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Application of mathematical models on efficiency evaluation and intervention of medical institutions in China

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Abstract

Background The efficiency of medical services directly impacts the economic burden of healthcare, making it crucial to analyze the input-output efficiency of various types of medical institutions. However, while hospitals had been extensively analyzed for their efficiency, other types of medical institutions had received limited attention in this regard.

Methods In this study, we employed data envelopment analysis (DEA) methods based on time series and internal benchmarks to autonomously assess the efficiency of 18 distinct categories of healthcare facilities in China over the past decade. The verification was conducted through the utilization of the critical incident technique (CIT). Additionally, we utilized the Delphi process (AHP) method to evaluate suppliers of medical consumables, implemented a multi-population genetic algorithm for managing these consumethod and analytic hierarchymables efficiently, and applied stakeholder theory to manage medical personnel efficiency.

Results Our findings indicated that medical institutions capable of providing clinical services exhibited higher levels of efficiency compared to those unable to do so. Multiple indicators suggested redundancy within these institutions. Notably, comprehensive benefit evaluation revealed that clinical laboratory had performed poorly over the past decade. We selected an inefficient medical institution for intervention in reagent management and the work efficiency of medical staff. After implementing the Delphi method and multi-population genetic algorithm for consumable replenishment, the reagent cost was reduced by 40%, 39% and 31% respectively in each of the three experimental groups, compared to the control group. By applying stakeholder theory and process reengineering methods, we were able to shorten quality control management time for medical staff in the experimental group by 41 min per day, reduce clinical service time by 25 min per day, and extend rest time by 70 min per day, while the quality indicators were all meeting the targets.

Conclusion By employing various mathematical models as described above, we were able to reduce costs associated with medical consumables and enhance medical personnel work efficiency without compromising quality objectives.

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Keywords DEA, CIT, Delphi, AHP, Multi-population genetic algorithm, Stakeholder, Medical institution, Medical consumable, Medical personnel efficiency

Introduction

The development of human health is directly determined by the quality and efficiency of medical and health services [1]. In recent years, there has been a significant increase in the number of various medical institutions worldwide; however, the application level of medical resource efficiency remains low [2]. With advancements in medical scientific research, the emergence of novel coronavirus outbreaks, and the acceleration of population aging, there has been an increase in medical and health expenses [3]. Simultaneously, inappropriate market competition, inadequate awareness regarding patent protection, delayed medical transformation, and other factors directly or indirectly contribute to unequal distribution of medical resources and low input-output efficiency in terms of health economic burden [4, 5]. The World Health Organization emphasizes that under current circumstances, all countries should adhere to principles of economic development while proactively enhancing national health resource utilization efficiency [6].

In recent years, public health events have emerged worldwide, exerting a profound impact on health economics [7]. The Middle East Respiratory Syndrome (MERS) outbreak occurred in Saudi Arabia in June 2012 and South Korea in May 2015, directly affecting an additional 28 countries. Consequently, Saudi Arabia experienced a decline of 2.71% in its GDP growth rate from 2012 to 2013, with a continuous downward trend until 2015. Following the Ebola outbreak in West Africa starting from March 2014, which affected nine countries, Guinea witnessed a remarkable decline in its GDP growth rate after experiencing a positive growth rate of 3.94% in 2013. Similarly, the Zika virus outbreak that began in Brazil in May 2015 severely impacted the country's low-growth economy and led to a significant decrease of -3.54% in its GDP growth rate. Furthermore, the global spread of COVID-19 since December 2019 has resulted in an unprecedented level of global debt amounting to $226 trillion USD since World War II. Therefore, conducting systematic evaluations on the efficiency of public health measures becomes imperative following these severe public health events [8].

The most commonly used methods for evaluating resource efficiency include Factor Analysis (FA), Correction of Least Squares Estimates(COLS), Stochastic Frontier Approach (SFA), and Data Envelopment Analysis (DEA) [9–12]. DEA is suitable for cases with multiple input and output factors, allowing for simultaneous statistical analysis of the technical efficiency and scale efficiency of the decision making unit (DMU) [13]. Compared to other evaluation methods, DEA can eliminate the influence of measurement unit selection and generate results solely based on mathematical design models, ensuring better impartiality and objectivity [14]. Additionally, DEA can assess the redundancy of input indicators and insufficiency of output indicators by analyzing DMU's relaxation variables [15]. Kohl S et al. [16] conducted a review on 262 studies regarding the application of DEA analysis in health resources. Yan C et al. [17] utilized DEA to analyze hospital efficiency in 31 provinces across China from 2005 to 2019. The study revealed that inefficiencies in Shanxi, Inner Mongolia, and Jilin primarily stem from scale inefficiency while those in Liaoning, Anhui, and Fujian were mainly attributed to technical inefficiency. Furthermore, specific redundant input indicators and insufficient output indicators provided clear rectification strategies for local government departments.

The utilization of the DEA model for institutional analysis poses challenges in obtaining specific data on input and output indicators, particularly those pertaining to economic evaluation [18]. The utilization of estimated data will diminish the efficacy of analysis outcomes. Therefore, acquiring dependable data is crucial for the application of the model. The limitations of DEA models have sparked extensive discussions, particularly regarding the comparability between DMUs [19]. The DEA models are commonly employed to assess DMUs that share similar characteristics, such as those among competitors. However, regardless of their similarities, each system remains distinct and unique in its own right [20]. The DEA model has been employed by scholars to address this contradiction in the assessment of internal benchmarks. Specifically, it allows an independent institution to compare its performance across different time periods [19, 21]. The internal benchmark DEA model based on time series was not only applied by some scholars for actual efficiency evaluation, but they also incorporated critical incident technique (CIT) to quantify the impact of management behavior or external events on efficiency. This approach has laid a strong foundation for the vertical evaluation of internal benchmarks in independent institutions [20].

The findings from previous studies indicate that medical consumables expenditure constitutes one-third of the total expenses incurred by healthcare institutions, with a consistent upward trajectory [22, 23]. The effective management of medical consumables costs can significantly reduce the financial burden on business activities [24]. In 1989, Japanese scholars enhanced the management model of medical consumables supply processing distribution (SPD) by drawing inspiration from Toyota's JIT inventory management approach, resulting in significant cost reductions for medical consumables [25, 26]. Schubert et al. [27] conducted a comparative study on the management of medical consumables in hospitals between the United States and France, focusing on cost control. They identified that the primary factor contributing to the difference in cost control was the collaboration mode with suppliers, leading them to advocate for implementing JIT management approach in hospital material management. The study conducted by Yu et al. [28] revealed that hospitals in Singapore commonly employ the strategy of outsourcing services for managing medical consumables, which unfortunately leads to a limited scope for price coordination in procurement and subsequently results in high costs associated with medical consumables. The study conducted by Liu [29] demonstrated the applicability of a multi-population genetic algorithm in designing an inventory management model and optimizing the SPD management model through simulation experiments, although its practical implementation remains unexplored.

The management of employee efficiency is a crucial concern for enhancing the input-output efficiency of medical institutions. Previous research has indicated that effectively managing employee efficiency necessitates integrating them with business process optimization [30]. The core data of the laboratory automation system in the Laboratory Department of Tongren Hospital was analyzed and evaluated by Tong et al. [31]. It was discovered that configuring the instrument for self-starting could advance the initial sample detection time by 0.5 h. Additionally, implementing a track logistics system and an automatic sample sorting system would further advance the review time for inspection reports by approximately 4.5 h, resulting in significant labor cost savings. The study conducted by Inal et al. [32] utilized DEA as the evaluation method and revealed that implementing the Six-sigma management system to streamline the workflow of laboratory quality control could result in a reduction of 3.38 h in sample turnaround time, thereby enhancing employees' work efficiency. The study conducted by Cao et al. [33] utilized Key Performance Indicators (KPIs) for the purpose of monitoring and enhancing the performance of hospital staff. Alvarez et al. [34] implemented a comprehensive 360 degree perspective assessment as a management strategy, conducting fair and objective performance evaluations for staff at all levels of the hospital. They established KPIs and implemented a reward and punishment mechanism to effectively enhance the efficiency of hospital staff in achieving the primary goals of the institution.

Currently, medical resources are primarily allocated to hospitals; however, non-hospital medical institutions also play a crucial role in the implementation of hierarchical diagnosis and treatment as well as the efficient allocation of medical resources, effectively addressing redundancy and insufficiency issues [35]. However, the attention and resource allocation to non-hospital medical institutions in various countries have led to an increasing redundancy of inputs in different aspects. Nevertheless, there has been a lack of evaluations regarding their input-output efficiency in recent years [36]. The promotion of non-hospital medical institutions' development, along with their emphasis on medical resource efficiency while delivering qualified services, plays a crucial role in regulating the overall efficiency of healthcare resources [37].

The motivation of this study was to identify and address redundant indicators through comprehensive efficiency analysis, in order to bridge the gap in recent years' efficiency analysis of non-hospital healthcare institutions in China. It served as a reference for enhancing the input-output efficiency of medical institutions and provided recommendations for the rational allocation of medical resources by the government, thereby mitigating regional health economic burdens. The primary objectives of this study were threefold. Firstly, the comprehensive analysis model was employed to objectively and effectively analyze the input-output efficiency of 18 different types of non-hospital medical institutions in China over the past decade. The second approach was to select an inefficient healthcare institution as the research subject, while ensuring its medical quality, in order to reduce the cost of utilizing high-value consumables. The third step was to identify the primary contradictions that impede the efficiency of individuals and intervene in them, aiming to enhance personnel efficiency in medical institutions while ensuring medical quality.

The significance of the findings of this study lied in its potential to provide valuable insights for healthcare policy makers and institutional managers, thereby offering guidance for enhancing the input-output efficiency of healthcare institutions and facilitating advancements in the meticulous management of medical establishments. The efficiency analysis of non-hospital medical institutions was initially conducted, leading to the identification of objectively existing inefficient DMUs. The specific redundancy indexes were determined through the analysis of efficiency results, and quantitative recommendations for allocating medical resources were proposed. The cost of consumables used in medical institutions was effectively reduced while ensuring medical quality through the practical application of quality indexes and a high-value consumables management model. This provided specific algorithms and models for fine management of consumables cost in medical institutions.

The breakthrough in improving personnel efficiency was identified through the application of quality indexes and semi-structured interviews, providing managers with valuable insights into methods for managing personnel efficiency. The innovation and uniqueness of this study lied in the application of a diverse range of mathematical models to assess the efficiency of medical institutions and identify areas for intervention. Simultaneously, it introduced the utilization management model based on genetic omics into medical institutions for the first time, substantiating its feasibility.

Materials and methods

Selection and classification of subjects

According to the institutional grouping method outlined in the China Health Statistical Yearbook (hereinafter referred to as the Yearbook), medical and health institutions were categorized into four distinct groups: hospitals, primary medical and health institutions, specialized public health institutions, and other institutions. To conduct our study, we initially excluded hospitals and focused on a total of 18 non-hospital medical institutions from the remaining three types of establishments. The 18 types of institutions included community service centers, health centers, outpatient departments, and nursing stations in primary medical and health institutions. They also encompassed Centers for Disease Control and Prevention (CDC), specialized disease prevention and control departments, health education centers, maternal and child healthcare departments, emergency centers, blood banks, health supervision centers, and family planning service departments in specialized public health institutions. Additionally, other institutions consisted of sanatoriums, inspection institutions, medical research centers, on-the-job medical training centers, clinical laboratory centers, and statistical information centers. To advanced this work while ensuring comparability between DMUs and the applicability of the DEA model, we had opted for an internal benchmark based on time series analysis to independently evaluate the efficiency of each of the 18 institutions. The study involved a longitudinal case study spanning 10 years for each of the 18 institutions. The Yearbook served as the primary source of our data, encompassing a statistical period from January 1 to December 31 each year. While certain indicators may not be collected with absolute precision due to exceptional circumstances, the data published in the Yearbook remains authoritative, accurate, and subject to rigorous auditing. Therefore, we had considered the statistical cycle of Yearbook as the DMU for each institution, with each institution having 11 DMUs. After considering the distinct characteristics and incomparability of these 18 institutions, we conducted an independent longitudinal evaluation of each institution's DMUs, with a specific focus on comparing the institution's performance across different time periods. Additionally, we employed critical incident technique (CIT) to analyze the precise impact of significant events on the institution's efficiency over time. The implementation of effective horizontal evaluation within the interagency framework was currently unattainable. However, institutions characterized by a significant number of inefficient DMUs would be selected for inclusion in the subsequent study.

Selection of input and output indicators

The statistical indicators included in the Yearbook were presented in Table S1. Firstly, similar indicators with comparable functions in efficiency analysis were merged and screened. Then, the selection of statistical indicators was conducted through a literature search method. Based on previous experience in selecting DEA model indicators, it was recommended to have half the number of input and output indicators compared to DMU to avoid bias caused by excessive indicator selection [16]. Six databases including Medline, Embase, Cochrane Library, Web of Science, CNKI and Wanfang were searched from 2017 to 2021. Taking the Medline database as an example, the following search strategy was employed: (("Efficiency, Organizational"[Mesh]) OR ((((((Organizational Efficiency[Title/Abstract])) OR (Administrative Efficiency[Title/Abstract])) OR (Program Efficiency[Title/Abstract]) OR (Efficiency, Program[Title/Abstract]). A total of 974 articles were retrieved. The inclusion and exclusion process diagram shown in Fig. S1 was used for reference screening resulting in a final selection of 43 papers as displayed in Table S2. Statistical analysis on citation frequency of indicators was performed and results were presented in Table S3. A total of 12 input indicators and 19 output indicators were identified. Considering data availability factors, the number of health technicians, number of beds and business activity expenses were ultimately chosen as input indicators while number of patients treated and total income were selected as output indicators.

After excluding redundant indicators from the Yearbook statistics, only six indicators remained for medical institutions that were unable to provide clinical services. These included X1 (business activity expenses), X2 (number of health technicians), X3 (total value of equipment over 10,000 yuan), X4 (floor area), and X5 (net assets) as input indicators, with Y (total income) as the output indicator. Pearson correlation analysis was conducted and the results were presented in Table S4. It was evident that there was no significant correlation between net assets and total income, so it was excluded.

The guidance of mathematical design for DEA model

The concept of returns to scale can be categorized into two types: Increasing Returns to Scale (IRS) and Decreasing Returns to Scale (DRS). When the increase in output is greater than the increase in input factors, it is referred to as IRS; conversely, when the increase in output is less than the increase in input factors, it is known as DRS. DEA models are further classified into Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). In the analysis of medical resource efficiency, return-to-scale tends to fluctuate under normal circumstances. Therefore, it became necessary to establish both CRS and VRS equations simultaneously for selecting the DEA model.

$$
\begin{aligned}
&\min \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\
&s.t. \sum_{j=1}^{n} \lambda_j X_{ij} + S_i^- = \theta x_{io}, \forall i, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \forall_r \\
&\lambda_j, s_i^-, s_r^+ \geq 0, \forall j, i, r,
\end{aligned} \tag{1}
$$

According to formula (1), supposed the optimal solution of the model was denoted by θ. Then:

Theorem 1: If θ=1 and S+=S-=0, the DMU was considered DEA effective, and both technical efficiency and scale efficiency of the DMU were valid in this case.

Theorem 2: If θ=1 and there existed at least one relaxation variable for input or output index, i.e., S+ or S- greater than 0, then the DMU was regarded as weakly DEA efficient. However, in this scenario, the DMU did not satisfy technical efficiency and scale efficiency requirements.

Theorem 3: If θ < 1, the DMU was deemed DEA invalid in terms of both technical efficiency and scale efficiency.

$$
\begin{aligned}
&\min\ \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\
&s.t. \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}, \forall i, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \forall_r \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j, s_i^-, s_r^+ \geq 0, \forall j, i, r,
\end{aligned} \tag{2}
$$

According to the model represented by formula (2), if the optimal solution was denoted as θ, then the DMU was considered VRS valid only when θ equaled 1 and both S- and S+equaled 0. In formula (2), assumed there were I DMUs, each with M inputs X and N outputs Y, and the input vector corresponding to the i-th DMU was setted as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iM})^T$, the output vector was setted as $y_i = (y_{i1}, y_{i2}, \ldots, y_{iM})^T$, The weight vector of the DMU was under consideration $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_I)^T$, The relaxation variable matrix associated with the input index was $IS = (IS_1, IS_2, \ldots, IS_M)^T$, The relaxation variable matrix associated with the output index was $OS = (OS_1, OS_2, \ldots, OS_N)^T$, The mathematical model of DEA-CRS was presented in formula (3), while the VRS model was illustrated in formula (4):

$$
\begin{aligned}
&TE = \min^{\theta} \\
&s.t. \begin{cases} x\lambda + IS = \theta \cdot x_i \\ y\lambda - OS = y_i \\ \lambda \geq 0, IS \geq 0, OS \geq 0 \end{cases}
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
&PTE = \min^{\theta} \\
&s.t. \begin{cases} x\lambda + IS = \theta \cdot x_i \\ y\lambda - OS = y_i \\ \lambda \geq 0, IS \geq 0, OS \geq 0 \end{cases}
\end{aligned} \tag{4}
$$

The Overall Efficiency (OE), Technical Efficiency (TE), and Scale Efficiency (SE) of DMU were determined. The investigation into input redundancy was conducted using relaxation variables S- and S+, while the evaluation of DMU incorporates both return to scale type and DEA effectiveness.

Replenishment strategy modeling for medical consumables

The study selected four clinical laboratory centers, belonging to the same labor body but located in different cities, namely A, B, C, and D. The specific experimental object used was five types of biochemical reaction reagents, while their consumption was relatively high and cost same. Center A served as the control group without any intervention measures implemented. Centers B, C, and D were designated as the experimental groups where an intervention strategy for consumables replenishment was carried out. The experiment spanned from November 2021 to April 2022 with each month serving as an intervention period. Throughout the implementation of the replenishment strategy, routine experimental tasks were conducted daily along with indoor quality control measures. After each intervention period concluded, both the variable cost of reagents and the rate of indoor quality out-of-control incidents were calculated for analysis purposes. The determination criteria were as follows: if during each intervention period the variable cost of any experimental group was lower than that of the control group then it would be deemed that the consumable replenishment strategy was effective; however if at any point during these periods one or more experimental groups exhibited a higher expected variable cost compared to that of the control group then it would be considered that the replenishment strategy was ineffective. Furthermore, if in any experimental group either their expected indoor quality control coefficient of variation exceeded its target value or there existed an incorrect test report then such experiments would be invalidated.

The model for managing inventory of medical consumables

The replenishment strategy for medical consumables stock could be formulated based on the Liu's multi-population genetic algorithm, as depicted by formula (6) to (10).

The safety inventory should be able to meet the stochastic procurement demand within the fixed procurement cycle, as depicted in formula (6). The safety inventory ss and the safety factor k, a constant, were essential components in this context. Additionally, the daily standard deviation of experimental demand σ and the lead time L, representing the duration from order placement to goods receipt, play crucial roles.

$$ss = k^{*}\sigma^{*}\sqrt{L} \tag{6}$$

The formula (7) was utilized to solve the order point. The order point, denoted as ROP, represented the inventory level at which medical consumables should be replenished. On the other hand, the expected demand for these consumables during the lead period was represented by Q_L .

$$ROP = Q_L + ss \tag{7}$$

The maximum inventory could be determined using Formula (8), where Q_{max} represented the upper limit of inventory, Q_{T+L} denoted the average demand for consumables during both the purchase cycle and lead period, and Q_s signified the safety stock required under maximum inventory conditions.

$$Q_{\max} = E\left(Q_{T+L}\right) + Q_s \tag{8}$$

The safety inventory solution must satisfy the demand for medical consumables during procurement cycles and lead times, as well as the availability formula (9) and (10) for order quantity solutions, where Q represented the order quantity, Q_{max} represented the maximum stock of medical consumables, and Q_n represented the current stock of medical consumables.

$$Q_s = k^{*}\sigma^{*}\sqrt{L+T} \tag{9}$$

$$Q = Q_{\max} - Q_n \tag{10}$$

The selection of quality indicators in the intervention experiment

In order to ensure the intervention experiment on the cost of medical consumables while maintaining quality and safety, utilized the information entropy weight method to analyze the survey results scale of 17 quality indicators throughout the entire process released by the Clinical Laboratory Center of the National Health Commission in 2018 in China. The survey involved a total of 12,597 laboratories, with data returned from 8,699 laboratories. The result data for the 17 quality indicators were normalized using sum of squares and some indicators exhibited consistent trends when reciprocated. The weights were then sorted using the information entropy weight method, as shown in Table S5. Finally, included inspection report error rate, unqualified rate of interstitial evaluation items, and unqualified rate of indoor quality control items for the intervention experiment.

The establishment of evaluation system for suppliers

The evaluation system for medical consumables suppliers was established using the SPD supply chain management model and CNAS ISO 15,189 quality management system, employing the Delphi method. Initially, three meetings were conducted with directors from various clinical departments, medical consumables suppliers, and procurement experts to determine the initial set of indicators to be included in the supplier evaluation system. Subsequently, a Delphi expert consultation form was compiled and distributed among 30 medical consumables management experts who participated in two rounds of consultations. Statistical analysis using SPSS 23.0 software was performed to obtain an AHP hierarchical analysis judgment matrix comprising average values and weight coefficients. Consistency testing was then carried out by assessing the CR value; a smaller CR value suggested better consistency. Generally, if the CR value was less than 0.1, it met the consistency test criteria. Additionally, RI (Random Index) value and CI (Consistency Index) value could be automatically derived based on the order of judgment matrix entries, $\mathrm{CR} = \mathrm{CI}/\mathrm{RI}$. The importance of evaluation indicators was categorized into five levels: "very important," "important," "general," "not very important," and "not important." Corresponding scores were assigned as follows: 5 points for "very important," 4 points for "important," 3 points for "general," 2 points for "not very important," and 1 point for "not important."

Semi-structured interviews from the perspective of stakeholders

The primary stakeholders of the clinical laboratory center, including institution managers, technicians, and quality managers, were intentionally sampled to conduct semi-structured interviews. The selection criteria for medical institutions under investigation were as follows: (1) Clinical laboratory centers must be representative in the surveyed areas; (2) They should support and cooperate with field research work; (3) They must express willingness to participate in research; (4) They should have a dedicated quality management department. Individual selection involved choosing one administrative person (manager), one technical management person (manager), five technical staff, and one quality manager. Interviews were conducted according to the outline provided in the Appendix.I. Interview data was analyzed using category analysis.

The process of reengineering business operations

The clinical laboratory center had undergone some information system upgrade, which includes the addition of self-start function for the biochemical analyzer line, automatic indoor quality control, automatic temperature and humidity wave point recording, double input of test application, as well as sample sorting equipment. Six technicians from the clinical laboratory center were selected as experimental subjects and their work contents were divided into five categories based on actual situations with 14 items in total. The classification method and work contents were shown in Table S6. Additionally these activities were recorded in a Tomato Clock management table (Fig. S2), where each small box represented 15 min. Work content records were filled out for two weeks before and after laboratory business process reengineering to analyze differences in total working hours among experimental subjects across various work contents, while also counting quality indicators to ensure that research on personnel efficiency was carried out under conditions of safety.

Statistics

The DEAP 2.1 software was utilized for the analysis of DEA effectiveness, comprehensive benefit, technical efficiency, scale efficiency, and relaxation variables S+and S- of DMU. Excel software was employed to examine the changes in input and output indicators. SPSS 23.0 was used to conduct Pearson correlation analysis on the input and output indicators. Additionally, SPSS 23.0 was utilized to normalize the sum of squares and analyze entropy weight. Prism 9.0 was applied to determine differences in indicators before and after interventions. Statistical analysis using SPSS 23.0 software was performed to obtain an AHP hierarchical analysis judgment matrix comprising average values and weight coefficients.

Results

The growth and efficiency analysis of the input-output indexes in primary medical and health institutions

The primary medical and health institutions primarily offer community residents with primary prevention, healthcare, health education, and disease management services [38]. They also establish health records for residents within their jurisdiction, handle common diseases, assist hospitals in the rehabilitation and nursing of certain illnesses, receive discharged patients referred by hospitals, and transfer patients beyond their capacity to hospitals [39]. Community service centers play a vital role in community development, with general practitioners acting as essential technical personnel, families forming the basic unit, and women, children, the elderly, chronic patients, individuals with disabilities, impoverished residents and others being the primary beneficiaries [40]. As of 2022 year-end statistics indicated that China had established 36,000 community service centers which serve as crucial medical establishments [41]. The total income of community service centers exhibited a consistent and steady increase over the years, with an average growth rate of 9.0%. This growth aligned with the comprehensive implementation of graded diagnosis and treatment policies and the robust expansion of business operations within community service centers since 2017. Correspondingly, business activity expenses also grew at a rate of 9.0%, mirroring the growth in total income. However, other indicators experienced relatively lower rates of growth. The average annual increase in health technicians stood at 4.6%, while the average rise in bed capacity was recorded at 3.3%. Although there was a decline in patients between 2019 and 2020, but they rebounded to reach levels comparable to those observed in 2019 by 2021 (Fig. 1A, B). The DEA analysis results revealed that the community service center exhibited ineffectiveness in 2015, 2017, and 2018, weakness in 2011, and strength in other years. The returns to scale of the invalid DMUs were on IRS. Redundancy was observed in the number of health technicians in 2015 and the number of beds in 2018. Insufficiency was identified in total income for output indicators in both 2017 and 2018, with the shortfall being three times greater in 2017 compared to that of 2018 (Fig. 1C).

The business activity expenses and total income of health centers, as a subordinate agency of community service centers, exhibited consistent growth trends with rates of 10.2% and 9.8%, respectively. Additionally, there had been a moderate increase in the number of health technicians (2.4%), beds (3.3%), and patients (2.0%) (Fig. 1D, E). However, similar to community service

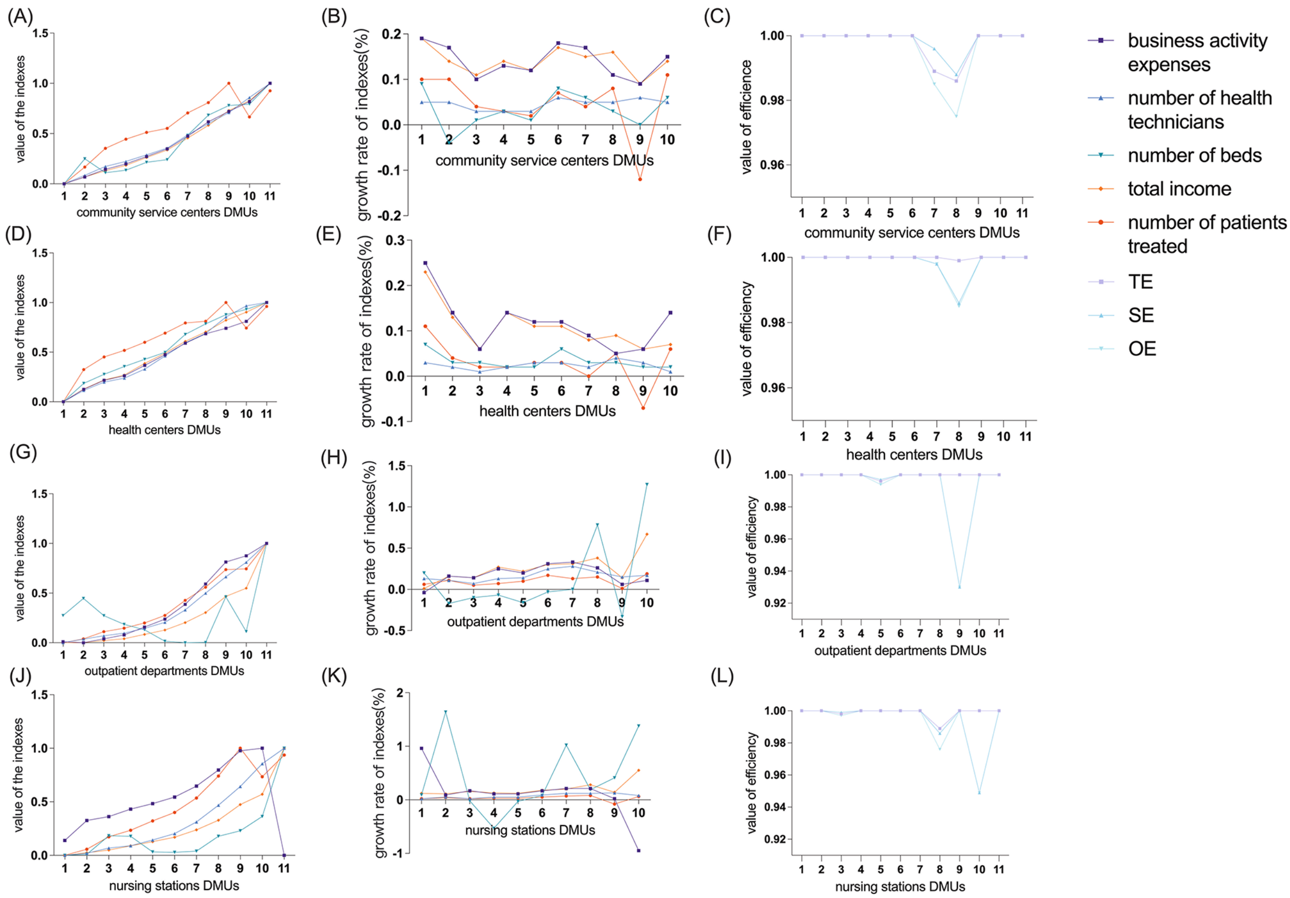

Fig. 1 The growth and efficiency analysis of the input-output index in primary medical and health institutions. **A** The changes of indicators in community service centers. **B** The growth rate of indicators in community service centers. **C** The changes in the TE, SE and OE of community service centers from 2011 to 2021. **D** The changes of indicators in health centers. **E** The growth rate of indicators in health centers. **F** The changes in the TE, SE and OE of health centers from 2011 to 2021. **G** The changes of indicators in outpatient departments. **H** The growth rate of indicators in outpatient departments. **I** The changes in the TE, SE and OE of outpatient departments from 2011 to 2021. **J** The changes of indicators in nursing stations. **K** The growth rate of indicators in nursing stations. **L** The changes in the TE, SE and OE of nursing stations from 2011 to 2021. The data was standardized using the min-max method in SPSS before creating the line chart of indicator changes, enabling simultaneous display of different data groups in the chart

centers, DEA analysis revealed inefficiency in 2017 and 2018 along with redundancy in business activity expenses and bed capacity in the health centers; nevertheless, the type of return to scale remains IRS (Fig. 1F). The outpatient departments, as a subordinate institution of health centers, primarily offered disease diagnosis and treatment services for patients, with significant increases observed in various input indicators. The average growth rates of business activity expenses, number of health technicians, and bed numbers reached 19.6%, 20.2%, and 26% respectively. Additionally, the total income also experienced substantial growth at an average rate of 30.8%. However, the increase in treated patients was relatively low at only 4.8% (Fig. 1G, H). Ineffectiveness was evident in the outpatient department during both 2015 and 2019, indicating diminishing returns to scale and redundancy reflected in business activity expenses (Fig. 1I).

The nursing stations primarily offer medication management, sample collection, and intravenous infusion services to patients. It had achieved the highest bed growth rate among the aforementioned four types of institutions at an average of 44.9%. Additionally, the total income growth rate had been remarkably high at 34.3% (Fig. 1J, K). However, according to DEA analysis results for 2013, 2018, and 2020, the performance was deemed ineffective with a decreasing return to scale. In 2013, the redundancy lied in the number of beds; in both 2018 and 2020 it pertained to bussincess activity expenses; furthermore, in 2020 there was also an insufficient in the number of patients (Fig. 1L). In summary, from the macro data, the input-output efficiency of China's primary medical and health institutions in the past 10 years was good, with the effectiveness reaching 70%, and the growth of input indicators was stable, but there were still many redundant beds and business costs, and the number of patients was still insufficient.

The growth and efficiency analysis of the input-output indexes in specialized public health institutions

The specialized disease prevention and control departments are dedicated to serving vulnerable populations or patients in a distinct medical specialty. Within these institutions, doctors and nurses focus on conducting research and providing treatment for specific diseases. Their responsibilities encompass not only the prevention, diagnosis, and treatment of the diseases but also an in-depth exploration of their underlying mechanisms [42]. Moreover, these specialized departments act as referral centers within general hospitals. The maternal and child healthcare departments primarily offer medical services pertaining to women's healthcare and child healthcare. They bear the primary responsibility for maternal healthcare, midwifery, prevention and treatment of gynecological disorders, child healthcare, and other clinical duties [43]. Similar to specialized disease prevention and control departments, China's allocation of medical resources is gradually shifting towards prioritizing maternal and child healthcare departments. This shift is evident in the reduction of obstetrics and pediatric care units within general hospitals. The input-output indicators of maternal and child healthcare departments, as a clinical service provider, exhibited similar patterns to those of general hospitals, demonstrating consistent growth. However, the specialized disease prevention and control department had experienced relatively slower growth in its input-output indicators, with several indicators showing negative trends from 2020 to 2021 (Fig. 2A, B, D, E). DEA analysis results indicated that the specialized disease prevention and control department exhibited inefficiency in both 2016 and 2019 due to business activity expenses; however, there were no deficiencies in output

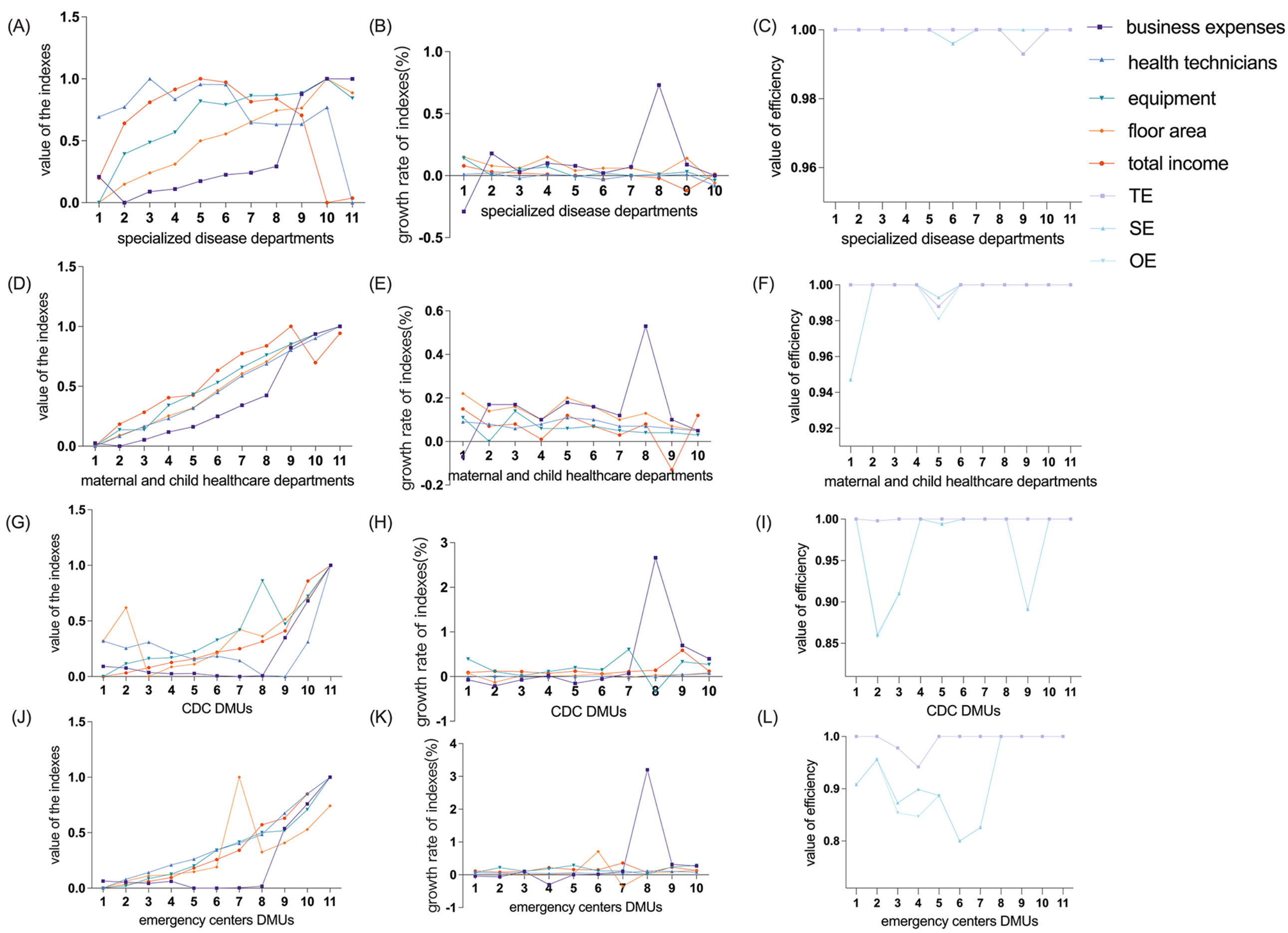

Fig. 2 The growth and efficiency analysis of the specialized public health institutions. **A** The changes of indicators in specialized disease prevention and control departments. **B** The growth rate of indicators in specialized disease prevention and control departments. **C** The changes in the TE, SE and OE of specialized disease prevention and control departments from 2011 to 2021. **D** The changes of indicators in maternal and child healthcare departments. **E** The growth rate of indicators in maternal and child healthcare departments. **F** The changes in the TE, SE and OE of maternal and child healthcare departments from 2011 to 2021. **G** The changes of indicators in CDC. **H** The growth rate of indicators in CDC. **I** The changes in the TE, SE and OE of CDC from 2011 to 2021. **J** The changes of indicators in emergency centers. **K** The growth rate of indicators in emergency centers. **L** The changes in the TE, SE and OE of emergency centers from 2011 to 2021. The data was standardized using the min-max method in SPSS before creating the line chart of indicator changes, enabling simultaneous display of different data groups in the chart

(Fig. 2C). The maternal and child healthcare departments exhibited inefficiency in 2011 and 2015, respectively, due to redundant business activity expenses and insufficient total revenue, as well as an excess number of beds and a shortage of patients. However, there was an indication of increasing returns to scale (Fig. 2F). In summary, the input-output indicators for specialized public health institutions providing clinical services showed minimal changes, while the DEA efficiency analysis results were favorable with over 80% effectiveness. The CDC's indicators had exhibited a gradual growth pattern, with an abrupt upsurge in business costs observed in 2019 that was unrelated to financial allocations but coincided with the onset of the COVID-19 pandemic (Fig. 2G, H). Meanwhile, other indicators had shown minimal growth over the past decade. In 2012, 2013, 2015, and 2019, the CDC experienced invalidity and redundancy solely based on AHP factors; however, the average growth rate of the floor area in recent years had remained at a mere 1.6% (Fig. 2I). Compared to the CDC, the emergency center's indicators exhibited a higher growth rate, particularly in terms of business costs, which experienced an average growth rate of 42.7% (Fig. 2J, K). Interestingly, its DEA analysis results had consistently been deemed invalid from 2011 to 2017 due to redundancy in both the number of health technicians and floor area. However, despited this redundancy, output had remained sufficient while scale efficiency had increased. Consequently, since 2018 it had proven consistently effective (Fig. 2L).

The primary responsibility of health education centers is to provide comprehensive health education. They are dedicated to enhancing public health awareness through educational initiatives, promotional campaigns, and personalized consultations. Their aim is to empower individuals with the necessary knowledge and skills to improve their lifestyle choices and overall well-being. The responsibilities of the institution have now been overshadowed by various other prominent organizations, indicating a decade-long period of inefficiency [44]. The business costs exhibited a downward trend and the business activities remained inactive; however, there was a sudden surge in 2019–2020, reaching approximately ten times that of 2018. Other input indicators had shown consistent annual growth (Fig. 3A, B). Consequently, the DEA efficiency analysis indicated effectiveness in 2018, while others proved to be ineffective. Despited an increasing return to scale, considering the actual circumstances and redundancy factors, the input efficiency remained low (Fig. 3C). The average increase in business costs of blood banks was 26.2%, and other indicators, such as those of health education centers, continued to steadily rise (Fig. 3D, E). DEA analysis results indicated that from 2011 to 2016, blood banks were deemed ineffective due to redundancy in the number of technical personnel and floor area; however, since 2017, they had been operating efficiently (Fig. 3F). The health supervision centers had experienced the highest average increase in bussiness costs, reaching approximately 99.7%, surpassing all other instruments. However, the other input indicators had remained relatively stable over the past decade (Fig. 3G, H). Similar to the blood banks, the efficiency of the health supervision centers had significantly improved and reached a state of effectiveness since 2017 (Fig. 3I). The family planning service department was specifically responsible for managing the birth rate, but with the implementation of China's two-child policy, its role had gradually diminished and been taken over by other larger agencies. This indicated that the input-output indexed had remained relatively unchanged over the past decade, representing the smallest variation among all institutions (Fig. 3J, K). Additionally, except for 2014, all other DMUs were deemed ineffective, suggesting redundancy across multiple measures (Fig. 3L). To summarize, the effectiveness of specialized public health institutions that offer clinical services were predominantly high. However, for those institutions that did not provide clinical services, there were numerous instances of inefficiency and redundant indicators. While it was important to note that the efficiency of health departments could not be solely evaluated based on total income, it was undeniable that such institutions were gradually being replaced or merged with larger establishments in practical applications.

The growth and efficiency analysis of the input-output indexes in other health institutions

Most of the sanatoriums in China were constructed during the 1950s and 1960s, serving distinct functions from hospitals. They are predominantly situated amidst picturesque mountains, beaches, and hot springs that possess natural healing properties. These closed-loop medical service institutions play a vital role. The cost of sanatoriums had witnessed a significant increase in 2019 and 2020; however, there had been a decline in total revenue and patient numbers in recent years (Fig. 4A, B). Nevertheless, the TE, OE, and SE of sanatoriums remained relatively high with an increasing return to scale (Fig. 4C). Inspection institutions and health supervision centers collaboratively carry out preventive and routine health supervision and administrative tasks in accordance with the law, conducting lawful inspections on food, drinking water, occupational diseases, medical facilities, as well as prevention of infectious diseases. Units and individuals found to be in violation of health regulations will face legal consequences. The expenditure of inspection institutions witnessed a significant increase in 2019; however, the number of healthcare personnel, floor area, and total value of equipment had shown a consistent decline year after year (Fig. 4D, E). DEA analysis results indicated that

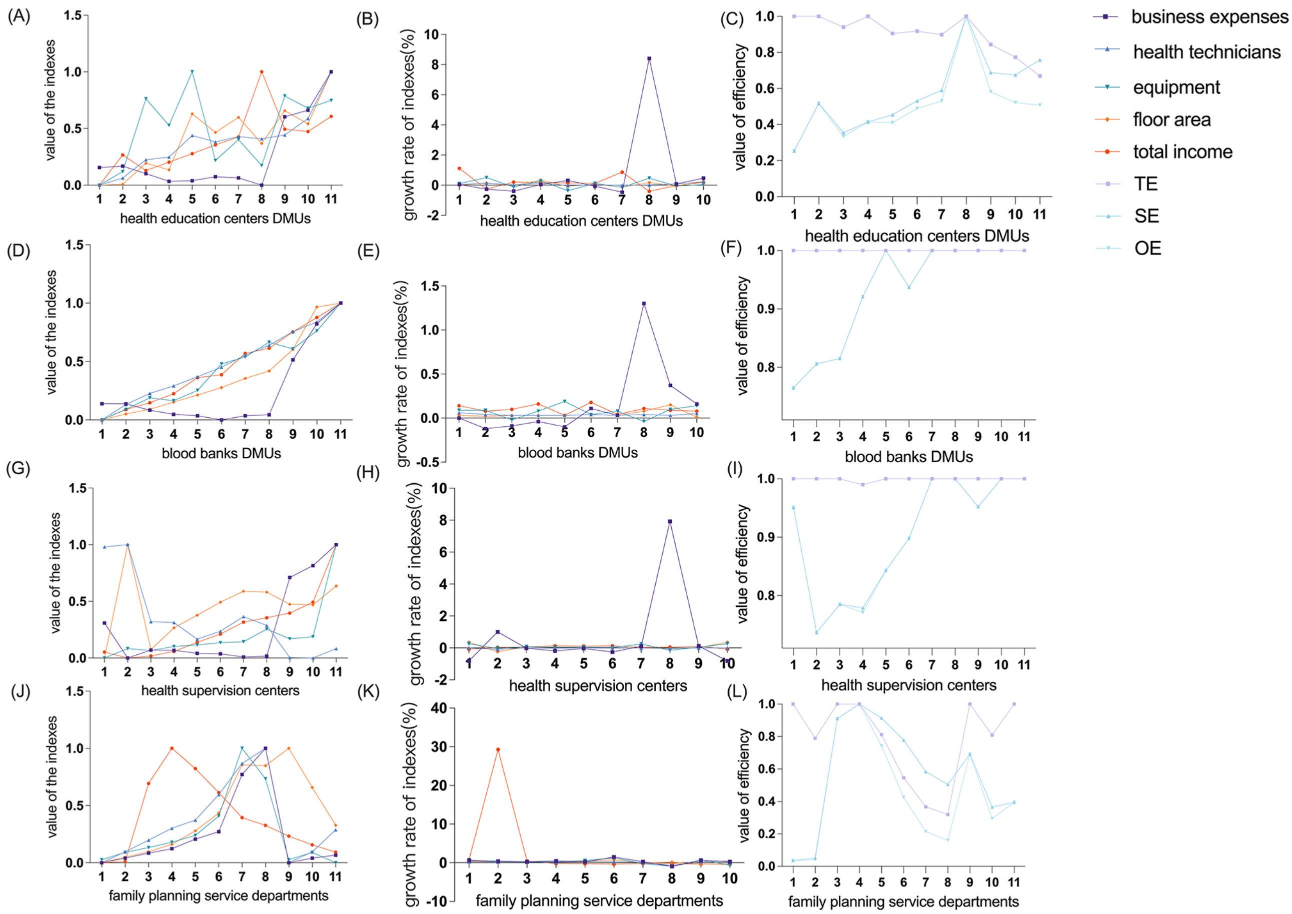

Fig. 3 The growth and efficiency analysis of the specialized public health institutions. **A** The changes of indicators in health education centers. **B** The growth rate of indicators in health education centers. **C** The changes in the TE, SE and OE of health education centers from 2011 to 2021. **D** The changes of indicators in blood banks. **E** The growth rate of indicators in blood banks. **F** The changes in the TE, SE and OE of blood banks from 2011 to 2021. **G** The changes of indicators in health supervision centers. **H** The growth rate of indicators in health supervision centers. **I** The changes in the TE, SE and OE of health supervision centers from 2011 to 2021. **J** The changes of indicators in family planning service departments. **K** The growth rate of indicators in family planning service departments. **L** The changes in the TE, SE and OE of family planning service departments from 2011 to 2021. The data was standardized using the min-max method in SPSS before creating the line chart of indicator changes, enabling simultaneous display of different data groups in the chart

since 2018 inspection institutions had been operating effectively but not prior to that period (Fig. 4F). Medical research centers are vital entities for medical research output. Their business activity expenses had been rising steadily with a remarkable surge observed in 2019 at an overall average growth rate of 64.4%. However, other indicators remained relatively stable (Fig. 4G, H). Similar to inspection institutions, DEA effectiveness was only achieved after 2017 while being largely ineffective before then (Fig. 4I).

The on-the-job medical training centers play a crucial role as vocational institutions, primarily catering to technicians involved in healthcare professions. In the healthcare industry, professionals such as doctors, nurses, and pharmacists require a strong knowledge base and up-to-date skills to effectively provide treatment, nursing care, and drug management services for patients. Additionally, the advancement of professional titles also involves a credit system where annual participation in health training and earning credits is necessary to meet promotion requirements. Despited the mostly ineffective efficiency analysis results of on-the-job medical training centers, all returns to scale indicated an increase. However, aligning with current circumstances, various input indicators for training institutions had been declining consistently over the past decade – this being the most stable downward trend among all institutions – with many training courses transitioning to online delivery methods (Fig. 5A, B,C). According to statistical information centers' data prior to 2018, there were no significant changes observed in various indicators; however, they displayed a downward trend. By 2019, total income even fell below baseline values but experienced sharp increases in cost and total income by 2020 (Fig. 5D, E). The five DMUs were invalid, however, the returns to scale exhibited consistent growth (Fig. 5F). Notably, the investment indicators

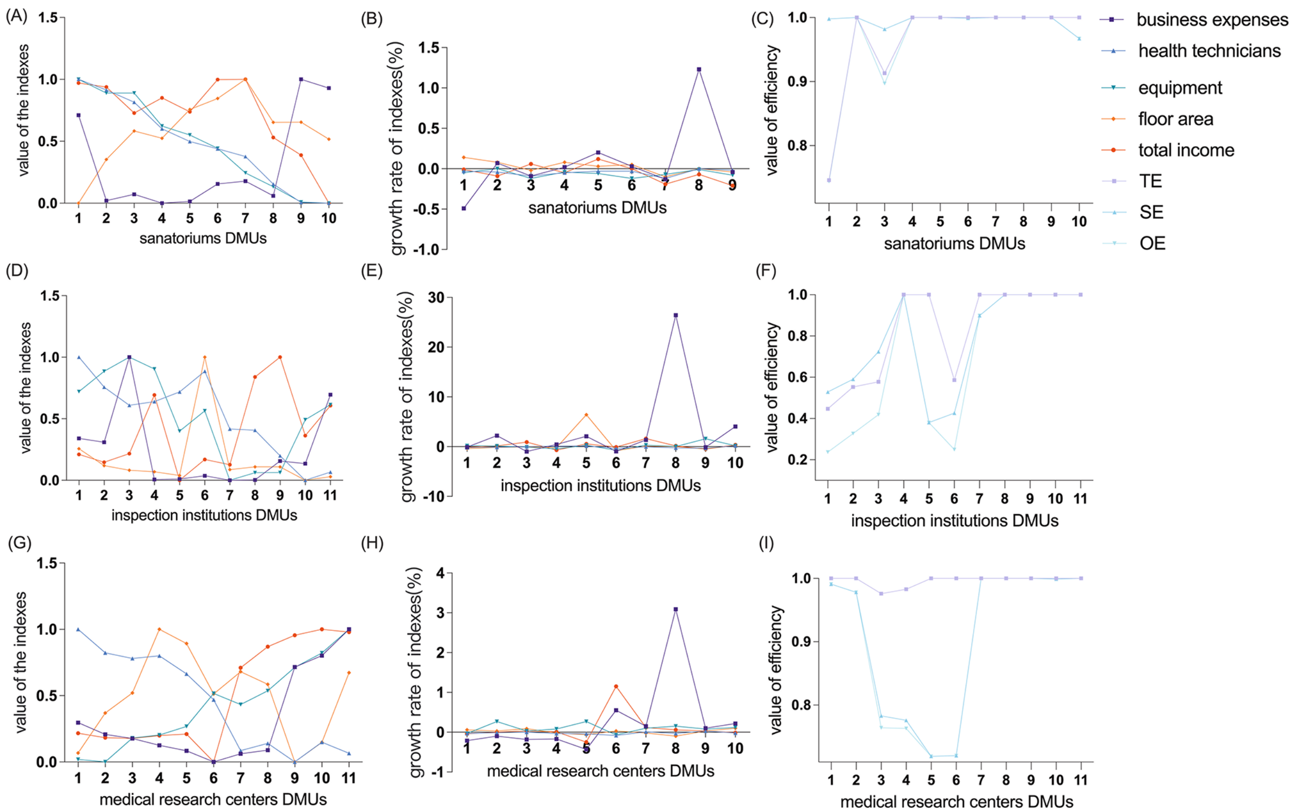

Fig. 4 The growth and efficiency analysis of the other health institutions. **A** The changes of indicators in sanatoriums. **B** The growth rate of indicators in sanatoriums. **C** The changes in the TE, SE and OE of sanatoriums from 2011 to 2021. **D** The changes of indicators in inspection institutions. **E** The growth rate of indicators in inspection institutions. **F** The changes in the TE, SE and OE of inspection institutions from 2011 to 2021. **G** The changes of indicators in medical research centers. **H** The growth rate of indicators in medical research centers. **I** The changes in the TE, SE and OE of medical research centers from 2011 to 2021

of clinical laboratory centers had experienced significant expansion. Specifically, the average growth rates for equipment and cost were 41.0% and 42.6%, respectively, with coefficients of variation at a mere 0.95 and 1.08, indicating rapid growth trends. Furthermore, the floor area witnessed an average growth rate of 36.0%, accompanied by a coefficient of variation as low as 0.51. Similarly, personnel demonstrated an average growth rate of 28.6% with a coefficient of variation at only 0.13. The average growth rate of total revenue was 47.9%, exhibiting a higher coefficient of variation at 2.78, primarily attributed to the significant surge observed in 2021. Excluding the data for 2021, the average growth rate of total income diminished substantially to a mere 2.0% (Fig. 5G, H). More specifically, clinical laboratory centers had demonstrated inefficiency from 2013 to 2020, deviating from other institutions, and experiencing a decline in returns (Fig. 5I).

Critical incident analysis

To understand the events that affected efficiency, we mapped the critical incidents (CIs) over time and identified five CIs.

From 2009 to 2011, China implemented a comprehensive healthcare reform aimed at deepening the healthcare system. The State Council issued five requirements for the new medical reform, which encompassed promoting primary medical security implementation, establishing national drug management guidelines, enhancing primary medical and health services, equalizing public medical resources distribution, and advancing public hospital reforms.

In 2017, The new rural cooperative medical insurance system phased out from the annals of Chinese history. The integration of urban residents' medical insurance and the new rural cooperative medical insurance system resulted in a unified and equitable healthcare coverage for both urban and rural populations. As of the end of 2017, China boasted over 1.35 billion individuals enrolled in medical insurance, maintaining a steady coverage rate exceeding 95%.

In 2018, the establishment of the National Health Commission led to the abolition of the National Health and Family Planning Commission, the Office for Deepening the Reform of the Medical and Health System, and the State Food and Drug Administration. Simultaneously,

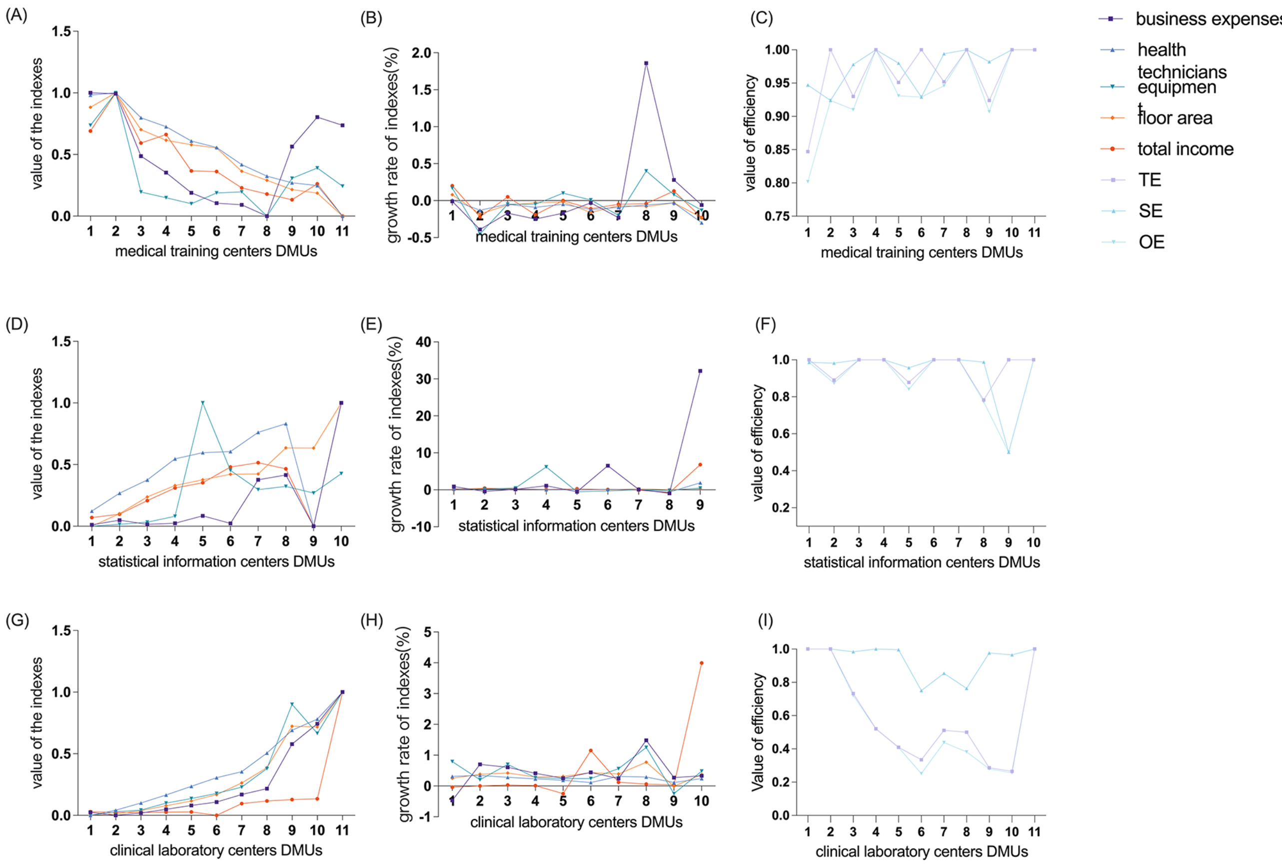

Fig. 5 The growth and efficiency analysis of the other health institutions. **A** The changes of indicators in on-the-job medical training centers. **B** The growth rate of indicators in on-the-job medical training centers. **C** The changes in the TE, SE and OE of on-the-job medical training centers from 2011 to 2021. **D** The changes of indicators in statistical information centers. **E** The growth rate of indicators in statistical information centers. **F** The changes in the TE, SE and OE of statistical information centers from 2011 to 2021. **G** The changes of indicators in clinical laboratory centers. **H** The growth rate of indicators in clinical laboratory centers. **I** The changes in the TE, SE and OE of clinical laboratory centers from 2011 to 2021. The raw statistics had been documented in Tables S7 through S42 within the supplementary materials

separate entities were established including the State Healthcare Security Administration, the State Administration for Market Supervision and Administration, as well as a Drug Supervision Department.

In 2019, with the emergence of the COVID-19, different regions underwent a range of measures from early lockdown to later precision prevention and control, as well as large-scale vaccination campaigns. Throughout this period, numerous protocols were implemented and the healthcare system faced significant challenges.

In 2020, the *1+4+2* medical insurance reform implemented. *1* refered to, by 2030, a comprehensive multi-level medical insurance system would be fully established, with basic medical insurance as the core, supported by medical assistance and complemented by commercial health insurance and charitable donations. *4* refered to the four mechanisms aimed at enhancing treatment guarantee, financing operations, medical insurance payments, and fund supervision. *2* signified the balanced improvement of both healthcare service supply and medical security services.

The impact of CIs on efficiency was determined by integrating them with the results of efficiency evaluation on the timeline (Fig. 6). The discontinuation of the new rural cooperative medical insurance system from 2017 to 2018 had a significant impact on community service centers and health centers (Fig. 6A-B). As primary healthcare institutions, these two units previously played a crucial role in rural areas; however, the reform of the medical insurance system temporarily shifted the focus to designated medical institutions in rural areas, resulting in reduced efficiency for these two units due to insufficient output during the reform period. It was not until the completion of the medical insurance reform in 2019 that the establishment and transformation of designated medical institutions were finalized, allowing community service centers and health centers to regain their status as designated medical facilities in rural areas. Additionally, amidst the COVID-19 outbreak, these grassroots

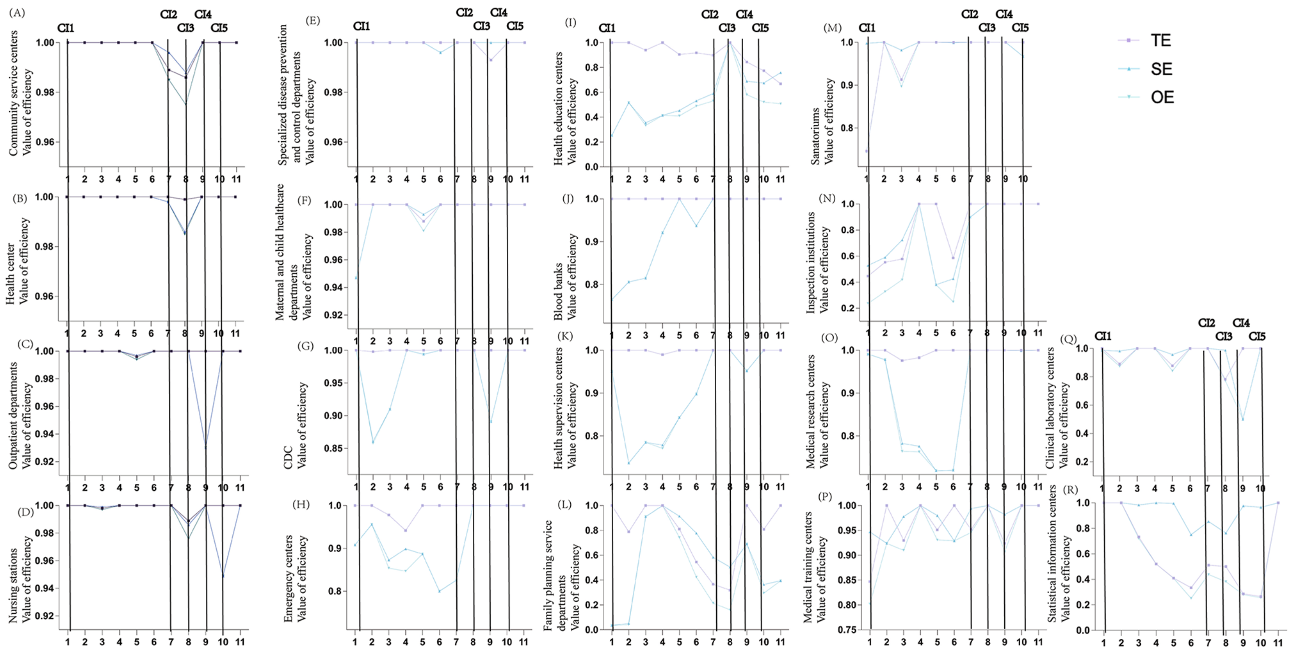

Fig. 6 The critical incident analysis (2001–2011). **A** Community service centers. **B** Health centers.**C.** Nursing stations. **D** Outpatient departments. **E** Specialized disease prevention and control departments. **F** Maternal and child healthcare departments. **G** Centers for disease control and prevention (CDC). **H** Emergency centers. **I** Health education centers. **J** Blood banks. **K** Health supervision centers. **L** Family planning service departments. **M** Sanatoriums. **N** Inspection institutions. **O** Medical research centers. **P** On-the-job medical training centers. **Q** clinical laboratory centers. **R** Statistical information centers

organizations actively conducted numerous nucleic acid testing and vaccination activities within their respective regions, thereby reaffirming their effectiveness through this efficiency evaluation. From 2009 to 2011, following the comprehensive reform of China's medical system, the majority of medical institutions demonstrated consistent or improved efficiency annually. However, during this period, the efficiency of family planning service departments consistently declined until 2018 when the unit was ultimately dissolved and integrated (Fig. 6L). In 2018, the establishment of the National Health Commission led to the cancellation or annexation of several institutions and a significant reduction in investments, thereby enhancing the efficiency of all units. However, during the initial stages of the COVID-19 outbreak in 2019, medical resources and inadequate output necessitated the relocation of institutions that were not involved in nucleic acid testing, vaccination tasks, or outpatient services, resulting in a decline in efficiency. Nevertheless, with the implementation of comprehensive epidemic response policies in 2020 and subsequent reintegration of medical resources along with active participation from various healthcare institutions in relevant tasks alongside the launch of the *1+4+2* medical insurance reform initiative; consequently witnessed a rapid rebounding efficiency across diverse medical establishments. The sensitivity and effectiveness of CIs on the efficiency of medical institutions can be observed, indicating that recording and analysis could facilitate the anticipation of similar events' impact on medical institution efficiency, enabling proactive preventive measures to be taken in advance.

The analysis of redundant indicators was conducted by utilizing the value of the relaxion variable S+and S-

After conducting an efficiency analysis of 18 units using the DEA model, simultaneous calculations were performed to determine the values of relaxation variables S+and S-. This enabled us to obtain the input redundancy rate and output underrate (Table S43-S78) for each unit and DMU. The selection process involved a total of 6 input indicators and 2 output indicators, as mentioned earlier. It was crucial to consider the specific characteristics of each unit when choosing appropriate indicators for efficiency analysis. The 18 units consisted of 11 DMUs for each, with 198 DMUs utilizing business activity expenses, number of health technicians, and total income as indicators. Additionally, there were 77 DMUs using the number of beds and the number of patients treated as indicators. Furthermore, there were 121 DMUs employing the floor area and the total value of equipment exceeding ¥10,000 as indices. Although we employed a time series analysis to assess the internal efficiency of each of the 18 units, it was not feasible to make cross-sectional comparisons among these units due to their inherent differences in nature. However, we could compute the redundancy of each indicator across all DMUs by calculating the ratio of redundant input indicators to the total number of selected input indicators. Similarly, this analysis was conducted for output indicators. The findings revealed that the floor area exhibited the highest proportion of redundant DMU, reaching 50.41%. This was followed by health technicians with a ratio of redundant DMU at 27.27%. Subsequently, in terms of equipment quantity, the proportion of redundant DMU stood at 26.54%. Furthermore, business activity expenses accounted for an 18.18% share of redundant DMU. Lastly, beds contributed to a proportion of redundant DMU amounting to 10.39% (Table 1). The intervention for floor area and equipment redundancy necessitates policy guidance from the government and a final decision on practical utilization by management. However, refinement of management measures could potentially intervene in health technicians' expenses and business activity costs.

The implementation of new consumable management mode contributed to cost reduction in reagent consumables

Due to the low efficiency analysis results of the clinical laboratory centers and the rapid increase in input year by year, coupled with the susceptibility of input-output efficiency to business costs, it had been decided to implement medical consumables intervention measures specifically targeting the clinical laboratory centers. Four centers under the same labor body located in different cities were selected for testing purposes. Group A was designated as the control group without any intervention, while groups B, C, and D were assigned as experimental groups. The first intervention on consumables management would be conducted from November 2021 to January 2022 using a replenishment strategy based on multi-population genetic algorithm. The second intervention period for consumables management evaluation and supplier re-screening would take place from February 2022 to April 2022 alongside implementation of the replenishment strategy. After implementing the consumables replenishment strategy based on a multi-population genetic algorithm, significant differences in consumables cost were observed between Group A and other groups during each intervention period. Group A exhibited the highest cost, while each experimental groups not only had lower costs compared to Group A but also experienced a decrease in cost with each intervention cycle (Fig. 7A).

The supplier of medical consumables was assessed using the Delphi method during the second stage of intervention. Amongst the total group of thirty experts involved in this study, their average age was found to be 48.50 ± 12.62 years old while their average working experience amounted to around 20.65 ± 8.13 years respectively. The majority of the experts (43.27%) were clinical

Table 1 The ratio of superfluous and suboptimal indicators for DMU

Medical institutions	Input indicators					Output indicators	
	business activity expenses	health technicians	beds	equipment	floor area	total income	number of patients treated
community health service center	0	1	1			2	0
health centers	2	0	2			0	0
outpatient departments	1	0	0			0	0
nursing stations	2	0	1			0	1
specialized disease prevention and treatment centers	2	1	0			0	0
maternal and child health centers	1	0	1			1	1
CDCs	0	1		0	3	0	
health education institutes	10	3		10	7	0	0
emergency centers	0	7		0	7	0	0
blood bank	0	5		1	5	0	0
family planning technical service centers	6	6		9	9	0	0
health supervision centers institutions	0	7		0	6	0	0
health authority institutes	0	7		0	6	0	0
medical research institutes	6	7		2	6	0	0
technician training institutions	2	3		2	3	0	0
clinical medical laboratory centers	1	1		6	8	0	0
statistical information centers	2	3		2	1	0	0
sanatoriums	1	2	3			2	1
sum	36	54	8	32	61	5	3
total	198	198	77	121	121	198	77
%	18.18	27.27	10.39	26.45	50.41	2.53	3.90

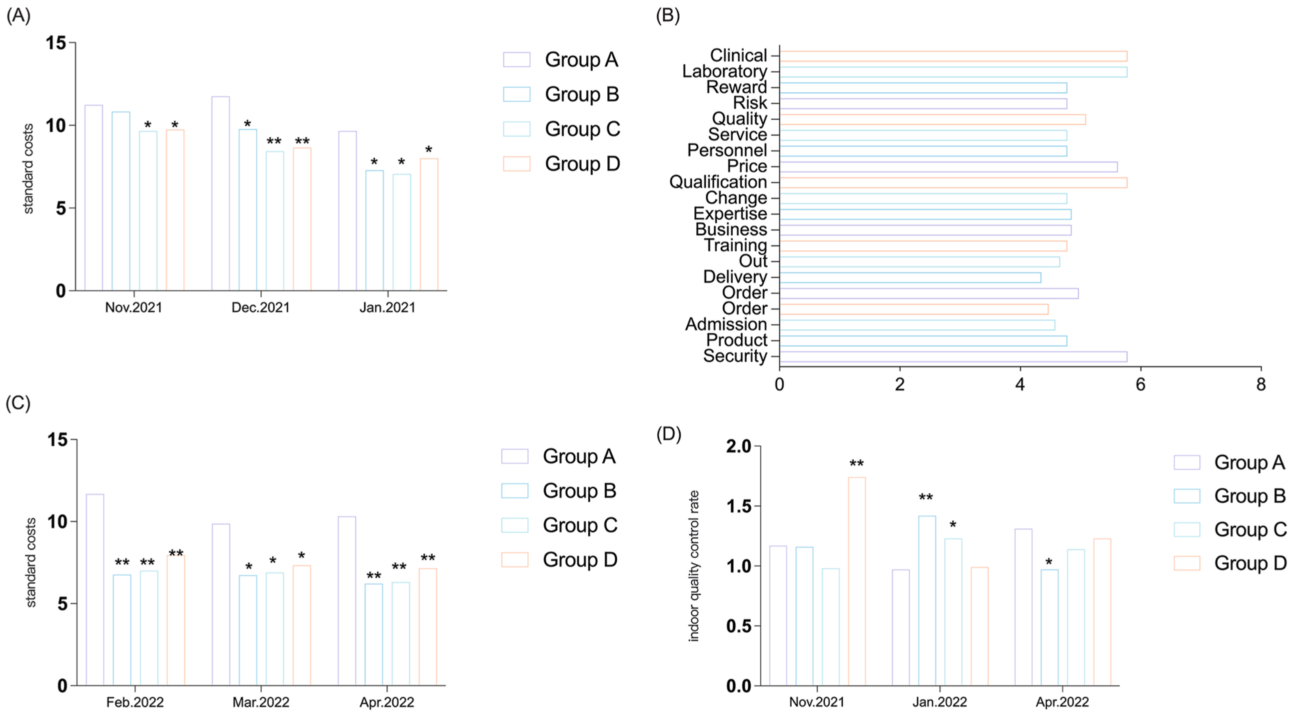

Fig. 7 The implementation of new consumable management mode contributed to cost reduction in reagent consumables. **A** The statistical analysis was conducted using Prism 9.0 software. Firstly, the normal distribution test was performed using the *Shapiro-Wilk* test. If the significance level was greater than 0.05, it indicated that the results adhere to a normal distribution, enabling further application of the *t-test*. The results were in accordance with the normal distribution from a statistical perspective. Subsequently, *t-tests* were carried out for each experimental group (groups B, C and D) in comparison with the control group (group A). Where $P<0.05$ indicated that the difference was statistically significant. The experimental results were obtained from five biochemical reagents with equivalent costs. **B** The weights of each index obtained through AHP hierarchical analysis using SPSS 23.0, which had successfully passed the consistency test. **C** The Delphi method was employed to construct a supplier evaluation table, which was utilized for assessing the three suppliers. The supplier with the highest score was chosen to supply biochemical reagents for the experimental group. The *t-tests* were carried out for each experimental group (groups B, C and D) in comparison with the control group (group A). Where $P<0.05$ indicated that the difference was statistically significant. The experimental results were obtained from five biochemical reagents with equivalent costs. **D** Conducted statistical analysis on indoor quality control. The *t-tests* were carried out for each experimental group (groups B, C and D) in comparison with the control group (group A). Where $P<0.05$ indicated that the difference was statistically significant

medical professionals, followed by experts in health management, procurement management, and supplier evaluation management. Additionally, 48% of the experts held an associate senior title or a doctor's degree or higher. A total of 30 expert consultation forms were issued and subsequently recovered, resulting in a positive coefficient of expertise among all the experts. The AHP hierarchical analysis judgment matrix was assessed for the scales obtained in the second round of consultation. The calculated CI value for the 20th-order judgment matrix was 0.000, and the corresponding RI value was 1.629, indicating that the CR value ($0.000<0.1$) confirmed the judgment matrix in this study passed the consistency test and exhibited consistent weights. The supplier evaluation system for medical consumables was presented in Table 2.

After confirming the weights of the three-tier indexes (Fig. 7B), an analysis was conducted on three suppliers capable of providing biochemical reagents, and the supplier with the highest score was selected to supply biochemical reagents for the experimental groups. Following three intervention cycles, group A still exhibited the highest reagent cost, with a more significant difference compared to other groups (Fig. 7C). Throughout the entire experiment period, there were no errors in inspection reports or unqualified results in external quality evaluations. The failure rate of internal quality control did not exceed the established quality index for each group, ensuring credibility of the experimental results. But the experimental and control groups exhibited no discernible pattern (Fig. 7D).

The application of stakeholder theory enabled to identify viable approaches for enhancing personnel efficiency

The management of employee efficiency is a crucial concern for enhancing the input-output efficiency of medical institutions. The enhancement of personnel efficiency could be achieved through the optimization of employee performance and the generation of higher output, particularly in the absence of workforce reductions. The enhancement of employee productivity was often closely

Table 2 The evaluation system for suppliers of medical consumables

The primary index	The two-tier index	The three-tier index	Weight coefficien
Product quality	Security	Security	5.78%
	Effectiveness	Product expiration date	4.78%
		Admission ratio	4.58%
Service level	Delivery service	Order response time	4.47%
		Order cycle	4.97%
		Delivery time	4.35%
		Out off stock notice	4.66%
	Technical support	Training	4.78%
		Business guidance	4.85%
		Expertise	4.85%
Service specification	Change notice	Change notice	4.78%
	Qualification certificate	Qualification certificate	5.78%
	Price	Price	5.62%
Internal control	Personnel management	Personnel management	4.78%
		Service management	4.78%
		Quality system	5.09%
		Risk management	4.78%
	Reward and punishment	Reward and punishment	4.78%
Customer experience	Laboratory satisfaction	Laboratory satisfaction	5.78%
	Clinical satisfaction	Clinical satisfaction	5.78%

linked to the optimization of work processes. However, identifying the pivotal point for improving workflow and personnel efficiency could be challenging. The decision was made to initially identify the shared requirements of diverse stakeholder groups through the application of stakeholder theory, following extensive meetings and consultations with experts. The improvement of the work process required collaboration among different groups to achieve completion. If it failed to meet the demands of the majority of stakeholder groups, rectifying the work process became a tug-of-war, hindering its implementation and effectiveness. The decision was made to conduct semi-structured interviews in order to identify strategies for enhancing work processes that align with the interests of multiple stakeholders, address the most pressing needs, minimize conflicts, and thereby facilitate seamless implementation and adoption. Improved work processes could enhance employee productivity, and this improvement could be measured using appropriate metrics.

The results were obtained through semi-structured interviews conducted with key stakeholders from clinical laboratory centers (Appendix II). Following the general analysis method, the interview findings were organized

Table 3 The main demands of key stakeholders

Stakeholders	Main demands
managers	Enhanced software for more efficient laboratory management
	Streamlined the interdepartmental collaboration process
	Enhance external training opportunities
	Refrain from employing empirical methodologies
	Enhance employees' sense of affiliation
	Reconfigure the laboratory protocols
	The management space allows for greater autonomy
technicians	Enhanced software for more efficient laboratory management
	Refrain from employing empirical methodologies
	Reconfigure the laboratory protocols
	Enhance the social acknowledgement of their efforts.
	The salary increment
	Enhance external training opportunities
	Enhance the implementation of customized KPIs
quality supervisor	Improved staff awareness of quality objectives
	Enhanced software for more efficient laboratory management
	Enhance the implementation of customized KPIs
	The salary increment
	The opportunity exists for upward mobility within the corporate hierarchy

and categorized. The primary demands of stakeholders were presented in Table 3.

The classification results indicated a unanimous demand for more advanced software for laboratory management among all stakeholders, leading to an upgrade of the laboratory's information management software. The specific details of this upgrade were described in the method section. Following the laboratory information system upgraded, the information input error rates for the experimental groups during intervention cycle were 0.56%, 0.64%, 0.42%, and 0.37% respectively, which all remained within the quality target of 3.00%. In addition, based on the submitted work content table by the study subjects, it was observed that quality management activities were reduced by 41 min per day, and clinical services were reduced by 25 min per day (Fig. 8A, B). There was no statistically significant difference in bio-safety management (a decrease of 1.42 min per day) (Fig. 8C), non-benefit output (a decrease of 2.15 min per day) (Fig. 8D), while rest time increased by 70 min per day (Fig. 8E). Therefore, a more intelligent medical laboratory information management system could enhance the work efficiency of clinical laboratory personnel while ensuring medical quality and safety.

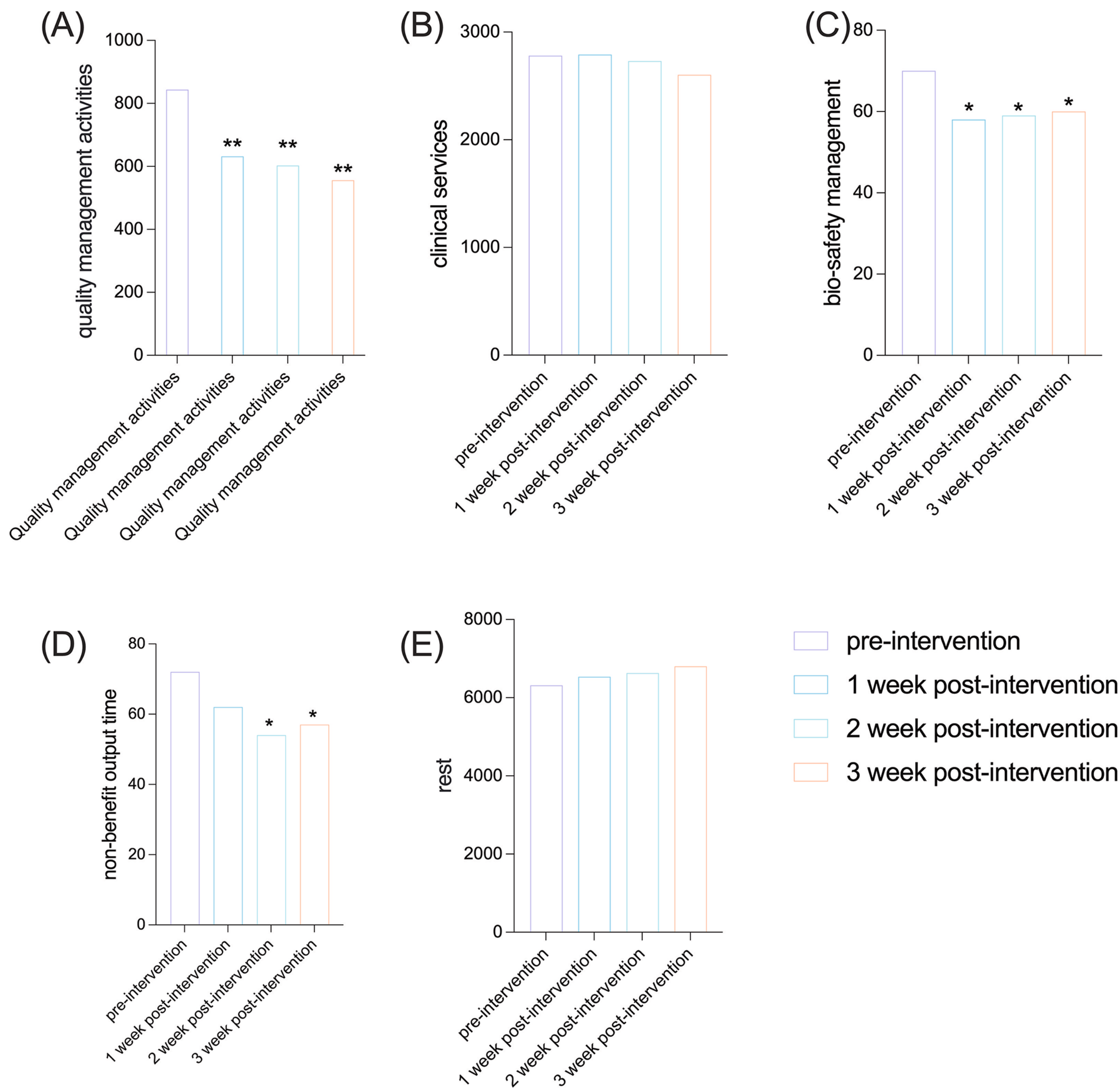

Fig. 8 The application of stakeholder theory enabled to identify viable approaches for enhancing personnel efficiency. After the intelligent upgrade of the laboratory information management system, Tomato-like statistics were conducted on the working and resting hours of the technical staff in the clinical laboratory center. The statistical analysis was conducted using Prism 9.0 software. Firstly, the normal distribution test was performed using the *Shapiro-Wilk* test. If the significance level was greater than 0.05, it indicated that the results adhere to a normal distribution, enabling further application of the *t-test*. The results were in accordance with the normal distribution from a statistical perspective. Prsim 9.0 *t-test* was utilized to assess the disparity between each experimental group and control group. Where $P<0.05$ indicated that the difference was statistically significant. The experimental results were obtained from six technicians. **A** Time spent on quality management activaties before and after the intervention. **B** Time spent on clinical services before and after the intervention. **C** Time spent on bio-safety management before and after the intervention. **D** Time spent on non-benefit out before and after the intervention. **E** Time spent on rest before and after the intervention

Discussion

The technical efficiency of most non-hospital medical institutions surpassed the scale efficiency. Previous studies on hospital efficiency evaluation had revealed a consistent increase in various types of hospital inputs since the public health event in December 2019 [45]. There existed a global disparity between technical efficiency and scale efficiency in hospitals. Chen et al. and Khokhar et al.argued that since 2019, the scale efficiency of hospitals had exceeded their technical efficiency, rendering scale expansion ineffective [46, 47]. However, when analyzing the efficacy of non-hospital medical institutions over the past decade, it was evident that their performance differs from that of hospitals during the same period. As depicted in Table 4, most inefficient DMUs exhibited higher levels of technical efficiency compared to scale efficiency.

Nevertheless, it should be noted that certain entities such as clinical laboratory centers demonstrated greater scale efficiencies than technical efficiencies. It was important to acknowledge that relying solely on DEA methods may not fully reflect effectiveness; therefore, an analysis considering actual circumstances became imperative [48]. For instance, Asamrew et al. [49] discovered that with automation and artificial intelligence becoming increasingly prevalent in healthcare settings, research focus would gradually shift towards mechanism exploration while also leading to more complex structures for research outcomes like papers, patents, and transformed commodities [50]. Consequently, expanding both the size and input-output capacity of medical institutes became crucial.

The classification of medical institutions was excessively complex and should be streamlined by merging. The health centers, outpatient departments, and nursing stations in primary medical and health institutions should be merged based on their actual work content and the relative stagnation of input and output. In this way, the size of health centers can make them the only subordinate agencies of community service centers. By adopting this approach, not only can the social standing of healthcare centers be enhanced, but also a greater number of community members will place trust in their diagnostic and treatment standards. This will alleviate the burden on various general hospitals and stimulate substantial improvements in input-output indicators, ultimately contributing to an overall increase in medical efficiency. The family planning service departments and health education centers in specialized public health institutions have been operating with inefficiency for nearly a decade. The diminishing base value of inputs necessitates timely reduction in investments related to building space and equipment, considering the increasing availability of internet-based platforms for disseminating medical education to the general public [51]. The suggestion is to integrate family planning service departments into community service centers for centralized management, in conjunction with the implementation of China's two-child policy. The increasing popularity of the Internet in China has led to a growing trend among medical media to utilize platforms such as WeChat, Tik ToK, and Weibo for disseminating medical knowledge. The topic of medical treatment, however, demands utmost caution and any misleading promotion can exacerbate the psychological burden on readers and give rise to grave social issues. Therefore, health education centers can opt to collaborate with these private media outlets in order to enhance the popularity and accuracy of public health knowledge, leveraging the advantages of a market economy while maintaining control over their input-output efficiency [52, 53].

Table 4 The number of SE and TE for each institution style

institution style	DMUs	in-valid DMUs	SE > TE	SE < TE	SE < TE
primary medical and health institutions	43	9	1	2	6
Specialized public health institutions	88	47	6	39	2
Other institutions	65	37	21	14	2
sum	196	93	28	55	10

The efficiency of China's clinical laboratory center is significantly influenced by market regulatory factors. In the past, China's hospital clinical laboratory capacity was relatively low and testing projects were limited, thus independent medical laboratories assumed the majority of testing tasks in the region [54]. However, in recent years, due to advancements in hospital clinical laboratory capabilities and a sudden surge in registrations of independent medical laboratories, market competition has intensified. The local market adjustments have led to an increase in market competitiveness for some independent medical laboratories through the implementation of discounted pricing strategies. However, there has been a decline in both the quality and timeliness of test results [55]. The analysis of efficiency results from clinical laboratory centers (including those within hospitals and independent facilities) revealed that as early as 2013, the increasing number of such centers led to redundant medical resources and an ineffective expansion in scale. Since the public health incident in December 2019, China had been conducting nucleic acid testing for a duration of three years. In order to prevent overwhelming public medical resources, a significant number of nucleic acid tests were being offered by independent medical laboratories at a cost. As these independent medical laboratories experience peak revenue towards the end of 2021, it stimulates increased resource allocation and market competition, thereby further intensifying market complexity. Although 2021 is the only effective DMU for clinical laboratory centers in nearly a decade, the procurement of additional equipment and hiring of more technicians may result in expanding redundancies and inefficiencies in the near future once nucleic acid testing ceases. Therefore, China must promptly adjust its market policies and inspection project fees to prevent the persistence of resource redundancy and inefficiency.

The development of medical institutions is equally significant to the stock market. The study conducted by Alatawi et al. [8] demonstrated that establishing stable living conditions is crucial for achieving effective and efficient management of medical institutions, highlighting the equal significance of both increasing and maintaining the stock of such institutions. The effective management of business costs and personnel efficiency is crucial for organizations with higher technical efficiency but lower scale efficiency. However, it is essential to ensure stable operations in order to exert control over these two variables. According to Nundoochan A [13], a more significant consequence is that many of the newly established institutions fail to sustain operations due to lack of experience. Additionally, the personnel and equipment they introduce result in an increased redundancy of overall medical resources upon closure. The construction and approval of new medical institutions should be carefully managed from a policy perspective, emphasizing the need to provide stable operating conditions for established medical institutions.

The efficient management of medical consumables cost is essential. The expenditure on medical supplies already constitutes one-third of the total budget for all types of medical institutions, and this proportion continues to increase rapidly. The discovery and implementation of various replenishment strategy models are gradually advancing [56]. When the order point and order quantity are fixed, inventory managers can identify the inventory location and intuitively observe storage capacity to replenish medical consumables. This eliminates the need for repetitive inventory checks and enhances personnel efficiency. The company's awareness of patent protection is increasing along with the improvement in diagnosis and treatment. Consequently, their medical products are frequently updated, leading to a rapid escalation in the cost of medical consumables [57, 58]. This situation significantly exacerbates the challenge of controlling costs associated with medical consumables. Schwartz et al. [59] and Wang et al. [58] propose that healthcare providers can establish partnerships with upstream suppliers in order to enhance their bargaining power and achieve cost reduction through bulk purchasing of reagents. It can also explore a viable outsourcing model for testing projects to address the issue of excessive waste of high-value reagents [59]. The selection of suppliers for medical consumables is crucial in terms of cost control. In recent years, commonly employed methods for supplier evaluation and selection include the TOPSIS method, entropy weight TOPSIS method, and AHP analytic hierarchy process [60, 61]. The AHP analytic hierarchy process is a comprehensive analysis approach that combines qualitative and quantitative indicators, widely utilized in supplier evaluation and selection [62]. Yang et al. [63] developed a scientific evaluation index system for suppliers of hospital emergency supplies to ensure the provision of such supplies during emergencies. Duan et al. [64] enhanced the AHP method and entropy weight TOPSIS method, and incorporated the gray correlation analysis method to render their evaluation results more rational.

The management of people's efficiency is often integrated with bonus management, thus necessitating each organization to compile the content of KPIs [65]. Guo et al. [66] conducted a study on 25 technicians from the Taihang Hospital, wherein he established a performance management system using the balanced scorecard approach and evaluated its application effectiveness. Following process reengineering implementation in a hospital by Li [67], it was observed that both error rate and negative feedback rate decreased. Therefore, when considering personnel efficiency, medical institutions should prioritize utilizing methods such as Delphi to develop a well-planned performance management system [68]. The enhancement of medical institutions' efficiency is a comprehensible topic that can be assessed and influenced through various statistical models.

Conclusions

We assessed the efficiency of 18 non-hospital medical institutions in China by constructing a time series-based internal benchmark DEA model for efficiency evaluation. By incorporating CIs, we observed a high level of concurrence between the evaluation results and the actual situation, affirming the success of our model construction and its objectivity and effectiveness in assessing unit efficiency. Through this evaluation, it became evident that units capable of providing medical services exhibit superior resource allocation, high efficiency levels, and minimal susceptibility to CIs. Conversely, through the utilization of relaxation variables S+and S-, we identified significant redundancies in floor area, equipment, personnel efficiency, and operational costs within units unable to provide medical services, highlighting ample room for rectification.

In order to intervene in inefficient institutions and reduced the cost of medical consumables, we initially utilized the information entropy weight method to conduct a weight analysis on quality indicators released by the Inspection Center of China Health Commission. This ensured that costs were reduced while maintaining qualified quality standards. Subsequently, we implemented a new inventory management model based on multi-population genetic algorithms for practical application. Results indicated that after the intervention period, the cost of medical consumables in all three experimental groups was lower than that of the control group, demonstrating effectiveness of this new inventory management model. We then employed both Delphi and APH methods to evaluate three different medical consumable suppliers and obtained an optimal supply strategy. After completion of our intervention period, costs associated with medical consumables in all three experimental groups were significantly lower than those observed within our control group; furthermore, performance related to quality indexes also improved considerably. Therefore, through utilization of information entropy weight method alongside Delphi and APH methods combined with implementation of a new mathematical inventory management model, we had successfully achieved our goal - effectively reducing costs associated with medical consumables while simultaneously ensuring qualified quality standards.

By conducting structured interviews, we conducted a thorough investigation into the key areas for enhancing personnel efficiency within the stakeholder groups of the intervention subjects. Subsequently, we identified an area for improvement that aligns with the interests of all parties involved. In response to this breakthrough, we implemented a reform by introducing smart office software. Furthermore, we continued to utilize quality indicators to monitor and control medical standards. Lastly, through the utilization of Tomato clock methodology, we accurately recorded employees' time allocation across various tasks. Through analyzing both quality indicators and time consumption data, it was observed that there was no significant difference in the time spent on medical tasks between the experimental group and control group after the intervention period. However, there was a notable reduction in time dedicated to quality management work and biosecurity measures; indicating that smart working practices have effectively enhanced employee productivity. These findings further validate that our breakthrough discovery through stakeholder theory and semi-structured interviews was indeed objective and effective in addressing workflow issues caused by insufficient interdepartmental collaboration and reduced employee efficiency.

In summary, we firmly believe that the efficiency of medical institutions can be enhanced through the integration of diverse mathematical models and courageous experimentation, which can then be applied to the management of these institutions. The implementation of meticulous management in medical institutions holds great promise as a strategic direction. However, given the unique nature of services provided by medical institutions, it is imperative to ensure that efficiency management is conducted with an unwavering commitment to maintaining high-quality standards. Moreover, there exist certain areas where the training of medical personnel and establishment of institutional authority may present slight contradictions with regards to efficiency management. These aspects will continue to be explored in our forthcoming research.

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

The research was organized and designed by Tai and Wu. Tai selected the mathematical model, while data collection was carried out by Tai, Li, and Wang. An interview was conducted by Tai and Dou. Statistical analysis was performed by Tai. The research object was provided by Wu. All authors actively participated in the discussion of the results and contributed to the revision of the final manuscript. Additionally, all authors thoroughly read and endorse the manuscript.

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Data availability

The entirety of the data generated or analyzed during the course of this study has been incorporated within this manuscript and its supplementary files. The data used in this study was sourced from the national center for health committee statistics of China, and it had been published on the official website of the National Health Commission at https://data.stats.gov.cn.

Declarations

Ethics approval and consent to participate

This study received ethical approval from the Research Ethics Committee (REC) of the Ping An Healthcare Diagnostics Center with the reference number '2021 Ethics approval (declaration) No. 67'. The study obtained voluntary and informed consent from all participants, who expressed their willingness to participate. Furthermore, each eligible participant was provided with detailed information about the study and their right to withdraw or decline participation at any point. Additionally, a unique identifier was assigned to ensure the confidentiality and privacy of respondents' data.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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