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Study of the medical service efficiency of county-level public general hospitals based on medical quality constraints: a cross-sectional study

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ABSTRACT

Objectives Since the new medical reform in 2009, county-level hospitals in China have achieved rapid development, but health resource waste and shortage issues still exist.

Design We applied the meta-frontier and slacks-based measurement-undesirable data envelopment analysis model to measure the medical service efficiency with or without medical quality constraints of the county-level public general hospitals (CPGHs). The assessment includes four inputs, three desirable outputs and one undesirable output. We conducted the assessment via Max-DEA V8.19 software. Moreover, we analyse the factors affecting CPGHs’ medical service efficiency based on the fractional response model.

Setting A total of 77 sample CPGHs were selected from Shanxi province in China from 2013 to 2018.

Results The results of this study showed that the efficiency level of county-level public hospitals in Shanxi Province is relatively low overall (the mean value of efficiency is 0.61 without quality constraints and 0.63 under quality constraints). This showed that ignoring medical quality constraints will result in lower efficiency and lower health resource usage for high medical quality hospitals. The medical service efficiency of CPGHs differs greatly among different regions. Under the meta-frontier, the hospitals in the central region had the highest efficiency (efficiency score 0.70), followed by those in the south (efficiency score 0.63) and the hospitals in the north had the lowest efficiency (efficiency score 0.54). Factors that have larger impacts on the service efficiency of county public hospitals are the average length of hospital stay, per capita disposable income and financial subsidy income.

Conclusions To improve CPGHs’ medical service efficiency, the government should increase investment in the northern region, and hospitals should improve the management level and allocate human resources rationally.

BACKGROUND

In March 2009, the Chinese government started a new medical reform. Since the implementation of the medical reform, China has made great achievements in expanding medical security services.1 2 The government has vigorously developed primary medical and health services and striving to improve the fairness of the health service distribution.3 However, the distribution of health resources in China is still unreasonable, and health resources are scarce.4 High-quality medical resources are mainly concentrated in cities, leading to a significant medical quality gap between urban and rural hospitals.5–7 Additionally, patients prefer to choose urban hospitals, which leads to the idleness of rural hospital resources.8 Health resource waste and shortage issues have seriously restricted the service ability of medical and health institutions and led to low medical efficiency.9 To solve these problems and improve the quality of medical services, the government has implemented a series of reforms in rural hospitals.1 10 China’s urban and rural medical system is mainly composed of urban tertiary hospitals, urban community hospitals, county-level hospitals and township health centres.11 Among them, county-level
The meta-frontier DEA model was first proposed by Battese and Rao.32 The meta-frontier refers to the potential technical level of all decision making units (DMUs), and the group frontier refers to the actual technical level of each DMU. The difference between them is the different technology sets to which they refer.

According to the meta-frontier DEA model of Battese et al.,33 we took the unexpected output into account. In this case, the technology set \((T^\text{meta})\) includes all technically feasible input–output combinations:

\[
T^\text{meta} = \left\{ (x, y, b) : x \geq 0, y \geq 0, b \geq 0; \text{x can produce } (y, b) \right\}
\]

In the above formulation, \(x\) is the input vector, \(y\) is the expected output vector and \(b\) is the unexpected output vector. That is, to obtain a certain output \(y\), the input \((x)\) must be satisfied under the given technological condition \((T^\text{meta})\). The production possibility set (meta-frontier) is as follows:

\[
P^\text{meta} (x) = \{ (y, b) : (x, y, b) \in T^\text{meta} \}
\]

Therefore, the technical efficiency function of the meta-frontier from the perspective of the output can be expressed as follows:

\[
TE^\text{meta} (x, y, b) = \inf_{\beta > 0} \{ y/\beta \in P^\text{meta} (y, b) \}
\]

According to the different levels of economic development, Shanxi Province is divided into three groups: Northern Shanxi, Central Shanxi and Southern Shanxi \((h=1, 2, 3)\). The group technology set is:

\[
T^h = \{ (x_h, y_h, b_h) : x_h \geq 0, y_h \geq 0, b_h \geq 0; x_h \rightarrow (y_h, b_h) \}, \quad h = 1, 2, 3
\]

The production set is as follows:

\[
P^h (x_h) = \{ (y_h, b_h) : (x_h, y_h, b_h) \in T^h \}, \quad h = 1, 2, 3
\]

The group technical efficiency \((h=1, 2, 3)\) can be expressed as:

\[
TE^h (x_h, y_h, b_h) = \inf_{\beta > 0} \{ y_h/\beta \in P^h (y_h, b_h) \}, \quad h = 1, 2, 3
\]
Meta-frontier technology is the envelope curve of the group frontier technology. So: \( T^{mu} = \{ T^1 \cup T^2 \cup T^3 \} \).

**Technology gap ratio**

The technology gap ratio (TGR)\(^{33}\) can be expressed by the meta-frontier and group technology efficiency functions (the results are shown in figure 1):

\[
TGR^h (x_h, y_h, b_h) = \frac{T_{meta}^h (x_h, y_h, b_h)}{T_{EB}^h (x_h, y_h, b_h)}, \quad h = 1, 2, 3
\]

Take R Hospital located in group 3 as an example, then

\[
T_{meta}^R (R) = \frac{OC}{OA} \cdot T^R (R) = \frac{OC}{OB} \cdot TGR^R (R)
\]

\[
T_{meta}^R = \frac{OC}{OA} \cdot OB \cdot OA
\]

If the TGR is less than 1 or there are obvious differences between the mean values of \( T_{meta}^R \) and \( T^R \), it is necessary to divide the CPGHs into different groups. In contrast, if the TGR is close to 1 or there are no obvious differences between the mean values of \( T_{meta}^R \) and \( T^R \), there is no need to divide the CPGHs into different groups.

**SBM-undesirable DEA model**

The SBM-undesirable DEA model\(^{34}\) of unexpected output is used to construct the efficiency measurement model under the meta-frontier and group frontier conditions, and the formula is:

\[
\rho^* = \min \left( 1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^u}{y_i^a} \right)
\]

Subject to

\[
\begin{align*}
x_0 &= \lambda x + s^-
y_0 &= \lambda y - s^g 
y_b^o &= \lambda y_b + s_b
\end{align*}
\]

\( L \leq e\lambda \leq U \)

\( S^- , S^g, S_b, \lambda \geq 0 \)

In the above formulation, \( X, Y, B \) represent the input and output vectors of different CPGHs each year. The meta-frontier represents 77 county regions, and the group frontier represents different groups in the 77 county regions; \( s^-, s^g \) and \( s_b \) are slack variables related to the input, expected output and unexpected output, respectively; \( r \) represents the \( r \)th DMU; and \( \rho^* \) represents the DMU to be assessed. The objective function \( \rho^* \) decreases with \( s_i^u \) (\( \forall h \)), \( s_i^g \) (\( \forall r \)) and \( s_i^b \) (\( \forall r \)), where \( 0 < \rho^* \leq 1 \).

Because the data are from multiple years, homogeneity for each CPGH and statistical relations should be considered. Therefore, we adopted the global reference model proposed by Pastor and Lovell\(^{35}\) to calculate the Malmquist index. This model can solve the comparability problem caused by considering different frontiers in efficiency evaluation.

**Disease complexity adjustment for discharged patients**

Since the disease complexity varies from hospital to hospital, it is unfair to simply input the approximate number of discharged patients into the input–output index. For example, hospitals with high technology levels are likely to treat patients with complicated conditions, and these hospitals will take more time to treat such a patient than to treat a patient with a mild illness. Hospitals with low technology levels can supply health services to patients with mild illness or light symptoms as a result of their limited technical capacities, and patients with severe illness may prefer directly seeking health services at high-level hospitals. Thus, 1000 patients in hospital-A will all have difficult and complicated diseases, and those in hospital-B will have mild diseases. However, when performing efficiency evaluation research, if a quantity of units 1000 is input without considering the complexity of the disease, it would be unfair to hospitals with high technical levels. However, the Romer index (RCI) can be used to adjust the number of discharged patients according to the average length of stay and bed usage rate.\(^{36}\) Given the poor quality of the patient records in county-level hospitals, we select the RCI index, which provides a reference for efficiency evaluation in underdeveloped areas. The specific adjustment methods were as follows:

\[
RCI_i = ALoS_i \times \left( \frac{OCC_i}{OCC} \right)
\]

In the above formula, \( ALoS_i \) refers to the average length of stay in the \( i \)th hospital, \( OCC \) refers to the bed usage rate of the \( i \)th hospital and \( OCC \) refers to the average bed usage rate of all evaluated hospitals. Therefore, the average length of stay will be adjusted upward for hospitals with higher bed usage rates than the average. The actual number of discharged patients (P) was adjusted based on the RCI of each hospital, and finally, the number of discharged patients (EP) adjusted according to the RCI index was obtained. The formula is as follows:
Fractional response model

The regression equation is:

\[
\text{EFFICIENCY}_{it} = \beta_0 + \beta_1 \ln \text{INCOME}_{it} + \beta_2 \ln \text{POPULATION}_{it} + \beta_3 \ln \text{SUBSIDY}_{it} + \beta_4 \ln \text{DAY}_{it} + \beta_5 \text{BEDRATIO}_{it} + \beta_6 \text{STAFFRATIO}_{it} + \varepsilon_{it}
\]

where \text{EFFICIENCY}_{it} represents the service efficiency of the hospital \(i\) in year \(t\), \(\beta_0\) is a constant term. \text{INCOME}_{it} and \text{POPULATION}_{it} represent the per capita disposable income and residents population of the district (county) where the hospital \(i\) is located in year \(t\), respectively; \text{SUBSIDY}_{it}, \text{DAY}_{it}, \text{BEDRATIO}_{it} and \text{STAFFRATIO}_{it} represent the subsidy, average length of hospital stay, hospital bed usage rate and the proportion of health technicians, respectively. \(\varepsilon_{it}\) is the error term. This paper uses Stata V.16.0 software for data processing and regression.

To examine the factors that influence the service efficiency of public hospitals, this paper uses the panel Tobit model with right-side restriction for regression. One of the defects of the Tobit model is that it has a strong dependence on distribution and is sensitive to the problem of heteroscedasticity. If the error term does not follow the normal distribution or has a heteroscedasticity issue, the estimation will be inconsistent. In addition, there are some problems in using the Tobit model to analyse the factors of hospital efficiency. In fact, the hospital efficiency in this paper is a natural consequence of the way DEA is defined, and the hospital efficiency measured according to the non-oriented energy-based model (EBM) model is inherently between 0 and 1, which is not because of the Tobit model that set the efficiency greater than 1 to the value of 1.

Papke and Wooldridge proposed the fractional response model (FRM) in 1996, which overcomes many of the limitations of linear and non-linear econometric models when studying bounded data. Ramalho et al further developed the FRM. The FRM is a non-linear model using the quasi-maximum likelihood estimation (QMLE). Compared with the Tobit model, the QMLE is asymptotically efficient and consistent because the FRM does not require distributional or heteroscedasticity assumptions on the DEA score. In addition, the advantages of the FRM are that it allows a non-linear relationship between hospital efficiency and its determinants, allows error terms to have autocorrelation, and does not allow the efficiency score to fall outside 0-1, which are in line with the research content of this paper. To this end, this paper uses the FRM for robustness testing. The specification is:

\[
E(y_i | x_i) = G(x_i \beta)
\]

where the subscript \(i\) represents hospital, \(x_i\) are the factors and \(\beta\) is the parameter to be estimated. \(G(\eta) = \exp(\eta) / [1 + \exp(\eta)]\) represents a probability distribution function in the form of logit whose domain is all real numbers and whose range is \((0, 1)\).

Referring to Papke and Wooldridge, the log-likelihood equation can be estimated by QMLE:

\[
l_i(\beta) = y_i \ln [G(x_i \beta)] + (1 - y_i) \ln [1 - G(x_i \beta)]
\]

Finally, maximise equation (15) to obtain the value of \(\beta\) in equation (13).

\[
\max_{\beta} \sum_{i=1}^{260} l_i(\beta)
\]

Patient and public involvement
No patient involved.

RESULTS AND ANALYSIS

Variable selection
The variables were selected according to previous empirical research and the literature. Input variables usually include labour and capital. In our study, the number of registered doctors and registered nurses were used to represent the elements of human resources as input variables. Beds and equipment valued above 10 000 yuan were used as capital elements. The total visits, the number of discharged patients (EP) adjusted by the RCI and the number of operations were used as output variables. At present, all critically ill patients in counties in China go to urban tertiary hospitals, so there are almost no death cases. Therefore, in this study, the number of adverse events was used to replace the unexpected output variable as a quality index. The descriptive statistics of the input–output indicators are shown in table 1.

The variables for FRM, the dependent variable is the service efficiency of public hospitals. As for the independent variables, according to the existing literature and the consideration of data availability and sample size, the following six types of factors affecting the service efficiency of county-level public hospitals were selected for analysis, including (1) external factors: per capita disposable income of residents (county-level economic factor), number of usual residents (county-level population factor); (2) internal factors: financial subsidy income (hospital-level financial factor), the proportion of health technicians (human resource factor), hospital bed usage rate (equipment implementation factor), average length of hospital stay (service delivery factor). The summary of variables for FRM is shown in table 2.

Test and analysis of the TGR
Under a quality constraint, a mean value comparison test of the obtained TGR was performed, as shown in table 3. Assuming that the mean value was 1 and the significance level was 95%, the results showed that the average TGR of each group was less than 1. After performing calculations, from 2013 to 2018, the mean value of the hospital TGR in the southern group was at the highest level, close to 1, reaching 0.93, followed by that of the central group of 0.91, and finally that of the northern group at only 0.63.
This result indicated that the southern group was closest to the meta-frontier of technology in county-level public general hospitals, followed by the central group and the northern group. Obviously, both the overall TGR and the regional TGR values were significantly different from the assumed mean value of 1. Therefore, the heterogeneity of the division of public hospitals in Shanxi Province was very obvious, and this finding agreed on the conditions of the DEA meta-frontier model; thus, the meta-frontier model could be suitably applied to analyse the results.

After calculating the efficiency of county-level general hospitals in Shanxi Province under meta-frontier and group frontier conditions, the temporal trends of the technology gaps in the north, central and southern regions under the quality constraint were further compared. The results are shown in figure 2.

Figure 2 shows that the mean value of the TGR in the southern and central regions of Shanxi Province was high, while that in the northern region was the lowest, indicating that the central and southern regions provide better hospital management and medical levels as a whole than did the northern region; additionally, they are closer to the technological frontier. The mean value of the TGR in the central and southern regions fluctuated at a high level and remained in a basically stable state, but the mean value of the TGR in the northern region considerably changed. Except for a slight increase in the mean TGR in 2016, other years experienced a downward trend, which indicated that the medical level in the northern region decreased and that different frontiers influenced the efficiency of county-level public general hospitals in different regions of Shanxi Province.

**Time series analysis of the technical efficiency of hospitals**

Figure 3A,B shows the trend of the average comprehensive efficiency of sample hospitals in Shanxi Province and in three major regions from 2013 to 2018 under the meta-frontier and group frontier, respectively. Taking the meta-frontier in figure 3A as a reference, the overall average medical service efficiency of county-level public general hospitals was more than 0.6, and the medical service efficiency in each region was relatively stable each year; notably, the efficiency in the northern region displayed a slow downward trend. Referring to figure 3B, the overall average efficiency for the group frontier was approximately 0.75, the southern region was relatively stable, and the trends in the northern and central regions involved inverted U-shaped curves in the early stage; however, all the regions experienced a significant increase in 2018.

Figure 3C,D shows the trend of the average comprehensive efficiency of the sample hospitals in Shanxi Province and in three major regions under the meta-frontier and the group frontier conditions, respectively, based on the quality constraints from 2013 to 2018. Taking the common
frontier in figure 3C as a reference, the overall average medical service efficiency of county-level public general hospitals was approximately 0.63, and the medical service efficiency trend in various regions displayed an inverted U-shaped curve in each year; that is, it fluctuated and rose from 2013 to 2016 and then dropped rapidly after 2016. Regarding figure 3D, the overall average efficiency under the group frontier was approximately 0.75, and the medical service efficiency trend in the northern region displayed a U-shaped curve that fluctuated and decreased from 2013 to 2016 and then rose slowly after 2016. Moreover, the efficiency trends in the central and southern regions were the same as those for the meta-frontier.

**Analysis of the differences in hospital technical efficiency**

The distribution of the service efficiency of public general hospitals in Shanxi Province is shown in figure 4. Graph A shows the distribution of hospital efficiency without quality constraints, and graph B presents the distribution of hospital efficiency under quality constraints. In terms of location, the peak position of the distribution curve in figure 4B moves to the right compared with that in figure 4A, indicating an overall efficiency improvement. The kurtosis of the distribution curve for the central and southern regions in figure 4B is greater than that in figure 4A, indicating that the distribution of the efficiency was more concentrated in B. The northern distribution curve in figure 4A displays an obvious bimodal state, indicating that the efficiency distribution was somewhat scattered. Therefore, quality constraints were very important in the hospital efficiency evaluation. A lack of quality constraints would lead to certain deviations in the evaluation results, and the results would not comprehensively reflect the actual operation status of the medical system.

An analysis of the hospital efficiency distribution in figure 4B was performed. First, for the location, the distribution curves of the hospital efficiency density in the northern, southern and central regions sequentially moved to the right. The distribution curves of the southern and central regions were closely interlaced, indicating that the hospital efficiency levels in the southern and central regions are similar and significantly higher than the level in the northern region.

Second, the distribution curve of the efficiency density in northern hospitals peaks, and the distribution curves of the efficiency density for the central and southern hospitals displays broad kurtosis.

Finally, in terms of shape, the distribution curve of the efficiency density for northern hospitals is bimodal, and those for the central and southern hospitals are unimodal, suggesting that most hospitals in the central and southern regions have little difference in medical level, while the medical level of northern hospitals is polarised; this relation reflects the concept of ‘the strong get stronger, and the weak get weaker’ (Matthew’s effect).

**Analysis of the changes in hospital technical efficiency rankings**

To show the changes in efficiency among the sample hospitals before and after the implementation of quality constraints, the comprehensive efficiency values of sample hospitals

<table>
<thead>
<tr>
<th>Region</th>
<th>Mean TGR</th>
<th>t</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>North</td>
<td>0.62649</td>
<td>−17.2815</td>
<td>0.000</td>
</tr>
<tr>
<td>Central</td>
<td>0.907907</td>
<td>−8.9249</td>
<td>0.000</td>
</tr>
<tr>
<td>South</td>
<td>0.9328708</td>
<td>−6.9778</td>
<td>0.000</td>
</tr>
<tr>
<td>Entire</td>
<td>0.8494894</td>
<td>−15.6809</td>
<td>0.000</td>
</tr>
</tbody>
</table>

TGR, technology gap ratio.
under the two constraint conditions were ranked, and the changes in hospital rankings were compared. The results are shown in Figure 5. In the northern region, the ranking of hospital 17 increased the fastest, and the rankings of hospitals 6 and 13 decreased most obviously. In the central region, the ranking of hospital 24 increased the fastest, and the ranking of hospital 29 decreased the most. In the southern region, the ranking of hospital 71 increased the fastest, and the ranking of hospital 67 decreased the most.

By analysing the unexpected outputs of adverse events at hospitals, it was found that the changes in efficiency rankings were related to the unexpected outputs of adverse events; notably, the efficiency ranking increased when the unexpected output level was low, and the ranking decreased when the unexpected output level was high. For example, the average unexpected output of hospitals in the northern region was −14.35, and that of hospital 17, with a medical quality higher than that of most hospitals, was −3.38. However, the average unexpected outputs of hospitals 6 and 13 were −23.78 and −31.08, respectively, and the corresponding medical quality was lower than that of other hospitals. Additionally, the average unexpected output values of hospitals in the central and southern regions were −15.3 and −19.22, respectively, and the average unexpected output values of hospitals 24 and 71 were only −3.09 and −3.49, respectively. Moreover, the average unexpected output values of hospitals 29 and 67 were −23.99 and −57.25, respectively.

The Spearman rank correlation test was used to determine whether there was a correlation between the hospital efficiency values under the two different constraints. The significance level was 1%. The results showed that there was a positive correlation between the efficiency values of sample hospitals under the two constraints. According to the results, the three regions were different: the southern region had the highest similarity, with a correlation coefficient of 0.9673, and the greatest difference was observed in the northern region, with a correlation coefficient of 0.8452.
**Analysis of factors affecting public hospital efficiency**

The result on factors affecting public hospital efficiency based on the FRM is shown in Table 4.

We can find that the coefficient of per capita income is positive and significant, that is, the improvement of residents’ per capita disposable income can improve the service efficiency of county public hospitals; population factor negatively impacts public hospital efficiency when the fixed effects are not controlled. After controlling for the fixed effects, the coefficient is significantly positive, that is, the resident population in the county where the hospital is located is positively correlated with the service efficiency of county public hospitals; The effect of financial subsidy income on the service efficiency of county public hospitals is significantly positive; the coefficient for the average length of hospital stay is the largest and significantly negative; and the proportion of health technicians has a significant positive impact on the service efficiency of public hospitals.

**DISCUSSION**

This paper used the meta-frontier model and SBM-undesirable model to calculate the efficiency of county-level public hospitals in Shanxi Province from 2013 to 2018. Then, we evaluated the reform effect and resource usage rate of county hospitals and explored the influence of medical quality on hospital efficiency. Moreover, we analyse the factors affecting public hospital efficiency based on the FRM.

The results of this study showed that the efficiency level of county-level public hospitals in Shanxi Province is relatively low overall (the mean value of efficiency is 0.61 without quality constraints and 0.63 under quality constraints). In other studies, the average efficiency of county hospitals in Chongqing was 0.83, in Anhui Province was 0.956 and in China, as a mean value, was 0.7, suggesting that the efficiency of county-level hospitals in Shanxi Province is obviously low; additionally, the usage rate of existing resources is relatively low, and the...
technology used in inefficient. To improve the efficiency level of county-level hospitals, in addition to increasing investments to alleviate resource shortages, it is necessary to improve the usage efficiency of resources, such as improving hospital management, rationally allocating human resources, and optimising capital investments.14

The results showed that the efficiency of county-level public hospitals in Shanxi Province did not improve and even declined in some areas from 2013 to 2018 (figure 2C). Although the reform of county-level hospitals was initiated in 2012, the effect was not remarkable, as also noted by Jiang et al. Moreover, the study found that there were regional differences in the efficiency of county-level public hospitals in Shanxi Province. The efficiency level of county-level public hospitals in the central and southern regions of Shanxi Province was high, while the efficiency level in the northern region was comparatively low (figure 2A,C); these trends were also reflected by the TGR distribution in each region (figure 1), which indicated that the county-level hospitals in the northern region were far from the technological frontier. Therefore, increasing the resource inputs for hospitals in the northern region of the province should be prioritised to improve their medical levels. Additionally, the population and economic level in northern Shanxi Province are lower than those in the central and southern regions45; thus, hospital efficiency may be related to the economic environment and population.

This study also showed that quality constraints had an important impact on hospital efficiency evaluation (figures 3 and 4). Neglecting medical quality output could lead to underestimates of the hospital efficiency level. This finding could potentially be attributed to the fact that medical quality is often related to hospital management and human resources.46 With improvements in hospital management and medical treatment ability, medical quality will also increase, as will the corresponding hospital efficiency. Improving the quality of medical services is often the goal of public hospitals.47 but many hospitals begin to expand blindly, resulting in inefficiency.20 41 48 Pang and Wang49 noted that improperly scaled expansion can lead to technical efficiency in the short term but not in the long term. Therefore, to improve the medical quality level, increasing the technological capacity and improving management are steps.

For the factors that influence public hospital efficiency, first, when the per capita disposable income of residents is high, people may pay more attention to their health, and have more requirements for the service and technical level of the hospital. Accordingly, health services will be used more rationally. Second, the more resident population in the region, the greater the intensity of the demand for medical services, and the hospital will continuously improve its medical service to meet the demand, thus making the hospital service more efficient. The reason for the low level of significance level is that: on the one hand, the resident population is the macro-level data, which has little impact on the efficiency of the micro-level hospital; on the other hand, the mobility of people seeking medical treatment is high, so the population of the area where the hospital is located has limited effect on the efficiency of the local hospital. Third, if the government increases the financial investment in the hospital, it will help the hospital to introduce high-tech equipment and improve the hospital’s infrastructure construction capacity, etc. Thus it will prompt the hospital to realise the rational allocation of resources under the guidance of the government’s policy of increasing the corresponding investment. As a result, the hospital achieves more efficient health service, improving the efficiency of hospital services. Fourth, the average length of hospital stay is an important factor affecting the service efficiency of public hospitals, and a longer length of hospital stay will reduce the service efficiency level of the hospital. This may be because a longer length of hospital stay means hospitals are not treating patients in a timely manner or have to deal with more severe cases, making hospital services less efficient. Fifth, the bed usage rate reflects the vacant beds in the hospital. The higher the hospital bed usage rate, the more patients can be provided with hospital-stay services at the same time, thereby increasing the hospital-stay service output and improving the hospital’s service efficiency. Sixth, for the positive impact of the proportion of health technicians, the reason may be that the higher the proportion of health technicians, the higher the level of medical service, and the further improvement of the service efficiency of the hospital.

Limitations and suggestions for future research
This study evaluated the efficiency of county public hospitals in Shanxi Province and explored the influence of scale on hospital efficiency. It provided a reference for the government and hospitals to reasonably allocate health resources. However, we believe that our research can be improved and extended in a number of directions. First, the study has Only 77 hospitals were chosen in one province, so the extrapolation of this study may be limited. Future studies can be conducted and include CPGHs in other provinces, which are divided by region. Second, we did not include the staff salary as the input variable, mainly due to data limitations. However, further analysis focusing on the staff salary variable is also necessary given that we are studying public hospitals’ efficiency, the salary paid to employees by the government is an important input indicator for evaluating public hospitals’ efficiency.

CONCLUSION
This showed that after the implementation of county-level public hospital reform, the efficiency level of county-level public hospitals in Shanxi Province did not improve but remained low. Notably, the usage rate of resources was low, and the reform effect was not obvious. There are differences in the efficiency of county-level hospitals in different regions, with the highest efficiency in the central region, the second-highest level in the southern region...
and the lowest level in the northern region. To improve the efficiency of hospitals, support to the northern region should be strengthened, hospital management should be improved, and health human resources should be rationally allocated.

The results also indicated that quality factors have a significant impact on hospital efficiency evaluation. The keys to improving the level of medical quality are to improve the proportion of technical personnel and the level of hospital management. The expansion of county-level hospitals should consider the economic level and service area in the region to avoid expansion and blind investment, potentially resulting in wasted resources.

According to the FRM regression results, it is concluded that the factors that have larger impacts on the service efficiency of county public hospitals are the average length of hospital stay, per capita disposable income and financial subsidy income. Shortening the average hospital stay can improve hospital efficiency. In areas with higher per capita disposable income of residents, the service efficiency of county-level public hospitals is higher. And the increase in subsidy has a positive effect on the improvement of hospital service efficiency. In addition, the county population, bed usage rate and the proportion of health technicians also have significant impacts on hospital service efficiency. The higher the population, the higher the hospital efficiency. Increasing the bed usage rate and the proportion of health technicians will also promote hospital service efficiency. However, only 77 hospitals in one province were selected for this study, so the extrapolation from this study may be limited.

**Contributors** All authors made significant contribution to this study. JL conceptualised the study. WL collected and analysed the data. BG wrote the first manuscript. The final version submitted for publication was read and approved by authors. JL and WL act as the guarantors of the article.

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**Patient and public involvement** Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

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**REFERENCES**


31 The data are mainly from the 2013-2019 Shanxi (a Province with a population of 37 million in China) statistical Yearbook and China health Statistics Yearbook, overall 77 CPGHs in Shanxi Province were selected. data from: the data is held in Baidu web disk. Available: https://pan.baidu.com/s/1Z8TraRG2naKX7BqNJ04EAQ


