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Review

Efficiency Measurement Using Data Envelopment Analysis (DEA) in Public Healthcare: Research Trends from 2017 to 2022

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Abstract: With the shifting healthcare environment, the importance of public healthcare systems is being emphasized, and the efficiency of public healthcare systems has become a critical research agenda. We reviewed recent research on the efficiency of public healthcare systems using DEA, which is one of the leading methods for efficiency analysis. Through a systematic review, we investigated research trends in terms of research purposes, specific DEA techniques, input/output factors used for models, etc. Based on the review results, future research directions are suggested. The results of this paper provide valuable information and guidelines for future DEA research on public healthcare systems.

Keywords: healthcare; DEA; systematic review; efficiency; productivity; medical resource

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1. Introduction

The aging population and low birth rate have led countries facing population de-cline to consider the option of immigration to maintain a stable workforce [1]. However, welcoming immigrants also brings about increased government spending on public health coverage [2]. Therefore, stakeholders are seeking ways to allocate medical resources efficiently and operate medical institutions effectively to optimize the use of the government's public health budget [3]. In light of the COVID-19 pandemic, the significance of public healthcare systems has been further emphasized, and research in this area has gained more attention [4–6]. Many countries are trying to establish a public healthcare system that can effectively cope with the pandemic. With this shifting healthcare environment, great attention is being paid to the efficient allocation and utilization of limited medical resources [4].

For the successful management and effective operation of the public healthcare system, objective and accurate measurement of the efficiency of the public healthcare system is required. When the level of efficiency of the system is objectively and properly diagnosed, problems can be identified and solutions can be developed based on them. Efficiency has long been an important research area in operations and service management. Researchers have been using several methods to measure efficiency. Data Envelopment Analysis (DEA) is one of the most widely adopted techniques, and DEA is a non-parametric method that has been used to measure the efficiency of various social and economic systems [5]. Through DEA, the efficiency of a Decision-Making Unit (DMU) can be measured and the levels of efficiency of different DMUs can be compared [7]. Research on the public healthcare industry has also employed DEA to analyze the efficiency of healthcare systems. Ever since [8]'s initial study that measured the efficiency of nursing services using DEA, various studies analyzed efficiencies using DEA in the healthcare industry [9,10]. Applying the efficiency concept to the healthcare industry, which is based on the primary public interest of human health, is by no means straightforward [11]. However, many researchers have successfully conducted empirical studies analyzing the efficiency of healthcare services and systems using DEA [11]. DEA has now been positioned as a leading method for efficiency analysis in the public healthcare sector [11,12], and healthcare research has become one of the research areas that most actively uses DEA [12,13].

As a result, there has been a gradual increase in the use of the DEA method to measure the efficiency of the public health field. With the recent COVID-19 crisis, the importance of measuring efficiency in the public health sector is expected to increase even further. Therefore, we review the recent studies in the public healthcare area that analyzed the efficiency using DEA. Through a systematic review, we understand the trend of efficiency research in the healthcare area. Specific research purposes for efficiency analysis in the healthcare industry and unique techniques of research methods are identified. Specifically, this research aims to address the following questions.

- What is the recent trend of efficiency research using DEA in the public healthcare sector?
- What is the popular selection and development of DEA models to analyze the efficiency of public healthcare?
- What subject has been examined in the recent DEA-based public healthcare research?

However, due to the pandemic, the medical industry is experiencing rapid changes, which emphasize the importance of efficient allocation of medical resources and require research from a different perspective than previous studies. Therefore, noting the difficulties of healthcare system management due to the pandemic and the efficiency issues that have emerged as a result, we focus on recent studies. By reviewing the efficiency studies that were published over the past 6 years, between 2017 and 2022, we identify the specific purposes of efficiency analysis of healthcare systems and the technical specificity to which DEA is applied. Based on the review results, directions for efficiency research that can help establish an effective healthcare system are suggested. Our research offers valuable insights into DEA techniques and the topics for efficiency re-search within the public healthcare field. The findings of our review can aid future studies in accurately diagnosing the efficiency of healthcare systems and identifying various factors that impact it. Additionally, our study highlights the current state of the use of DEA models in the public health sector, providing guidance to researchers who aim to develop more in-depth DEA models. With reference to the results of our study, it is possible to apply advanced DEA models to the public health field.

In the following, chapter 2 explains the selection process of the papers for review in this research, and chapter 3 categorizes the papers and summarizes the latest research trends through a detailed review. In chapter 4, we discuss the implications and meanings of the review results. Conclusions of the review and future research directions are suggested in chapter 5.

2. Search Process

For a systematic review, we first selected studies in the healthcare area that analyzed efficiency through DEA between 2017 and 2022. In this process, we followed the flow of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [14] for a clear and reliable review (Figure 1). Research papers were searched on Web of Science, Science Direct, Scopus, and Google Scholar using the keywords "public healthcare", "efficiency", and "data envelopment analysis." This also includes research from various publishers, including Elsevier, Emerald, Wiley, Springer, Taylor Francis Online, and the Multidisciplinary Digital Publishing Institute (MDPI). Through this process, a total of 934 research papers were collected. Then, we reviewed the abstracts of the 496 papers collected and excluded the papers whose main analysis subject did not belong to the public healthcare industry and papers published in non-periodical publications (e.g., books). Review papers were also excluded. Through this process, 255 papers were selected. After reviewing these 255 papers in detail, papers using efficiency analysis techniques other than DEA, such as Stochastic Frontier Analysis (SFA), were excluded. Lastly, considering the unity of the analysis level, we excluded the papers that included the efficiency of the public healthcare industry as one of the sub-fields for the administrative districts' (e.g., country, state, and province) efficiency which was the papers' main purpose of investigation. Among the last excluded literature, 14 review papers on the efficiency of public healthcare and medical systems using DEA were present. Through this screening process, 123 articles were finally selected for review.

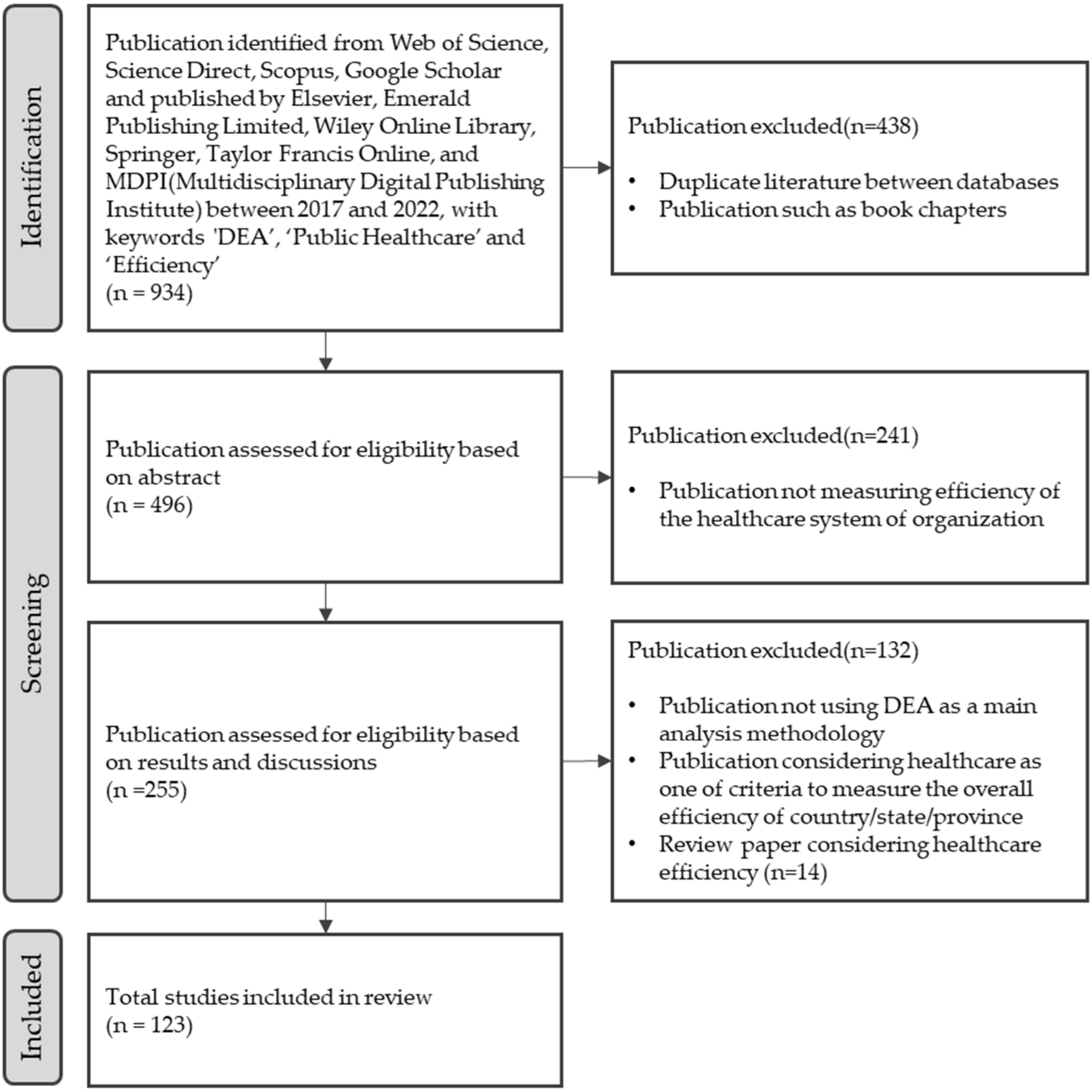

Figure 1. Selection process based on PRISMA.

3. Results

The papers selected were thoroughly reviewed, and the number of papers was ag-gregated the detailed criteria for each category specified in the research framework (Figure 2). The four categories in the framework are General, Research Purpose and Meth-ods, DMU and Variables, and Regions and Public Analysis subjects. These criteria can be grouped into three areas: (1) research characteristics, (2) DEA technical aspects, and (3) properties of analysis subjects.

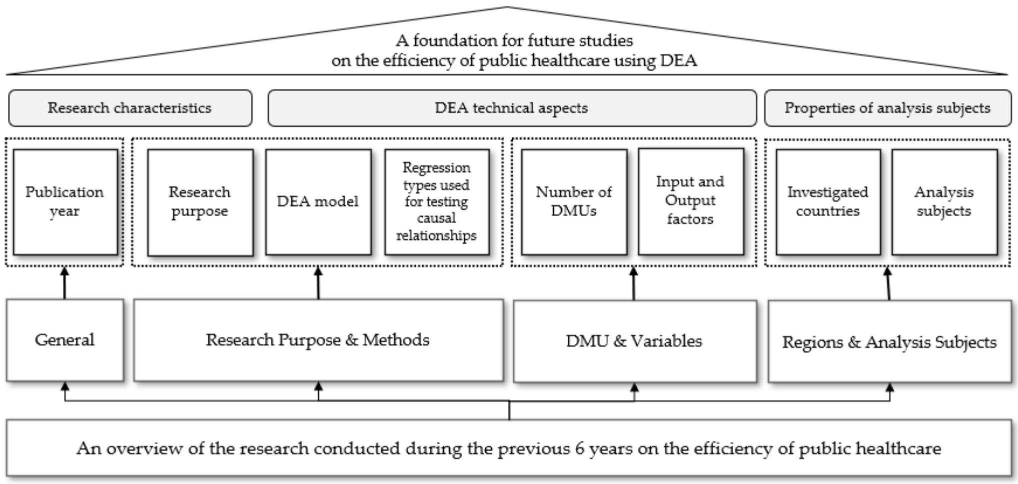

Figure 2. Conceptual research framework.

As presented in Table 1, the number of studies analyzing the efficiency of using DEA in the public healthcare industry has been continuously increasing. In particular, the research has been active since 2020. In contrast, a total of 40 papers (32.53%) were published until 2020, 21 papers (22.92%) were published in 2020 when the COVID-19 pandemic was declared, 35 papers (39.58%) were published in 2021, and 27 papers (21.95%) were published in 2022. This shows that COVID-19 has greatly increased researchers' interest in the issue of efficiency in the public healthcare industry [4,5]. The specific results of the review of the selected papers are as follows.

Table 1. Publications per year.

Year	# of Publications	%
2022	27	21.95%
2021	35	28.46%
2020	21	17.07%
2019	16	13.01%
2018	12	9.76%
2017	12	9.76%
Total	123	100.00%

3.1. Research Purposes & Methods

The purpose of the studies was divided into five types (Table 2). The first was to compare the efficiency between DMUs. This corresponds to the most general purpose of efficiency studies using DEA. The majority of selected studies were conducted for this purpose. The second purpose was the identification of the variables affecting the efficiency and the empirical testing of the causality. Studies with this purpose went one step further than simply measuring the efficiency of different DMUs. These studies identify factors affecting efficiency and conduct statistical analyses to prove the causal relationship between the factors and efficiency. The third type of purpose was the methodological improvement of DEA. Studies with this purpose focused on developing a new DEA model using advanced techniques and/or combining DEA with other theories. By applying the developed model to healthcare data, the studies demonstrated the validity of the developed model. For example, [15] suggested a new model by applying game theory and K-means cluster analysis to the traditional DEA model. [16] proposed a new model through an application of team theory. The fourth was to investigate the changes in efficiency over time. DEA analysis using cross-sectional data allows only a comparison of efficiency between DMUs at a specific time period. On the other hand, studies investigating the changes in efficiency over time analyze panel data and find the trend of efficiency changes as time passes. These studies evaluate whether efficiency is improving or deteriorating over time, and the trend of efficiency change is compared between different DMUs. The last are public health studies that do not fall under the above four.

Table 2. Research purpose.

Research Purpose	# of Publications
Identifying factors affecting efficiencies or analyzing the relationship between efficiencies and key factors	83
Comparing efficiencies between DMUs	70
Analyzing changes in efficiency over time	18
Other Public Health Considerations	10
Exploring new DEA approaches	6
Total	188

Note: As many papers have multiple purposes, the total number of publications is larger than the sample size.

Table 2 shows the five types of research purposes and the number of studies that addressed each purpose. Quite a number of studies addressed multiple purposes; thus, the total number of studies exceeds the sample size. For example, many studies have aimed not only to compare the efficiency between DMUs but also to identify factors leading to the differences in efficiency between DMUs. Some studies conducted cross-sectional analysis for a specific time period to measure and compare the efficiency of different DMUs and then also analyzed the efficiency changes over time to investigate efficiency trends over time.

We identified specific techniques that were used in the reviewed papers. Table 3 shows the diverse DEA techniques used in the studies and the number of studies that use each technique. As many studies adopted multiple techniques, the total number of studies exceeds the sample size. The basic DEA model was the most widely adopted. The basic DEA model is divided into the Charnes-Cooper-Rhodes (CCR) vs. Banker-Charnes-Cooper (BCC) models according to its assumptions related to returns to scale [17,18]. Simple BCC and Simple CCR were employed in a total of 19 and 14 studies, respectively.

Table 3. DEA model.

DEA Model	# of Publications
Simple CCR	55
Simple BCC	45
Network DEA	20
Bootstrapping	17
Slack-Based Measure	13
Super Efficiency	7
Metafrontier	7
Malmquist Index/Window DEA	7
Dynamic DEA	6
Directional Distance Functions	4
Context-dependent DEA	3
Etc.	3
Total	187

Note: As many papers employed multiple DEA models, the total number of publications is larger than the sample size.

In order to overcome the limitations of the simple CCR/BCC models, modified DEA models such as the Slack-Based Model [10,19–21], Supper Efficiency model [22–24], the Network-DEA model [25–27], and the Bootstrapping model [28–31] were also employed. Directional Distance Function, which is a more generalized form than the Radial model, was also adopted [10,11,32]. The Metafrontier model, which calculates efficiency by constructing a single efficiency frontier for the entire data composed of groups with different characteristics, was also used [27,32,33]. Studies that analyzed panel data used the techniques of the Malmquist Index [32,34–36] and Window-DEA [5], as well as the

Malmquist-Luenberger index, which is a more advanced technique of the Malmquist Index [37]. Besides these techniques, the use of the latest DEA techniques, such as Dynamic DEA [38,39], context-dependent DEA [40,41], and game-cross efficiency model [15,42] were also witnessed. These techniques were counted as etc. Many studies adopted multiple techniques simultaneously to analyze scale efficiency by comparing the results of applying the CCR and BCC models or to compare the differences in efficiency according to different techniques [27].

The studies aimed at identifying variables affecting efficiency, after deriving efficiency scores and performing regression analysis using various factors that can affect efficiency as independent variables and efficiency scores as dependent variables. We summarize the regression types that were used for testing causal relationships in Table 4. Since these studies use the efficiency scores as the dependent variable, there is a constraint that the value of the dependent variable cannot be less than 0. Therefore, Tobit regression, or truncated regression, was mostly performed. Besides these, Ordinary Least Squares (OLS) regression [20,29,43], Generalized Linear Mixed Model (GLMM) regression [44], Logistic regression [30], Spatial Durbin Model [45], and multilevel zero-one inflated beta regression [37] were also used to verify the causal relationship between efficiency and independent factors.

Table 4. Regression types used for testing causal relationships.

Regression Types	# of Studies
Other regressions (OLS, GLMM, Logistic regression, SDM, etc.)	22
Tobit regression	21
Truncated regression	7
Etc.	41
Total	91

3.2. DMUs & Variables

The number of DMUs used for analysis was also investigated (Table 5). The number of DMUs plays an important role in the validity of the analysis in DEA studies. As the number of DMUs increases, the chance of capturing high-performance DMUs that determine the efficiency frontier also increases, and thus the accuracy of the analysis can be improved [46]. Previous literature provides guidelines about the appropriate size of DMUs for DEA. The appropriate number of DMUs is closely related to the number of input and output variables used in the DEA model. For the minimum number of DMUs, [47] suggested twice the sum of the number of input and output variables. [48] suggested that it should be three times bigger. As shown in Table 5, about 85.37% of studies used 100 or fewer DMUs, and 74.80% used 50 or fewer. Studies used 20 or fewer were 27.64%. The minimum number of DMUs analyzed in one time period was counted for studies using panel data. The result shows that, due to limitations in data, securing a sufficient number of DMUs is difficult.

Table 5. Number of DMUs.

# of DMUs	# of Publications	%
≤ 20	34	27.64%
$20 < \quad \leq 50$	58	47.15%
$50 < \quad \leq 100$	13	10.57%
$100 < \quad \leq 200$	6	4.88%
$200 < \quad \leq 50$	3	2.44%
$500 < \quad \leq 70$	2	1.63%
$700 < \quad \leq 1000$	4	3.25%
$1000 <$	3	2.44%
Total	123	100.00%

We identified the input and output factors that were used to calculate efficiency scores in the reviewed papers. In order to perform DEA, input and output factors have to be decided. The selection of appropriate input and output factors is important as it determines the measurement validity of whether the efficiency is correctly calculated. Diverse variables are used for input and output factors and can be classified into several types. [49] reviewed 172 papers that analyzed the efficiency of healthcare systems and divided input factors into physical inputs vs. financial inputs, and output factors into healthcare services-related outputs vs. healthcare outcomes-related outputs. Recently, [50] also reviewed 262 papers that calculated the efficiency scores of healthcare systems. They classified input factors into 12 categories and output factors into 9 categories. Input factor categories include beds, medical staff, nurses, non-medical staff, overall staff, supplies, equipment and infrastructure, total costs, service and performance, socio-economic, and others. Output factor categories were outpatients, other/total cases, inpatients, surgery, services, performance/quality, revenue, case mix, and others. We reviewed input/output factors and classified the identified factors into 10 input categories and 13 output categories, referring to the previous studies (Tables 6 and 7).

Table 6. Input factors.

Input Factor Category	# of Uses
Number of medical staff	81
Number of beds	72
Number of non-medical staff	56
Costs and Expenditure	45
Number of overall staff	33
Assets	32
Macroeconomic factors (e.g., population)	16
Budgets and investment	10
Number of hospitals and healthcare centers	8
COVID-19 specific factors	6

Table 7. Output factors.

Output Factor Category	# of Uses
Number of outpatients	63
Number of inpatients	62
Healthcare outcomes	42
Length of stay and hospitalization	26
Number of surgeries	18
Emergency services	18
Financial factors other than revenue and profit (e.g., EBITDA)	15
Bed occupancy rate	13
Counseling and medical consultation	11
COVID-19 specific factors	6
Revenue and profit	4
Number of hospitals and healthcare centers	4
Etc.	29

The identified input factors were categorized into: (1) number of medical staff, (2) number of beds, (3) number of non-medical staff, (4) costs and expenditures, (5) number of overall staff, (6) assets (e.g., supplies, equipment, infrastructure, etc.), (7) macroeconomic factors (e.g., the population, population covered by medical care, etc.), (8) budgets and investments, (9) number of hospitals and healthcare centers, (10) COVID-19 specific factors (e.g., number of quarantine centers, number of people quarantined, etc.). Among these, the most used input factors were those belonging to labor-related categories, such as the number of medical staff (number of uses: 81) and the number of non-medical staff (number of uses: 56). Input factors related to physical assets, such as those belonging to assets (number of uses: 32) and beds (number of uses: 72), were also frequently used. Financial factors belonging to the categories of costs and expenditures (number of uses: 45) and budgets and investments (number of uses: 10) were also used.

The identified output factors were categorized into (1) number of inpatients (e.g., number of inpatients, number of discharges, etc.), (2) number of outpatients (e.g., number of outpatients, number of visits, etc.), (3) healthcare outcomes (e.g., death rate, life expectancy, survival rate, malnutrition rate, etc.), (4) length of stay and hospitalization, (5) number of surgeries, (6) emergency services, (7) financial factors other than revenue and profit (e.g., EBITDA), (8) bed occupancy rate, (9) counseling and medical consultation, (10) COVID-19 specific factors (e.g., number of recoveries, number of positive cases, etc.), (11) revenue and profit, (12) number of hospitals and healthcare centers, and (13) etc. The factors belonging to the number of inpatients (number of uses: 62) and outpatients (number of uses: 63) were the most widely adopted output variables. Factors related to healthcare outcomes were also frequently used (number of uses: 42). This means how many outpatients and inpatients are treated and how many surgeries are performed are the most important criteria to evaluate the efficiency of public healthcare systems. Some studies used unique output factors suitable for their research purposes. These factors include items dispensed [27], time for diagnosis or treatment [42], the number of medical disputes [51], satisfaction with the public healthcare system [52], the number of family planning participants in healthcare centers [53], the number of diagnostic procedures [36], and the number of residents [24]. These factors were classified as etc.

3.3. Regions and Analysis Subjects

The studies showed variations in the countries analyzed (Table 8). The studies were divided into multi-country studies and single-country studies. A total of 16 studies (13.01%) analyzed data from multiple countries. For example, [31] analyzed data from 38 countries that are members of the Organization for Economic Cooperation and Development (OECD). [54] analyzed data from 15 European Union (EU) member countries. [21] analyzed data from 21 emerging countries. [19] and [55] analyzed data from multiple countries that belong to OECD. [25] analyzed data from 34 developing Asian countries. [11] analyzed 185 regions in 17 European countries, and [10] analyzed 181 WHO member countries. The remaining 107 studies analyzed the efficiency of healthcare systems or services within a single country. Many papers analyzed data from Asian countries. In particular, 30 (28.04%) papers analyzed China's public healthcare systems. Single-country studies include the studies that investigated Iran, Brazil, and Taiwan.

The public healthcare industry is broad and includes various sub-sectors. It includes various fields such as medical device manufacturing, pharmaceuticals, medical insurance, as well as traditional medical services that provide medical care to patients. We investigated, among the broad healthcare industry, which specific areas were analyzed in the selected papers. As shown in Table 9, the subjects of 57 (83.74%) studies were hospitals and the healthcare system. 'Healthcare system' refers to the entire system for delivering healthcare services to the target population and was allocated when the overall efficiency of countries/states/provinces was analyzed. After COVID-19, studies analyzing the efficiency of the responses to COVID-19 were published [26,55,56]. The efficiency of pharmacy [27] and healthcare resource allocation [16,42] were also analyzed. Besides these studies, studies that analyzed healthcare tourism efficiency [54], healthcare policy, and healthcare employment contract efficiency [55,57] were also found (these studies were assigned to "etc." in Table 9).

Table 8. Investigated countries.

Country	# of Publications	%
Brazil	5	4.67%
Chile	1	0.93%
China	30	28.04%
Czech Republic	1	0.93%
Ecuador	1	0.93%
Egypt	1	0.93%
Greece	1	0.93%
Hungary	1	0.93%
India	4	3.74%
Indonesia	1	0.93%
Iran	7	6.54%
Italy	1	0.93%
Japan	1	0.93%
Jordan	1	0.93%
Kenya	2	1.87%
Kosovo	2	1.87%
Malaysia	3	2.80%
Mexico	1	0.93%
Middle East	2	1.87%
Morocco	1	0.93%
New Zealand	4	3.74%
Norway	1	0.93%
Pakistan	1	0.93%
Poland	2	1.87%
Portugal	2	1.87%
Saudi Arabia	2	1.87%
Serbia	1	0.93%
Slovakia	1	0.93%
South Africa	5	4.67%
South Korea	1	0.93%
Spain	3	2.80%
Taiwan	5	4.67%
Tanzania	1	0.93%
Tunisia	2	1.87%
Turkey	4	3.74%
The U.S.	4	3.74%
Zimbabwe	1	0.93%

Table 9. Analysis subjects.

Subjects	# of Publications	%
Hospitals	57	46.34%
Overall healthcare system/network	46	37.40%
Resource allocation	9	7.32%
Responsiveness to COVID-19	5	4.07%
Etc.	5	4.07%
Pharmacy	1	0.81%
Total	123	100.00%

4. Discussion

We reviewed recent studies that used DEA to analyze efficiency in the public healthcare industry. The number of studies published after 2020 accounted for 67.48%, showing that many researchers are paying attention to the efficiency issue in the public healthcare systems. Through a systematic review, the following research trends were identified.

First, the research purposes of the investigated papers were classified into four categories: efficiency comparison between DMUs, identification of variables affecting efficiency and test of causality, methodological advancement of DEA, and investigation of the changes in efficiency over time. The purpose most frequently addressed was the comparison of the efficiency of DMUs. There were also many papers that aimed to find the variables affecting efficiency. Papers that trace changes in efficiency over time using panel data were also found. These papers investigate efficiency trends over time using the Malmquist Index or Window-DEA method. By examining the improvement or deterioration of efficiency, these papers can provide public healthcare providers and policymakers with more detailed guidelines for productivity management. Many papers addressed two or more research purposes simultaneously. Rather than just measuring the efficiency of DMUs, many papers also identified factors affecting the efficiency. These papers conducted statistical analyses to examine causal relationships between independent factors and efficiency scores, and suggest solutions for efficiency improvement.

Diverse, specific DEA techniques were also identified. While most studies used simple CCR or BCC models, modified DEA models such as the Slack-Based Model, the Supper efficiency model, the Network-DEA model, the Bootstrapping model, and the Metafrontier model were also employed. In addition, new DEA application techniques, such as Dynamic DEA [38] and context-dependent DEA [41], have been developed. It was also noteworthy that the combination with other research methods is increasing. By applying Game theory [15,58], Propensity Score Matching (PSM) [30], Social Network Analysis (SNA) [57], etc., new models were developed and advanced analyses were tried, indicating the maturation of DEA as a research method. Figure 3 is a word cloud containing several DEA techniques in 123 documents. The word cloud on the left shows DEA, the primary analysis method, and the word cloud on the right shows follow-up methodologies.

Figure 3. Word-cloud of DEA Methods (**Left**) and Post-hoc Analysis (**Right**).

The combination with statistical analyses to test causal relationships was also conspicuous. Diverse regression analyses were conducted after efficiency scores were calculated. These studies show that, beyond measuring efficiency, DEA research can provide concrete and practical guidelines to improve the productivity of public healthcare systems by identifying factors affecting efficiency.

Input and output variables and DMU numbers were identified as being important to the validity of the analysis in DEA research. 10 categories of input factors corresponding to major resources in public healthcare systems and 13 categories of output factors corresponding to critical performance measures in healthcare systems were identified. For input variables, labor-related variables, including the number of medical staff and non-medical staff, were most widely used. For output variables, the number of inpatients, outpatients, and healthcare outcomes played important roles. 68.08% of research was conducted with fewer than 50 DMUs, implying the difficulties in securing enough DMUs for analyses. This raises the need for systematic management of healthcare system data.

Papers showed variations in terms of regions investigated. In particular, there were many studies that analyzed data from Asian countries such as China, Taiwan, and India. This shows that Asian countries are increasingly concerned with the efficiency of their public healthcare systems. The efficient use of medical resources and high-quality medical services are becoming more important as people's welfare improves in Asian countries where the economy has grown.

Figure 4 shows a Map Chart corresponding to the number of studies by country. Many studies are distributed in emerging economies rather than developed countries on the map chart. Developed countries were mainly dealt with in comparative studies between countries using OECD and WHO data [31,54,55,59–61]. In Europe, comparative studies were conducted between regions within the EU, and US studies were conducted on private medical insurance and private medical systems [62–66].

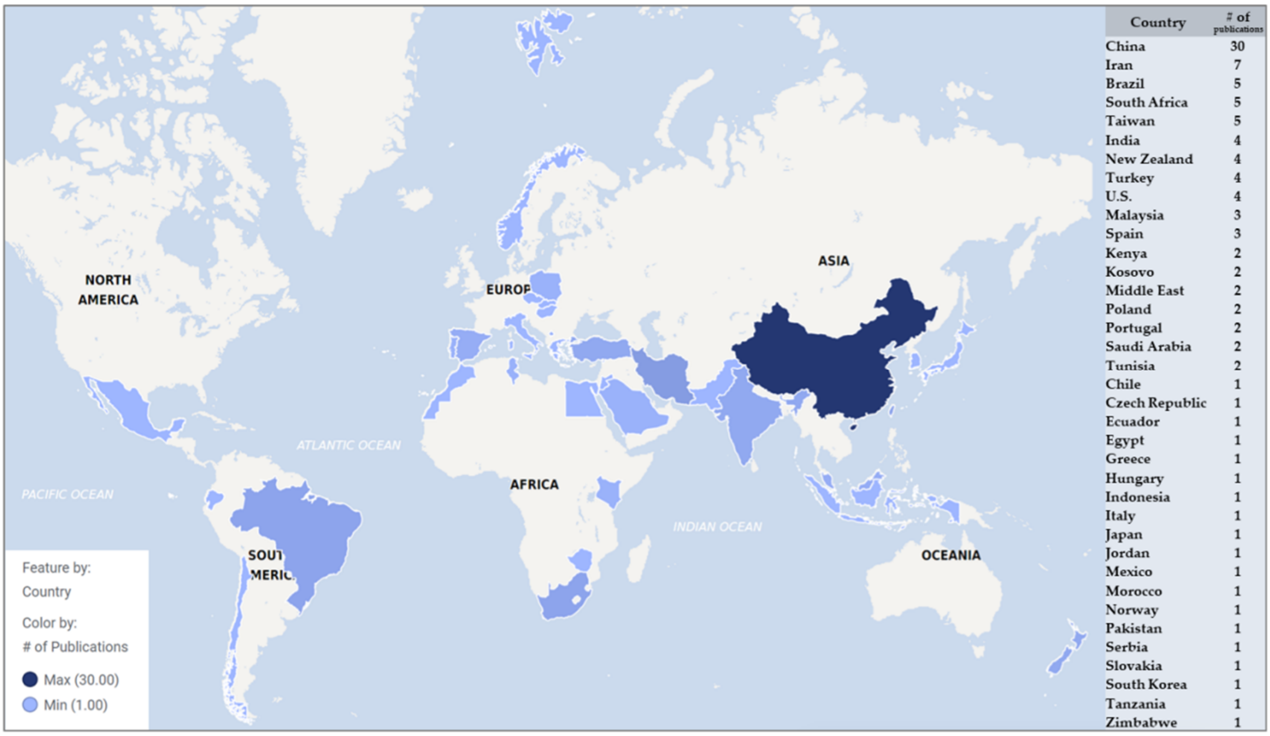

Figure 4. Map chart by the number of publications.

Research on China has been actively conducted from 2017 to 2022, and the number of studies has increased. Since China's Public Health Care Reform in 2009, several studies have been conducted to compare regions or measure changes over time to analyze the efficiency changes and effects of hospitals and regional medical systems. [67–69]. In particular, studies have shown that rural areas need new policies for government financial assistance because the imbalance is more significant than in urban areas. In addition, detailed studies were conducted on pediatric public healthcare [67], allocation of medical personnel and clinical departments [70], and comparative studies on efficiency according to hospital type and size. In addition [52], comparative research on regional efficiency was conducted concerning the COVID-19 quarantine system due to the reform of China's public health system in 2009 [71].

The following most active research country is Iran. Studies comparing public hospitals between teaching hospitals and non-teaching hospitals [72], comparing COVID-19 quarantine efficiency between hospitals [73], allocating intensive care unit human resources [74], and the rest of the studies have analyzed the efficiency of local public hospitals. Research on Brazil has been conducted for three consecutive years in 2019, 2020, and 2021 and deals with public hospitals [75] and COVID-19 quarantine resource allocation [76]. Individual country studies mainly deal with studies on whether government support budgets for public health are efficiently operated in each region and hospital. Most research results mention preparing detailed financial support policies to alleviate regional imbalances. In particular, in rural areas, it is concluded that the inefficiency of the public health system is high and that more careful attention is needed.

While health needs and expenditures in the conflict zones, such as Palestine, Kosovo, and Jordan, are growing, international donations are declining. Evaluating the productive efficiency of public hospitals is becoming increasingly critical [77–80]. Figure 5 shows the number of publications by country and year. China has been publishing research steadily for six years. Iran and Spain have been undergoing for the last four years (2019–2022), and India has been continuously researching for four years, but research has not been conducted since the end of COVID-19 in 2022. Most of the remaining countries had a single-year study, so the continuity of research needed to be higher.

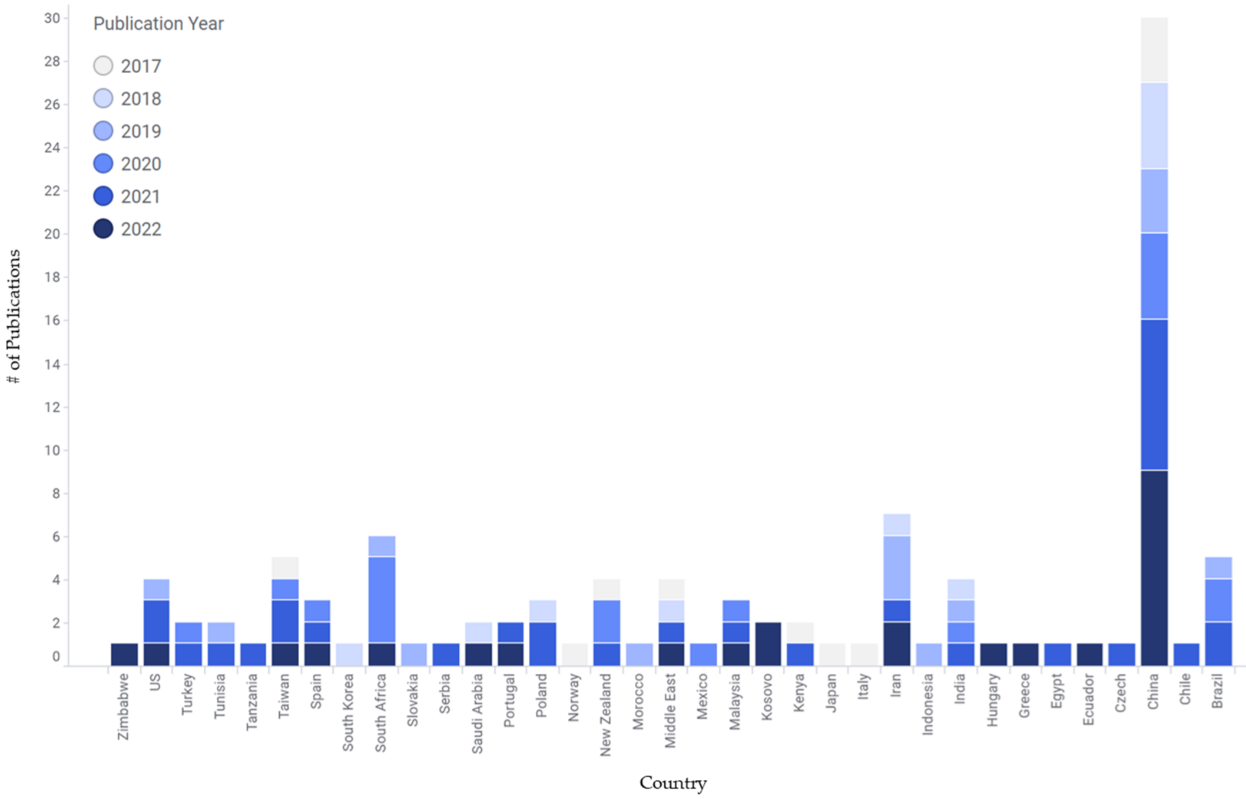

Figure 5. Number of publications by Countries and Year.

In terms of specific subjects of efficiency analysis, most of the studies analyzed the efficiency of traditional hospitals and general healthcare systems. A wide range of areas is included in the public healthcare industry. Other than traditional healthcare services and systems, diverse subjects need to be further investigated. For example, digital healthcare is rapidly growing. In order to contribute to building an efficient public healthcare system that can cope with the future pandemic successfully, future research needs to include these new healthcare service formats. During the pandemic, the problem related to vaccine and new drug development, supply, and distribution was another important issue. Thus, research on an efficient medical supply chain is also needed.

5. Conclusions

In light of population changes such as low birth rates and aging, the efficient operation of the public health system will be increasingly crucial in the future [1,81]. In addition, many countries are suffering from a shortage of medical resources and experiencing difficulties in providing efficient healthcare services after the COVID-19 outbreak. With this shifting healthcare environment, the importance of public healthcare systems is being emphasized. Now, how to manage public healthcare systems more efficiently and utilize medical resources in a better way has become a critical research agenda [35]. As such, there is a growing need for active research aimed at improving the efficient utilization of medical resources and developing effective healthcare systems.

Therefore, we reviewed recent research on the efficiency of public healthcare systems so that related research can be conducted more actively. We also investigated research trends through a systematic review and found that a total of 123 papers were selected after a rigorous selection process. The findings of this study provide valuable information for conducting DEA in the healthcare research area. First, we showed how the DEA method can be used in the public healthcare research area by clarifying the purposes of recent DEA papers. The majority of studies used DEA to analyze efficiency, identify factors influencing efficiency, and examine efficiency trends over time. Second, by identifying various DEA techniques, methodological guidelines for future research were provided. Simple CCR or BCC models were still widely used, but more complex models were increasingly applied to improve efficiency measurements. Third, the number of DMUs used in DEA analysis and the types of input and output variables were revealed through our review. These findings will provide a useful reference for collecting data and developing DEA models in the public healthcare industry. We also took a closer look at the geographical origin of the studies and found a significant amount of them come from Asia. It is anticipated that efficiency studies in the public health sector will be conducted more actively in developing countries that are currently experiencing increasing demand for public healthcare services. The findings suggest that further research is needed to develop and apply DEA models to analyze the efficiency of public healthcare systems in these countries, which may have unique characteristics and challenges. Lastly, in terms of subjects, research was mostly conducted on hospitals, healthcare system, or networks, and issues related to resource allocation and COVID-19 responsiveness. In addition to the traditionally widely studied subjects of hospitals and healthcare systems, it was found that new topics such as efficiency related to pandemics, specifically COVID-19, have emerged.

To further advance efficiency research in the public healthcare area, there are two directions for possible expansion. The first direction involves expanding the DEA methodology. This may include the use of advanced DEA models, such as network DEA or Metafrontier DEA, to measure the efficiency of public healthcare systems. Future research may explore the combination of DEA with other methods, such as stochastic frontier analysis (SFA) or game theory, to further enhance the accuracy and relevance of measuring the efficiency of public healthcare systems.

Another direction is to expand policy and management topics in the public health sector. First, it is necessary to examine the efficiency of public and private medical care by country beyond the regional level. Existing public health research is conducted around the impact of government-level support on regional imbalances. Although some studies have conducted efficiency comparison studies between public and private hospitals [29,82,83], a cross-country comparison has yet to be made. Second, since few studies analyze efficiency changes over time regarding COVID-19, it is also necessary to compare public health efficiency before and after COVID-19. In order to better prepare for future pandemics, research is also needed to identify factors that effectively mitigate the devastating impact of COVID-19. Finally, as various new types of healthcare systems, including digital healthcare,

are growing, future research on the efficiency of new healthcare systems is needed. It is also worth examining the efficient healthcare supply chain from a broad perspective that covers the entire public health network.

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