İŞLETME AKADEMİSİ DERGİSİ
JOURNAL OF BUSINESS ACADEMY
2025, 6(4), 277-287
https://doi.org/10.26677/TR1010.2025.1616

Meta Analysis of Technical Efficiency Studies in Healthcare Systems

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Abstract

Technical efficiency is crucial in health systems for effective resource management, cost control, patient safety, and quality care. This study aimed to compare the technical efficiency of different health systems through a systematic review and meta-analysis following PRISMA guidelines. Literature published between 2014 and 2024 was searched in PubMed, Web of Science, Scopus, Science Direct, and EBSCO using the keywords "Technical Efficiency" and "Healthcare Systems." Only full-text, peer-reviewed English studies were included. Out of 278 studies identified, seven met the inclusion criteria. The meta-analysis showed positive and statistically significant mean differences, indicating improvements in technical efficiency across models. Overall, enhancing efficiency in health systems supports better resource utilization and higher-quality patient care. The consistent positive outcomes provide valuable insights for future research and the development of effective health policies.

Keywords: Healthcare Systems, Technical Efficiency, Meta Analysis, PRISMA.

Received: 29 October 2025 **Accepted:** 3 December 2025

Article Classification: Research Article

1.INTRODUCTION

Globally, health services are at the forefront of public policy planning and implementation. The main reason for this is that the effective production and delivery of health services have a significant impact on social growth and development (Clayton, 2010). In addition to the production and delivery of these services, the amount and allocation of resources in terms of access to and utilization of health services also become important in shaping countries' health policies (Ahmed et al., 2019). Especially in underdeveloped and developing countries, most of the resources allocated to health services are used inefficiently, and public resources are spent on health services that are inappropriate or do not serve any purpose. This situation causes most of the national resources of countries to be wasted (Collins & Green, 1994). Therefore, there is an effort to measure the performance of health systems and thus ensure more efficient use of resources (Ravangard et al., 2014; Nassar et al., 2020).

One of the keyways to measure how well a health system is working is by looking at technical efficiency. Technical efficiency is a performance criterion that measures how much output an enterprise produces with certain inputs. In fact, this indicator is an assessment tool that compares the inputs and outputs from the health sector with the resources available in the country (Ravangard et al., 2014). Technical efficiency is commonly used to measure how well health services perform at both small and large scales, because it helps compare and evaluate various units and systems (Cylus et al., 2016).

Data Envelopment Analysis (DEA) is commonly used to assess how efficient health systems are operating (Bwana, 2015; Stefko et al., 2018; Kohl et al., 2019; Mishra, 2019; Top et al., 2020; Chen et al., 2020; Li et al., 2021). DEA is a method that doesn't assume a specific mathematical form to measure how efficiently performance is achieved (Jacobs et al., 2006). Another way to define DEA is as a method that helps assess and compare how efficiently different entities use their inputs to produce outputs, and it's commonly applied in

Suggested Citation
Biçer, İ., Aras, Y., Selvi Sarıgül, S. (2025). Meta Analysis of Technical Efficiency Studies in Healthcare Systems, Journal of Business Academy, 6 (4), 277-287.

making decisions and distributing resources (Cooper et al., 2001). n DEA, there are two models that help decision-making units assess their efficiency based on the weights of input and output factors. These models are Constant Return to Scale (CRS) and Variable Return to Scale (VRS) (Cooper et al., 2006). The CRS model, based on the assumption of Constant Return to Scale, is based on linear programming and calculates an aggregate efficiency measure. In this model, information about inefficiently utilized resources and their quantities can be obtained. In addition, the CRS model uses the concepts of virtual input and virtual output, which characterize the total input and total output situations (Coelli et al., 1996). The CRS model is seen as a realistic assumption when all decision-making units are operating at their optimal scale. However, this model does not consider factors like government interference, lack of perfect competition, and financial limitations that stop decision-making units from reaching their optimal scale. Because of this, a modified version of the CRS model has been suggested to better fit the assumption of Variable Returns to Scale (Çavmak, 2017). Unlike the CRS model, the VRS model can calculate efficiency scores as technical efficiency and scale efficiency. Moreover, in this model, it can be determined whether inefficient decision-making units are caused by scale inefficiency or operational inefficiency (Coelli et al., 1996). However, since the VRS and CRS models differ in their treatment of returns to scale, the technical efficiency scores obtained may also differ (Taboada et al., 2020). Namely, since the technical efficiency score can be evaluated on its own in the VRS model, this score is higher than the technical efficiency scores calculated using the CRS model (Mirmozaffari & Kamal, 2023). In other words, since the VRS model recognizes that different decision-making units can operate under different returns to scale, it provides more flexibility and generally leads to a higher efficiency assessment (Cook et al., 2014). Finally, while the CRS model is appropriate for benchmarking when scale is not important, the VRS model is more appropriate when it is important to understand technical efficiency without scale effects (Podinovski, 2004).

While the current literature contains numerous case studies and analyses using a single model to measure the technical efficiency of health systems, there is no systematic review or meta-analysis that systematically synthesizes or quantitatively compares how different DEA approaches and assumptions (particularly CRS and VRS) yield different results on the same data sets and/or different health systems. There is significant heterogeneity among studies in terms of input/output choices, scale assumptions, and application contexts, making it difficult to provide policymakers and researchers with clear guidance on which model is more reliable under which conditions. To address this gap, this study will systematically collect and classify the findings of existing studies, compare the effects of CRS and VRS assumptions in DEA outputs on efficiency estimates, and, if possible, use meta-analytic methods to examine consolidated efficiency levels according to model preferences and the sources of heterogeneity (region, income level, health system type, input/output selection, etc.). Finally, our findings aim to provide methodological recommendations for DEA applications and contribute to the development of more comparable and policy-oriented efficiency indicators for health systems.

2.MATERIALS AND METHODS

2.1.Aim of the Study

The aim of this study was to compare the technical efficiencies of different health systems and identify best practices by systematically reviewing the findings of studies in the existing literature to identify and evaluate the technical efficiency levels of health systems according to different models.

2.2.Study Design

This study was carried out as a systematic review and meta-analysis, and it followed the PRISMA guidelines to properly report the findings of the systematic review and meta-analysis (Panic et al., 2013).

2.3.Search Strategy, Accessed Databases and Search Method

For the period from 2014 to 2024, searches were conducted in the PubMed, Web of Science, Scopus, Science Direct, and EBSCO databases using the terms “Technical Efficiency” and “Healthcare Systems”. During the search process, it was made sure that these keywords appeared in the title, abstract, or keywords section of the articles.

2.4.Study Inclusion and Exclusion Criteria

For this review, the researchers established a set of predefined inclusion and exclusion criteria to ensure methodological rigor and to focus the analysis on studies directly relevant to the technical efficiency of healthcare systems. Only studies that fully met the following inclusion criteria were considered:

(1) empirical research articles written in English;

(2) published in peer-reviewed scientific journals; and

(3) containing the full text.

After applying these inclusion criteria, a total of 278 studies published between 2014 and 2024 were identified as potentially relevant.

2.5.Selection of Scanned Articles and Data Extraction Procedures

Following the initial identification stage, the titles, abstracts, and keywords of all 278 studies were independently screened by the researchers. This screening process aimed to eliminate studies that did not align with the purpose of the review. As a result of this detailed evaluation, several categories of exclusion were applied. Specifically:

- 23 studies did not conduct any form of efficiency analysis, making them irrelevant to the review's objective.
- 95 studies were excluded because they were not related to healthcare services in a broad or system-level context.
- 80 studies focused on very specific healthcare units (e.g., dialysis centers, nursing homes), particular services (e.g., pharmaceuticals, haemodialysis), or specific diseases (e.g., cancer), and therefore did not assess efficiency at the level of public or general healthcare systems.
- 6 studies were excluded because they relied solely on single-country datasets, whereas the review required studies with broader or comparative system-level analyses.
- 2 studies did not employ Data Envelopment Analysis (DEA), the methodological framework required for inclusion.
- 4 studies were excluded due to the unavailability of their full text.
- 16 studies did not clearly specify the DEA model used (CRS/VRS), or did not apply either model appropriately, resulting in methodological ambiguity.
- 45 duplicate records were identified and removed using Zotero reference management software.

In total, 271 studies were excluded based on these criteria. After the complete screening and eligibility assessment, 7 studies remained and were included in the final analysis. These articles constituted the evidence base for evaluating technical efficiency within healthcare systems across the studied period (Figure 1).

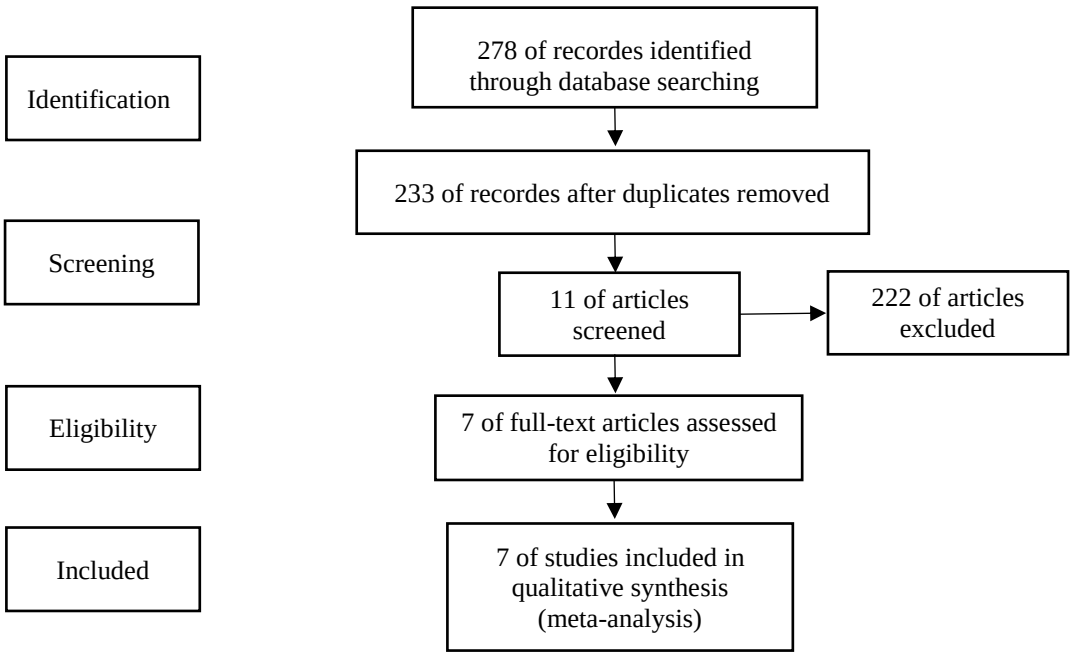


Figure 1. PRISMA Diagram

2.6.Quality Assessment of Studies

The AXIS (Appraisal tool for Cross-Sectional Studies) tool was used to evaluate the quality of the publications being studied. AXIS is meant to assess both the quality and how well cross-sectional studies are reported. It provides a structured approach to assess various aspects of study methodology, reporting and potential biases. Using the AXIS tool, the reliability and validity of the studies included in meta-analyses can be ensured, thus obtaining more accurate and reliable findings (Downes et al., 2016). Using the AXIS evaluation tool, the publications were evaluated separately by 2 researchers who were not involved in the data collection stage of the study.

2.7.Meta-Analysis Procedures

After collecting the relevant studies and calculating the effect sizes, the meta-analysis stage is started. There are 3 basic stages of the meta-analysis process: Selection of the effect model, heterogeneity test and determination of publication bias (Field & Gillet, 2010).

There are two main approaches to meta-analysis: fixed effect models and random effect models. The fixed effect model assumes that all the studies included in the analysis are part of the same group or population, and they all have the same average effect size (Hunter & Schmidt, 2000). In the fixed effect model, the sample effect sizes are expected to be similar because they all come from the same population where the average effect remains consistent. However, the random effect model suggests that the average effect size can change from one study to another. Since the studies included in a meta-analysis often come from different populations with varying average effects, the effect sizes are likely to be different. This is why they are considered heterogeneous (Field & Gillett, 2010). The random effects model is usually the better choice. This makes it easier to apply the findings to a larger group or population (Borenstein et al., 2009).

There are various types of effect size and which one to use depends on the data and the research purpose. Common effect sizes used in meta-analyses are as follows (Sullivan & Feinn, 2012):

- Correlation Coefficient (r): It is used when examining the relationship between two continuous variables.
- Mean Difference (MD): It is used when comparing the means of two groups. It is usually shown as Cohen's d and expresses the difference between two means in units of standard deviation. In this study MD method was used showing the results.
- Odds Ratio (OR): This measure is used in studies where the outcome has only two possible results. It compares the chance of an event happening in one group to the chance of it happening in another group. If the value is more than 1, it means the event is more likely in the first group. If it's less than 1, the event is less likely in the first group. A value of exactly 1 means there's no difference between the two groups.
- Risk Ratio (RR) or Relative Risk: Similar to the odds ratio but based on the probability of an event occurring in each group. It is widely used in clinical and epidemiological studies. MD was used in line with the aim of this study.

In the second stage of the meta-analysis process, it is tested whether the publications are heterogeneous. For the heterogeneity test, the *Q statistic* (Cochran's Q test) is first obtained (Cochran, 1954). Cochran's Q test checks if the differences in effect sizes are bigger than what would happen randomly. If the result is significant (p less than 0.05), it suggests there is heterogeneity (Pereira et al., 2010). Secondly, the I^2 statistic is obtained. The I^2 statistic is used to describe the percentage of total variation between studies. I^2 ranges between 0 and 100%. 0% indicates that there is no heterogeneity, while heterogeneity increases as the value increases. A value above 75% is considered high heterogeneity. This statistic is less affected by the number of studies compared to other methods used to estimate heterogeneity and provides an easily interpretable measure (Higgins et al., 2003).

In the third step of the meta-analysis process, they check for publication bias. One common method used is Begg's rank correlation test. This test gives a p-value that shows if the correlation seen is statistically significant. If the p-value is less than 0.05, it suggests there might be publication bias present (Begg & Mazumdar, 1994).

A funnel plot is also used to show the effect size, how different the results are, and whether there is a bias in the studies that are published (Chandler et al., 2019). Funnel plots are a type of scatter plot that show how much each study covers the topic by displaying something like the number of participants or the error range, compared to how much effect each study found (Godavitarne et al., 2018). Standardized measures of binary effect size, such as odds ratio or risk ratio, can be used to display the effect size of the study (Liu, 2011). Funnel plots can show one or more regions where results are statistically significant, such as p-values less than 0.1, 0.05, or 0.01 along with corresponding confidence intervals of 90%, 95%, or 99%. They can help spot unusual results and support decisions about further analysis (Page et al., 2021; Mavridis and Salanti, 2014). Funnel plots can also include a second vertical line that shows a null effect, like an odds ratio of 1. This helps spot studies where the effect size is near zero and might not be statistically significant (Sterne et al., 2011).

Forest plots, also called blobbograms, give a visual summary of the results from several studies in a meta-analysis. Each study is shown as a point that represents the effect size, like an odds ratio, risk ratio, or mean difference, along with its confidence interval (Dettori et al., 2021). The Jamovi Project V. 2.5 was used to analyses the data.

3.RESULTS

The analysis used the standardized mean difference to show the main results. A random-effects model was used to analyze the data. The amount of variation between the results, called Tau squared, was calculated using the restricted maximum likelihood method (Viechtbauer, 2005). The report also includes the Q-test for heterogeneity, which was introduced by Cochran in 1954, along with the estimate of Tau squared and the I^2 statistic.

General information about the studies included in the meta-analysis is presented in Table 1.

Table 1. Studies Details Used Meta-analysis

Author(s)	Year	Countries	DEA Model	Sample Size (DMU number)
Asandului et al.	2013	European Union	CRS and VRS	28
Lee	2016	Global Competitiveness Index	CRS and VRS	30
Ahmed et al.	2018	Asia Countries	CRS and VRS	22
Singh et al.	2021	ASEAN Countries	Malmquist TFP (DEA based), and VRS	10
Ravangard et al.	2014	ECO Countries	CRS (input-oriented) and VRS	10
Lacko et al.	2023	European Union	CRS and VRS, Malmquist	27
Lo Storto & Goncharuk	2017	European Countries	CRS and VRS	30

Seven studies were included in the analysis. The differences in means, measured in standardized terms, ranged from 0.0731 to 1.6157, and all of them were positive. Using a random-effects model, the average standardized mean difference was found to be 0.688, with a 95% confidence interval ranging from 0.263 to 1.113, as shown in Table 2. This suggests that the average outcome was significantly different from zero, with a z-score of 3.175 and a p-value of 0.001.

Table 2. Random-Effects Model (k =7)

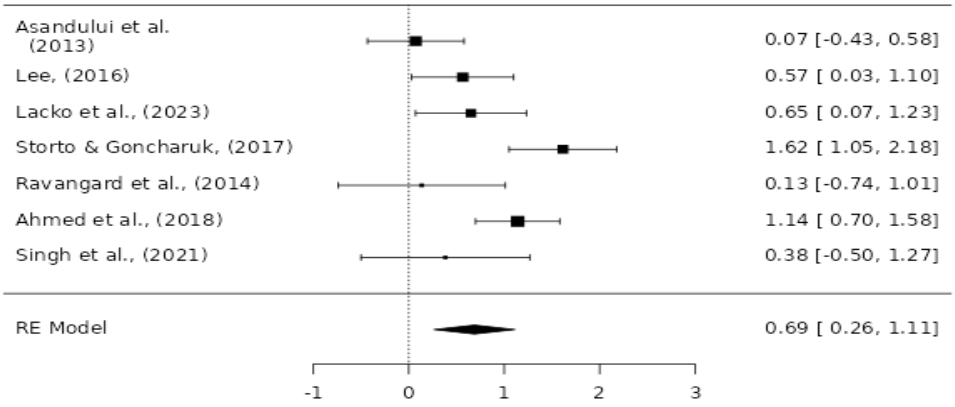
	Estimate	se	Z	p	CI Lower Bound	CI Upper Bound
Intercept	0.688	0.217	3.175	0.001	0.263	1.113

According to the Q-test, the true outcomes seem to be different from each other (Q(6) = 22.050, p = 0.001, tau^2 = 0.228, I^2 = 72.11%) (Table 3). The 95% prediction interval for the true outcomes ranges from -0.340 to 1.717. So even though the average outcome is positive, there is still some variation. When looking at the standardized residuals, none of the studies had values higher than ±2.6901, which means there were no clear outliers in this model. When using Cook's distances, none of the studies were identified as having too much influence. Both the rank correlation and regression tests didn't indicate any funnel plot asymmetry, with p-values of 0.772 and 0.328 respectively.

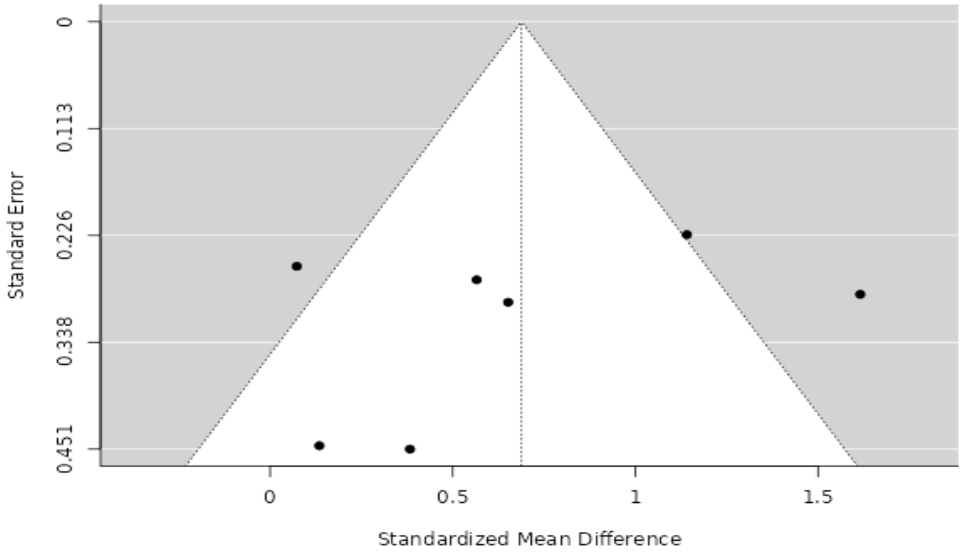
In addition, studies on healthcare system efficiency show a generally positive effect. The effect is statistically significant (RE model: 0.69). The most consistent positive effect was provided by Ahmed (2018) and Storto & Goncharuk (2017) (Graphic 1).

Table 3. Heterogeneity Statistics

Tau^2	I^2	H^2	R^2	df	Q	p
0.2287 (SE= 0.1887)	72.11%	3.586	.	6.000	22.051	0.001



Graphic 1. Forest Plot



Graphic 2. Funnel Plot

Checking for publication bias is a key step in meta-analysis. To do this, the study used a funnel plot and the Begg and Mazumdar rank correlation test (see Table 4). The funnel plot in Graphic 2, along with the statistical results from the Begg and Mazumdar test in Table 3 ($p > 0.05$), show that there is no sign of publication bias.

Table 4. Publication Bias Assessment

Test Name	value	p
Fail-Safe N	93.000	< .001
Begg and Mazumdar Rank Correlation	-0.143	0.773
Egger's Regression	-0.977	0.329
Trim and Fill Number of Studies	1.000	.

4. CONCLUSION, DISCUSSION AND RECOMMENDATIONS

The way health systems use their resources efficiently helps make the most of health results, and it also builds trust because people know their money is being used well to meet their health needs. Making health systems more efficient can save money and help provide more health services to more people (Cylus et al., 2016). This shows how important it is for health systems to be technically efficient. In this case, the goal of this study is to look at how efficient different health systems are by carefully going through the results of existing research. The study aims to find out and assess the levels of technical efficiency in health systems based on the different models that have been used.

After reviewing the relevant literature related to the study's purpose, a meta-analysis was carried out using seven articles. During this process, a heterogeneity test was done, and the random effects model was chosen as the appropriate approach. The differences in effectiveness scores were shown visually through a forest plot and a funnel plot. Publication bias was also checked. The results of the analysis showed that the standardized mean differences across different models were statistically significant. The Q-test indicated that the results were heterogeneous. In the end, the analysis found no evidence of publication bias.

In DEA applications, efficiency scores vary because CRS and VRS models have different approaches to scale (Taboada et al., 2020). VRS generally yields higher scores by separating technical efficiency from scale effects and acknowledging that units can operate under different scale returns (Mirmozaffari & Kamal, 2023; Cook et al., 2014). While CRS is suitable for fixed-scale comparisons, VRS is suitable for examining technical efficiency adjusted for scale effects (Podinovski, 2004). Scores vary depending on the model used (İlgün et al., 2022), and empirical comparisons show that the differences between CRS and VRS are significant but generally limited (Suin-Guaraca, 2023). According to the findings obtained because of the analysis conducted within the scope of the research, it was determined that there is a positive relationship between the average efficiency scores in the studies conducted using CRS and VRS models. This emphasizes the complementary features of the models.

While the CRS model evaluates efficiency scores under the assumption that all decision units operate at the same scale, the VRS model offers a more flexible assessment by considering changes in economies of scale. The positive relationship between the efficiency scores of these two models generally indicates that high-performing units perform well under both fixed and variable scale conditions (Zarrin & Brunner, 2023). Moreover, this finding suggests to researchers and practitioners that it is valuable to include both models in the analysis process. Both approaches provide effective evaluations from different perspectives. This finding indicates an important understanding of the confirmatory nature of models. The agreement between CRS and VRS models increases the reliability of RIA analyses and reinforces the validity of the results. Moreover, this positive relationship indicates that both models can be useful in the performance evaluation processes of systems. Especially in terms of management and strategic planning, a more comprehensive and balanced analysis can be made when the results of both models are evaluated together. This can also provide guidance for efficiency enhancement and improvement efforts (Podinovski, 2004).

The findings of the study show that the analyzed studies generally show a positive effect and that this effect is statistically significant. The use of the random effect model provides more reliable and generalizable results by considering the heterogeneity in the studies (Borenstein et al., 2009). As a result, this analysis reveals that the overall effect of the evaluated studies is positive and statistically significant.

Increasing efficiency in health systems can contribute to more effective use of resources and improved patient care. The consistency and positive results of the studies analyzed provide important guidance for future research and health policymaking. This meta-analysis reveals that improving technical efficiency in health systems is an important and achievable goal.

The findings indicate that improving technical efficiency in healthcare systems can enhance resource utilization and strengthen patient care. Recommendations for policymakers and managers are as follows: both CRS and VRS results should be reported together in performance evaluations to distinguish between technical and scale-related inefficiencies; data quality, input/output selection, and scale effects should be considered when designing efficiency-enhancing interventions; capacity/scale optimization and targeted resource reallocation should be implemented for units where scale-related inefficiencies are identified.

Future studies should develop standardized input/output definitions and reporting practices; promote sensitivity methods such as bootstrap and random effects meta-regression; conduct longitudinal (panel) DEA analyses, comparisons of network/metafunctional DEA approaches with SFA; prioritizing disaggregated analyses for regional and income level subgroups and experimental/pilot studies measuring the effects of efficiency-enhancing interventions would be beneficial.

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