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Journal:	*BMJ Open*
Manuscript ID	bmjopen-2024-088462
Article Type:	Original research
Date Submitted by the Author:	09-May-2024

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Keywords:	Health, HEALTH ECONOMICS, HEALTH SERVICES ADMINISTRATION & MANAGEMENT

Research on the Efficiency of TCM Resource Allocation in County-level TCM Hospitals: Based on a Three-Stage DEA Model

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ABSTRACT

Objective The primary objective of this study was to evaluate the efficiency of Traditional Chinese Medicine (TCM) resource allocation in county-level TCM hospitals in Zhejiang Province, China, by employing a three-stage Data Envelopment Analysis (DEA) model.

Design This study utilized a three-stage DEA model to assess efficiency, incorporating environmental variables and adjusting for random errors. The analysis relied on data from 68 county-level TCM hospitals. Four input and five output indicators pertinent to TCM services were selected.

Results The results of the first stage of DEA revealed that the distribution of efficiency values showed substantial variation, with 30.88% of the hospitals exhibiting a combined technical efficiency below 0.7, indicating severe inefficiency, while only 16.18% of the hospitals achieved a score of 1 in technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE), which stood at 41.18% and 17.65%, respectively. The difference in scale efficiency proved to be statistically significant (P=0.021) when hospitals were categorised by bed size. Further analyses using SFA regression accounted for environmental variables such as GDP per capita, population density, and the number of hospitals. In the final stage of the DEA, the input variables were refined to enhance the overall efficiency scores, with the adjusted TE, PTE, and SE of hospitals increasing to 0.809, 0.833, and 0.917, respectively. Additionally, the study highlighted significant differences in efficiency across regions. The highest adjusted TE scores were observed in the western (0.860) and eastern (0.844) regions of Zhejiang, which excelled in resource allocation, technology, and management.

Conclusions The study demonstrated that the relationship between hospital size and efficiency is non-linear and influenced by diverse factors including management practices, resource allocation, and technological capabilities. By promoting regional collaboration through the rollout of smart healthcare solutions, these hospitals can optimise resource allocation and enhance overall service quality.

Keywords County-level TCM hospitals; the three-stage DEA; Resource allocation efficiency

Strengths and limitations of this study

- This study innovatively applied a three-stage DEA model to effectively identify and quantify the potential impacts of environmental factors and random errors on hospital efficiency.
- Four input indicators and five output indicators related to TCM services were selected in this study, which can fully reflect the efficiency of TCM resource allocation in county-level TCM hospitals.
- Based on the data of 68 county-level TCM hospitals, the sample size was large enough to represent the overall situation of county-level TCM hospitals in Zhejiang Province.
- The cross-sectional nature of the data used in this study may limit the ability to make causal inferences about the observed relationships.
- The selection of indicators may be subjective. The selection of different indicators may have an impact on the evaluation results.

INTRODUCTION

The influence of TCM in the international arena has increased gradually with changes in global health concepts and a renewed interest in traditional medicine. Several countries and regions have begun to introduce TCM technologies and services, expanding their local application and development gradually.[1] Although the total volume of health resources, including TCM resources, has increased annually in recent years, the uneven distribution of resources and the scarcity of high-quality medical and health resources remain prominent.[2–4] With TCM's increasing prominence in healthcare, determining how to allocate TCM resources scientifically and rationally has become a focal point for policymakers and hospital administrators. In recent years, China has attached great importance to the development of TCM, marking a critical period of high-quality development in Chinese medicine. As an essential component of primary healthcare services, county-level TCM hospitals must explore the optimal allocation of their TCM resources and improve their service capacity.[5,6] Therefore, studying the allocation efficiency of TCM resources is crucial to enhancing the service quality of county-level TCM hospitals and meeting public health needs.

Historically, academics have placed significant emphasis on the study of resource allocation efficiency, developing the theory of resource allocation, and refining efficiency measurement methods and models to enhance the precision of resource allocation efficiency assessments. The predominant efficiency measurement methods are parametric and non-parametric methods, represented by Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), respectively.[7] Compared to SFA, DEA is more adept at handling the production process of multiple inputs and multiple outputs, as it does not impose restrictive constraints between inputs and outputs, nor does it require the specification of the production frontier's functional form. The model's high extensibility leads researchers to frequently prefer the non-parametric method represented by DEA.[8–10] Sherman[11] utilized the DEA model to assess the efficiency of seven Massachusetts teaching hospitals and became the first scholar to apply DEA models in healthcare. Since then, DEA has been widely used to evaluate efficiency in healthcare.

Ahmed et al.[12] employed output-oriented data envelopment analysis and discovered that approximately 91.3% of Asian countries are inefficient in utilizing healthcare resources. Athanassopoulos et al.[13] analyzed the operational efficiency of 98 public hospitals in Greece and determined that inefficiencies are prevalent. Gok and Sezen's [14] research evaluated the efficiency scores of 523 hospitals of various sizes in Turkey systematically and comprehensively, revealing a negative correlation between the efficiency of healthcare organizations and their size. Alatawi et al.[15] utilized input-oriented DEA-BCC and DEA-CCR models to assess the technical efficiency of 91 public hospitals in Saudi Arabia in 2017, finding that the average hospital efficiency value was 0.76 and 75.8% of public hospitals exhibited technical inefficiency.

In the assessment of county hospital efficiency, Man-li et al.[16] employed DEA to evaluate the technical efficiency and productivity of county public hospitals in East, Central, and West China following the public hospital reform in 2012. Qian et al.[17] demonstrated the negative impact of county public hospitals in Shandong Province on efficiency and scale through DEA and statistical tests. Regarding hospital efficiency influencing factors, Zhao et al.[18] identified that the scale of county-level hospitals in Henan Province was over-expanded, as evidenced by DEA models. These hospitals were generally technically inefficient, yet productivity increased, influenced by factors such as government subsidies, hospital size, and average length of stay. Samut and Cafri[19] examined the factors influencing the operating efficiency of primary healthcare institutions in 29 OECD countries from 2000 to 2010. Their analysis revealed that income level, economic development, and education level had a significant influence. Amin et al.[20] discovered that the primary cause of low hospital productivity is the negative change in scale efficiency and that a decline in technical efficiency significantly affects total hospital productivity.

Additionally, the use of a two-stage DEA model is common for measuring hospital efficiency and exploring influencing factors; moreover, the combination of the DEA model and the Tobit regression model is frequently employed. For instance, Yousefi et al.[21] employed a two-stage DEA model to evaluate the technical efficiency of 15 public hospitals in Iran. The analysis revealed that the technical, pure technical, and scale efficiencies were 0.935, 0.961, and 0.987, respectively. Furthermore, the analysis indicated that population size significantly influenced the technical efficiency of these hospitals. Sarabi Asiabar et al.[22] utilized the DEA-BCC model to assess the technical efficiency of 29 public hospitals in Tehran between 2012 and 2016, subsequently applying the Tobit regression model to analyze the influencing factors. Khan and Nasrulddin[23] employed DEA-BCC and DEA-CCR models to measure the technical efficiency of Saudi Arabian hospitals from 1979 to 2020, and they utilized a Tobit regression model to analyze the influencing factors. Although the two-stage DEA model can explore the influencing factors of efficiency, it does not reduce the interference of random and environmental factors on efficiency values. Consequently, to accommodate both random errors and environmental factors, the three-stage DEA model was utilized in the evaluation of hospital efficiency.[24,25]

As a distinctive medical resource in China, TCM holds an important position in traditional medical services. To gain a deeper understanding of the efficiency of TCM resource allocation in county-level TCM hospitals, this study employs the three-stage DEA model. It aims to enhance the efficiency of TCM resource allocation, compare the efficiency of hospitals of varying sizes, and identify key factors affecting efficiency, to provide more scientific decision-making support for resource allocation in county-level TCM hospitals and promote the rational utilisation and overall enhancement of TCM resources. This approach is also expected to offer more scientific decision support for resource allocation in county-level TCM hospitals and promote the rational use of TCM resources and the overall improvement of service quality. Zhejiang Province, located in the eastern coastal area of China, boasts a long history of TCM development and a solid foundation. The province features a large number of widely distributed county-level TCM hospitals, providing rich materials and a diverse range of samples for the study. Simultaneously, Zhejiang Province leads in healthcare reform and the development of TCM. Its successes and challenges may serve as a model for other regions.

METHODS

Sample selection and data sources

The data and information for this study were sourced from the 2022 Compendium of Hospitals of the TCM Category of the Zhejiang Provincial Health Commission, and the 2022 official statistical yearbook of the Zhejiang Provincial Bureau of Statistics. Zhejiang Province has a total of 95 hospitals categorised under TCM. Given the DEA model's emphasis on the relative comparability of similar units, the study initially screened 71 county-level TCM hospitals. However, due to missing data, three hospitals were excluded, resulting in 68 county-level TCM hospitals being included in the final analysis.

The 68 county-level TCM hospitals included in the study are situated in 68 county-level cities across Zhejiang Province, collectively covering 75.56% of the province's counties. They are distributed across five regions—eastern, southern, western, northern, and central Zhejiang—aligned with the administrative divisions where the hospitals are located. According to Gok and Sezen's classification method, the county-level TCM hospitals in the sample are classified into four groups based on their bed capacity (number of actual open beds): <200, 200-299, 300-499, and 500 and above.[14,15]

Data envelopment analysis

Three-stage data envelopment analysis is a method developed based on DEA. It is mainly used to evaluate the relative efficiency of decision-making units with multiple inputs and multiple outputs, especially to reflect the efficiency of decision-making units more realistically after removing the influence of environmental factors and random disturbances.[26] The modelling approach consists of three main stages.

In the first stage, which involves conducting a conventional DEA analysis, the

DEA model was introduced in 1978 by American operations researchers Charnes, Cooper, and others.[27] It is a non-parametric, non-stochastic model designed for measuring and evaluating efficiency, based on the concept of the "production frontier."[28] The model employs a linear programming approach to construct a production frontier, utilizing input and output indicators from decision-making units. Effective units are positioned on the frontier, while ineffective ones are positioned below it. This arrangement allows for the measurement of the extent to which units deviate from the frontier.[29] There are two types of DEA models: the first is the CCR model, which assumes constant returns to scale. Under this model, an increase in input will proportionately increase output, implying that the sector size does not impact production efficiency. However, this assumption often proves challenging in practice; the policy system and economic development levels may prevent maintaining sector production at a reasonable size, and thus obscure the determination of size impact on production efficiency. Based on these limitations, Charnes and other scholars revised the CCR model and proposed the BCC model, which assumes variable returns to scale.[30]

In addition, DEA models can be categorised as input-oriented or output-oriented. The former emphasizes reducing inputs while maintaining constant outputs, whereas the latter focuses on increasing outputs while keeping inputs constant.[31,32] Considering that the returns to scale for health resource allocation are variable, this study employs the input-oriented BCC model. The model equations are presented below:

$$\min\theta-\varepsilon(\hat{e}^{T}S^{-}+e^{T}S^{+})$$
$$\text{s.t.}\begin{cases}\sum_{j=i}^{n}X_j\lambda_j+S^{-}=\theta X_0\\ \sum_{j=i}^{n}Y_j\lambda_j+S^{+}=Y_0\\ \lambda_j\geq 0,S^{-},S^{+}\geq 0\end{cases} \tag{1}$$

Where, j=1,2,...,n denote decision units, X and Y are input and output vectors, respectively.

The efficiency value measured by the BCC model is called the combined Technical Efficiency (TE), and it can be further decomposed into the product of Scale Efficiency (SE) and Pure Technical Efficiency (PTE), i.e., TE=SE*PTE.[33,34]

TE measures the ability of a decision-making unit to optimise output with specific inputs under fixed production conditions and provides a comprehensive assessment of resource allocation and use efficiency. PTE reflects the impact of management skills and technical expertise on production efficiency, helping to evaluate whether a decision-making unit's management and technology are optimal. SE assesses the impact of production scale on a decision-making unit's efficiency, focusing on whether the scale is optimised.

The second stage typically involves constructing a regression model akin to Stochastic Frontier Analysis (SFA). This model estimates the influence of environmental factors on efficiency scores through regression analysis, using environmental factors as independent variables and efficiency scores obtained in the first stage as dependent variables.[35] The SFA regression model is applied to decompose the slack variables identified in the first stage into three components:

random factors, environmental factors, and managerial inefficiency.[36,37] Initially, the first-stage DEA model is analyzed to obtain the slack variables for each decision-making unit. The formula is presented as follows:

$$S_{ni} = x_{ni} - x_{ni}^{*}(n = 1,2,...,N; i = 1,2,...,I) \quad (2)$$

S_{ni} represents the slack variable for the nth input indicator of the ith decision unit, x_{ni} represents the actual value of the input indicator of each decision unit, and x_{ni}^{*} represents the predicted value of the input indicator of each decision unit. The SFA regression function is constructed using the slack variables as the response variables and the environmental factor variables as the independent variables in the analysis. The function is detailed below:

$$S_{ni} = f(Z_i;\beta_n) + v_{ni} + \mu_{ni}; i = 1,2,...,I; n = 1,2,...,N \quad (3)$$

In this function, Z_i represents the total number of environmental variables, and β_n is the value of the coefficient measured by the environmental variables. In addition, the function contains a mixed error term, $v_{ni} + \mu_{ni}$, where v_{ni} represents random error and μ_{ni} represents management inefficiency.

The SFA regression model adjusts for environmental and stochastic factors to normalize the overall technical efficiency across all decision-making units, ensuring uniform environmental conditions and stochastic influences. The mathematical expression for the function, which relates to the adjusted input variables, is presented below:

$$X_{ni}^{A} = X_{ni} + [max(f(Z_i;\hat{\beta}_n)) - f(Z_i;\hat{\beta}_n)] + [max(v_{ni}) - v_{ni}]$$
$$i = 1,2,...,I; n = 1,2,...,N \quad (4)$$

where X_{ni}^{A} represents the adjusted input values and Xni represents the pre-adjusted input values. The expression $[\max(f(Z_i;\hat{\beta}_n)) - f(Z_i;\hat{\beta}_n)]$is used to place all decision-making units in a consistent external environment to ensure a fair comparison of environmental factors. Meanwhile, $[\max(v_{ni}) - v_{ni}]$serves to adjust the random errors of all decision-making units to the same level to accurately assess their efficiency. To effectively eliminate the effects of random errors on the slack variables, further decomposition of these errors and efficiency residuals is necessary. This approach allows us to obtain the predicted random error values for each decision-making unit. For this purpose, this study employs the formula for calculating management inefficiency, as derived by Rodenyue[38], presented below:

$$E(\mu|\varepsilon) = \sigma_* \left[\frac{\phi(\lambda \frac{\varepsilon}{\sigma})}{\Phi(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma} \right] \quad (5)$$

Where, $\sigma_* = \frac{\sigma_\mu \sigma_v}{\sigma}, \sigma = \sqrt{\sigma_\mu^2 + \sigma_v^2}$, $\lambda = \sigma_\mu / \sigma_v$, $\gamma = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_v^2}$.

Based on the above equation, we can derive the extent to which random error and management inefficiency factors influence the slack variable. When the value of γ variable approaches 1, it indicates a significant impact of management inefficiency; conversely, when the value of γ variable approaches 0, it indicates a significant impact of random error.

Selection of variables

In DEA, the selection of input and output indicators is crucial. Building on in-depth analyses and summaries of similar studies, and incorporating the advice of relevant experts, this study meticulously adheres to established principles for the selection of indicators. Considering the operational characteristics of county-level TCM hospitals, we selected a series of indicators that effectively capture the unique aspects of TCM.

Initially, the input indicators primarily encompass human resources and hardware facilities. Regarding human resources, Chinese medicine practitioners (including assistant practitioners) constitute the core strength of TCM hospitals; their numbers directly influence the quality and scale of TCM services provided. Conversely, the number of TCM pharmacists reflects the hospital’s professional competence in managing and using Chinese medicines, indicating the level of investment in this area. In the realm of hardware facilities, the number of actual open beds significantly reflects the scale and service capacity of a hospital and influences patient choice significantly. Furthermore, The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment reflects the TCM hospital's investment in TCM diagnostic and therapeutic equipment. Modern TCM diagnostic and therapeutic equipment plays a crucial role in enhancing service quality and efficiency, with its total value directly indicating the hospital's investment in equipment renewal and upgrading.

Secondly, regarding output indicators, the total number of consultations and discharges accurately reflects the volume and scale of services provided by a TCM hospital. These indicators are crucial for assessing the operational efficiency and TCM service capacity of TCM hospitals, visually representing the actual outcomes in the provision of TCM services. TCM decoction pieces, a vital component of TCM treatment, and the number of prescriptions directly indicate the level of activity and patient acceptance of TCM in hospitals. Therefore, this indicator, the number of TCM decoction piece prescriptions, can illustrate the actual effectiveness of TCM hospitals in utilizing TCM. The income from TCM medical service projects represents the economic efficiency and earning power of TCM hospitals. This indicator not only reflects the economic efficiency of providing TCM services but is also a key metric for assessing TCM hospital operations. Conversely, the bed utilisation rate reflects the efficiency of hospital bed usage. The bed utilisation rate is an essential indicator of hospital efficiency and service quality. A high rate indicates that the hospital efficiently provides more services with limited resources, demonstrating effective operation and management.

The selection of these indicators was based on a thorough consideration of the operational characteristics of county-level TCM hospitals and the distinct attributes of TCM. This study ultimately selected four input and five output indicators to comprehensively and accurately represent the inputs and outputs of TCM services, thereby providing robust data support for the DEA analysis. According to Hollingsworth[39], the number of units used for efficiency assessment should be at least three times the sum of input and output indicators. In this study, 68 county-level TCM hospitals were assessed, exceeding the required minimum of three times the sum of input and output indicators, thus aligning with Hollingsworth's principle. Furthermore, the collected data on input and output indicators were analyzed for correlation using Pearson's correlation coefficient in SPSS 25.0 software, with specific results presented in **Supplemental Table 1.** The results show that the correlation coefficients between input and output indicators are both positive and highly significant.

In addition to the input and output variables previously discussed, selecting environmental variables is crucial for developing the SFA model in this three-stage DEA framework. According to the "separation hypothesis" by Simar and Wilson[40], environmental variables significantly affect input-output efficiency. These variables are beyond the control of individual decision-making units and are free from subjective influences. Consequently, based on a review and synthesis of relevant literature, this study selected three environmental variables: per capita GDP, population density, and the number of hospitals in the county.

Per capita GDP, an important macroeconomic indicator, reflects the economic development level of a region.[41] The level of economic development is closely related to hospital operational efficiency; regions with stronger economies typically possess more substantial medical resources, advanced medical technology, and superior management systems, all of which contribute to higher operational efficiency. Furthermore, population density influences the service radius and mode of hospitals; highly populated areas generally demonstrate a greater demand for medical resources, directly impacting hospital operational efficiency. Lastly, the number of hospitals directly influences the distribution and competition for medical resources, subsequently affecting the operational efficiency of county hospitals. A greater number of hospitals increases competition, potentially driving improvements in service quality and management to enhance competitiveness. However, this can also lead to resource dispersal and waste, thereby reducing operational efficiency.

Statistical methods

The study employed the Pearson correlation coefficient to assess the correlation between input-output variables and utilized the Kruskal-Wallis H non-parametric test to compare the efficiency, including TE, PTE, and SE, of hospitals with varying numbers of beds. The $\chi 2$ test was utilized to examine differences in returns to scale (RTS) among TCM hospitals with varying bed sizes. Descriptive analysis and statistical testing of the data were conducted using SPSS 25.0 software, while the three-stage DEA was measured and analyzed using DEAP 2.1 software in conjunction with Frontier 4.1 software.

Patient and public involvement

No patient is involved.

RESULT

Description of variables

In 2022, the data indicated that the average number of Chinese medicine practitioners and TCM pharmacists per county-level TCM hospital were 85 and 15, respectively; the average number of actual open beds was 340; and the total value of

TCM diagnosis and treatment equipment per hospital exceeded 10,000 RMB, amounting to 3.33 million RMB. These hospitals recorded an average of 527,280 consultations, 11,662 discharges, and 148,740 TCM decoction piece prescriptions. The average income from TCM medical service projects per hospital was 18.742 million yuan, with an average bed utilization rate of 73%. The average per capita GDP of the 68 counties corresponding to the 68 county-level TCM hospitals was 106,442 yuan, ranging from a high of 357,159 yuan to a low of 437,88 yuan. This indicates significant economic disparities among the regions. The average population density was 867 people per square kilometre, with extremes ranging from 74 to 9,891 people per square kilometre, reflecting significant variations between counties. Additionally, the number of hospitals per county varied significantly, from as few as 2 to as many as 79, averaging 13 hospitals per county. See **Supplemental Table 2** for details.

Stage 1: Traditional DEA model analysis

Of the hospitals, only 11 (16.18%) achieved a TE efficiency of 1, 28 (41.18%) reached a PTE efficiency of 1, and 12 (17.65%) attained an SE efficiency of 1. Significant variances exist in the efficiency scores among the hospitals, with 21 (30.88%) recording a combined technical efficiency below 0.7, suggesting low overall efficiency. Conversely, most hospitals achieved an SE greater than 0.8. See **Supplemental Table 3** for more details.

The sample hospitals were categorised according to bed size, and **Table 1** displays the results of the statistical analysis of efficiency values and returns to scale (RTS) for hospitals with different bed sizes. Overall, the analysis shows that 12 (17.56%) hospitals with an SE score of 1 operate under constant returns to scale (CRS), 17 (25%) are under increasing returns to scale (IRS), and the remaining 39 (57.35%) operate under diminishing returns to scale (DRS). Over half of the hospitals are experiencing diminishing efficiency at their current size, indicating that further expansion will not enhance efficiency. Conversely, hospitals in the IRS are likely undergoing rapid growth, requiring additional resources to support expansion, and expected to achieve greater economies of scale as they grow.

The study categorized hospital bed sizes into four categories: small (<200 beds), lower-middle (200-299 beds), upper-middle (300-499 beds), and large (≥500 beds).[14,15] **Table 2** presents the results of statistical analyses for overall efficiency, PTE, and SE across different hospital bed size categories. The analysis found no statistically significant differences in TE (P=0.416, P>0.05) and PTE (P=0.457, P>0.05) among the four hospital size categories, whereas differences in SE (P=0.021, P<0.05) were statistically significant, indicating varying levels of scale efficiency. For TE, small and lower-middle hospitals exhibited slightly higher efficiency values of 0.806 and 0.824, respectively, compared to those of large and upper-middle hospitals. In terms of PTE, large hospitals demonstrated higher efficiency values than upper-middle hospitals, suggesting better quality service provision. In terms of SE, neither small nor large hospitals matched the medium-sized hospitals in efficiency of resource allocation and economies of scale. Generally, small hospitals were more efficient in terms of TE and PTE, yet less so in SE. Conversely, while large hospitals excelled in technical efficiency, they lagged in scale efficiency compared to other categories. Upper-middle hospitals, however, underperformed in both scale and technical efficiencies.

According to the results in **Table 1**, the differences in RTS among the four groups of hospitals, categorized by bed size, are statistically significant (p<0.001). Five (31.25%) small-sized hospitals are operating at CRS, indicating that inputs and outputs are balanced and these hospitals are optimally operated. The remaining 11 (68.75%) are experiencing IRS and require expansion to enhance efficiency. In contrast, most hospitals in the lower-middle (58.82%) and upper-middle (78.26%) categories operate under DRS, indicating input redundancy. Only one large hospital (8.33%) operates at CRS, while the remaining 11 (91.67%) are under DRS, suggesting that downsizing could optimise resource allocation in these facilities.

Stage 2: SFA regression analysis

Since the first-stage DEA analysis did not account for confounding factors like environmental variables and random errors, a second-stage SFA regression analysis was necessary to accurately reflect the operational efficiency of the county-level TCM hospitals and to re-measure and adjust the input indicators. Using Frontier 4.1 software, the slack variables of the input indicators from the first-stage DEA were used as explanatory variables along with per capita GDP, population density, and the number of hospitals. Subsequent SFA regression analyses on these slack variables are detailed in **Table 3**. The regression analyses indicated that the effects of most environmental variables on the slack values of all inputs were statistically significant. The generalized one-sided likelihood ratio tests for the four regressions were significant at the 1% level, underscoring the validity of the SFA regression and the importance of excluding environmental factors in measuring the comprehensive efficiency of each county-level Chinese hospital. The γ values, which were close to 1 and statistically significant, suggest that management inefficiency is the primary factor contributing to the operational inefficiencies of county-level TCM hospitals.

In analysing the impact of environmental factors on slack variables, the key lies in understanding the positive and negative coefficients. Positive coefficients suggest that an increase in the factor will augment the input slack variable—thereby reducing output and impeding hospital efficiency. Conversely, negative coefficients imply that an increase in the factor will decrease the input slack variable—thereby increasing output and enhancing hospital efficiency. The coefficients of per capita GDP are negatively associated with the slack variables for Chinese medicine practitioners, number of beds, and TCM diagnostic and treatment equipment, all significant at the 1% level. This suggests that an increase in GDP decreases the redundancy of these inputs, thereby promoting hospital efficiency. Population density negatively affects the slack variables for Chinese medicine practitioners and TCM diagnostic and treatment equipment, significantly at the 5% level, and also impacts the number of beds negatively, albeit significantly only at the 10% level. This indicates a complex, bi-directional impact of population density on the efficiency of county-level TCM hospitals. The coefficients for the number of hospitals are positive and significant at the 1% level for both the number of beds and the value of TCM diagnostic and treatment equipment, indicating a substantial impact on the efficiency of allocating these resources. In contrast, the coefficients for Chinese medicine practitioners and TCM pharmacists are not significant, underscoring a lesser impact in these areas.

Stage 3: DEA model analysis with adjusted input variables

After adjusting the input indicators in the second stage, the input-oriented BCC model analysis was reconducted using DEAP 2.1 software to re-measure the efficiency values of each decision-making unit. The adjusted TE, PTE, and SE values of county-level TCM hospitals in Zhejiang Province increased to 0.809, 0.833, and 0.917, respectively. The number of hospitals with CRS remained unchanged. Additionally, eight hospitals transitioned from DRS and CRS to IRS. Concurrently, a paired t-test comparing efficiency values from the first and third stages (**Table 4**) revealed statistically significant differences in TE ($p=0.017$, $p<0.05$) and SE ($p=0.027$, $p<0.05$), while differences in PTE were not statistically significant. These findings underscore the necessity of the second-stage SFA regression analysis and confirm that the TE and SE of county-level TCM hospitals are significantly influenced by external factors.

The study adopted a regional perspective, and Zhejiang Province was segmented into the central, southern, western, northern, and eastern parts. The findings are presented in **Table 5**. A horizontal comparison of the efficiency values of the five regions reveals the adjusted average TE values, ranking them as follows: western (0.860) > eastern (0.844) > southern (0.805) > northern (0.796) > central (0.731). Despite adjustments, both TE and PTE remain relatively high in the East and West, suggesting that TCM resource allocation, technology, and management are at an advanced level. However, a notable decline in SE in the West suggests that its current operational scale does not optimize economic efficiency. Significant disparities exist between the efficiency of the northern and central regions compared to other regions. The exclusion of environmental factors led to increased TE, PTE, and SE in the northern region, resulting in the most substantial improvement in comprehensive efficiency. The efficiency values of the southern region exhibit minimal change before and after adjustment, indicating a relatively accurate representation. Overall, the findings suggest that the three-stage DEA model yields more scientifically rigorous results than the first-stage DEA model, offering a more systematic and objective approach to efficiency evaluation.

DISCUSSION

This study conducted a comprehensive examination of the efficiency of TCM resource allocation in county-level TCM hospitals utilizing a three-stage DEA model. Initially, hospitals were categorized based on bed size, revealing variations in efficiency performance among hospitals of different sizes. However, the analyses at this stage were unable to fully eliminate the interference of environmental variables and random errors. Consequently, in the second stage, we employed SFA regression analysis to refine the input indicators for a more precise reflection of hospital efficiency. Following the adjustment, we observed improvements in the TE, PTE, and SE of county-level TCM hospitals, further reinforcing the importance of environmental variable stripping. In the third stage, we repeated the DEA analysis using the adjusted input indicators and observed varying changes in efficiency across different regions. Overall, 12 county-level TCM hospitals exhibited high efficiency; however, 56 of the sampled Chinese hospitals demonstrated lower efficiency, in line with the consensus among experts that more than 70 percent of hospitals experience an imbalance between inputs and outputs.[17,42,43]

A common phenomenon in Chinese hospitals is the blind pursuit of bed size expansion, which extends to county-level TCM hospitals as well.[17,44] During the initial phase, we categorized the sample hospitals based on bed size and conducted RTS statistical analysis to explore the differences in efficiency performance among hospitals of different sizes. The results indicate that more than half of the hospitals are experiencing diminishing efficiency at their current size, suggesting that simple scale expansion does not always lead to higher efficiency. Currently, county-level TCM hospitals are in a critical period of rapid development, where many are inclined to blindly expand their bed sizes in pursuit of wider development space and improved service capacity. However, this expansion behavior often lacks scientific planning and reasonable assessment, potentially resulting in an imbalance in resource allocation and lower operational efficiency. Additionally, a small proportion of hospitals with the IRS status might be in the rapid development stage, requiring more resources to support their expansion, and are expected to achieve higher economic efficiency through scale expansion. Numerous previous studies have verified that the relationship between hospital efficiency and size is not merely a direct positive or negative correlation, but is influenced by a variety of factors, including geographic location, government policy orientation, internal management efficiency, rationality of resource allocation, and technological innovation capability.[45,46] These factors are interrelated and work together to render hospital efficiency a complex and multidimensional concept. The findings of this study align with previous findings, thus reinforcing the complexity of the relationship between hospital efficiency and size and emphasizing the necessity of conducting the second phase of the study.

When examining bed size specifically, hospitals of varying sizes demonstrate distinct characteristics in terms of their TE, PTE, and SE. Small and lower-middle hospitals exhibit relatively higher efficiency in terms of TE and PTE, possibly due to their more flexible management and operational practices. However, regarding SE, these hospitals may face constraints due to resource inputs and economies of scale, resulting in lesser performance compared to medium hospitals. Large hospitals, although performing well in PTE, exhibited relatively lower performance in terms of SE and TE, likely attributable to the complexity of their management and operations. The study additionally found that over 70% of organizations in both upper-middle and large hospitals were in the stage of DRS. This finding aligns with the study which noted that the majority of county hospitals in Hubei Province generally demonstrate DRS when the number of beds exceeds the bed size of upper-middle hospitals as defined in this study. However, it is important to note that certain studies have indicated that county-level public hospitals need to reach a bed count of 1,100 or more to reach saturation with scale effects.[15,17] Given that our study focuses on county-level TCM hospitals, which differ significantly from public hospitals in terms of operation mode, service content, and management strategies, different considerations must be taken into account regarding scale expansion. This comparison of varying magnitudes complicates direct comparison, further emphasizing the unique characteristics of county-level TCM hospitals regarding resource allocation and efficiency management. Hence, when formulating development strategies for county-level TCM hospitals, it is essential to fully consider their unique operating environments and characteristics, while avoiding simply applying the experiences and standards of other types of hospitals.

During the second stage of the SFA regression analysis, we further explored how environmental variables affect hospital operational efficiency. Our findings indicate that environmental factors such as per capita GDP, population density, and the number of hospitals significantly influence hospital efficiency. Our study results indicate that the growth of GDP per capita can effectively minimize input redundancy in terms of the number of TCM pharmacists, beds, and the total value of TCM diagnosis and treatment equipment. This reduction positively influences the resource allocation efficiency of county-level TCM hospitals. This finding is consistent with previous studies, which have demonstrated a negative relationship between GDP per capita and input slack.[38,47,48] In other words, as GDP per capita increases, the input redundancy of healthcare organizations gradually decreases, thereby contributing to the improvement of overall service efficiency. Additionally, we observe that residents in economically developed regions tend to have higher healthcare needs, potentially leading to a greater allocation of health resources to these regions. This phenomenon not only highlights the close connection between economic development and healthcare resource allocation but also underscores the importance of county-level TCM hospitals fully considering regional economic differences and differences in residents' needs during development. Population density, as an important indicator that reflects the degree of regional population agglomeration, was confirmed to significantly reduce the redundancy of TCM pharmacists as well as the total value of TCM diagnosis and treatment equipment in this study. This finding suggests that in areas with higher population densities, county-level TCM hospitals are more inclined to minimize input redundancy, thus utilizing resources more effectively and improving resource allocation efficiency, which aligns with the findings of Alatawi et al.[49,50] However, it is noteworthy that in areas with higher population density, although county-level TCM hospitals had reduced input redundancy in terms of TCM pharmacists and TCM diagnosis and treatment equipment, they may have invested excessively in the number of beds and failed to achieve optimal allocation by population density. This tendency may stem from hospitals overly pursuing an increase in the number of beds during expansion, neglecting the actual demand and the improvement of service efficiency. Additionally, with the increase in the number of hospitals, the slackness of investment in beds and TCM diagnosis and treatment equipment in county-level TCM hospitals has become more prominent. Regarding resource allocation, the increase in the number of hospitals may have led to an uneven distribution of resources within the region, resulting in some hospitals experiencing a surplus or shortage of beds and equipment. This uneven allocation of resources not only impacts the efficiency of resource allocation in hospitals but may also negatively affect the quality and accessibility of healthcare services.

Through adjusting the input indicators of the sample hospitals, the adjusted TE, PTE, and SE all improved compared to the results of the first stage, further confirming that the influence of environmental factors and other variables on the efficiency of hospital resource allocation should not be overlooked. The transformation of hospitals from DRS and CRS to IRS indicates that hospitals need to carefully assess their resources and capabilities to ensure that expansion brings tangible benefits and to avoid the risks associated with blind expansion. From a regional perspective, a significant disparity exists in the efficiency of TCM resource allocation among TCM hospitals across different regions of Zhejiang Province. Upon comparing the efficiency values of different regions horizontally, we find that the TE in the west and east is relatively high, and the results of pre-and post-adjustments are more stable, possibly related to the more excellent technology and management level in these regions. Some studies have indicated that the special geographical conditions of the western region have led to higher-quality telemedicine services, which not only reflects the region's technological advancement but also its higher management efficiency. However, this also restricts to some extent the circulation and rational allocation of TCM resources, which may lead to the inefficiency of the healthcare service supply chain in certain respects, thus affecting the improvement of scale efficiency. The efficiency levels in the northern and central regions are relatively low, especially in the northern region. Although there are improvements in PTE and SE, there remains a significant gap compared to other regions. This indicates that there is still significant potential for these regions to improve management efficiency and expand the scale of TCM medical resources. Research has shown that regional economic development directly influences medical information seekers. Additionally, patients in the northern part of the country may be more inclined to choose the higher level of medical services in Shanghai. Additionally, the northern part of the country should strengthen its healthcare system, improve management level and resource allocation efficiency, and utilize Shanghai's economic and technological resources appropriately. This can help promote the healthcare system and facilitate the integration of Shanghai, thus improving its medical resource utilization efficiency and narrowing the gap with other regions.

To achieve a more balanced and coordinated regional distribution of TCM resources, it is imperative to enhance the rational allocation and efficient use of TCM resources by strengthening smart healthcare, enhancing inter-regional cooperation and exchanges, and promoting the overall upgrading of healthcare services. This will ensure that residents in all regions have access to high-quality TCM services.

CONCLUSIONS

Using a three-stage DEA model, this study analyzed the health resource allocation efficiency of county-level TCM hospitals in depth and revealed that the relationship between hospital size and efficiency is non-linear, being affected by various factors such as resource allocation, management efficiency, and technological capacity. Environmental variables, including per capita GDP and population density, significantly affect the service efficiency of county-level TCM hospitals. Furthermore, there are significant differences among county-level TCM hospitals across different regions, emphasizing the importance of rational planning and scientific management. The study suggests that county-level TCM hospitals should give due consideration to regional economic conditions and residents' needs when formulating development strategies. Moreover, they should promote rational allocation and efficient use of healthcare resources by strengthening smart healthcare and regional cooperation, aiming to enhance the efficiency of resource allocation and service quality in hospitals. These findings are anticipated to serve as important references for future hospital management and policy formulation.

Limitations

While the study on the efficiency of TCM resource allocation at county-level TCM hospitals in Zhejiang Province utilizing a three-stage DEA model provides comprehensive insights, it also has several limitations. These findings are specific to county-level TCM hospitals in Zhejiang Province and may not be directly applicable to other regions or types of hospitals without consideration of regional and operational differences. The study is based on data from a single year (2022), which may not reflect longer-term trends or account for year-to-year fluctuations in hospital performance and resource utilization. While the study includes several important environmental variables such as GDP per capita and population density, there may be other unmeasured factors such as policy changes, patient demographics, or cultural attitudes towards TCM that could affect the results. Areas for potential future in-depth research include longitudinal studies, exploration of additional environmental factors, and the possible integration of other analytical models to capture dynamic and qualitative aspects of hospital efficiency.

Patient consent for publication Not required.

Competing interests None declared.

Ethics approval Ethical approval was gained from the Ethics Committee of the Affiliated Hospital of Zhejiang University of Chinese Medicine.

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Table 1 Statistical analysis results of the returns to scale of hospitals with different bed sizes

	Returns to scale					
	CRS	**IRS**	**DRS**	**Total**	**χ2 value**	**P value**
<200	5(31.25%)	11(68.75%)	0(0%)	16(100%)	33.654	<0.001
200-299	3(17.65%)	4(23.53%)	10(58.82%)	17(100%)		
300-499	3(13.04%)	2(8.70%)	18(78.26%)	23(100%)		
>=500	1(8.33%)	0(0%)	11(91.67%)	12(100%)		
Total	12(17.65%)	17(25.00%)	39(57.35%)	68(100%)		

Table 2 Statistical analysis results of the efficiency of hospitals with different bed sizes

	Bed size	Average	SD	χ2	P
TE	>=500	0.743	0.133	2.845	0.416
	300-499	0.773	0.156		
	200-299	0.824	0.128		
	<200	0.806	0.195		
PTE	>=500	0.901	0.114	2.604	0.457
	300-499	0.852	0.167		
	200-299	0.861	0.127		
	<200	0.906	0.148		
SE	>=500	0.829	0.125	9.776	0.021
	300-499	0.912	0.093		
	200-299	0.959	0.07		
	<200	0.887	0.14		

Table 3 SFA regression analysis results

	Chinese medicine practitioners (including assistant practitioners)	TCM pharmacist	Number of beds (actual open beds)	The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment
constant	-66.15***	9.09***	60.46***	471.36***
GDP per capita	13.05**	-1.81***	-24.75***	-70.14***
population density	-2.75	-0.65**	1.74*	-119.23***
Number of hospitals	4.27	1.07	31.78***	124.97***
σ2	1029.21***	61.01***	10495.09***	194014.28***
γ	0.99***	0.99***	0.99***	0.99***
log likelihood function	-274.94***	-180.14***	-361.4***	-449.82***
LR test of the one-sided error	51.66***	50.39***	36.64***	59.25***

Note: *** ,** and * indicate the significant p value at the 1%,5% and 10%.

Table 4 **Classification of technical efficiency scores and scale returns by hospital location**

	TE		PTE		SE	
	stage 1	stage 3	stage 1	stage 3	stage 1	stage 3
Total	68					
Mean	0.788	0.809	0.876	0.883	0.903	0.917
SD	0.155	0.146	0.143	0.129	0.113	0.103
Min	0.410	0.454	0.499	0.542	0.536	0.562
Eastern	17.000					
Mean	0.826	0.844	0.915	0.910	0.906	0.928
SD	0.122	0.117	0.115	0.102	0.096	0.087
Min	0.633	0.692	0.663	0.701	0.735	0.722
Southern	20.000					
Mean	0.797	0.805	0.881	0.886	0.906	0.908
SD	0.164	0.159	0.144	0.124	0.117	0.116
Min	0.517	0.481	0.625	0.653	0.561	0.562
Western	6.000					
Mean	0.857	0.860	0.923	0.942	0.929	0.910
SD	0.129	0.128	0.093	0.062	0.110	0.103
Min	0.689	0.701	0.774	0.845	0.721	0.756
Northern	17.000					
Mean	0.753	0.796	0.853	0.868	0.893	0.923
SD	0.150	0.149	0.152	0.145	0.136	0.118
Min	0.485	0.533	0.499	0.542	0.536	0.578
Central	8.000					
Mean	0.709	0.731	0.792	0.807	0.892	0.907
SD	0.207	0.168	0.190	0.177	0.114	0.090
Min	0.410	0.454	0.562	0.589	0.725	0.771

Table 5 Paired sample t-test of three kinds of efficiency in the first and third stages.

	TE		PTE		SE	
	stage 1	stage 3	stage 1	stage 3	stage 1	stage 3
Mean	0.788	0.809	0.876	0.883	0.903	0.917
SD	0.155	0.146	0.143	0.129	0.113	0.103
t	-2.451		-1.237		-2.264	
P	0.017		0.22		0.027	

Supplemental Table 1

The results from table show that the correlation coefficients between input and output indicators are both positive and highly significant.

S1 Correlation analysis of the inputs and outputs

	Chinese medicine practitioners (including assistant practitioners)	TCM pharmacist	Number of beds (actual open beds)	The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment	Total number of consultations	Number of discharges	Number of prescriptions of TCM decoction pieces	Income of TCM medical service projects	Bed utilization rate
Chinese medicine practitioners (including assistant practitioners)	1								
TCM pharmacist	0.629**	1							
Number of beds (actual open beds)	0.840**	0.610**	1						
The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment	0.443**	0.288*	0.451**	1					
Total number of consultations	0.853**	0.698**	0.781**	0.387**	1				
Number of discharges	0.827**	0.524**	0.888**	0.41[illegible]**	0.791**	1			
Number of prescriptions of TCM decoction pieces	0.711**	0.610**	0.697**	0.33[illegible]**	0.789**	0.654**	1		
Income of TCM medical service projects	0.489**	0.396**	0.616**	0.252*	0.617**	0.560**	0.501**	1	
Bed utilization rate	0.299*	0.143	0.330**	0.22[illegible]	0.229	0.477**	0.134	0.053	1

Note: *** ,** and * indicate the significant p value at the 1%,5% and 10%.

Supplemental Table 2

The table presents a descriptive summary of the inputs, outputs, and environmental variables for the 68 county-level TCM hospitals.

S2 Descriptive statistics of inputs, outputs and environmental variables

Indicators	Max	Min	Mean	SD
Inputs				
Chinese medicine practitioners (including assistant practitioners)	212	15	85	50
TCM pharmacist	41	3	15	8
Number of beds (actual open beds)	1012	36	340	195
The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment	2210	1	333	342
Outputs				
Total number of consultations	1095946	83268	527280	266208
Number of discharges	39121	921	11662	7785
Number of prescriptions of TCM decoction pieces	628542	13051	148740	113255
Income of TCM medical service projects	110902	1738	18742	17614
Bed utilization rate (%)	104.81	25.82	73	17
Environmental variables				
Per capita GDP (RMB)	357159	43788	106442	54095
Population density (persons/km²)	9891	74	867	1296
Number of hospitals	79	2	16	13

Supplemental Table 3

The Table displays the distribution of efficiency scores among the sample hospitals.

S3 Distribution of the efficiency scores for the sample hospitals

Efficiency	1	>0.9	0.8-0.9	0.7-0.8	<0.7	Mean
TE	11 16.18%	10 14.71%	13 19.12%	13 19.12%	21 30.88%	0.788
PTE	28 41.18%	11 16.18%	8 11.76%	10 14.71%	11 16.18%	0.876
SE	12 17.65%	32 47.06%	11 16.18%	10 14.71%	3 4.41%	0.903

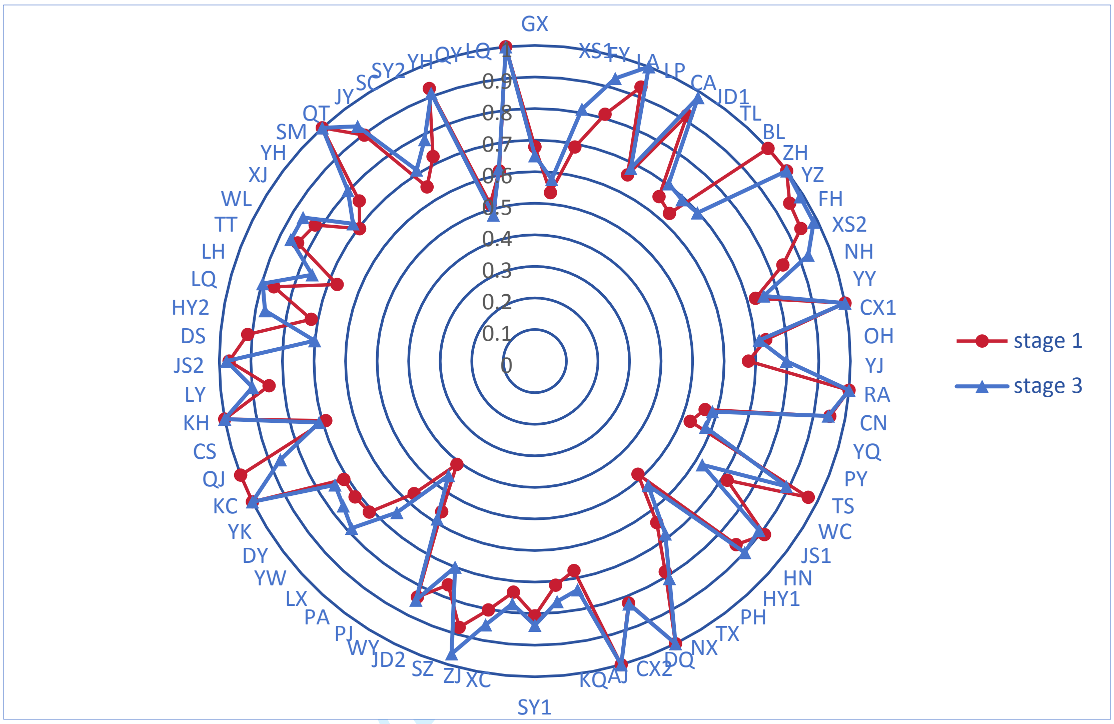

Figure 1 Comparison before and after TE adjustment in county-level Traditional Chinese medicine hospitals.

The figure displays a radar chart illustrating changes in TE values before and after adjustments, demonstrating that the adjusted efficiency values of county-level TCM hospitals now more accurately reflect the true efficiency by eliminating the impacts of environmental variables, management inefficiency, and random disturbances.

BMJ Open

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Journal:	*BMJ Open*
Manuscript ID	bmjopen-2024-088462.R1
Article Type:	Original research
Date Submitted by the Author:	06-Aug-2024
Complete List of Authors:	Xiao, Xiaoyue; Zhejiang Chinese Medical University, School of Humanities and Management Shen, Keyi; Zhejiang Chinese Medical University, School of Humanities and Management Zheng, Xinyue; Zhejiang Chinese Medical University, School of Humanities and Management Wu, Dan; Zhejiang Chinese Medical University, School of Humanities and Management Pei, Tong; Zhejiang Chinese Medical University, School of Humanities and Management Lin, Xin-hao; Zhejiang Chinese Medical University, School of Humanities and Management Meng, Xuehui; Zhejiang Chinese Medical University, Department of Health Service Management
Primary Subject Heading:	Medical management
Secondary Subject Heading:	Health policy, Health services research, Health economics, Medical management, Public health
Keywords:	Health, HEALTH ECONOMICS, HEALTH SERVICES ADMINISTRATION & MANAGEMENT

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An Analysis of Resource Allocation Efficiency in 68 County-Level Traditional Chinese Medicine Hospitals in China

ABSTRACT

Objective Analysing and evaluating how efficiently health resources are allocated to county-level Traditional Chinese Medicine (TCM) hospitals in Zhejiang Province, this study aims to provide empirical evidence for improving operational efficiency and optimizing resource allocation in these hospitals.

Design and Setting The study employed a three-stage Data Envelopment Analysis (DEA) model to assess efficiency, utilizing data from 68 county-level TCM hospitals. Four input and five output indicators related to TCM services were selected for the analysis.

Results The first-stage DEA results indicated that in 2022, the technical efficiency (TE) of TCM hospitals in Zhejiang Province was 0.788, the pure technical efficiency (PTE) was 0.876, and the scale efficiency (SE) was 0.903. The classification of hospitals into four groups based on bed size showed statistically significant differences in returns to scale (RTS) ($P<0.001$). The Stochastic Frontier Analysis (SFA) regression results were significant at the 1% level across four regressions, showing that environmental variables such as per capita GDP, population density, and the number of hospitals had an impact on efficiency. In the third stage DEA, after adjusting the input variables, the TE, PTE, and SE improved to 0.809, 0.833, and 0.917, respectively. The adjusted mean TE rankings by region were: West (0.860) > East (0.844) > South (0.805) > North (0.796) > Central (0.731).

Conclusion There is an imbalance between the inputs and outputs of county-level TCM hospitals. Each region must consider factors such as the local economy, population, and medical service levels, along with the specific development characteristics of hospitals, to reasonably determine the scale of county-level TCM hospital construction. Emphasis should be placed on improving hospital management and technical capabilities, coordinating regional development, promoting the rational allocation and efficient use of TCM resources, and enhancing the efficiency of resource allocation in county-level TCM hospitals.

Keywords County-level TCM hospitals; three-stage DEA; resource allocation efficiency

Strengths and limitations of this study

- The study employed a three-stage DEA model, ensuring reliable results.
- The analysis was based on data from 68 county-level TCM hospitals, providing an adequate sample size.
- The use of input and output indicators specific to TCM services in China added an innovative aspect to the research.
- The data used in the study were cross-sectional, limiting the ability to draw causal inferences.
- The research was confined to Zhejiang Province and did not include data from other provinces in China.

INTRODUCTION

As global health concepts shift and traditional medicine is re-evaluated, the international influence of TCM has been steadily increasing. Several countries and regions have begun introducing TCM techniques and services, gradually expanding their application and development locally.[1] In recent years, China has placed great emphasis on the development of TCM, marking a critical period for its high-quality advancement. TCM has significant differences in its core concepts and practice methods from other medical systems. The differences in the theoretical basis, diagnostic methods, and treatment methods of TCM determine the unique mode of treatment and service characteristics of TCM hospitals.[2,3] Therefore, the experience of public hospitals cannot be directly applied. Within China's hierarchical medical service system, county-level TCM hospitals serve as leaders of the rural three-tier TCM service network and as vital links in the urban-rural TCM service system. These hospitals bear significant responsibility for providing primary TCM services, connecting higher-level hospitals with grassroots medical institutions, and ensuring the continuity and accessibility of TCM services.[4,5] Despite the annual growth in total health resources and TCM resources, issues such as uneven resource distribution and the scarcity of high-quality medical and health resources remain prominent.[6–9] The scientific and rational allocation of TCM resources has become a focal point for policymakers and hospital administrators.

Efficiency in the allocation of health resources is a key indicator for measuring the level of allocation, as it evaluates whether health management departments achieve the same output with more economical and fewer resource inputs or obtain greater output with limited resources. For county-level TCM hospitals, the pressing issue is how to enhance the overall efficiency of health resource allocation under current conditions, ensuring balanced regional development of TCM health services and meeting public health service needs. However, current studies on resource allocation efficiency often focus on calculating efficiency values and distribution, rarely considering environmental factors. Additionally, most research subjects are public hospitals, with little focus on county-level TCM hospitals. Therefore, it is essential to study and analyze the resource allocation efficiency of county-level TCM hospitals, systematically identify current issues, suggest improvements, and provide recommendations. This is crucial for accelerating the development of county-level TCM hospitals in Zhejiang Province and promoting the sustainable and high-quality development of the TCM sector.

The predominant efficiency measurement methods are parametric and non-parametric, represented by Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), respectively.[10] Compared to SFA, DEA is more adept at handling the production process involving multiple inputs and multiple outputs, as it does not impose restrictive constraints between inputs and outputs, nor does it require the specification of the production frontier's functional form.[11–13] The model's high extensibility often leads researchers to prefer the non-parametric method represented by DEA. The three-stage DEA model combines the advantages of DEA and SFA, being capable of handling complex production processes with multiple inputs and outputs, while also identifying and quantifying the impact of environmental variables on hospital efficiency. This model eliminates the interference of environmental factors, thereby enhancing its interpretability and analytical depth.

In summary, to thoroughly understand the resource allocation efficiency of county-level TCM hospitals, the factors influencing their efficiency, and the differences in efficiency among them, this study employs a three-stage DEA model. It aims to delve into and enhance the efficiency of TCM resource allocation in county-level hospitals, compare the efficiency of hospitals of different sizes, and explore the factors affecting efficiency.

The expectation is to provide more scientific decision support for resource allocation in county-level TCM hospitals, promote the rational use of TCM resources, and improve overall service quality. Zhejiang Province, located in the eastern coastal area of China, has a long history and a solid foundation in TCM development. Its numerous and widely distributed county-level TCM hospitals provide abundant material and a broad sample for research. Recently, Zhejiang Province has introduced a series of policy measures to promote TCM development, emphasizing the need to strengthen TCM inheritance and innovation, enhance TCM service capabilities, and optimize TCM resource allocation. Zhejiang Province is at the forefront of medical reform and TCM development, and its successes and challenges can provide valuable lessons for other regions.

METHODS

Sample selection and data sources

The data and information for this study were sourced from the 2022 Compendium of Hospitals of the TCM Category of the Zhejiang Provincial Health Commission and the 2022 official statistical yearbook of the Zhejiang Provincial Bureau of Statistics. Zhejiang Province has a total of 95 hospitals categorized under TCM. Given the DEA model's emphasis on the relative comparability of similar units, the study initially screened 71 county-level TCM hospitals. However, three county-level TCM hospitals were excluded from the final analysis due to different service orientations and missing data, such as bed numbers. Therefore, a total of 68 county-level TCM hospitals were included in the final analysis.

The 68 county-level TCM hospitals included in the study are situated in 68 county-level cities across Zhejiang Province, collectively covering 75.56% of the province's counties. They are distributed across five regions—eastern, southern, western, northern, and central Zhejiang—aligned with the administrative divisions where the hospitals are located. According to Gok and Sezen's classification method, the county-level TCM hospitals in the sample are classified into four groups based on their bed capacity (number of actual open beds): small (<200), lower-middle (200-299), upper-middle (300-499), and large (≥500).[14,15]

Three-stage data envelopment analysis

Three-stage DEA is a method developed based on DEA. It is mainly used to evaluate the relative efficiency of decision-making units with multiple inputs and multiple outputs, particularly to reflect the efficiency of decision-making units more realistically after removing the influence of environmental factors and random disturbances.[16] The modeling approach consists of three main stages.

In the first stage, which involves conducting a conventional DEA analysis, the DEA model was introduced in 1978 by American operations researchers Charnes, Cooper, and others.[17] It is a non-parametric, non-stochastic model designed for measuring and evaluating efficiency, based on the concept of the "production frontier."[18] The model employs a linear programming approach to construct a production frontier, utilizing input and output indicators from decision-making units. Effective units are positioned on the frontier, while ineffective ones are positioned below it. This arrangement allows for the measurement of the extent to which units deviate from the frontier.[19] There are two types of DEA models: the first is the CCR model, which assumes constant RTS. Under this model, an increase in input will proportionately increase output, implying that the sector size does not impact production efficiency. However, this assumption often proves challenging in practice; the policy system and economic development levels may prevent maintaining sector production at a reasonable size, and thus obscure the determination of size impact on production efficiency. Based on these limitations, Charnes and other scholars revised the CCR model and proposed the BCC model, which assumes variable RTS.[20]

In addition, DEA models can be categorized as input-oriented or output-oriented. The former emphasizes reducing inputs while maintaining constant outputs, whereas the latter focuses on increasing outputs while keeping inputs constant.[21,22] Considering that the RTS for health resource allocation is variable, this study employs the input-oriented BCC model. The model equations are presented below:

$$\min\theta-\varepsilon(\hat{e}^{T}S^{-}+e^{T}S^{+})$$
$$\text{s.t.}\begin{cases}\sum_{j=i}^{n}X_j\lambda_j+S^{-}=\theta X_0\\ \sum_{j=i}^{n}Y_j\lambda_j+S^{+}=Y_0\\ \lambda_j\geq 0, S^{-}, S^{+}\geq 0\end{cases} \tag{1}$$

Where, j=1,2,...,n denote decision units, X and Y are input and output vectors, respectively.

The efficiency value measured by the BCC model is called the combined Technical Efficiency (TE), and it can be further decomposed into the product of Scale Efficiency (SE) and Pure Technical Efficiency (PTE), i.e., TE=SE*PTE.[23,24]

The second stage involves SFA regression. The SFA model was first proposed by Aigner et al. in 1977. This parametric estimation method for production frontiers has gradually been used in various fields for efficiency evaluation research. The main advantage of this method is that it considers the effects of random factors on output variables.[25] It is based on a defined production frontier and decomposes the error term into random error and technical inefficiency, with random error being removed before the efficiency evaluation of decision-making units. Subsequently, in 2002, Fried et al. suggested that traditional DEA models have certain biases in efficiency analysis since the calculated TE values are influenced by random factors, environmental conditions, and managerial inefficiency.[26,27] Therefore, these three factors should be effectively separated. They used the SFA regression model to decompose the slack variables calculated in the first stage into the aforementioned three factors, thus fully eliminating the impact of environmental and random factors on the DEA model. See **Appendix 1** for details of the calculation process

The third stage involves DEA efficiency evaluation with adjusted inputs. In this stage, efficiency evaluation is conducted using adjusted input data and original output data, after removing the influence of environmental factors and random errors. First, input indicators are adjusted based on the regression analysis results from the second stage to eliminate the interference of external environmental factors and random errors. Then, the output indicator data remain unchanged, and the adjusted input data are substituted into the DEA model for calculation. Finally, this stage provides more accurate and realistic efficiency evaluation results, providing scientific evidence for decision-makers.

Selection of variables

In DEA, the selection of input and output indicators is of utmost importance. Based on the relevant principles of indicator selection, in-depth analyses of similar studies, and consultation with relevant experts, we have selected a series of indicators with Chinese medicine service characteristics.[28–30]The four input indicators include the number of Chinese medicine practitioners (including assistant practitioners), the number of TCM pharmacists, the actual number of open beds, and the total value of more than 10,000 RMB of TCM diagnosis and treatment equipment. The five output indicators include the total number of consultations, the total number of discharges, the number of TCM decoction piece prescriptions, the income from TCM medical service projects, and the bed utilization rate.

The selected indicators are closely related to the characteristics and services of TCM hospitals, and the data are accessible, which benefits the evaluation of their core competitiveness. However, the data have limitations and may not fully reflect the efficiency of health resource allocation in county-level TCM hospitals. For example, the total income from TCM medical service projects may overlook income that is not derived from these projects. The evaluation system consists entirely of quantitative indicators, potentially ignoring non-quantitative factors (such as hospital culture, patient satisfaction, etc.) that impact the efficiency of health resource allocation.

The input indicators primarily encompass two aspects: human resources and hardware facilities. TCM human resources are the core strength of TCM hospitals, and their number directly determines the quality and scale of TCM services that the hospital can provide. In terms of hardware facilities, the number of open beds serves as a key indicator of the hospital's size and service capacity. The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment directly reflects the hospital's investment in equipment updates and upgrades.

Among the output indicators, the total number of consultations and discharges directly reflect the hospital's service volume, serving as key indicators for measuring the hospital's operational efficiency and service capacity. TCM decoction pieces are a crucial treatment method and a unique indicator differentiating TCM from other medical systems. The number of TCM decoction piece prescriptions reflects the hospital's effectiveness in using TCM. The income from TCM medical service projects reflects the hospital's economic benefits and revenue-generating capacity, indicating its economic efficiency in providing TCM services. This is also one of the distinctive indicators of TCM hospitals. The bed utilization rate indicates the efficiency of bed utilization in the hospital.

According to Hollingsworth[31], the number of units used for efficiency assessment should be at least three times the sum of input and output indicators. In this study, 68 county-level TCM hospitals were assessed, exceeding the required minimum of three times this sum, thus aligning with Hollingsworth's principle. Furthermore, the collected input and output indicator data were analyzed for correlation using Pearson's correlation coefficient in SPSS 25.0 software. The results show that the correlation coefficients between input and output indicators are positive and highly significant. See **Sup Table 1** for more details.

In addition to the input and output variables previously discussed, the selection of environmental variables is crucial for developing the SFA model within this three-stage DEA framework. According to the Separation Hypothesis by Simar and Wilson[32], environmental variables significantly affect input-output efficiency. These variables are beyond the control of individual decision-making units and free from subjective influences. Based on a review and synthesis of relevant literature, this study selected three environmental variables: per capita GDP, population density, and the number of hospitals in the county.[30,33,34]

Statistical methods

The study employed the Pearson correlation coefficient to assess the correlation between input-output variables and utilized the Kruskal-Wallis H non-parametric test to compare the efficiency, including TE, PTE, and SE, of hospitals with varying numbers of beds. The $\chi 2$ test was utilized to examine differences in RTS among TCM hospitals with varying bed sizes. Descriptive analysis and statistical testing of the data were conducted using SPSS 25.0 software, while the three-stage DEA was measured and analyzed using DEAP 2.1 software in conjunction with Frontier 4.1 software.

Patient and public involvement

No patient is involved.

RESULT

Description of variables

Table 1 provides a descriptive summary of the inputs, outputs, and environmental variables for 68 county-level TCM hospitals. The data show that in 2022, each county-level TCM hospital had an average of 85 Chinese medicine practitioners and 15 TCM pharmacists, an average of 340 actual open beds, and the total value of TCM diagnosis and treatment equipment per hospital, which exceeded 10,000 RMB, averaged 3.33 million yuan. In 2022, these 68 county-level TCM hospitals had an average total number of consultations of 527,280, an average number of discharged patients of 11,662, and an average number of TCM decoction piece prescriptions of 148,740. Income from TCM medical service projects per hospital was 18.742 million yuan, and the average bed utilization rate was 73%. The corresponding 68 counties had a per capita GDP ranging from 43,788 to 357,159 yuan, with an average of 106,442 yuan. The average population density per county ranged from 74 to 9,891 people per square kilometer. The number of hospitals per county ranged from a maximum of 79 to a minimum of 2.

Table 1 Descriptive statistics of inputs, outputs and environmental variables

Indicators	Max	Min	Mean	SD
Inputs				
Chinese medicine practitioners (including assistant practitioners)	212	15	85	50
TCM pharmacist	41	3	15	8
Number of beds (actual open beds)	1012	36	340	195
The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment	2210	1	333	342
Outputs				
Total number of consultations	1095946	83268	527280	266208
Number of discharges	39121	921	11662	7785
Number of prescriptions of TCM decoction pieces	628542	13051	148740	113255
Income of TCM medical service projects	110902	1738	18742	17614
Bed utilization rate (%)	104.81	25.82	73	17
Environmental variables				
Per capita GDP (RMB)	357159	43788	106442	54095
Population density (persons/km²)	9891	74	867	1296
Number of hospitals	79	2	16	13

Stage 1: Traditional DEA model analysis

An analysis of the first-stage health resource allocation efficiency of county-level TCM hospitals in Zhejiang Province in 2022 showed that in 2022, the TE of TCM hospitals in Zhejiang Province was 0.788, PTE was 0.876, and the SE was 0.903. Specifically, 11 hospitals (16.18%) had a TE of 1, 28 hospitals (41.18%) had a PTE of 1, and only 12 hospitals (17.65%) had a SE of 1. There were 21 hospitals (30.88%) with a TE of less than 0.7, indicating that the overall TE of county-level TCM hospitals was relatively low. However, 55 hospitals (80.88%) had a SE greater than 0.8, indicating a relatively high SE. See **Sup Table 2** for more details.

The study conducted a statistical analysis of the TE, PTE, and SE of hospitals with varying bed sizes. The results showed that the differences in TE (P=0.416, P>0.05) and PTE (P=0.457, P>0.05) among the four comparison groups were not statistically significant, whereas the difference in SE (P=0.021, P<0.05) was statistically significant. This indicates that hospital bed size has a significant impact on the efficiency of health resource allocation. See **Sup Table 3** for more details.

The efficiency values and RTS statistical analysis results for different types of hospitals based on bed size are shown in **Table 2**. Overall, the results indicated that 12 hospitals (17.56%) with an SE score of 1 were in the CRS state, 17 hospitals (25%) were in the IRS state, and the remaining 39 hospitals (57.35%) were in the DRS state. More than half of the hospitals exhibited decreasing efficiency at their current scale, indicating that further expansion will not yield higher efficiency. Hospitals with the RTS of IRS are likely to be in a phase of rapid growth, needing to invest more resources to support their growth, and may be able to realize greater economies of scale through expansion.

Table 2 Statistical analysis results of the returns to scale of hospitals with different bed sizes

Bed size	Returns to scale					
	CRS	IRS	DRS	Total	$\chi 2$ value	P value
<200	5(31.25%)	11(68.75%)	0(0%)	16(100%)	33.654	<0.001
200-299	3(17.65%)	4(23.53%)	10(58.82%)	17(100%)		
300-499	3(13.04%)	2(8.70%)	18(78.26%)	23(100%)		
>=500	1(8.33%)	0(0%)	11(91.67%)	12(100%)		
Total	12(17.65%)	17(25.00%)	39(57.35%)	68(100%)		

CRS, constant returns to scale; DRS, decreasing returns to scale; IRS, increasing returns to scale.

The RTS differences among the four groups of hospitals with different bed sizes were statistically significant (P<0.001). Among the small hospitals, 5 (31.25%) were in the CRS stage, indicating a relative balance between inputs and outputs and an optimal operational status. The remaining 11 (68.75%) hospitals were in the IRS stage, indicating a need to expand their scale to improve efficiency. In the lower-middle (58.82%) and upper-middle (78.26%) hospitals, most were in the DRS stage, indicating an excess of inputs. Among the large hospitals, only one (8.33%) was in the CRS stage, while the remaining 11 (91.67%) were in the DRS stage, indicating a need for a reduction in scale and further optimization of resource allocation.

Stage 2: SFA regression analysis

The slack variables of input indicators calculated in the first-stage DEA model analysis (**Sup Table 4**) were used as the dependent variables, while per capita GDP, population density, and the number of hospitals were used as independent variables. The SFA regression analysis was then performed on the input slack variables, and the regression results are shown in **Table 3**. The regression analysis results showed that the influence of environmental variables on the input slack values was statistically significant. The generalized likelihood ratio test for the four regressions was significant at the 1% level, indicating the validity of the SFA regression. This highlights the necessity of removing environmental factors when calculating the comprehensive efficiency of county-level TCM hospitals. The γ values were close to 1, indicating that the influence on the input slack variables was due to management factors in TCM hospitals, with random disturbances having a very minor impact.

Table 3 SFA regression analysis results

	Chinese medicine practitioners (including assistant practitioners)	TCM pharmacist	Number of beds (actual open beds)	The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment
constant	-66.15***	9.09***	60.46***	471.36***
GDP per capita	13.05**	-1.81***	-24.75***	-70.14***
population density	-2.75	-0.65**	1.74*	-119.23***
Number of hospitals	4.27	1.07	31.78***	124.97***
σ2	1029.21***	61.01***	10495.0[illegible]***	194014.28***
γ	0.99***	0.99***	0.99***	0.99***
log likelihood function	-274.94***	-180.14***	-361.4***	-449.82***
LR test of the one-sided error	51.66***	50.39***	36.64***	59.25***

Note: *** ,** and * indicate the significant p value at the 1%,5% and 10%.

When analyzing the impact of various factors on slack variables, the key lies in the coefficients of environmental factors, whether positive or negative. A positive coefficient means that an increase in the factor will increase the input slack variable, thereby reducing output and being detrimental to improving hospital efficiency; a negative coefficient means that an increase in the factor will decrease the input slack variable, thereby increasing output and helping to improve the efficiency of county-level TCM hospitals. Per capita GDP had negative coefficients for the input slack variables of TCM pharmacists, the number of beds, and the total value of TCM equipment, all significant at the 1% level. GDP growth can reduce these input redundancies, thus promoting hospital efficiency. However, an increase in per capita GDP increases the input redundancy of TCM practitioners, thereby reducing the efficiency of county-level TCM hospitals. Population density had a negative effect on the slack variables of TCM pharmacists and the total value of TCM equipment, both significant at the 5% level. It also had a negative effect on the slack variable of the number of beds, but only significant at the 10% level. This indicates that population density has a dual impact on the overall efficiency of county-level TCM hospitals. The number of hospitals had a positive impact on the slack variables of bed numbers and the total value of TCM equipment, both significant at the 1% level. The number of hospitals in a region greatly affects the use of hardware facilities, including beds and equipment, and thus efficiency.

Stage 3: DEA model analysis with adjusted input variables

After adjusting the input indicators in the second stage, DEAP2.1 software was used again for input-oriented BCC model analysis, and the efficiency values of each decision-making unit were recalculated. The adjusted TE, PTE, and SE of county-level TCM hospitals in Zhejiang Province were 0.809, 0.833, and 0.917, respectively, which all increased compared to the first-stage efficiency values. At the same time, paired t-tests were conducted on the TE, PTE, and SE of the first and third stages (see **Table 4**). It was found that the differences in TE ($p=0.017$, $p<0.05$) and SE ($p=0.027$, $p<0.05$) before and after adjustment were statistically significant. This further confirmed the necessity of performing SFA regression analysis in the second stage, as the TE and SE of county-level TCM hospitals are influenced by external factors to some extent.

Table 4 Paired sample t-test of three kinds of efficiency in the first and third stages

	TE		PTE		SE	
	stage 1	**stage 3**	**stage 1**	**stage 3**	**stage 1**	**stage 3**
Mean	0.788	0.809	0.876	0.883	0.903	0.917
SD	0.155	0.146	0.143	0.129	0.113	0.103
t	-2.451		-1.237		-2.264	
P	0.017		0.22		0.027	

According to the results of the three-stage DEA analysis, there are significant differences in the operational efficiency of TCM hospitals across different regions in China. From a regional perspective, the efficiency values before and after adjustment for the eastern, southern, western, northern, and central regions of Zhejiang Province are shown in **Table 5**. The adjusted TE rankings for each region are as follows: West (0.860) > East (0.844) > South (0.805) > North (0.796) > Central (0.731). Regardless of the adjustments, the TE and PTE of the eastern and western regions are relatively high, indicating that the allocation of TCM resources, technology, and management is at a relatively optimal level. However, the SE in the western region has significantly decreased, indicating that its current operational scale has not achieved maximum economic efficiency. The efficiency values of the northern and central regions showed significant differences before and after adjustments when compared to other regions. Particularly, after eliminating the interference of environmental factors, the TE, PTE, and SE of the northern region all increased, with the most substantial increase in TE. The efficiency values in the southern region changed minimally before and after the adjustments, reflecting a relatively accurate representation of its efficiency.

Table 5 Classification of technical efficiency scores and scale returns by hospital location

	TE		PTE		SE	
	stage 1	stage 3	stage 1	stage 3	stage 1	stage 3
Total	68					
Mean	0.788	0.809	0.876	0.883	0.903	0.917
SD	0.155	0.146	0.143	0.129	0.113	0.103
Min	0.410	0.454	0.499	0.542	0.536	0.562
Eastern	17					
Mean	0.826	0.844	0.915	0.910	0.906	0.928
SD	0.122	0.117	0.115	0.102	0.096	0.087
Min	0.633	0.692	0.663	0.701	0.735	0.722
Southern	20					
Mean	0.797	0.805	0.881	0.886	0.906	0.908
SD	0.164	0.159	0.144	0.124	0.117	0.116
Min	0.517	0.481	0.625	0.653	0.561	0.562
Western	6					
Mean	0.857	0.860	0.923	0.942	0.929	0.910
SD	0.129	0.128	0.093	0.062	0.110	0.103
Min	0.689	0.701	0.774	0.845	0.721	0.756
Northern	17					
Mean	0.753	0.796	0.853	0.868	0.893	0.923
SD	0.150	0.149	0.152	0.145	0.136	0.118
Min	0.485	0.533	0.499	0.542	0.536	0.578
Central	8					
Mean	0.709	0.731	0.792	0.807	0.892	0.907
SD	0.207	0.168	0.190	0.177	0.114	0.090
Min	0.410	0.454	0.562	0.589	0.725	0.771

DISCUSSION

This study conducted an in-depth analysis of the efficiency of health resource allocation in county-level TCM hospitals using a three-stage DEA model. Ahmed et al.[35] used an output-oriented DEA and found that approximately 91.3% of Asian countries were inefficient in utilizing medical resources. Sun et al.[36] used data envelopment analysis to find that the overall operating efficiency of public hospitals in Fujian Province was low. Alatawi et al.[15] measured the TE of 91 public hospitals in Saudi Arabia in 2017 and found that 75.8% of public hospitals exhibited technical inefficiency. Similarly, our study found that the resource utilization efficiency of county-level TCM hospitals in Zhejiang Province was low; 56 county-level TCM hospitals that were not in CRS status were inefficient, and more than 70% of the hospitals showed an imbalance between inputs and outputs. This is consistent with the conclusions of many studies.

In Chinese hospitals, there is a common phenomenon of blindly pursuing an increase in bed size, and county-level TCM hospitals are no exception. The study results show that more than 50% of hospitals have exhibited decreasing efficiency at their current scale. Many county-level TCM hospitals tend to blindly expand bed size in pursuit of broader development space and enhanced service capacity. Many previous studies have confirmed that the relationship between hospital efficiency and scale is not simply directly positive or negative but is influenced by multiple factors. Gok and Sezen[14] evaluated the efficiency scores of 523 hospitals of different sizes in Turkey and found a negative correlation between the efficiency of Turkish healthcare institutions and their scale. Qian et al.[37] revealed the negative effects of efficiency and scale in county-level public hospitals in Shandong Province. Amin et al.[38] found that the main cause of low hospital productivity was negative changes in SE. Zhao et al.[39] found through the DEA model that excessive scale expansion of county-level hospitals in Henan Province led to lower efficiency. Simple expansion is not an effective solution for increasing efficiency; it may lead to an imbalance in resource allocation and a decline in hospital operational efficiency.

From the perspective of different bed sizes, the study found that over 70% of upper-middle and large hospitals were in the DRS stage. Studies have shown that county-level public hospitals need to reach more than 1,100 beds to achieve SE saturation.[15,37] County-level TCM hospitals and public hospitals have significant differences in operating models, service content, and management strategies, resulting in different considerations for scale expansion. This further highlights the uniqueness of county-level TCM hospitals in resource allocation and efficiency management. Therefore, when developing strategies for the growth of county-level TCM hospitals, it is necessary to fully consider their unique operating environments and characteristics. Hospitals should be encouraged to adopt refined management practices to improve the utilization and service quality of existing beds rather than merely pursuing scale expansion.

The second-stage SFA regression analysis results showed that environmental factors such as per capita GDP, population density, and the number of hospitals significantly impact the efficiency of county-level TCM hospitals. Among these, the growth in per capita GDP can effectively reduce the input redundancy of TCM pharmacists, the number of beds, and the total value of TCM equipment. Multiple studies have shown a negative relationship between per capita GDP and input slack, meaning that as per capita GDP increases, the input redundancy of medical institutions gradually decreases, thereby helping to improve overall service efficiency.[40–42] Residents in economically developed areas often have higher healthcare demands, which may lead to more health resources being allocated to these areas. In response to differences in economic development levels across regions, the government should formulate differentiated policy support measures, such as financial subsidies and tax incentives, to incentivize county-level TCM hospitals in economically underdeveloped areas to improve service efficiency.

Population density was found to have a significant negative impact on the redundancy of TCM pharmacists and the total value of TCM equipment in this study. This finding suggests that in areas with higher population density, county-level TCM hospitals are more inclined to reduce the redundancy of these two inputs, thereby utilizing resources more effectively and improving resource allocation efficiency. This is similar to the conclusion of Zhang, Su et al.[34,43], who found that the more concentrated the residential area, the more convenient the supply of healthcare services, reducing supply costs and increasing the utilization of healthcare services. However, it is worth noting that in areas with high population density, the investment in the number of beds may be relatively excessive, failing to achieve an optimal allocation that matches the population density.

A greater number of hospitals implies competition for resources and reflects the level of healthcare services in a region. An increase in the number of hospitals will provide patients with more choices of medical care. This may lead to polarization in the number of healthcare services and affect the efficiency of hospital resource allocation. Therefore, the Government should strengthen supervision and assessment, and intervene in a timely manner to encourage county-level Chinese medicine hospitals to carry out special diagnostic and treatment services and give full play to the advantages of Chinese medicine features, which will be conducive to optimizing the allocation of resources, thereby improving the overall efficiency of health resource allocation.

From a regional perspective, there are significant differences in the efficiency of TCM resource allocation among hospitals in different areas of Zhejiang Province. The SE is relatively high in the western and eastern regions, while it is relatively low in the northern and central regions. Particularly in the northern region, there were improvements in PTE and SE after excluding environmental factors. Therefore, there is a need to strengthen the local medical system, cautiously expand the production scale, and improve hospital management levels. The management and resource allocation models of the eastern and southern regions can be appropriately referenced to coordinate regional development, enhance cooperation and exchange between regions, improve overall medical services, and achieve rational allocation and efficient utilization of TCM resources.

Limitations

This study utilized a three-stage DEA model to analyze the efficiency of TCM resource allocation in county-level TCM hospitals in Zhejiang Province, providing detailed insights, but it also has some limitations. Although the DEA model has shown great potential in evaluating the efficiency of healthcare services, it does not directly include considerations for dimensions such as medical quality, health outcomes, and case mix differences. The study results are specific to county-level TCM hospitals in Zhejiang Province and may not be directly applicable to other regions or types of hospitals. This study relies on data from a single year (2022), which may not reflect the long-term trends and annual fluctuations in hospital efficiency. The subjective nature of indicator selection may not fully capture the true situation of county-level TCM hospitals, potentially leading to biased results. Future research could include longitudinal studies, exploration of additional environmental factors such as policy changes or cultural attitudes towards TCM, and integration of other analytical models to capture the dynamic and qualitative aspects of hospital efficiency.

CONCLUSIONS

This study utilized a three-stage DEA model to analyze in depth the efficiency of health resource allocation in county-level TCM hospitals and found an imbalance between hospital inputs and outputs. Most hospitals should avoid blindly expanding their scale to seek efficiency improvements. Environmental factors such as per capita GDP, population density, and the number of hospitals significantly impact the efficiency of health resource allocation in county-level TCM hospitals, and there are clear differences in TCM resource allocation efficiency among different regions. Therefore, each region needs to base its plans on local TCM healthcare resources, fully considering factors such as the local economy, population, and medical service levels. Considering the specific development characteristics of hospitals, regions should reasonably determine the scale of county-level TCM hospital construction, improve infrastructure and medical equipment, focus on improving hospital management and technical skills, encourage resource sharing and cooperation between regions, and coordinate regional development. This will promote the rational allocation and efficient utilization of TCM resources, thereby providing high-level, high-quality TCM healthcare services to residents. It is hoped that these findings will provide important references for future hospital efficiency evaluation research and policy-making.

Contributors XX, KS,XZ and XM contributed to the conception and design of the project; DW, TP and XL contributed to the analysis and interpretation of the data; XM gave guidance on the writing of the article; and XX, KS and XZ drafted the article. All authors supplied critical revisions to the manuscript and gave final approval of the version to be published. XX is the guarantor.

Patient consent for publication Not required.

Funding This study was supported by the Zhejiang Soft Science Research program project (2024C35124).

Competing interests None declared.

Ethics approval Ethical approval was gained from the Ethics Committee of the Affiliated Hospital of Zhejiang University of Chinese Medicine.

Data availability statement Data were extracted from the hospital databases at Administration of Statistics. Data are available upon reasonable request.

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Appendix 1:

Three-stage data envelopment analysis is a method developed based on DEA. It is mainly used to evaluate the relative efficiency of decision-making units with multiple inputs and multiple outputs, especially to reflect the efficiency of decision-making units more realistically after removing the influence of environmental factors and random disturbances.[26] The modelling approach consists of three main stages.

In the first stage, which involves conducting a conventional DEA analysis, the DEA model was introduced in 1978 by American operations researchers Charnes, Cooper, and others.[27] It is a non-parametric, non-stochastic model designed for measuring and evaluating efficiency, based on the concept of the "production frontier."[28] The model employs a linear programming approach to construct a production frontier, utilizing input and output indicators from decision-making units. Effective units are positioned on the frontier, while ineffective ones are positioned below it. This arrangement allows for the measurement of the extent to which units deviate from the frontier.[29] There are two types of DEA models: the first is the CCR model, which assumes constant returns to scale. Under this model, an increase in input will proportionately increase output, implying that the sector size does not impact production efficiency. However, this assumption often proves challenging in practice; the policy system and economic development levels may prevent maintaining sector production at a reasonable size, and thus obscure the determination of size impact on production efficiency. Based on these limitations, Charnes and other scholars revised the CCR model and proposed the BCC model, which assumes variable returns to scale.[30]

In addition, DEA models can be categorised as input-oriented or output-oriented. The former emphasizes reducing inputs while maintaining constant outputs, whereas the latter focuses on increasing outputs while keeping inputs constant.[31,32] Considering that the returns to scale for health resource allocation are variable, this study employs the input-oriented BCC model. The model equations are presented below:

$$\min\theta - \varepsilon(\hat{e}^T S^- + e^T S^+)$$

$$\text{s.t.}\begin{cases} \sum_{j=i}^{n} X_j\lambda_j + S^- = \theta X_0 \\ \sum_{j=i}^{n} Y_j\lambda_j + S^+ = Y_0 \\ \lambda_j \geq 0, S^-, S^+ \geq 0 \end{cases} \tag{1}$$

Where, j=1,2,...,n denote decision units, X and Y are input and output vectors, respectively.

The efficiency value measured by the BCC model is called the combined Technical Efficiency (TE), and it can be further decomposed into the product of Scale Efficiency (SE) and Pure Technical Efficiency (PTE), i.e., TE=SE*PTE.[33,34]

TE measures the ability of a decision-making unit to optimise output with specific inputs under fixed production conditions and provides a comprehensive assessment of resource allocation and use efficiency. PTE reflects the impact of management skills and technical expertise on production efficiency, helping to evaluate whether a decision-making unit's management and technology are optimal. SE assesses the impact of production scale on a decision-making unit's efficiency, focusing on whether the scale is optimised.

The second stage typically involves constructing a regression model akin to Stochastic Frontier Analysis (SFA). This model estimates the influence of environmental factors on efficiency scores through regression analysis, using environmental factors as independent variables and efficiency scores obtained in the first stage as dependent variables.[35] The SFA regression model is applied to decompose the slack variables identified in the first stage into three components: random factors, environmental factors, and managerial inefficiency.[36,37] Initially, the first-stage DEA model is analyzed to obtain the slack variables for each decision-making unit. The formula is presented as follows:

$$S_{ni} = x_{ni} - x_{ni}^{*}(n = 1,2,\ldots,N; i = 1,2,\ldots,I) \quad (2)$$

S_{ni} represents the slack variable for the nth input indicator of the ith decision unit, x_{ni} represents the actual value of the input indicator of each decision unit, and x_{ni}^{*} represents the predicted value of the input indicator of each decision unit. The SFA regression function is constructed using the slack variables as the response variables and the environmental factor variables as the independent variables in the analysis. The function is detailed below:

$$S_{ni} = f(Z_i; \beta_n) + v_{ni} + \mu_{ni}; i = 1,2,\ldots,I; n = 1,2,\ldots,N \quad (3)$$

In this function, Z_i represents the total number of environmental variables, and β_n is the value of the coefficient measured by the environmental variables. In addition, the function contains a mixed error term, $v_{ni} + \mu_{ni}$, where v_{ni} represents random error and μ_{ni} represents management inefficiency.

The SFA regression model adjusts for environmental and stochastic factors to normalize the overall technical efficiency across all decision-making units, ensuring uniform environmental conditions and stochastic influences. The mathematical expression for the function, which relates to the adjusted input variables, is presented below:

$$X_{ni}^{A} = X_{ni} + [max(f(Z_i; \widehat{\beta}_n)) - f(Z_i; \widehat{\beta}_n)] + [max(v_{ni}) - v_{ni}]$$
$$i = 1,2,\ldots,I; n = 1,2,\ldots,N \quad (4)$$

where X_{ni}^{A} represents the adjusted input values and Xni represents the pre-adjusted input values. The expression $[\max(f(Z_i; \widehat{\beta}_n)) - f(Z_i; \widehat{\beta}_n)]$ is used to place all decision-making units in a consistent external environment to ensure a fair comparison of environmental factors. Meanwhile, $[\max(v_{ni}) - v_{ni}]$ serves to adjust the random errors of all decision-making units to the same level to accurately assess their efficiency. To effectively eliminate the effects of random errors on the slack variables, further decomposition of these errors and efficiency residuals is necessary. This approach allows us to obtain the predicted random error values for each decision-making unit. For this purpose, this study employs the formula for calculating management inefficiency, as derived by Rodenyue[38], presented below:

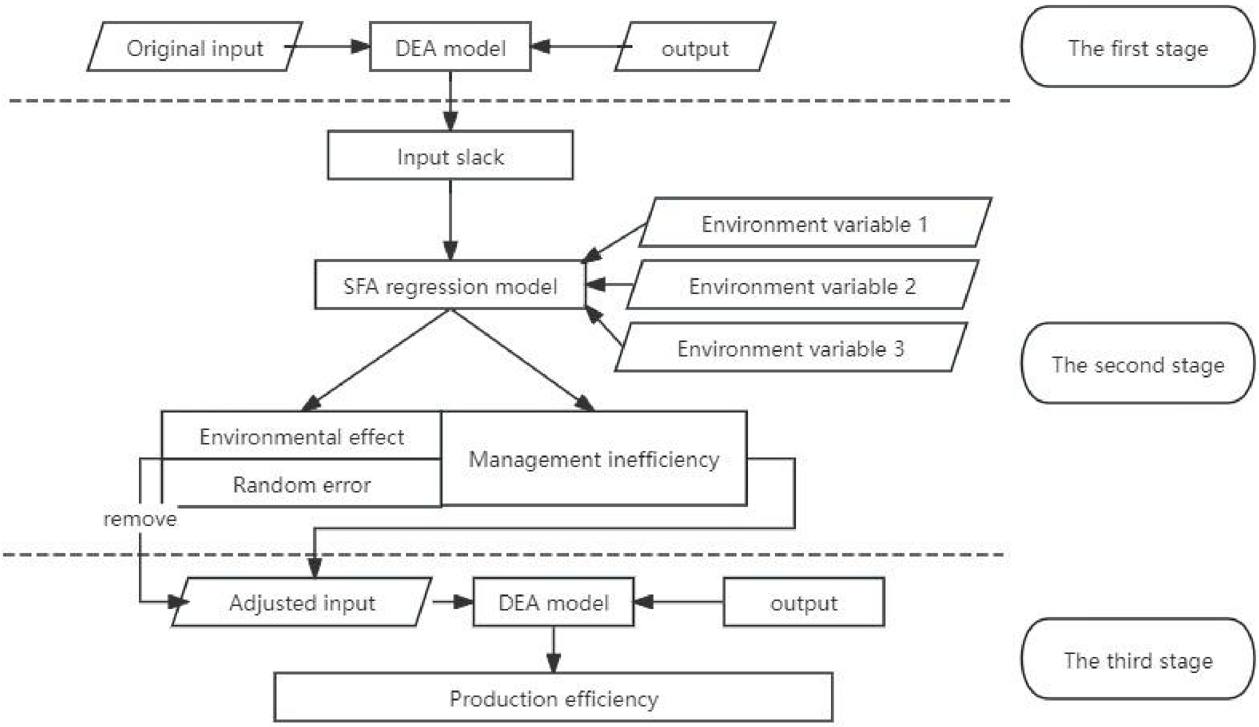
$$E(\mu|\varepsilon) = \sigma_{*}\left[\frac{\phi(\lambda\frac{\varepsilon}{\sigma})}{\Phi(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma}\right] \quad (5)$$

Where, $\sigma_{*} = \frac{\sigma_\mu \sigma_v}{\sigma}$, $\sigma = \sqrt{\sigma_\mu^2 + \sigma_v^2}$, $\lambda = \sigma_\mu / \sigma_v$, $\gamma = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_v^2}$.

Based on the above equation, we can derive the extent to which random error and management inefficiency factors influence the slack variable. When the value of γ variable approaches 1, it indicates a significant impact of management inefficiency; conversely, when the value of γ variable approaches 0, it indicates a significant impact of random error.

The third stage involves DEA efficiency evaluation with adjusted inputs. In this stage, efficiency evaluation is conducted using adjusted input data and original output data, after removing the influence of environmental factors and random errors. First, input indicators are adjusted based on the regression analysis results from the second stage to eliminate the interference of external environmental factors and random errors. Then, the output indicator data remain unchanged, and the adjusted input data are substituted into the

DEA model for calculation. Finally, this stage provides more accurate and realistic efficiency evaluation results, providing scientific evidence for decision-makers.



Three-stage DEA model flow chart

Sup Table 1

The results from table show that the correlation coefficients between input and output indicators are both positive and highly significant.

S1 Correlation analysis of the inputs and outputs

	Chinese medicine practitioners (including assistant practitioners)	**TCM pharmacist**	**Number of beds (actual open beds)**	**The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment**	**Total number of consultations**	**Number of discharges**	**Number of prescriptions of TCM decoction pieces**	**Income of TCM medical service projects**	**Bed utilization rate**
Chinese medicine practitioners (including assistant practitioners)	1								
TCM pharmacist	0.629**	1							
Number of beds (actual open beds)	0.840**	0.610**	1						
The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment	0.443**	0.288*	0.451**	1					
Total number of consultations	0.853**	0.698**	0.781**	0.387**	1				
Number of discharges	0.827**	0.524**	0.888**	0.410**	0.791**	1			
Number of prescriptions of TCM decoction pieces	0.711**	0.610**	0.697**	0.33[illegible]**	0.789**	0.654**	1		
Income of TCM medical service projects	0.489**	0.396**	0.616**	0.252*	0.617**	0.560**	0.501**	1	
Bed utilization rate	0.299*	0.143	0.330**	0.22[illegible]	0.229	0.477**	0.134	0.053	1

Note: *** ,** and * indicate the significant p value at the 1%,5% and 10%.

Sup Table 2

The Table displays the distribution of efficiency scores among the sample hospitals.

S2 Distribution of the efficiency scores for the sample hospitals

Efficiency	1	>0.9	0.8-0.9	0.7-0.8	<0.7	Mean
TE	11 16.18%	10 14.71%	13 19.12%	13 19.12%	21 30.88%	0.788
PTE	28 41.18%	11 16.18%	8 11.76%	10 14.71%	11 16.18%	0.876
SE	12 17.65%	32 47.06%	11 16.18%	10 14.71%	3 4.41%	0.903

Sup Table 3

S3 Statistical analysis results of the efficiency of hospitals with different bed sizes

	Bed size	Average	SD	χ2	P
TE	>=500	0.743	0.133	2.845	0.416
	300-499	0.773	0.156		
	200-299	0.824	0.128		
	<200	0.806	0.195		
PTE	>=500	0.901	0.114	2.604	0.457
	300-499	0.852	0.167		
	200-299	0.861	0.127		
	<200	0.906	0.148		
SE	>=500	0.829	0.125	9.776	0.021
	300-499	0.912	0.093		
	200-299	0.959	0.070		
	<200	0.887	0.140		

Sup Table 4

S4 Input slack in 68 county-level TCM hospitals

DUM	Input slack variable 1	Input slack variable 2	Input slack variable 3	Input slack variable 4
1	13.334	0.463	217.653	6.481
2	0	0	0	0
3	0	0	0	0
4	10.531	15.402	34.871	38.07
5	0	0	0	0
6	29.632	3.662	149.823	363.764
7	2.346	5.18	73.479	152.815
8	32.903	12.702	134.602	492.429
9	31.343	4.038	84.13	82.11
10	0	0	0	0
11	0	0	0	0
12	0	0	0	0
13	18.208	4.496	2.193	133.519
14	2.679	1.98	9.346	124.08
15	44.726	13.945	100.622	103.315
16	0	0	0	0
17	0	0	0	0
18	68.873	4.04	129.86	51.944
19	0	0	0	0
20	0	0	0	0
21	25.48	22.819	95.925	256.483
22	22.284	5.968	238.412	68.956
23	0	0	0	0
24	0	0	0	0
25	0	0	0	0
26	0	0	0	0
27	63.048	7.51	156.213	296.163
28	95.35	4.947	139.141	198.292
29	19.334	5.196	93.551	70.761
30	0	0	0	0
31	27.106	1.949	50.877	25.438
32	0	0	0	0
33	33.708	3.597	132.557	67.82
34	0	0	0	0
35	73.192	4.797	88.295	196.287
36	23.118	2.315	135.38	41.677

37	0	0	0	0
38	0	0	0	0
39	0	0	0	0
40	7.393	8.505	40.34	125.315
41	44.674	7.878	195.777	159.672
42	14.331	3.04	83.381	287.56
43	57.793	5.428	135.697	415.295
44	15.493	20.767	90.864	71.996
45	18.808	14.319	29.71	571.156
46	22.895	12.729	244.79	705.815
47	0	0	0	0
48	0	0	0	0
49	6.543	4.872	22.788	87.184
50	0	0	0	0
51	9.539	4.98	38.466	207.124
52	1.145	3.13	16.585	2110.148
53	1.587	2.243	3.704	110.363
54	0	0	0	0
55	6.354	6.185	35.829	412.297
56	5.84	11.861	38.909	40.025
57	15.118	2.902	39.788	19.545
58	0	0	0	0
59	20.018	2.12	107.117	66.057
60	12.704	6.355	52.064	121.315
61	0	0	0	0
62	0	0	0	0
63	12.231	2.374	53.681	52.622
64	12.972	4.105	54.05	92.68
65	2.021	10.882	8.799	182.95
66	1.633	0.544	7.078	169.507
67	12.4	1.59	88.964	239.134
68	0	0	0	0

Resource Allocation Efficiency in 68 County-Level Traditional Chinese Medicine Hospitals in China: A Data Envelopment Analysis

Journal:	*BMJ Open*
Manuscript ID	bmjopen-2024-088462.R2
Article Type:	Original research
Date Submitted by the Author:	04-Oct-2024
Complete List of Authors:	Xiao, Xiaoyue; Zhejiang Chinese Medical University, School of Humanities and Management Shen, Keyi; Zhejiang Chinese Medical University, School of Humanities and Management Zheng, Xinyue; Zhejiang Chinese Medical University, School of Humanities and Management Wu, Dan; Zhejiang Chinese Medical University, School of Humanities and Management Pei, Tong; Zhejiang Chinese Medical University, School of Humanities and Management Lin, Xin-hao; Zhejiang Chinese Medical University, School of Humanities and Management Meng, Xuehui; Zhejiang Chinese Medical University, Department of Health Service Management
Primary Subject Heading:	Medical management
Secondary Subject Heading:	Health policy, Health services research, Health economics, Medical management, Public health
Keywords:	Health, HEALTH ECONOMICS, HEALTH SERVICES ADMINISTRATION & MANAGEMENT

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Resource Allocation Efficiency in 68 County-Level Traditional Chinese Medicine Hospitals in China: A Data Envelopment Analysis

ABSTRACT

Objective Analysing and evaluating how efficiently health resources are allocated to county-level Traditional Chinese Medicine (TCM) hospitals in Zhejiang Province, this study aims to provide empirical evidence for improving operational efficiency and optimizing resource allocation in these hospitals.

Design and Setting The study employed a three-stage Data Envelopment Analysis (DEA) model to assess efficiency, utilizing data from 68 county-level TCM hospitals. Four input and five output variables related to TCM services were selected for the analysis.

Results The first-stage DEA results indicated that in 2022, the technical efficiency (TE) of TCM hospitals in Zhejiang Province was 0.788, the pure technical efficiency (PTE) was 0.876, and the scale efficiency (SE) was 0.903. The classification of hospitals into four groups based on bed size showed statistically significant differences in returns to scale (RTS) ($P<0.001$). The Stochastic Frontier Analysis (SFA) regression results were significant at the 1% level across four regressions, showing that environmental variables such as per capita GDP, population density, and the number of hospitals impacted efficiency. In the third stage DEA, after adjusting the input variables, the TE, PTE, and SE improved to 0.809, 0.833, and 0.917, respectively. The adjusted mean TE rankings by region were: West (0.860) > East (0.844) > South (0.805) > North (0.796) > Central (0.731).

Conclusion There is an imbalance between the inputs and outputs of county-level TCM hospitals. Each region must consider factors such as the local economy, population, and medical service levels, along with the specific development characteristics of hospitals, to reasonably determine the scale of county-level TCM hospital construction. Emphasis should be placed on improving hospital management and technical capabilities, coordinating regional development, promoting the rational allocation and efficient use of TCM resources, and enhancing the efficiency of resource allocation in county-level TCM hospitals.

Keywords County-level TCM hospitals; three-stage DEA; resource allocation efficiency

Strengths and limitations of this study

- The study employed a three-stage DEA model, ensuring reliable results.
- The analysis was based on data from 68 county-level TCM hospitals, providing an adequate sample size.
- The use of input and output variables specific to TCM services in China added an innovative aspect to the research.
- The data used in the study were cross-sectional, limiting the ability to draw causal inferences.
- The research was confined to Zhejiang Province and did not include data from other

provinces in China.

INTRODUCTION

As global health concepts shift and traditional medicine is re-evaluated, the international influence of TCM has been steadily increasing. Several countries and regions have begun introducing TCM techniques and services, gradually expanding their application and development locally.[1] In recent years, China has attached great importance to the development of TCM, marking a critical period for its high-quality advancement. TCM has significant differences in its core concepts and practice methods from other medical systems. The differences in the theoretical basis, diagnostic methods, and treatment means of TCM determine the unique mode of treatment and service characteristics of TCM hospitals.[2,3] Therefore, the experience of public hospitals cannot be directly applied. Within China's hierarchical medical service system, county-level TCM hospitals serve as leaders of the rural three-tier TCM service network and as vital links in the urban-rural TCM service system. These hospitals bear significant responsibility for providing primary TCM services, connecting higher-level hospitals with grassroots medical institutions, and ensuring the continuity and accessibility of TCM services.[4,5] Despite the annual growth in total health resources and TCM resources, issues such as uneven resource distribution and the scarcity of high-quality medical and health resources remain prominent.[6–9] The scientific and rational allocation of TCM resources has become a focal point for policymakers and hospital administrators.

Efficiency in the allocation of health resources is a key variable for measuring the level of allocation, as it evaluates whether health management departments achieve the same output with more economical and fewer resource inputs or obtain greater output with limited resources. For county-level TCM hospitals, the pressing issue is how to enhance the overall efficiency of health resource allocation under current conditions, ensuring balanced regional development of TCM health services and meeting public health service needs. However, current studies on resource allocation efficiency often focus on calculating efficiency values and distribution, rarely considering environmental factors. Additionally, most research subjects are public hospitals, with little focus on county-level TCM hospitals. Therefore, it is essential to study and analyze the resource allocation efficiency of county-level TCM hospitals, systematically identify current issues, suggest improvements, and provide recommendations. This is crucial for accelerating the development of county-level TCM hospitals in Zhejiang Province and promoting the sustainable and high-quality development of the TCM sector.

The predominant efficiency measurement methods are parametric and non-parametric, represented by Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), respectively.[10] Compared to SFA, DEA is more adept at handling the production process involving multiple inputs and multiple outputs, and it does not impose restrictive constraints between inputs and outputs, and there is no need to consider the functional form of the production frontier, and the model is highly expandable,[11–13] so the researchers are more likely to use the non-parametric method represented by DEA. The three-stage DEA model combines the advantages of DEA and SFA, being capable of handling complex production processes with multiple inputs and outputs, while also identifying and quantifying the impact of environmental variables on hospital efficiency. This model eliminates the interference of environmental factors, thereby enhancing its interpretability and analytical depth.

In summary, to thoroughly understand the resource allocation efficiency of county-level TCM hospitals, the factors influencing their efficiency, and the differences in efficiency among them, this study employs a three-stage DEA model. It aims to delve into and enhance the efficiency of TCM resource allocation in county-level hospitals, compare the efficiency of hospitals of different sizes, and explore the factors affecting efficiency. The expectation is to provide more scientific decision support for resource allocation in county-level TCM hospitals, promote the rational use of TCM resources, and improve overall service quality. Zhejiang Province, located in the eastern coastal area of China, has a long history and a solid foundation in TCM development. Its numerous and widely distributed county-level TCM hospitals provide abundant material and a broad sample for research. Recently, Zhejiang Province has introduced a series of policy measures to promote TCM development, emphasizing the need to strengthen TCM inheritance and innovation, enhance TCM service capabilities, and optimize TCM resource allocation. Zhejiang Province is at the forefront of medical reform and TCM development, and its successes and challenges can provide valuable lessons for other regions.

METHODS

Sample selection and data sources

The data and information for this study were sourced from the 2022 Compendium of Hospitals of the TCM Category of the Zhejiang Provincial Health Commission and the 2022 official statistical yearbook of the Zhejiang Provincial Bureau of Statistics. Zhejiang Province has a total of 95 hospitals categorized under TCM. Given the DEA model's emphasis on the relative comparability of similar units, the study initially screened 71 county-level TCM hospitals. However, three county-level TCM hospitals were excluded from the final analysis due to different service orientations and missing data, such as bed numbers. Therefore, a total of 68 county-level TCM hospitals were included in the final analysis.

The 68 county-level TCM hospitals included in the study are situated in 68 county-level cities across Zhejiang Province, collectively covering 75.56% of the province's counties. They are distributed across five regions—eastern, southern, western, northern, and central Zhejiang—and are aligned with the administrative divisions where the hospitals are located. According to Gok and Sezen’s classification method, the county-level TCM hospitals in the sample are classified into four groups based on their bed capacity (number of actual open beds): small (<200), lower-middle (200-299), upper-middle (300-499), and large (≥500).[14,15]

Three-stage data envelopment analysis

Three-stage DEA is a method developed based on DEA. It is mainly used to evaluate the relative efficiency of multi-input and multi-output decision-making units, especially after removing the influence of environmental factors and random errors, it can reflect the efficiency of decision-making units more realistically.[16] The modelling approach consists of three main stages.

In the first stage, which involves conducting a conventional DEA analysis, the DEA model was introduced in 1978 by American operations researchers Charnes, Cooper, and others.[17] It is a non-parametric, non-stochastic model designed for measuring and evaluating efficiency, based on the concept of the "production frontier."[18] The model employs a linear programming approach to construct a production frontier, using input and output variables for decision-making units. Effective units are positioned on the frontier, while ineffective ones are positioned below it. This arrangement provides a measure of the extent to which units deviate from the frontier.[19] There are two types of DEA models: the first is the CCR model, which assumes constant RTS. Under this model, an increase in input will proportionately increase output, implying that the sector size does not impact production efficiency. However, this assumption often proves challenging in practice, the policy system and economic development levels may prevent sectoral production from remaining at a reasonable scale, blurring judgements about the impact of scale on production efficiency. Based on these limitations, Charnes and other scholars revised the CCR model and proposed the BCC model, which assumes variable RTS.[20]

In addition, DEA models can be categorized as input-oriented or output-oriented. The former emphasizes reducing inputs while maintaining constant outputs, whereas the latter focuses on increasing outputs while keeping inputs constant.[21,22] Considering that the RTS for health resource allocation is variable, this study employs the input-oriented BCC model. The model equations are presented below:

$$\min\theta-\varepsilon(\hat{e}^{T}S^{-}+e^{T}S^{+})$$
$$\text{s.t.}\begin{cases}\sum_{j=i}^{n}X_j\lambda_j+S^{-}=\theta X_0\\ \sum_{j=i}^{n}Y_j\lambda_j+S^{+}=Y_0\\ \lambda_j\geq 0,S^{-},S^{+}\geq 0\end{cases} \tag{1}$$

Where, j=1,2,...,n denote decision units, X and Y are input and output vectors, respectively.

The efficiency value measured by the BCC model is called the combined Technical Efficiency (TE), and it can be further decomposed into the product of Scale Efficiency (SE) and Pure Technical Efficiency (PTE), i.e., TE=SE*PTE.[23,24]

The second stage is SFA regression. The SFA model was first pioneered in 1977 by Aigner et al. . which is a parameter estimation method of production frontier, and now it has been gradually used in various fields for efficiency evaluation research. The main advantage of this method is that it takes into account the role of random factors on output variables,[25] the method to a determined production frontier as a premise, through the decomposition of the error term, to obtain the random error and technical inefficiency of the two aspects, which is to be eliminated after the random error and then the decision-making unit of the efficiency evaluation analysis. Subsequently, in 2002, Fried et al. suggested that traditional DEA models have certain biases in efficiency analysis since the calculated TE values are influenced by random factors, environmental conditions, and managerial inefficiency.[26,27] Therefore, these three factors should be effectively separated. They used the SFA regression model to decompose the slack variables calculated in the first stage into the aforementioned three factors, which fully eliminated the influence of environmental and random factors on the DEA model. See **Appendix 1** for details of the calculation process.

The third stage is the DEA efficiency evaluation with adjusted inputs. In this stage, efficiency evaluation is conducted using adjusted input data and original output data, after removing the influence of environmental factors and random errors. First, input variables are adjusted based on the regression analysis results from the second stage to eliminate the interference of external environmental factors and random errors. Then, the output variable data remain unchanged, and the adjusted input data are substituted into the DEA model for calculation. Finally, this stage provides more accurate and realistic efficiency evaluation results, providing scientific evidence for decision-makers.

Selection of variables

In DEA, the selection of input and output variables is of utmost importance. Based on the relevant principles of variable selection, in-depth analyses of similar studies, and consultation with relevant experts, we have selected a series of variables with Chinese medicine service characteristics.[28–30]The four input variables include the number of Chinese medicine practitioners (including assistant practitioners), the number of TCM pharmacists, the actual number of open beds, and the total value of more than 10,000 RMB of TCM diagnosis and treatment equipment. The five output variables include the total number of consultations, the total number of discharges, the number of TCM decoction piece prescriptions, the income from TCM medical service projects, and the bed utilization rate.

The selected variables are closely related to the characteristics and services of TCM hospitals, and the data are accessible, which benefits the evaluation of their core competitiveness. However, the data have limitations and may not fully reflect the efficiency of health resource allocation in county-level TCM hospitals. For example, the total income from TCM medical service projects may overlook income that is not derived from these projects. The evaluation system consists entirely of quantitative variables, potentially ignoring non-quantitative factors (such as hospital culture, patient satisfaction, etc.) that impact the efficiency of health resource allocation.

The input variables primarily encompass two aspects: human resources and hardware facilities. TCM human resources are the core strength of TCM hospitals, and their number directly determines the quality and scale of TCM services that the hospital can provide. In terms of hardware facilities, the number of open beds serves as a key indicator of the hospital's size and service capacity. The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment directly reflects the hospital's investment in equipment updates and upgrades.

Among the output variables, the total number of consultations and discharges directly reflect the hospital's service volume, serving as key indicators for measuring the hospital's operational efficiency and service capacity. TCM decoction pieces are a crucial treatment method and a unique indicator differentiating TCM from other medical systems. The number of TCM decoction piece prescriptions reflects the hospital's effectiveness in using TCM. The income from TCM medical service projects reflects the hospital's economic benefits and revenue-generating capacity, indicating its economic efficiency in providing TCM services. This is also one of the distinctive indicators of TCM hospitals. The bed utilization rate indicates the efficiency of bed utilization in the hospital.

According to Hollingsworth[31], the number of units used for efficiency assessment should be at least three times the sum of input and output variables. In this study, 68 county-level TCM hospitals were assessed, exceeding the required minimum of three times this sum, thus aligning with Hollingsworth's principle. Furthermore, the collected input and output variable data were analyzed for correlation using Pearson's correlation coefficient in SPSS 25.0 software. The results show that the correlation coefficients between input and output variables are positive and highly significant. See **Sup Table 1** for more details.

In addition to the input and output variables previously discussed, the selection of environmental variables is crucial for developing the SFA model within this three-stage DEA framework. According to the Separation Hypothesis by Simar and Wilson[32], environmental variables significantly affect input-output efficiency. These variables are beyond the control of individual decision-making units and free from subjective influences. Based on a review and synthesis of relevant literature, this study selected three environmental variables: per capita GDP, population density, and the number of hospitals in the county.[30,33,34]

Statistical methods

The study employed the Pearson correlation coefficient to assess the correlation between input-output variables and utilized the Kruskal-Wallis H non-parametric test to compare the efficiency, including TE, PTE, and SE, of hospitals with varying numbers of beds. The $\chi 2$ test was utilized to examine differences in RTS among TCM hospitals with varying bed sizes. Descriptive analysis and statistical testing of the data were conducted using SPSS 25.0 software, while the three-stage DEA was measured and analyzed using

DEAP 2.1 software in conjunction with Frontier 4.1 software.

Patient and public involvement

No patient is involved.

RESULT

Description of variables

Table 1 provides a descriptive summary of the inputs, outputs, and environmental variables for 68 county-level TCM hospitals. The data show that in 2022, each county-level TCM hospital had an average of 85 Chinese medicine practitioners and 15 TCM pharmacists, an average of 340 actual open beds, and the total value of TCM diagnosis and treatment equipment per hospital, which exceeded 10,000 RMB, averaged 3.33 million yuan. In 2022, these 68 county-level TCM hospitals had an average total number of consultations of 527,280, an average number of discharged patients of 11,662, and an average number of TCM decoction piece prescriptions of 148,740. Income from TCM medical service projects per hospital was 18.742 million yuan, and the average bed utilization rate was 73%. The corresponding 68 counties had a per capita GDP ranging from 43,788 to 357,159 yuan, with an average of 106,442 yuan. The average population density per county ranged from 74 to 9,891 people per square kilometre. The number of hospitals per county ranged from a maximum of 79 to a minimum of 2.

Table 1 Descriptive statistics of inputs, outputs and environmental variables

Variables	Max	Min	Mean	SD
Inputs				
Chinese medicine practitioners (including assistant practitioners)	212	15	85	50
TCM pharmacist	41	3	15	8
Number of beds (actual open beds)	1012	36	340	195
The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment	2210	1	333	342
Outputs				
Total number of consultations	1095946	83268	527280	266208
Number of discharges	39121	921	11662	7785
Number of prescriptions of TCM decoction pieces	628542	13051	148740	113255
Income of TCM medical service projects	110902	1738	18742	17614
Bed utilization rate (%)	104.81	25.82	73	17
Environmental variables				
Per capita GDP (RMB)	357159	43788	106442	54095
Population density (persons/km^2)	9891	74	867	1296
Number of hospitals	79	2	16	13

Stage 1: Traditional DEA model analysis

An analysis of the first-stage health resource allocation efficiency of county-level TCM hospitals in Zhejiang Province in 2022 showed that in 2022, the TE of TCM hospitals in Zhejiang Province was 0.788, PTE was 0.876, and the SE was 0.903. Specifically, 11 hospitals (16.18%) had a TE of 1, 28 hospitals (41.18%) had a PTE of 1, and only 12 hospitals (17.65%) had a SE of 1. There were 21 hospitals (30.88%) with a TE of less than 0.7, indicating that the overall TE of county-level TCM hospitals was relatively low.

However, 55 hospitals (80.88%) had a SE greater than 0.8, indicating a relatively high SE. See **Sup Table 2** for more details.

The study conducted a statistical analysis of the TE, PTE, and SE of hospitals with varying bed sizes. The results showed that the differences in TE (P=0.416, P>0.05) and PTE (P=0.457, P>0.05) among the four comparison groups were not statistically significant, whereas the difference in SE (P=0.021, P<0.05) was statistically significant. This indicates that hospital bed size has a significant impact on the efficiency of health resource allocation. See **Sup Table 3** for more details.

The efficiency values and RTS statistical analysis results for different types of hospitals based on bed size are shown in **Table 2**. Overall, the results indicated that 12 hospitals (17.56%) with an SE score of 1 were in the CRS state, 17 hospitals (25%) were in the IRS state, and the remaining 39 hospitals (57.35%) were in the DRS state. More than half of the hospitals exhibited decreasing efficiency at their current scale, indicating that further expansion will not yield higher efficiency. Hospitals with the RTS of IRS are likely to be in a phase of rapid growth, needing to invest more resources to support their growth, and may be able to realize greater economies of scale through expansion.

Table 2 Statistical analysis results of the returns to scale of hospitals with different bed sizes

Bed size	Returns to scale					
	CRS	IRS	DRS	Total	χ2 value	P value
<200	5(31.25%)	11(68.75%)	0(0%)	16(100%)	33.654	<0.001
200-299	3(17.65%)	4(23.53%)	10(58.82%)	17(100%)		
300-499	3(13.04%)	2(8.70%)	18(78.26%)	23(100%)		
>=500	1(8.33%)	0(0%)	11(91.67%)	12(100%)		
Total	12(17.65%)	17(25.00%)	39(57.35%)	68(100%)		

CRS, constant returns to scale; DRS, decreasing returns to scale; IRS, increasing returns to scale.

The RTS differences among the four groups of hospitals with different bed sizes were statistically significant (P<0.001). Among the small hospitals, 5 (31.25%) were in the CRS stage, indicating a relative balance between inputs and outputs and an optimal operational status. The remaining 11 (68.75%) hospitals were in the IRS stage, indicating a need to expand their scale to improve efficiency. In the lower-middle (58.82%) and upper-middle (78.26%) hospitals, most were in the DRS stage, indicating an excess of inputs. Among the large hospitals, only one (8.33%) was in the CRS stage, while the remaining 11 (91.67%) were in the DRS stage, indicating a need for a reduction in scale and further optimization of resource allocation.

Stage 2: SFA regression analysis

The slack variables of input variables calculated in the first-stage DEA model analysis (**Sup Table 4**) were used as the dependent variables, while per capita GDP, population density, and the number of hospitals were used as independent variables. The SFA regression analysis was then performed on the input slack variables, and the regression results are shown in **Table 3**. The regression analysis results showed that the influence of environmental variables on the input slack values was statistically significant. The generalized likelihood ratio test for the four regressions was significant at the 1% level, indicating the validity of the SFA regression. This highlights the necessity of removing environmental factors when calculating the comprehensive efficiency of county-level TCM hospitals. The γ values were close to 1, indicating that the influence on the input slack variables was due to management factors in TCM hospitals, with random disturbances having a very minor impact.

Table 3 SFA regression analysis results				
	Chinese medicine practitioners (including assistant practitioners)	**TCM pharmacist**	**Number of beds (actual open beds)**	**The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment**
constant	-66.15***	9.09***	60.46***	471.36***
GDP per capita	13.05**	-1.81***	-24.75***	-70.14***
population density	-2.75	-0.65**	1.74	-119.23***
Number of hospitals	4.27	1.07	31.78***	124.97***
σ2	1029.21***	61.01***	10495.09***	194014.28***
γ	0.99***	0.99***	0.99***	0.99***
log likelihood function	-274.94***	-180.14***	-361.4***	-449.82***
LR test of the one-sided error	51.66***	50.39***	36.64***	59.25***

Note: ***,** and * indicate the significant p-value at the 1%,5% and 10%.

When analyzing the impact of various factors on slack variables, the key lies in the coefficients of environmental factors, whether positive or negative. A positive coefficient means that an increase in the factor will increase the input slack variable, thereby reducing output and being detrimental to improving hospital efficiency; a negative coefficient means that an increase in the factor will decrease the input slack variable, thereby increasing output and helping to improve the efficiency of county-level TCM hospitals. Per capita GDP had negative coefficients for the input slack variables of TCM pharmacists, the number of beds, and the total value of TCM equipment, all significant at the 1% level. GDP growth can reduce these input redundancies, thus promoting hospital efficiency. However, an increase in per capita GDP increases the input redundancy of TCM practitioners, thereby reducing the efficiency of county-level TCM hospitals. Population density had a negative effect on the slack variables of TCM pharmacists and the total value of TCM equipment, both significant at the 5% level. It also had a negative effect on the slack variable of the number of beds, but only significant at the 10% level. This indicates that population density has a dual impact on the overall efficiency of county-level TCM hospitals. The number of hospitals had a positive impact on the slack variables of bed numbers and the total value of TCM equipment, both significant at the 1% level. The number of hospitals in a region greatly affects the use of hardware facilities, including beds and equipment, and thus efficiency.

Stage 3: DEA model analysis with adjusted input variables

After adjusting the input variables in the second stage, DEAP2.1 software was used again for input-oriented BCC model analysis, and the efficiency values of each decision-making unit were recalculated. The adjusted TE, PTE, and SE of county-level TCM hospitals in Zhejiang Province were 0.809, 0.833, and 0.917, respectively, which all increased compared to the first-stage efficiency values. At the same time, paired t-tests were conducted on the TE, PTE, and SE of the first and third stages (see **Table 4**). It was found that the differences in TE ($p=0.017$, $p<0.05$) and SE ($p=0.027$, $p<0.05$) before and after adjustment were statistically significant. This further confirmed the necessity of performing SFA regression analysis in the second stage, as the TE and SE of county-level TCM hospitals are influenced by external factors to some extent.

Table 4 Paired sample t-test of three kinds of efficiency in the first and third stages

	TE		PTE		SE	
	stage 1	**stage 3**	**stage 1**	**stage 3**	**stage 1**	**stage 3**
Mean	0.788	0.809	0.876	0.883	0.903	0.917
SD	0.155	0.146	0.143	0.129	0.113	0.103
t	-2.451		-1.237		-2.264	
P	0.017		0.22		0.027	

According to the results of the three-stage DEA analysis, there are significant differences in the operational efficiency of TCM hospitals across different regions in China. From a regional perspective, the efficiency values before and after adjustment for the eastern, southern, western, northern, and central regions of Zhejiang Province are shown in **Table 5**. The adjusted TE rankings for each region are as follows: West (0.860) > East (0.844) > South (0.805) > North (0.796) > Central (0.731). Regardless of the adjustments, the TE and PTE of the eastern and western regions are relatively high, indicating that the allocation of TCM resources, technology, and management is at a relatively optimal level. However, the SE in the western region has significantly decreased, indicating that its current operational scale has not achieved maximum economic efficiency. The efficiency values of the northern and central regions showed significant differences before and after adjustments when compared to other regions. Particularly, after eliminating the interference of environmental factors, the TE, PTE, and SE of the northern region all increased, with the most substantial increase in TE. The efficiency values in the southern region changed minimally before and after the adjustments, reflecting a relatively accurate representation of its efficiency.

Table 5 Classification of technical efficiency scores and scale returns by hospital location

	TE		PTE		SE	
	stage 1	stage 3	stage 1	stage 3	stage 1	stage 3
Total	68					
Mean	0.788	0.809	0.876	0.883	0.903	0.917
SD	0.155	0.146	0.143	0.129	0.113	0.103
Min	0.410	0.454	0.499	0.542	0.536	0.562
Eastern	17					
Mean	0.826	0.844	0.915	0.910	0.906	0.928
SD	0.122	0.117	0.115	0.102	0.096	0.087
Min	0.633	0.692	0.663	0.701	0.735	0.722
Southern	20					
Mean	0.797	0.805	0.881	0.886	0.906	0.908
SD	0.164	0.159	0.144	0.124	0.117	0.116
Min	0.517	0.481	0.625	0.653	0.561	0.562
Western	6					
Mean	0.857	0.860	0.923	0.942	0.929	0.910
SD	0.129	0.128	0.093	0.062	0.110	0.103
Min	0.689	0.701	0.774	0.845	0.721	0.756
Northern	17					
Mean	0.753	0.796	0.853	0.868	0.893	0.923
SD	0.150	0.149	0.152	0.145	0.136	0.118
Min	0.485	0.533	0.499	0.542	0.536	0.578
Central	8					
Mean	0.709	0.731	0.792	0.807	0.892	0.907
SD	0.207	0.168	0.190	0.177	0.114	0.090
Min	0.410	0.454	0.562	0.589	0.725	0.771

DISCUSSION

This study conducted an in-depth analysis of the efficiency of health resource allocation in county-level TCM hospitals using a three-stage DEA model. Ahmed et al.[35] used an output-oriented DEA and found that approximately 91.3% of Asian countries were inefficient in utilizing medical resources. Sun et al.[36] used data envelopment analysis to find that the overall operating efficiency of public hospitals in Fujian Province was low. Alatawi et al.[15] measured the TE of 91 public hospitals in Saudi Arabia in 2017 and found that 75.8% of public hospitals exhibited technical inefficiency. Similarly, our study found that the resource utilization efficiency of county-level TCM hospitals in Zhejiang Province was low; 56 county-level TCM hospitals that were not in CRS status were inefficient, and more than 70% of the hospitals showed an imbalance between inputs and outputs. This is consistent with the conclusions of many studies.

In Chinese hospitals, there is a common phenomenon of blindly pursuing an increase in bed size, and county-level TCM hospitals are no exception. The study results show that more than 50% of hospitals have exhibited decreasing efficiency at their current scale. Many county-level TCM hospitals tend to blindly expand bed size in pursuit of broader development space and enhanced service capacity. Many previous studies have confirmed that the relationship between hospital efficiency and scale is not simply directly positive or negative but is influenced by multiple factors. Gok and Sezen[14] evaluated the efficiency scores of 523 hospitals of different sizes in Turkey and found a negative correlation between the efficiency of Turkish healthcare institutions and their scale. Qian et al.[37] revealed the negative effects of efficiency and scale in county-level public hospitals in Shandong Province. Amin et al.[38] found that the main cause of low hospital productivity was negative changes in SE. Zhao et al.[39] found through the DEA model that excessive scale expansion of county-level hospitals in Henan Province led to lower efficiency. Simple expansion is not an effective solution for increasing efficiency; it may lead to an imbalance in resource allocation and a decline in hospital operational efficiency.

From the perspective of different bed sizes, the study found that over 70% of upper-middle and large hospitals were in the DRS stage. Studies have shown that county-level public hospitals need to reach more than 1,100 beds to achieve SE saturation.[15,37] County-level TCM hospitals and public hospitals have significant differences in operating models, service content, and management strategies, resulting in different considerations for scale expansion. This further highlights the uniqueness of county-level TCM hospitals in resource allocation and efficiency management. Therefore, when developing strategies for the growth of county-level TCM hospitals, it is necessary to fully consider their unique operating environments and characteristics. Hospitals should be encouraged to adopt refined management practices to improve the utilization and service quality of existing beds rather than merely pursuing scale expansion.

The second-stage SFA regression analysis results showed that environmental factors such as per capita GDP, population density, and the number of hospitals significantly impact the efficiency of county-level TCM hospitals. Among these, the growth in per capita GDP can effectively reduce the input redundancy of TCM pharmacists, the number of beds, and the total value of TCM equipment. Multiple studies have shown a negative relationship between per capita GDP and input slack, meaning that as per capita GDP increases, the input redundancy of medical institutions gradually decreases, thereby helping to improve overall service efficiency.[40–42] Residents in economically developed areas often have higher healthcare demands, which may lead to more health resources being allocated to these areas. In response to differences in economic development levels across regions, the government should formulate differentiated policy support measures, such as financial subsidies and tax incentives, to incentivize county-level TCM hospitals in economically underdeveloped areas to improve service efficiency.

Population density was found to have a significant negative impact on the redundancy of TCM pharmacists and the total value of TCM equipment in this study. This finding suggests that in areas with higher population density, county-level TCM hospitals are more inclined to reduce the redundancy of these two inputs, thereby utilizing resources more effectively and improving resource allocation efficiency. This is similar to the conclusion of Zhang, Su et al.[34,43], who found that the more concentrated the residential area, the more convenient the supply of healthcare services, reducing supply costs and increasing the utilization of healthcare services. However, it is worth noting that in areas with high population density, the investment in the number of beds may be relatively excessive, failing to achieve an optimal allocation that matches the population density.

A greater number of hospitals implies competition for resources and reflects the level of healthcare services in a region. An increase in the number of hospitals will provide patients with more choices of medical care. This may lead to polarization in the number of healthcare services and affect the efficiency of hospital resource allocation. Therefore, the Government should strengthen supervision and assessment, and intervene promptly to encourage county-level Chinese medicine hospitals to carry out special diagnostic and treatment services and give full play to the advantages of Chinese medicine features, which will be conducive to optimizing the allocation of resources, thereby improving the overall efficiency of health resource allocation.

From a regional perspective, there are significant differences in the efficiency of TCM resource allocation among hospitals in different areas of Zhejiang Province. The SE is relatively high in the western and eastern regions, while it is relatively low in the northern and central regions. Particularly in the northern region, there were improvements in PTE and SE after excluding environmental factors. Therefore, there is a need to strengthen the local medical system, cautiously expand the production scale, and improve hospital management levels. The management and resource allocation models of the eastern and southern regions can be appropriately referenced to coordinate regional development, enhance cooperation and exchange between regions, improve overall medical services, and achieve rational allocation and efficient utilization of TCM resources.

Limitations

This study utilized a three-stage DEA model to analyze the efficiency of TCM resource allocation in county-level TCM hospitals in Zhejiang Province, providing detailed insights, but it also has some limitations. Although the DEA model has shown great potential in evaluating the efficiency of healthcare services, it does not directly include considerations for dimensions such as medical quality, health outcomes, and case mix differences. The study results are specific to county-level TCM hospitals in Zhejiang Province and may not be directly applicable to other regions or types of hospitals. This study relies on data from a single year (2022), which may not reflect the long-term trends and annual fluctuations in hospital efficiency. The subjective nature of variable selection may not fully capture the true situation of county-level TCM hospitals, potentially leading to biased results. Future research could include longitudinal studies, exploration of additional environmental factors such as policy changes or cultural attitudes towards TCM, and integration of other analytical models to capture the dynamic and qualitative aspects of hospital efficiency.

CONCLUSIONS

This study utilized a three-stage DEA model to analyze in depth the efficiency of health resource allocation in county-level TCM hospitals and found an imbalance between hospital inputs and outputs. Most hospitals should avoid blindly expanding their scale to seek efficiency improvements. Environmental factors such as per capita GDP, population density, and the number of hospitals significantly impact the efficiency of health resource allocation in county-level TCM hospitals, and there are clear differences in TCM resource allocation efficiency among different regions. Therefore, each region needs to base its plans on local TCM healthcare resources, fully considering factors such as the local economy, population, and medical service levels. Considering the specific development characteristics of hospitals, regions should reasonably determine the scale of county-level TCM hospital construction, improve infrastructure and medical equipment, focus on improving hospital management and technical skills, encourage resource sharing and cooperation between regions, and coordinate regional development. This will promote the rational allocation and efficient utilization of TCM resources, thereby providing high-level, high-quality TCM healthcare services to residents. It is hoped that these findings will provide important references for future hospital efficiency evaluation research and policy-making.

Contributors XX, KS, XZ and XM contributed to the conception and design of the project; DW, TP and XL contributed to the analysis and interpretation of the data; XM gave guidance on the writing of the article; and XX, KS and XZ drafted the article. All authors supplied critical revisions to the manuscript and gave final approval for the version to be published. XX is the guarantor.
Patient consent for publication Not required.
Funding This study was supported by the Zhejiang Soft Science Research program project (2024C35124).
Competing interests None declared.
Ethics approval Ethical approval was gained from the Ethics Committee of the Affiliated Hospital of Zhejiang University of Chinese Medicine.
Data availability statement Data were extracted from the hospital databases at the Administration of Statistics. Data are available upon reasonable request.

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Appendix 1:

Three-stage data envelopment analysis is a method developed based on DEA. It is mainly used to evaluate the relative efficiency of decision-making units with multiple inputs and multiple outputs, especially to reflect the efficiency of decision-making units more realistically after removing the influence of environmental factors and random disturbances.[26] The modelling approach consists of three main stages.

In the first stage, which involves conducting a conventional DEA analysis, the DEA model was introduced in 1978 by American operations researchers Charnes, Cooper, and others.[27] It is a non-parametric, non-stochastic model designed for measuring and evaluating efficiency, based on the concept of the "production frontier."[28] The model employs a linear programming approach to construct a production frontier, utilizing input and output indicators from decision-making units. Effective units are positioned on the frontier, while ineffective ones are positioned below it. This arrangement allows for the measurement of the extent to which units deviate from the frontier.[29] There are two types of DEA models: the first is the CCR model, which assumes constant returns to scale. Under this model, an increase in input will proportionately increase output, implying that the sector size does not impact production efficiency. However, this assumption often proves challenging in practice; the policy system and economic development levels may prevent maintaining sector production at a reasonable size, and thus obscure the determination of size impact on production efficiency. Based on these limitations, Charnes and other scholars revised the CCR model and proposed the BCC model, which assumes variable returns to scale.[30]

In addition, DEA models can be categorised as input-oriented or output-oriented. The former emphasizes reducing inputs while maintaining constant outputs, whereas the latter focuses on increasing outputs while keeping inputs constant.[31,32] Considering that the returns to scale for health resource allocation are variable, this study employs the input-oriented BCC model. The model equations are presented below:

$$\min\theta - \varepsilon(\hat{e}^{T}S^{-} + e^{T}S^{+})$$
$$\text{s.t.}\begin{cases} \sum_{j=i}^{n} X_j\lambda_j + S^{-} = \theta X_0 \\ \sum_{j=i}^{n} Y_j\lambda_j + S^{+} = Y_0 \\ \lambda_j \geq 0, S^{-}, S^{+} \geq 0 \end{cases} \tag{1}$$

Where, j=1,2,...,n denote decision units, X and Y are input and output vectors, respectively.

The efficiency value measured by the BCC model is called the combined Technical Efficiency (TE), and it can be further decomposed into the product of Scale Efficiency (SE) and Pure Technical Efficiency (PTE), i.e., TE=SE*PTE.[33,34]

TE measures the ability of a decision-making unit to optimise output with specific inputs under fixed production conditions and provides a comprehensive assessment of resource allocation and use efficiency. PTE reflects the impact of management skills and technical expertise on production efficiency, helping to evaluate whether a decision-making unit's management and technology are optimal. SE assesses the impact of production scale on a decision-making unit's efficiency, focusing on whether the scale is optimised.

The second stage typically involves constructing a regression model akin to Stochastic Frontier Analysis (SFA). This model estimates the influence of environmental factors on efficiency scores through regression analysis, using environmental factors as independent variables and efficiency scores obtained in the first stage as dependent variables.[35] The SFA regression model is applied to decompose the slack variables identified in the first stage into three components: random factors, environmental factors, and managerial inefficiency.[36,37] Initially, the first-stage DEA model is analyzed to obtain the slack variables for each decision-making unit. The formula is presented as follows:

$$S_{ni} = x_{ni} - x_{ni}^{*}(n = 1,2,\ldots,N; i = 1,2,\ldots,I) \tag{2}$$

S_{ni} represents the slack variable for the nth input indicator of the ith decision unit, x_{ni} represents the actual value of the input indicator of each decision unit, and x_{ni}^{*} represents the predicted value of the input indicator of each decision unit. The SFA regression function is constructed using the slack variables as the response variables and the environmental factor variables as the independent variables in the analysis. The function is detailed below:

$$S_{ni} = f(Z_i; \beta_n) + v_{ni} + \mu_{ni}; i = 1,2,\ldots,I; n = 1,2,\ldots,N \tag{3}$$

In this function, Z_i represents the total number of environmental variables, and β_n is the value of the coefficient measured by the environmental variables. In addition, the function contains a mixed error term, $v_{ni} + \mu_{ni}$, where v_{ni} represents random error and μ_{ni} represents management inefficiency.

The SFA regression model adjusts for environmental and stochastic factors to normalize the overall technical efficiency across all decision-making units, ensuring uniform environmental conditions and stochastic influences. The mathematical expression for the function, which relates to the adjusted input variables, is presented below:

$$X_{ni}^{A} = X_{ni} + [max(f(Z_i; \widehat{\beta}_n)) - f(Z_i; \widehat{\beta}_n)] + [max(v_{ni}) - v_{ni}]$$
$$i = 1,2,\ldots,I; n = 1,2,\ldots,N \tag{4}$$

where X_{ni}^{A} represents the adjusted input values and Xni represents the pre-adjusted input values. The expression $[\max(f(Z_i; \widehat{\beta}_n)) - f(Z_i; \widehat{\beta}_n)]$ is used to place all decision-making units in a consistent external environment to ensure a fair comparison of environmental factors. Meanwhile, $[\max(v_{ni}) - v_{ni}]$ serves to adjust the random errors of all decision-making units to the same level to accurately assess their efficiency. To effectively eliminate the effects of random errors on the slack variables, further decomposition of these errors and efficiency residuals is necessary. This approach allows us to obtain the predicted random error values for each decision-making unit. For this purpose, this study employs the formula for calculating management inefficiency, as derived by Rodenyue[38], presented below:

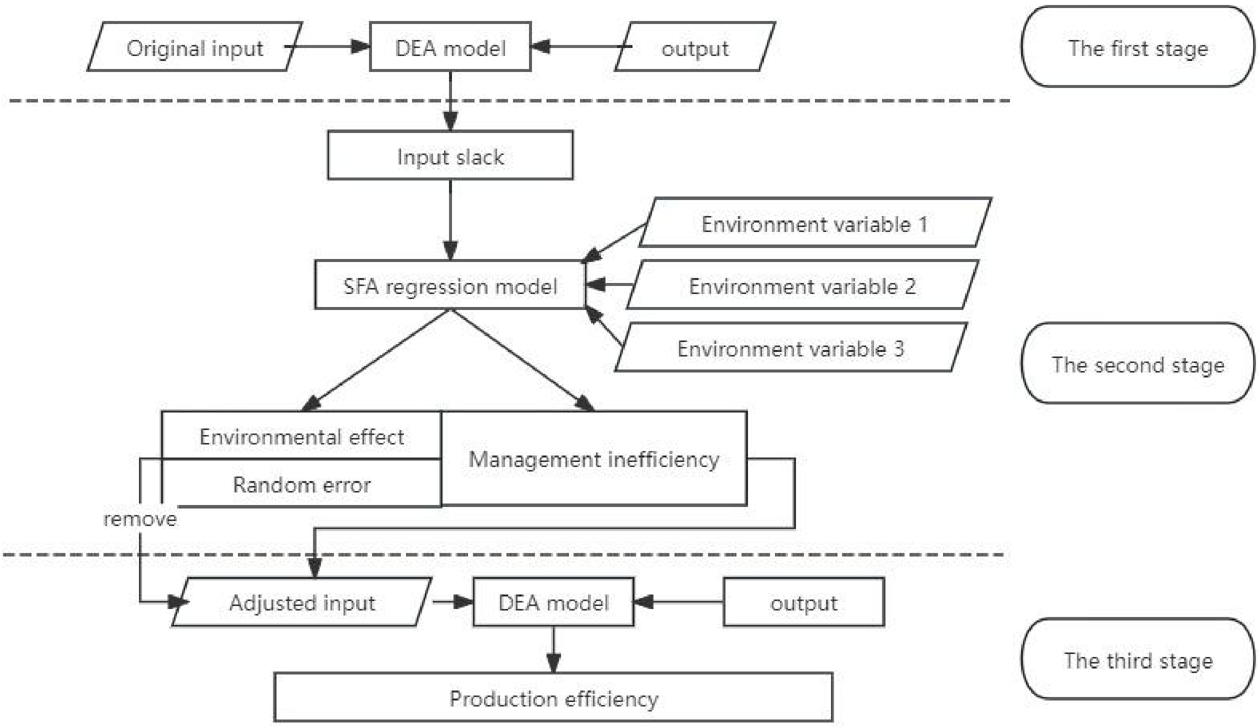
$$E(\mu|\varepsilon) = \sigma_{*}\left[\frac{\phi(\lambda\frac{\varepsilon}{\sigma})}{\Phi(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma}\right] \tag{5}$$

Where, $\sigma_{*} = \frac{\sigma_{\mu}\sigma_{v}}{\sigma}$, $\sigma = \sqrt{\sigma_{\mu}^{2} + \sigma_{v}^{2}}$, $\lambda = \sigma_{\mu}/\sigma_{v}$, $\gamma = \frac{\sigma_{\mu}^{2}}{\sigma_{\mu}^{2}+\sigma_{v}^{2}}$.

Based on the above equation, we can derive the extent to which random error and management inefficiency factors influence the slack variable. When the value of γ variable approaches 1, it indicates a significant impact of management inefficiency; conversely, when the value of γ variable approaches 0, it indicates a significant impact of random error.

The third stage involves DEA efficiency evaluation with adjusted inputs. In this stage, efficiency evaluation is conducted using adjusted input data and original output data, after removing the influence of environmental factors and random errors. First, input indicators are adjusted based on the regression analysis results from the second stage to eliminate the interference of external environmental factors and random errors. Then, the output indicator data remain unchanged, and the adjusted input data are substituted into the

DEA model for calculation. Finally, this stage provides more accurate and realistic efficiency evaluation results, providing scientific evidence for decision-makers.



Three-stage DEA model flow chart

Sup Table 1

The results from table show that the correlation coefficients between input and output indicators are both positive and highly significant.

S1 Correlation analysis of the inputs and outputs

	Chinese medicine practitioners (including assistant practitioners)	**TCM pharmacist**	**Number of beds (actual open beds)**	**The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment**	**Total number of consultations**	**Number of discharges**	**Number of prescriptions of TCM decoction pieces**	**Income of TCM medical service projects**	**Bed utilization rate**
Chinese medicine practitioners (including assistant practitioners)	1								
TCM pharmacist	0.629**	1							
Number of beds (actual open beds)	0.840**	0.610**	1						
The total value of more than 10,000 RMB of TCM diagnosis and treatment equipment	0.443**	0.288*	0.451**	1					
Total number of consultations	0.853**	0.698**	0.781**	0.387**	1				
Number of discharges	0.827**	0.524**	0.888**	0.410**	0.791**	1			
Number of prescriptions of TCM decoction pieces	0.711**	0.610**	0.697**	0.33[illegible]**	0.789**	0.654**	1		
Income of TCM medical service projects	0.489**	0.396**	0.616**	0.252*	0.617**	0.560**	0.501**	1	
Bed utilization rate	0.299*	0.143	0.330**	0.22[illegible]	0.229	0.477**	0.134	0.053	1

Note: *** ,** and * indicate the significant p value at the 1%,5% and 10%.

Sup Table 2

The Table displays the distribution of efficiency scores among the sample hospitals.

S2 Distribution of the efficiency scores for the sample hospitals

Efficiency	**1**	**>0.9**	**0.8-0.9**	**0.7-0.8**	**<0.7**	**Mean**
TE	11 16.18%	10 14.71%	13 19.12%	13 19.12%	21 30.88%	0.788
PTE	28 41.18%	11 16.18%	8 11.76%	10 14.71%	11 16.18%	0.876
SE	12 17.65%	32 47.06%	11 16.18%	10 14.71%	3 4.41%	0.903

Sup Table 3

S3 Statistical analysis results of the efficiency of hospitals with different bed sizes

	Bed size	Average	SD	χ2	P
TE	>=500	0.743	0.133	2.845	0.416
	300-499	0.773	0.156		
	200-299	0.824	0.128		
	<200	0.806	0.195		
PTE	>=500	0.901	0.114	2.604	0.457
	300-499	0.852	0.167		
	200-299	0.861	0.127		
	<200	0.906	0.148		
SE	>=500	0.829	0.125	9.776	0.021
	300-499	0.912	0.093		
	200-299	0.959	0.070		
	<200	0.887	0.140		

Sup Table 4

S4 Input slack in 68 county-level TCM hospitals

DUM	Input slack variable 1	Input slack variable 2	Input slack variable 3	Input slack variable 4
1	13.334	0.463	217.653	6.481
2	0	0	0	0
3	0	0	0	0
4	10.531	15.402	34.871	38.07
5	0	0	0	0
6	29.632	3.662	149.823	363.764
7	2.346	5.18	73.479	152.815
8	32.903	12.702	134.602	492.429
9	31.343	4.038	84.13	82.11
10	0	0	0	0
11	0	0	0	0
12	0	0	0	0
13	18.208	4.496	2.193	133.519
14	2.679	1.98	9.346	124.08
15	44.726	13.945	100.622	103.315
16	0	0	0	0
17	0	0	0	0
18	68.873	4.04	129.86	51.944
19	0	0	0	0
20	0	0	0	0
21	25.48	22.819	95.925	256.483
22	22.284	5.968	238.412	68.956
23	0	0	0	0
24	0	0	0	0
25	0	0	0	0
26	0	0	0	0
27	63.048	7.51	156.213	296.163
28	95.35	4.947	139.141	198.292
29	19.334	5.196	93.551	70.761
30	0	0	0	0
31	27.106	1.949	50.877	25.438
32	0	0	0	0
33	33.708	3.597	132.557	67.82
34	0	0	0	0
35	73.192	4.797	88.295	196.287
36	23.118	2.315	135.38	41.677

37	0	0	0	0
38	0	0	0	0
39	0	0	0	0
40	7.393	8.505	40.34	125.315
41	44.674	7.878	195.777	159.672
42	14.331	3.04	83.381	287.56
43	57.793	5.428	135.697	415.295
44	15.493	20.767	90.864	71.996
45	18.808	14.319	29.71	571.156
46	22.895	12.729	244.79	705.815
47	0	0	0	0
48	0	0	0	0
49	6.543	4.872	22.788	87.184
50	0	0	0	0
51	9.539	4.98	38.466	207.124
52	1.145	3.13	16.585	2110.148
53	1.587	2.243	3.704	110.363
54	0	0	0	0
55	6.354	6.185	35.829	412.297
56	5.84	11.861	38.909	40.025
57	15.118	2.902	39.788	19.545
58	0	0	0	0
59	20.018	2.12	107.117	66.057
60	12.704	6.355	52.064	121.315
61	0	0	0	0
62	0	0	0	0
63	12.231	2.374	53.681	52.622
64	12.972	4.105	54.05	92.68
65	2.021	10.882	8.799	182.95
66	1.633	0.544	7.078	169.507
67	12.4	1.59	88.964	239.134
68	0	0	0	0