMU3	1.0000	0.9839	0.9627	0.9093	0.9640	15
DMU4	1.0000	1.0000	1.0000	1.0000	1.0000	1
DMU5	0.7984	0.8556	0.8770	0.7988	0.8325	34
DMU6	1.0000	1.0000	1.0000	1.0000	1.0000	1
DMU7	0.9016	0.9879	0.9999	0.9475	0.9592	16
DMU8	0.9060	0.8650	0.8304	0.8194	0.8552	31
DMU9	0.8734	0.7887	0.8273	0.8413	0.8327	33
DMU10	0.6294	1.0000	0.9999	0.8573	0.8717	28
DMU11	1.0000	1.0000	1.0000	1.0000	1.0000	1
Southeast						
DMU12	1.0000	0.9996	1.0000	1.0000	0.9999	9
DMU13	0.6873	0.6431	0.6293	0.5967	0.6391	37
DMU14	0.9682	0.8640	0.9099	0.8155	0.8894	26
DMU15	0.9962	1.0000	0.9531	0.8326	0.9455	20
DMU16	1.0000	1.0000	1.0000	1.0000	1.0000	1

Table 2. (continued)

DMUs	CU indicator				Average	
	2018	2019	2020	2021	Value	Rank
DMU17	1.0000	0.9799	1.0000	0.9845	0.9911	11
Main Urban						
DMU18	0.9924	0.9702	0.9936	0.8195	0.9439	21
DMU19	1.0000	1.0000	1.0000	1.0000	1.0000	1
DMU20	1.0000	1.0000	1.0000	1.0000	1.0000	1
DMU21	1.0000	0.8999	0.8811	0.8550	0.9090	24
DMU22	0.9306	0.8699	0.9938	0.8154	0.9024	25
DMU23	0.6538	0.5763	0.6666	0.5228	0.6049	38
DMU24	0.9855	0.9689	0.9752	0.9042	0.9585	17
DMU25	0.9658	0.8877	0.8403	0.5612	0.8138	35
DMU26	1.0000	0.9089	1.0000	0.7819	0.9227	23
DMU27	0.8898	0.8864	0.8795	0.8164	0.8680	29
DMU28	0.9043	0.8098	0.8815	0.6579	0.8134	36
DMU29	0.8572	0.9440	0.7999	0.8036	0.8512	32
DMU30	0.9078	0.8306	0.9866	0.7708	0.8740	27
DMU31	1.0000	1.0000	1.0000	1.0000	1.0000	1
DMU32	1.0000	1.0000	0.9739	0.9962	0.9925	10
DMU33	0.9713	0.9566	0.9516	0.9297	0.9523	19
DMU34	1.0000	1.0000	1.0000	1.0000	1.0000	1
DMU35	1.0000	0.9010	0.8156	0.7431	0.8649	30
DMU36	1.0000	1.0000	1.0000	0.9093	0.9773	13
DMU37	1.0000	1.0000	0.9709	0.7785	0.9374	22
DMU38	0.9925	0.9871	1.0000	0.9630	0.9857	12
Average	0.9421	0.9293	0.9368	0.8637	0.9180	-

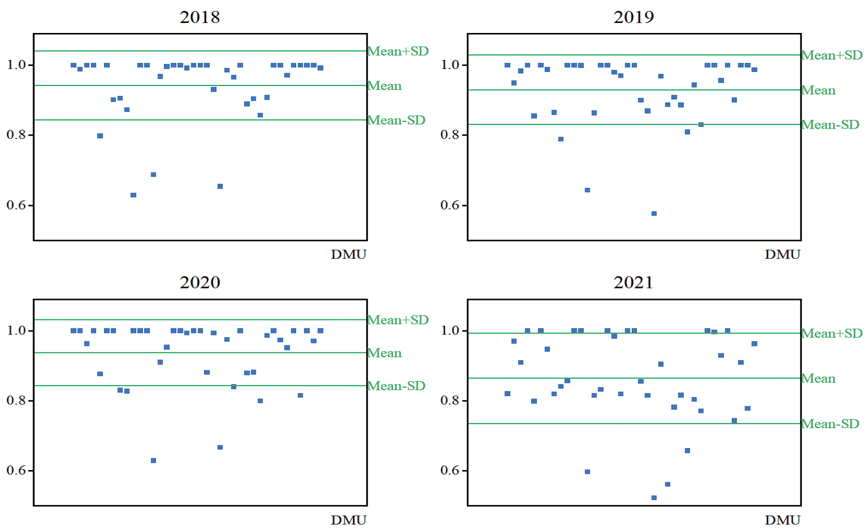

Fig. 5. The distribution of CU values incorporating undesirable outputs.

To emphasize the necessity of incorporating mortality as an undesirable output, we conduct a comparative analysis of CU measurements derived from both traditional and new models. The results of the traditional model measurements, displayed in Table 3, reveal an average CU value of 0.9276 across the period, which surpasses the average of 0.9180 obtained from the new model. The variance suggests that the traditional model tends to overestimate CU values, implying a gap between reported utilization and actual efficiency, thereby emphasizing the importance of including factors like mortality in CU assessments. This observation is consistent with the notion that undesirable outputs reflect resource waste, implying that the utilized capacity must effectively converted into productive outputs. Consequently, optimizing resource utilization should encompass not only capacity but also substantive outcomes, including enhanced health metrics and reduced mortality rates. By incorporating undesirable outputs, the new model provides a more comprehensive assessment of healthcare efficiency, enabling policymakers to make informed decisions about resource allocation and service delivery. While only two districts achieved full CU over the four years, a majority (23/38) demonstrated average CU values exceeding the overall mean. Furthermore, the rankings of the 4-year average CU values for the 33 districts reveal discrepancies between the two models, with 17 districts exhibiting higher rankings under the model that considers undesirable outputs. This discrepancy highlights the impact of including mortality as an undesirable output on the relative performance assessment of healthcare institutions. Conversely, five districts retained identical rankings under both models, indicating consistent performance regardless of the analytical framework employed.

Table 3
CU indicators with undesirable outputs from 2018 to 2021.

DMUs	CU indicator				Average	
	2018	2019	2020	2021	Value	Rank
Northeast						
DMU1	1.0000	0.9876	1.0000	0.8703	0.9645	18
DMU2	0.9998	0.9508	1.0000	1.0000	0.9876	12
DMU3	1.0000	0.9988	0.9701	0.9360	0.9762	15
DMU4	1.0000	1.0000	1.0000	1.0000	1.0000	1
DMU5	0.9644	0.9092	0.9306	0.8697	0.9185	26
DMU6	1.0000	0.9983	1.0000	1.0000	0.9996	3
DMU7	0.9914	0.9871	0.9998	0.9802	0.9897	8
DMU8	0.9132	0.8017	0.7682	0.7529	0.8090	35
DMU9	0.9050	0.8244	0.8522	0.8439	0.8564	32
DMU10	0.7184	0.7188	0.9998	0.8837	0.8302	34
DMU11	0.9894	1.0000	1.0000	0.9640	0.9884	11
Southeast						
DMU12	1.0000	0.9974	1.0000	1.0000	0.9994	4
DMU13	0.6632	0.7232	0.6696	0.6795	0.6839	38
DMU14	0.9714	0.8894	0.9349	0.8605	0.9140	27
DMU15	0.9980	1.0000	0.9928	0.9179	0.9772	14
DMU16	0.9887	1.0000	1.0000	1.0000	0.9972	6

Table 3. (continued)

DMUs	CU indicator				Average	
	2018	2019	2020	2021	Value	Rank
DMU17	1.0000	0.9742	0.9988	0.9850	0.9895	9
Main Urban						
DMU18	0.9992	0.9712	1.0000	0.9195	0.9725	16
DMU19	1.0000	1.0000	1.0000	1.0000	1.0000	1
DMU20	0.9036	0.9428	0.8389	0.7690	0.8636	30
DMU21	1.0000	0.9210	0.9068	0.8530	0.9202	24
DMU22	0.9708	0.9264	1.0000	0.8687	0.9415	22
DMU23	0.7956	0.7816	0.8236	0.6862	0.7718	37
DMU24	0.9661	0.9617	0.9778	0.8999	0.9513	20
DMU25	0.9486	0.9180	0.9113	0.7174	0.8738	28
DMU26	1.0000	0.9334	1.0000	0.8371	0.9426	21
DMU27	0.9654	0.9418	0.9261	0.8439	0.9193	25
DMU28	0.8819	0.8484	0.8916	0.7680	0.8475	33
DMU29	0.8711	0.8662	0.7555	0.7109	0.8009	36
DMU30	0.9412	0.7956	0.9170	0.8323	0.8715	29
DMU31	1.0000	0.9944	1.0000	1.0000	0.9986	5
DMU32	1.0000	0.9901	1.0000	0.9762	0.9916	7
DMU33	0.9817	0.9287	0.9616	0.8912	0.9408	23
DMU34	0.9771	0.9801	1.0000	1.0000	0.9893	10
DMU35	0.9109	0.8831	0.8243	0.8247	0.8608	31
DMU36	1.0000	0.9912	0.8995	0.9373	0.9570	19
DMU37	1.0000	1.0000	0.9676	0.8940	0.9654	17
DMU38	1.0000	0.9827	1.0000	0.9627	0.9863	13
Average	0.9531	0.9295	0.9400	0.8878	0.9276	-

We further analyze the differences in numerical distribution by comparing the kernel density plots of the results obtained from the two models (see Fig. 6). The figure illustrates that the results from the new model exhibit a less concentrated distribution around 1.0000 compared to the traditional model. The broader distribution of CU values in the new model provides a more nuanced understanding of CU and underscores the variability in healthcare efficiency across different districts. Notably, the significant divergence between the computed results of the new model and the traditional model reinforces the necessity of introducing undesirable outputs, thereby emphasizing the value of adopting more comprehensive approaches in healthcare management assessment and policy decision-making.

4.2. Analysis of overcapacity

Fig. 7 categorizes the 38 districts based on the three CU situations defined in Section 3.1. Notably, the number of districts with full CU decreased significantly from 18 in 2018 to 9 in 2021. Conversely, districts

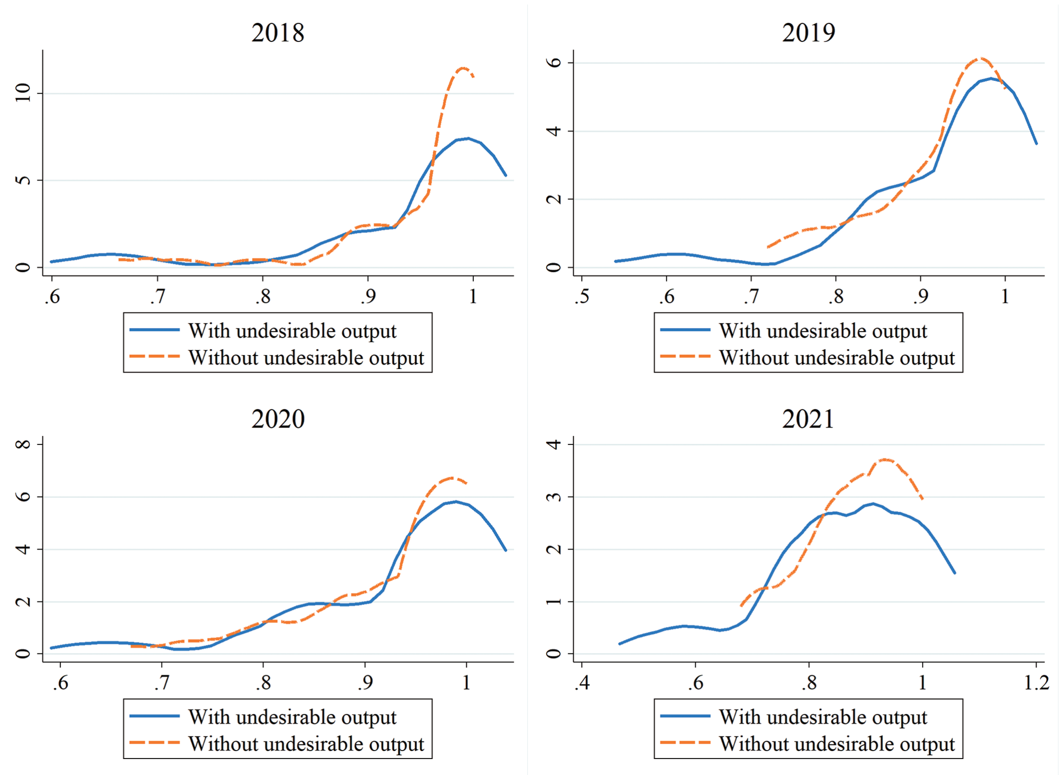

Fig. 6. Kernel density diagram of CU results.

with factor-specific excess capacity rose from 5 to 10 during the same period, while the number in a state of absolute excess capacity remained stable. Most districts facing underutilization fall into the category of absolute excess capacity, indicating a shortfall in health personnel and medical equipment relative to fixed inputs (beds). While beds are tangible, easily quantifiable, optimizing human resources and equipment requires more nuanced planning. Consequently, the healthcare policy has historically focused on bed numbers, leading to their overaccumulation. Despite increases in healthcare personnel and medical equipment, these resources still exist in relative deficit within the current healthcare landscape.

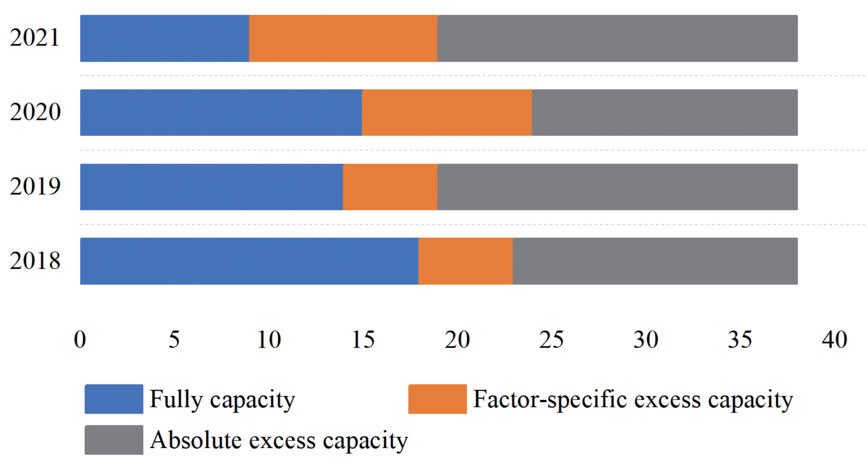

Fig. 7. CU analysis from 2018 to 2021.

In the case of factor-specific excess capacity, specific variable inputs in excess can be identified. This study focuses on two variable inputs, allowing us to further classify factor-specific excess capacity into personnel-specific excess capacity and equipment-specific excess capacity. Using the method for measuring optimal variable inputs outlined in Section 3.2, we can derive the necessary personnel or equipment inputs to achieve full capacity and compare these with the actual values. Based on the difference, we can assess excess: (1) a positive difference indicates insufficient actual inputs, while (2) a negative difference suggests excessive actual inputs. Fig. 8 illustrates the districts with personnel-specific or equipment-specific excess capacity for each year. In 2019, more districts exhibit equipment overcapacity, likely reflecting strategic investments to meet rising healthcare demands. However, in the subsequent years, personnel overcapacity was more prevalent, suggesting potential inefficiencies in human resources allocation. Overall, factor-specific excess capacity is predominantly driven by personnel, with most regions lacking equipment-specific excess capacity. Notably, investments in medical equipment have not been excessive, despite various factors influencing purchasing decisions. These findings underscore the need for strategic resource allocation in healthcare management, emphasizing the balance between investments in personnel and equipment to optimize service delivery efficiency and effectiveness.

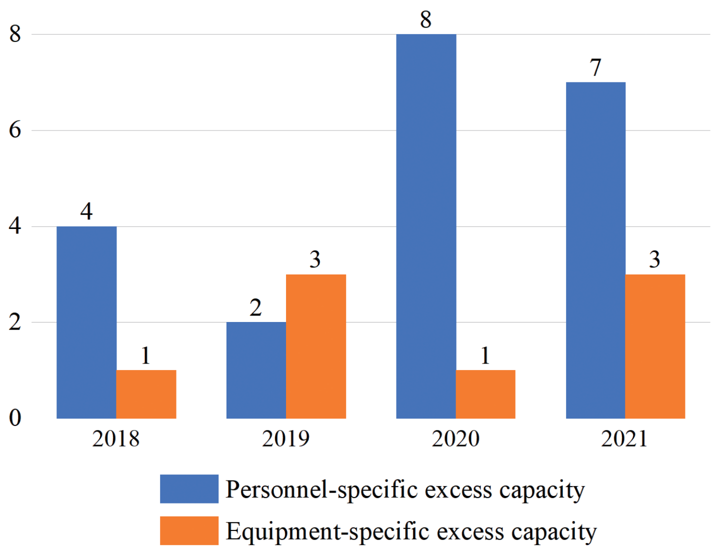

Fig. 8. Factor-specific excess capacity analysis from 2018 to 2021.

4.3. Regional variations in CU

Chongqing comprises 38 districts, each exhibiting significant differences in natural, economic, and social characteristics. To promote integrated collaborative development, the Chongqing Urban and Rural Master Plan (2014–2020) outlines a partial development framework comprising "one area and two clusters". The "one area" refers to the metropolitan area (Main Urban), consisting of 21 districts, while the "two clusters" include the northeastern Chongqing Township Cluster (Northeast), centered around Wanzhou District and encompassing 11 neighboring districts, as well as the southeastern Chongqing Township Cluster (Southeast), centered around Qianjiang District with six neighboring districts. The Main Urban area mainly serves urban functions, while the northeastern and southeastern clusters focus on ecological nourishment and protection. These three functional areas differ significantly in terms of their roles, population densities, economic levels and healthcare resource allocations. Fig. 9 illustrates the disparities in the number of medical and health institutions, beds, and physicians across these areas. The Main Urban area shows a substantial advantage in the number of institutions, fixed asset investments, and healthcare professionals. While the gaps in healthcare resources between the Southeast and Northeast clusters is narrower, the Northeast possesses a relative advantage. However, the CU rate of healthcare institutions is a complex, systematic issue, influenced not only by the availability of healthcare resources but also a variety of other factors.

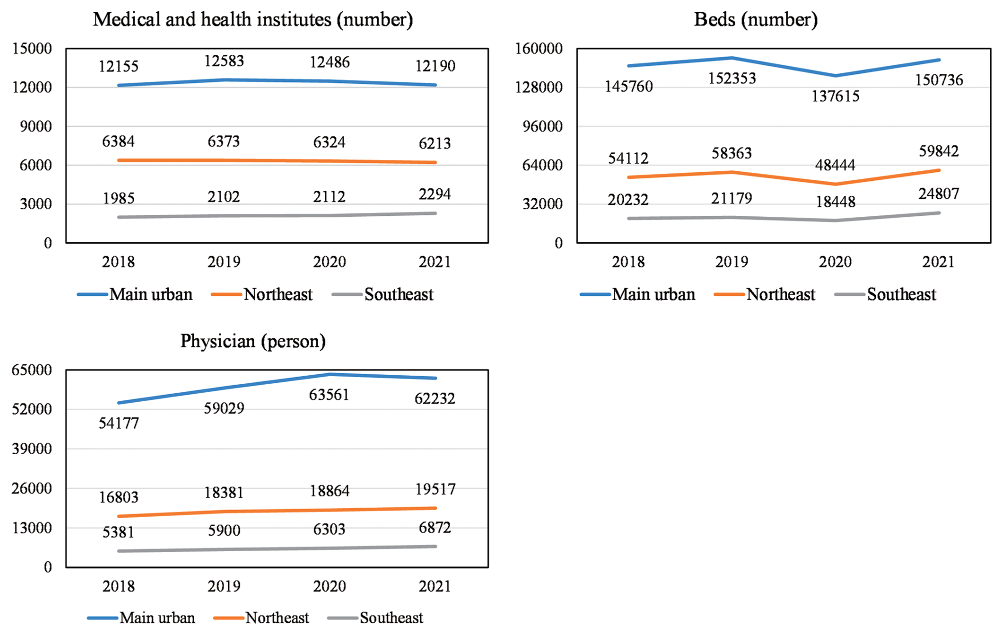

Fig. 9. Differences in health care resources among the three functional areas.

Combining the results of the CU measurements for each district, Fig. 10 illustrates the changes in average CU values from 2018 to 2021 across three functional areas. The observed decrease in CU values by 2021 indicates potential challenges in resource optimization and utilization efficiency within the healthcare sector. This decline may stem from evolving healthcare demands, shifting policy priorities, or systemic inefficiencies that impede effective resource allocation. Among the regions, the Northeast exhibits the highest level of CU, having increased its CU value from 2018 to 2019. The CU values for the Main Urban and Southeast areas follow similar trends from 2018 to 2020, with the Sourtheast showing slightly lower CU values. However, from 2020 to 2021, the Main Urban area experienced a significant drop in CU, despite maintaining the highest CU value among the three regions. This indicates that, although the Main Urban area is well-resourced, it does not fully leverage its capacity. Conversely, the Southeast faces a shortage of medical resources and underutilization, likely due to managerial and technological shortcomings. Overall, these trends underscore the dynamic nature of healthcare resource utilization and the need for ongoing monitoring and adaptive strategies to enhance efficiency and address disparities across regions.

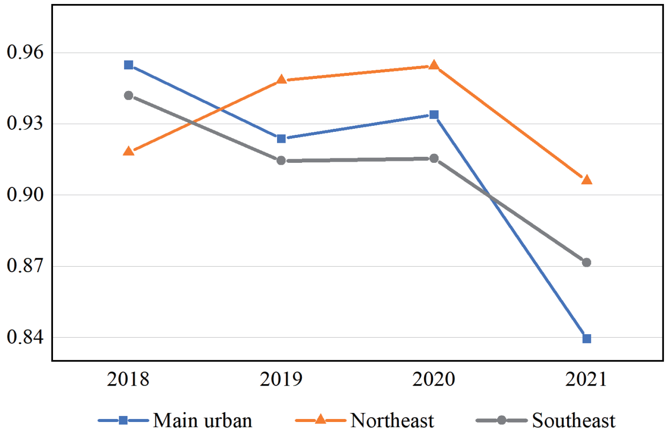

Fig. 10. CU in the three functional areas from 2018 to 2021.

We also count the overcapacity situation in each of the three functional areas, as shown in Fig. 11. Across all areas, both full CU and absolute excess capacity are prevalent, indicating a complex landscape of resource utilization dynamics. Some districts effectively maximize resources, while others struggle with effective allocation. Notably, all districts in the Northeast were in one of these two situations during 2018 and 2019. The Southeast experiences the most significant equipment surplus, with 1 to 2 districts reporting equipment-specific excess capacity annually from 2018 to 2020. In contrast, the Main Urban and the Northeast regions each identified a single district with equipment surplus in only one specific year. Personal-specific excess capacity occurs in the Main Urban area, where three districts were overstaffed in 2018, two in 2019, and five in both 2020 and 2021. This overstaffing is particularly concerning, as it highlights a lack of effective resource utilization in some healthcare facilities. Conversely, overstaffing is less common in Northeast and Southeast, suggesting relatively effective human resource management practices in these regions, which contribute to a more balanced resource allocation and utilization.

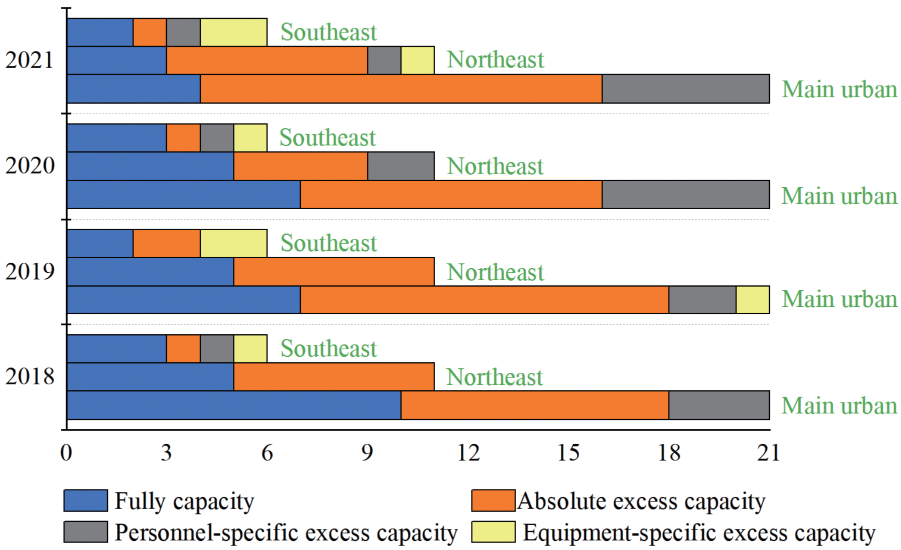

Fig. 11. Factor-specific excess capacity analysis in the three functional areas.

4.4. Truncated Tobit regression analysis

This section examines the impact of external environmental variables on CU in healthcare. Economy factors influence public sector capacity through government inputs and purchasing power (Polidano, 2000). Kaya and Cafrı (2016) include GDP per capita as an environmental variable affecting health system efficiency. Guyer (1999) identifies population and urbanization as the key determinants. Liu *et al*. (2022) highlight population density and urbanization level as indicators influencing the efficiency of pediatric services.

Building on these studies, we select RGDP per capita, population density, and urbanization rate as proxies for economy conditions, population characteristics, and urbanization. These factors affect the operation of the healthcare system without directly interfering with efficiency assessment. Definitions and explanations of these indicators are provided in Table 4. We employ the Tobit regression method to analyze the impact of external environmental variables on CU, as this approach is suitable for cases where the dependent variable is continuously truncated. Previous studies indicate that truncated Tobit regression offers more accurate estimates than Bootstrap (Yang *et al*., 2019b; Fukuyama *et al*., 2022) and OLS regression (Banker *et al*., 2019).

Table 4
Explanations of independent variables.

Independent variables	Units	Definitions or explanations
RGDP per capita	10 thousand yuan/person	The measure shows the region's total economic output divided by its total population for each year for each district. GDP per capita is calculated by dividing the GDP of a region by the population (number of inhabitants) living there.
Population density	person/square kilometer	The number of people living per unit of area. It is calculated by dividing the total population of a region by its land area.
Urbanization rate	%	The proportion of a country's population lives in urban areas as opposed to rural areas. The urbanization rate is calculated by dividing the urban population by the total population and then multiplying the result by 100 to express the urbanization rate as a percentage.

The Tobit regression results, presented in Table 5, reveal a significant negative correlation between RGDP per capita and CU value (measured by revenue-based indicator). Conversely, there is a significant positive correlation between population density and CU value. However, the urbanization rate did not exhibit a significant relationship with CU value. These findings contradict those of Kaya and Cafrı (2016), suggesting that abundant health resources in affluent areas are not effectively converted into enhanced service capacity. Additionally, some studies indicate that regions with lower economic levels can achieve substantial improvements in health service efficiency through the implementation of effective policies (Balabanova *et al*., 2013; Leng *et al*., 2019). Higher population density is associated with improved public sector performance and capacity, benefiting from economies of scale and reduced transportation and heating costs (Hauner and Kyobe, 2010).

Table 5
Results of the truncated Tobit regression analysis.

Dependent variable	Independent variables	Coefficients	Std. Err.	z	P>|z|
CU	RGDP per capita	-0.0346915**	0.0075735	-4.58	0.000
	Population density	0.0001249**	0.0020929	-0.16	0.009
	Urbanization rate	-0.0003364	0.0000475	2.63	0.872
	_cons	1.121046	0.0976189	11.48	0.000

*Note: **Coefficient is significant at the 0.01 level (2-tailed)*

5. Conclusions and Implications

5.1. Conclusion

The Chinese Government has been committed to prioritizing public health, especially since the implementation of the new round of health system reform in 2009. The scale of health investment has expanded, particularly in medical equipment. This study measures the CU rates of medical and healthcare institutions across all districts of Chongqing, a major city in Southwest China, from 2018 to 2021. By including medical equipment inputs—often overlooked in prior research—and incorporating mortality as an undesirable output in the input-output system, we reveal that previous studies may have overestimated CU in the healthcare sector.

Our findings indicate that medical equipment and health personnel are underutilized in most districts, although surplus equipment is rare. During the observation period, most regions with underutilized capacity are in a situation of absolute excess capacity, indicating that the inputs of medical equipment and health personnel are insufficient relative to fixed inputs. Furthermore, regression analysis reveals a significant negative correlation between RGDP per capita and CU levels, suggesting challenges in effectively managing health resources in affluent regions.

5.2. Policy implications

Our study's findings on medical equipment shortages and the inefficiencies in healthcare resource allocation align with broader healthcare reform goals outlined by the Chinese government. The latest *Decision of the Central Committee of the Communist Party of China* (2024) calls for deepening the reform of the medical and health system, with a focus on promoting the equitable distribution of high-quality medical resources across regions and improving the development mechanism of medical equipment. The reform highlights the need for targeted investments in healthcare infrastructure to ensure that medical resources are effectively distributed in line with needs. In the light of these findings, we propose the following policy recommendations for public health managers, ensuring alignment with the broader objectives outlined in the national healthcare reforms.

Addressing Equipment Shortages: Empirical measurements show that, although medical equipment inputs continue to grow at a high rate, equipment-specific excess capacity is rare. Additionally, our supplementary survey indicates that while healthcare staff are generally familiar with medical equipment management policies, 72.12% believe there is still a need to increase medical equipment (see supplementary B). In response to these challenges, we recommend avoiding a "one-size-fits-all" approach to anti-corruption measures in healthcare, which may inadvertently exacerbate equipment shortages. Instead, the government should focus on ensuring fair competition and transparency, such as through mandatory disclosure of payments made by equipment suppliers to hospitals. Recent efforts by the Chongqing Municipal Health Commission and the Finance Bureau to regulate medical equipment procurement emphasize the need for a standardized process and improved financial support. Moreover, in alignment with the national health reform goals of promoting a more balanced regional distribution of high-quality medical resources, we recommend expanding and upgrading medical equipment in underserved areas, particularly in grassroots healthcare institutions. This approach will support the expansion and sinking of high-quality medical resources and help reduce regional disparities, fulfilling one of the key objectives of the 2024 healthcare reforms.

Optimizing Resource Utilization: This study finds regional disparities in CU, with affluent areas not fully leveraging their rich medical resources. Despite economic advantages, the Main Urban area exhibits suboptimal CU compared to Northeast Chongqing. The negative correlation between RGDP per capita and CU suggests that resource management capacities in affluent regions may be lacking. Innovative policies and effective governance are crucial for driving substantial improvements in health services (Balabanova *et al*., 2013). To address this, policymakers should move beyond simply investing in resources and focus on creating robust management policies that improve both resource utilization and service provision. This recommendation aligns with the national healthcare reform's emphasis on accelerating the construction of a hierarchical diagnosis and treatment system. Optimizing medical resource allocation and fostering collaboration between healthcare institutions in neighboring regions will ensure more equitable resource distribution. Encouraging the use of advanced medical technologies is essential for enhancing diagnostic efficiency and ensuring that healthcare services are provided in the most cost-effective manner.

Strengthening Emergency Response Capacities: The significant decline in CU in 2021 may relate to the public health impact of the COVID-19 pandemic. The unprecedented strain on global public health systems required more than "normal" emergency surge capacity (Klein *et al*., 2022). While community-based responses were emphasized, the observed decrease in outpatient visits indicates a need to bolster the response capabilities of medical and healthcare institutions. Institutions should enhance their emergency plans to ensure quick resource deployment and agile resource allocation in crises. Government support and financial assistance should be directed toward strengthening inter-institutional collaboration and resource sharing, which will improve response efficiency. In alignment with the national goal of strengthening grassroots medical and health services, additional investments should be made in primary healthcare facilities and their capacity to manage emergencies. This could include improving infrastructure, staffing, and medical equipment at the local level, in support of building a more resilient healthcare system.

5.3. Implications for broader context

This study significantly enhances the accuracy and realism of capacity measurement in medical and public health by integrating previously overlooked factors—namely, medical equipment and mortality rates—into input-output system. Utilizing the Resource-Based View (RBV), we demonstrate how effective management of medical equipment can improve organizational performance and health outcomes. This theoretical perspective enriches the discourse on resource management in public organizations, emphasizing the importance of leveraging key resources for optimal results. Furthermore, our findings underscore the necessity for targeted policy interventions that promote transparency and accountability in the allocation and utilization of medical resources. By advocating for governance structures that support the efficient use of healthcare assets, our study offers practical recommendations for policymakers aiming to enhance the effectiveness of public health systems.

The findings of this study, based on the data from Chongqing, provide valuable insights that may be applicable to other regions in China. As one of China's largest municipalities, Chongqing exemplifies a unique mix of urban and rural healthcare challenges. Its demographic diversity, economic conditions, and public health infrastructure may reflect those in other metropolitan areas across the country. The issues identified in our analysis—such as capacity underutilization and inadequate management of medical resources—are not confined to Chongqing. Previous studies have indicated that challenges in optimizing healthcare services and resource allocation are widespread in China (e.g. Liu *et al*, 2016; Li *et al*., 2020). This suggests that the barriers to effective health management observed in Chongqing may signal broader systemic issues within the national public health framework.

The need for improved governance and resource management highlighted in our findings aligns with ongoing discussions about healthcare reforms in China. Policymakers at both local and national levels can benefit from the lessons learned in Chongqing when devising strategies to enhance the efficiency and effectiveness of healthcare systems nationwide. To further validate the generalizability of our findings, future research should replicate this study in other provinces and municipalities. Comparative analyses could determine whether the trends observed in Chongqing are consistent across different contexts, thereby enriching our understanding of public health management in diverse urban settings in China.

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