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Resource allocation efficiency in 68 county-level traditional Chinese medicine hospitals in China: a data envelopment analysis

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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 optimising resource allocation in these hospitals.

Design and setting The study employed a three-stage Data Envelopment Analysis (DEA) model to assess efficiency, using 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 the bed size showed statistically significant differences in returns to scale (p<0.001). The Stochastic Frontier Analysis 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.

STRENGTHS AND LIMITATIONS OF THIS STUDY

- ⇒ The study employed a three-stage Data Envelopment Analysis model, ensuring reliable results.
- ⇒ The analysis was based on data from 68 county-level traditional Chinese medicine (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 traditional Chinese medicine (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 analyse 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 with SFA, DEA is more adept at handling the production process involving multiple inputs and multiple outputs, it does not impose restrictive constraints between inputs and outputs, there is no need to consider the functional form of the production frontier, and the model is highly expandable[11–13]; therefore, 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, emphasising the need to strengthen TCM inheritance and innovation, enhance TCM service capabilities and optimise 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 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, 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 returns to scale (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 categorised as input-oriented or output-oriented. The former emphasises 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 as

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

where j=1,2,…,n denote decision units and 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), ie, 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 online supplemental 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 29 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 utilisation 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 utilisation rate indicates the efficiency of bed utilisation 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 analysed 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 online supplemental 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's correlation coefficient to assess the correlation between input–output variables and used 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 used 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 analysed using DEAP 2.1 software in conjunction with Frontier 4.1 software.

Patient and public involvement

No patient is involved.

RESULTS

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 utilisation rate was 73%. The corresponding 68 counties had a per

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	1 095 946	83 268	527 280	266 208
Number of discharges	39 121	921	11 662	7785
Number of prescriptions of TCM decoction pieces	628 542	13 051	148 740	113 255
Income of TCM medical service projects	110 902	1738	18 742	17 614
Bed utilisation rate (%)	104.81	25.82	73	17
Environmental variables				
Per capita GDP (RMB)	357 159	43 788	106 442	54 095
Population density (persons/km^2)	9891	74	867	1296
Number of hospitals	79	2	16	13

capita GDP ranging from 43 788 to 3 57 159 yuan, with an average of 106 442 yuan. The average population density per county ranged from 74 to 9891 people per square kilometre. The number of hospitals per county ranged from a maximum of 79 to a minimum of 2.

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, the 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 online supplemental 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 online supplemental 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 realise greater economies of scale through expansion.

The RTS differences among the four groups of hospitals with different bed sizes were statistically significant (p<0.001). Among the small hospitals, five (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 optimisation of resource allocation.

Stage 2: SFA regression analysis

The slack variables of input variables calculated in the first-stage DEA model analysis (online supplemental 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 generalised 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.

When analysing 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

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.

Table 3 Stochastic Frontier Analysis 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%.

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 with 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.

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 with 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 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	

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 using 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 utilisation 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 1100 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 utilisation 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 incentivise 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 using 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 utilisation 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 polarisation 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 optimising 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 utilisation of TCM resources.

Limitations

This study used a three-stage DEA model to analyse 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 used a three-stage DEA model to analyse 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 utilisation 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.

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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:

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

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:

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

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:

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

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:

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

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:

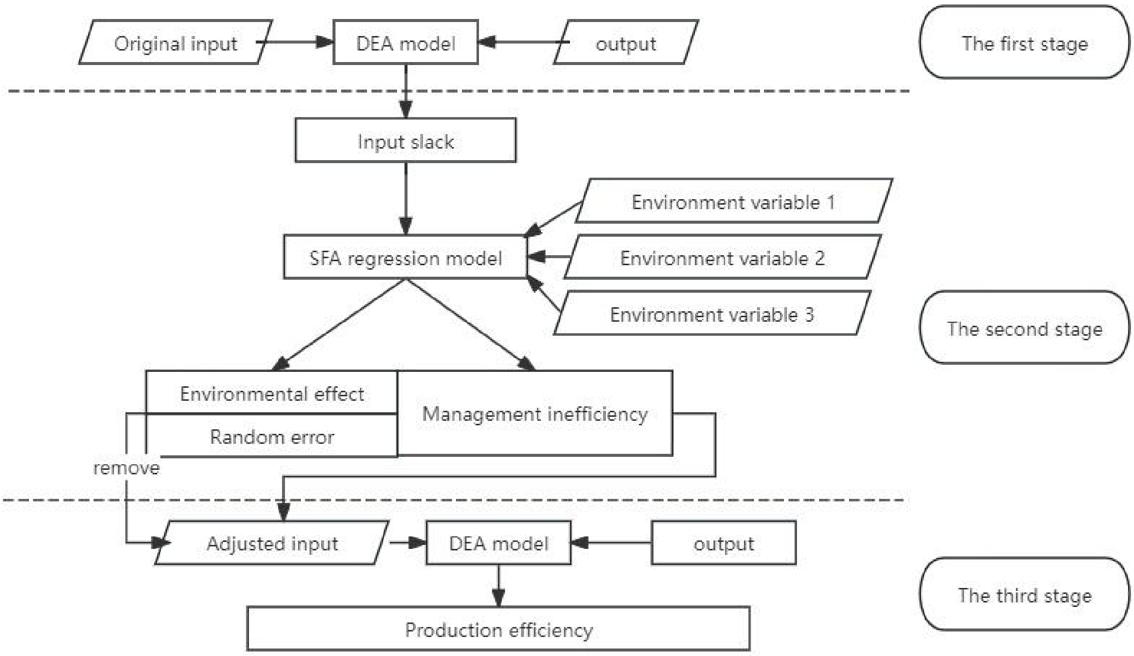
$$E(\mu|\varepsilon) = \sigma_{*}\left[\frac{\phi(\lambda\frac{\varepsilon}{\sigma})}{\Phi(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma}\right] \qquad (5)$$

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**	0.416**	0.791**	1			
Number of prescriptions of TCM decoction pieces	0.711**	0.610**	0.697**	0.338**	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	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