Hacettepe Journal of Health Administration, 2025; 28(2), 277-292

https://doi.org/10.61859/hacettepesid.1637590

RESEARCH ARTICLE

AN INVESTIGATION INTO THE FACTORS INFLUENCING THE TECHNICAL EFFICIENCY OF PUBLIC HOSPITALS: DATA ENVELOPMENT ANALYSIS BASED ON DATA AT THE PROVINCIAL LEVEL

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ABSTRACT

This study evaluates the technical efficiency of public hospitals in Turkey using Data Envelopment Analysis (DEA) at the provincial level and identifies the factors affecting efficiency scores. Efficiency scores were calculated for 81 provinces, and multivariate regression analysis was conducted to examine the influence of healthcare infrastructure, human resources, and service delivery indicators on technical efficiency. The findings reveal that while a higher bed density (beds per 10,000 population) positively impacts efficiency, an excessive number of intensive care beds and qualified hospital beds have a detrimental effect on efficiency. This province-based and comprehensive study takes into account the structural differences among regions in Turkey and employs k-means clustering analysis to classify provinces according to their efficiency patterns. Furthermore, by identifying key determinants through regression analysis, the study provides concrete intervention areas for policymakers and healthcare administrators. Thus, this research offers a data-driven and management-oriented evaluation of hospital efficiency specifically within the Turkish healthcare system and delivers original findings that can support regional planning, resource allocation, and service optimization strategies for those working in the field of health management. The results emphasize the critical need to reinforce an efficiency-oriented perspective in healthcare service delivery through infrastructure optimization and effective resource utilization.

Keywords: *Technical efficiency, data envelopment analysis, Turkish health system, hospitals, health management*

ARTICLE INFO

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Recieved: 11.02.2025
Accepted: 19.06.2025

Cite This Paper:

Yorgancıoğlu Tarcan, G. & Yalçın Balçık, P. (2025). An Investigation Into The Factors Influencing The Technical Efficiency Of Public Hospitals: Data Envelopment Analysis Based On Data At The Provincial Level. Hacettepe Sağlık İdaresi Dergisi, 28(2), 277-292. https://doi.org/10.61859/hacettepesid.1637590

ARAŞTIRMA MAKALESİ

KAMU HASTANELERİNİN TEKNİK ETKİNLİĞİNİ ETKİLEYEN FAKTÖRLER ÜZERİNE BİR İNCELEME: İL DÜZEYİNDE VERİLERE DAYALI VERİ ZARFLAMA ANALİZİ

Gamze YORGANCIOĞLU TARCAN *
Pınar YALÇIN BALÇIK **

ÖZ

Bu çalışma, Türkiye'deki kamu hastanelerinin teknik etkinliğini il düzeyinde Veri Zarflama Analizi (VZA) yöntemiyle değerlendirmekte ve etkinlik düzeylerini etkileyen faktörleri ortaya koymaktadır. 81 il için verimlilik puanları hesaplanmış, ardından sağlık altyapısı, insan kaynakları ve hizmet sunumu göstergelerinin teknik verimlilik üzerindeki etkisini incelemek amacıyla çok değişkenli regresyon analizi yapılmıştır. Bulgular, yatak yoğunluğunun (her 10.000 kişiye düşen yatak sayısı) verimliliği olumlu etkilediğini; ancak yoğun bakım yataklarının ve nitelikli hastane yataklarının aşırı sayıda olmasının verimlilik üzerinde olumsuz bir etkisi olduğunu ortaya koymaktadır. Bu il bazlı ve kapsamlı çalışma, Türkiye'deki bölgeler arası yapısal farklılıkları göz önünde bulundurarak, illeri verimlilik desenlerine göre sınıflandırmak için k-ortalama (k-means) kümeleme analizini kullanmaktadır. Ayrıca, regresyon analizi yoluyla temel belirleyicileri ortaya koyarak politika yapıcılar ve sağlık yöneticileri için somut müdahale alanları önermektedir. Bu yönüyle çalışma, Türk sağlık sistemi özelinde hastane verimliliğini veri temelli ve yönetim odaklı bir yaklaşımla değerlendirmekte; sağlık yönetimi alanında çalışanlar için bölgesel planlama, kaynak tahsisi ve hizmet optimizasyon stratejilerine katkı sağlayacak özgün bulgular sunmaktadır. Elde edilen sonuçlar, sağlık hizmet sunumunda altyapının iyileştirilmesi ve kaynakların etkin kullanımı yoluyla verimlilik odaklı bir bakış açısının güçlendirilmesi gerekliliğini vurgulamaktadır.

Anahtar Kelimeler: *Teknik etkinlik, veri zarflama analizi, Türk sağlık sistemi, hastaneler, sağlık yönetimi*

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Gönderim Tarihi: 11.02.2025
Kabul Tarihi: 19.06.2025

Atıfta Bulunmak İçin:

Yorgancıoğlu Tarcan, G. & Yalçın Balçık, P. (2025). An Investigation Into The Factors Influencing The Technical Efficiency Of Public Hospitals: Data Envelopment Analysis Based On Data At The Provincial Level. Hacettepe Sağlık İdaresi Dergisi, 28(2), 277-292. https://doi.org/10.61859/hacettepesid.1637590

I. INTRODUCTION

Given the growing demand for healthcare services and the finite nature of available resources, the efficient use of existing resources has become more critical than ever. The OECD's 2024 report, emphasizes that performance assessment in health systems is essential for supporting optimal resource allocation and evaluating the achievement of key policy objectives (OECD, 2024). In order to overcome operational limitations and improve their services, healthcare organizations are increasingly compelled to measure the performance of the care they provide. As emphasized by the World Health Organization (WHO) in its 2021 report titled *Health Systems Performance Assessment: A Framework for Policy Analysis*, "Health policy-making and reform require, first and foremost, a sound understanding of how a health system is performing" (WHO, 2021). This highlights that performance assessment in health systems is not only essential for monitoring and evaluation but also serves as a strategic requirement for optimizing resource use and driving operational improvements.

Productivity, as one of the measurable dimensions of healthcare system performance, has gained increasing importance in recent years (Hollingsworth, 2008). Despite significant investments in healthcare systems across the globe, the anticipated improvements in health outcomes have not consistently been achieved. This discrepancy has drawn growing attention to the need for evaluating how efficiently health systems utilize their resources, especially in light of evolving demographic, technological, and environmental challenges. According to the OECD's renewed framework on health system performance (OECD, 2024), merely increasing financial and physical inputs is insufficient unless these resources are effectively aligned with the changing demands and systemic pressures of modern healthcare. The report underlines that enhancing system efficiency requires a broader transformation—one that encompasses stronger governance, strategic health workforce planning, and the effective integration of digital health technologies. This approach has become particularly crucial following the vulnerabilities revealed by the COVID-19 pandemic.

It is vital to get insights into the functioning of these health institutions in order to measure the efficiency of the health institutions that deliver services using these resources. By conducting an efficiency analysis, we are able to determine how well these organizations meet their goals with the fewest possible resources or produce the most they are capable of using the resources they do have (Banker et al., 1984). In addition to this, it gives useful information regarding the efficiency with which resources are utilized and the process by which inputs are transformed into outputs (Waldman, 1997). There is an increasing demand for medical services despite the restricted availability of resources. It is essential to measure the efficiency of the delivery of healthcare services in order to maximize the use of available resources, evaluate performance, and ultimately achieve better health outcomes. Healthcare institutions can work toward the goal of providing better services to the general population if they place a strong emphasis on productivity and make efficient use of available resources (Zere et al., 2006; Varabyova and Schreyogg, 2013). A number of studies and reports from organizations such as the OECD and the World Health Organization as well as academic researchers highlight the significance of performance measurement in healthcare systems and the potential for enhancing efficiency to meet the ever-evolving demands for healthcare.

Efficiency is a fundamental component of hospital performance, as it directly influences the quality of care, patient outcomes, and the optimal use of healthcare resources. For administrators and policymakers, understanding the drivers of hospital efficiency is essential for enhancing operational performance and ensuring effective healthcare delivery. Identifying the factors that shape technical efficiency not only facilitates the prudent use of limited resources but also strengthens broader outcomes such as service quality, public health impact, and institutional performance. Numerous studies have utilized systematic approaches to assess hospital efficiency and examine its determinants, often categorized under input, process, and output dimensions. Input factors include staffing levels, equipment, and infrastructure, while process-related aspects encompass workflow optimization, quality improvement initiatives, and the use of health information technologies (Imani et al., 2022). Output measures typically reflect patient outcomes and safety indicators, although some studies also consider patient satisfaction (Mark et al., 2009). Furthermore, hospital characteristics such as ownership, size, and type have been shown to significantly influence efficiency levels (Kakeman et al., 2016; Kalhor et al., 2016). Ultimately, a comprehensive evaluation of hospital efficiency should integrate both quantitative and qualitative indicators across the input–process–output continuum to support evidence-based improvements in healthcare delivery (Imani et al., 2022).

The ability of a healthcare organization to offer high-quality patient care while simultaneously maximizing resource utilization, avoiding waste, and improving processes is what we mean when we talk about hospital efficiency. It entails improving patient outcomes and overall performance by streamlining the management of employees, medical equipment, facilities, and financial resources. Hospitals that operate efficiently strive to minimize patient wait times, maximize patient flow, cut down on readmission rates, and keep their costs as low as possible without compromising the quality of care they provide. When analyzing hospital efficiency with Data Envelopment Analysis (DEA), valuable information is acquired that can then be used to evaluate hospital performance and determine whether or not hospitals are making effective use of the resources at their disposal. DEA approach is a multi-criteria method that measures performance by combining many input and output factors. It is utilized to evaluate different hospitals and determine which ones provide the best care. As inputs variables, the majority of studies used the number of staff members and the cost of staff, hospital beds and other facility resources, medical and administrative equipment and technology, the cost of drugs and medical supplies, and other operational expenses (electricity, water, cleaning, maintenance, etc.). The performance of the hospital's healthcare services, as well as the consequences of those services, is represented by the outputs utilized in hospital efficiency analysis. Among the many outputs that may be taken into consideration are the following: the number of surgical procedures and medical interventions carried out by the hospital; length of hospital stay as well as discharge time; level of patient satisfaction; quality of services and outcomes provided by the hospital (e.g., infection rates, complications); need for post-treatment outpatient care; other service outputs (radiology reports, laboratory results, etc.), and the need for post-treatment outpatient care (Hollingsworth, 2008). In order to determine if hospitals are making efficient use of their resources in comparison to other hospitals that are comparable to them, DEA conducts an efficiency study using these inputs and outputs. DEA provides useful insights to administrators and health officials by measuring the efficiency of a hospital. These insights enable administrators and policymakers to discover areas for improvement and optimize the allocation of resources.

The purpose of this study is to determine the technical efficiency of all public hospitals operating in Turkey using data envelopment analysis and to examine the variables that may affect efficiency. For this purpose, the correlation between the selected variables was first examined, and then data envelopment analysis was conducted on a province basis. After conducting data envelopment analysis, the scores were grouped into two main clusters using the k-means clustering technique. Multivariate linear regression analysis was also used to identify independent variables that could potentially influence hospital efficiency. The subsequent section elaborates on the research methodology in detail.

II. METHODS

2.1. Data Envelopment Analysis

Data Envelopment Analysis is a non-parametric, linear programming-based frontier analysis technique that constructs an efficiency frontier from observed data to evaluate the relative performance of decision-making units (DMUs). DEA is particularly well-suited for assessing the efficiency of complex service organizations—such as hospitals—where multiple inputs and outputs must be considered simultaneously. The original form of this method, the CCR model, was developed by Charnes, Cooper, and Rhodes (1978) and measures overall efficiency under the assumption of constant returns to scale. Later, the BCC model, introduced by Banker, Charnes, and Cooper (1984), extended the approach by incorporating variable returns to scale, thereby enabling the analysis of efficiency differences arising from scale effects in production. As a result, the BCC model allows for a more refined evaluation by distinguishing between pure technical efficiency and scale efficiency.

In recent years, the DEA has been used extensively to evaluate hospitals' relative efficiency. DEA was chosen over other approaches like regression analysis and stochastic frontier analysis (SFA) for several reasons. Among these are the following explanations: One of the multicriteria decision-making techniques used by DMUs to ascertain the relationship between inputs and outputs, it is comparatively simple and does not necessitate any prior assumptions about the variables chosen or information about the weights that must be assigned to the chosen inputs and outputs (Kamel and Mousa, 2021). There is currently no research of the Ministry of Health data published in its most recent edition, despite the fact that comparable studies have been conducted to assess the efficacy of the Turkish health system and health services. Furthermore, in contrast to previous research, this study employed a province-based methodology.

To compute DEA, two fractional programming models must be solved under the assumptions of variable return to scale (VRS) and constant return to scale (CRS). Building on the work of Banker et al. later developed the variable return to scale (VRS) model for DEA. In terms of how these two models differ, the CRS model assumes that the rates of increase in outputs and inputs are equal, whereas the VRS model allows for the possibility that the rates of increase in outputs and inputs may differ because it computes technical efficiency and scale activities separately. In addition, the CRS model assumes that the rate of increase in inputs and outputs is simultaneously the same. Because technical efficiency and scale activities can be calculated independently, the VRS model can only quantify pure technical efficiency. This explains why the VRS model makes it possible. Compared to CRS models, a greater amount of choice variables were found to be advantageous in VRS models (Banker et al., 1984). The following equation was used in this study to apply the VRS model: a set of input and output variables was identified based on a review of previous research concerning the measurement of hospital efficiency. This selection ensures that the DEA model accurately reflects the multidimensional nature of healthcare service provision.

The efficiency score (Eff) for each province is defined as:

Eff = θ, where $\mathbf{0 < \theta \leq 1}$

This study applies the input-oriented DEA-VRS (Variable Returns to Scale) model to measure the technical efficiency of provinces in utilizing healthcare resources. The model formulation is as follows:

Minimize: θ

Subject to:

∑ (j=1 to n) λj × (UrbanPopulationj, RuralPopulationj, NonSpecialistsj, Specialistsj, NursesAndMidwivesj, QualifiedBedsj, BedsPer10kj, Hospitalsj, IntensiveCareBedsj) ≤ θ × Inputo

∑ (j=1 to n) λj × (TotalVisitsj, Inpatientsj, Surgeriesj) ≥ Outputo

∑ (j=1 to n) λj = 1

λj ≥ 0, for all j

Where:

- **θ** represents the technical efficiency score of the province under evaluation. A value of 1 indicates full efficiency, while values below 1 indicate varying degrees of inefficiency.

- **Input variables** include: Urban population, rural population, number of non-specialist physicians, number of specialist physicians, number of nurses and midwives, number of qualified beds, number of beds per 10,000 people, number of hospitals, and number of intensive care beds.

- **Output variables** are: Number of outpatient visits, number of inpatients, and number of surgical operations classified under categories A, B, and C.

- **λj** denotes the weight assigned to each peer province in constructing the efficiency frontier.

This model enables the identification of efficient and inefficient provinces based on how well healthcare inputs are converted into service outputs. By minimizing θ, the model seeks the maximum proportional reduction in inputs while maintaining current output levels, thereby reflecting pure technical efficiency under variable returns to scale.

2.2. Data and Variables

This research identified a set of input and output variables that were included in the analysis, and it did so by drawing from previous research that had been done on the subject of the measurement of hospital efficiency. The data for indicators (Input variable; urban and rural population, number of non specialist, number of specialists, number of nurse and midwife, number of qualified bed, number of beds per 10000 people, number of hospitals, number of intensed bed; Output variable; number of visits, number of inpatient, number of A, B C grouped surgeries) for 81 Turkish provinces obtained from Turkey Statistical Yearbook, which was issued by the Ministry of Health (2023).

Previous studies in the field of healthcare efficiency that employed comparable inputs and outputs were extensively consulted in selecting the variables presented in Table 1. For instance, Hofmarcher et al. (2002) included patient days, medical staff, and the number of beds as input indicators in a DEA model measuring hospital efficiency in Austria, emphasizing the role of human resources and infrastructure in hospital performance. Similarly, Applanaidu et al. (2014) considered the number of doctors, nurses, and beds as key input indicators, alongside output measures such as the number of outpatients, inpatients, surgeries, and deliveries, thereby capturing both volume and complexity of services. Consistent patterns are observed in studies by Yildirim et al. (2019) and Ravaghi et al. (2019), which have systematically employed beds, physicians, and nurses as inputs and inpatient admissions, outpatient visits, and surgeries as outputs for hospital efficiency evaluation. Furthermore, Hollingsworth (2008) conducted a comprehensive review and highlighted the frequent use of staffing levels, bed counts, and service volumes in healthcare efficiency measurements. Rosko and Mutter (2008) reinforced these findings, arguing that human resource availability, hospital infrastructure, and service delivery complexity should form the basis for input and output selection in DEA studies. Additionally, Worthington (2004) and O'Neill et al. (2008) identified similar variable structures across a range of hospital efficiency analyses in both developed and developing countries, further validating the robustness of these choices. Thus, the selected inputs and outputs in the present study are firmly grounded in internationally recognized practices and methodological standards, ensuring both the validity and comparability of the resulting efficiency scores.

Table 1. Inputs and outputs of the DEA

	INPUTS		**OUTPUTS**
X1	Rural Population (RP)	Y1	Number of Surgery (NS)
X2	Urban Population (UP)	Y2	Number of Inpatient (I)
X3	Number of Non Specialist (NNS)	Y3	Number of Visit (V)
X4	Number of Nurse and Midwife (NM)		
X5	Number of Qualified Bed (QB)		
X6	Number of beds per 10000 people (B/10000)		
X7	Number of Specialists (S)		
X8	Number of Hospitals (H)		
X9	Number of intensed bed (IB)		

III. RESULTS

The DEA can be used to non-parametrically examine the relative and comparative efficiency levels of decision-making units with extensive input and output variables. This analysis is based on linear programming. Efficiency-rated decision-making units are given a score of 1, whereas inefficient-rated units are given a value lower than 1. The appropriateness of the variables used in the analysis is indicated by the presence of a correlation, at least on some level, between the variables used as input and the variables used as output in DEA. Conversely, there should not be a significant degree of correlation between the input variables used in DEA. Therefore, it was determined that there was no high-level correlation and that the very high correlation between the input variables employed in the study was managed. It is evident that the variables do not have a multicollinearity issue. (Table 2).

Table 2. Correlations Table

	RP	UP	NNS	NM	V	NS	I	QB	B/10000	S	H	IB
RP	1.00											
UP	-0.36	1.00										
NNS	-0.29	0.28	1.00									
NM	-0.32	0.19	0.29	1.00								
V	-0.34	0.20	0.18	0.19	1.00							
NS	-0.33	0.16	0.18	0.16	0.13	1.00						
I	-0.34	0.19	0.11	0.20	0.48	0.17	1.00					
QB	-0.29	0.13	0.38	0.20	0.14	0.15	0.12	1.00				
B/10000	0.14	0.13	0.34	0.10	0.05	0.09	0.09	0.12	1.00			
S	-0.29	0.17	0.13	0.20	0.29	0.20	0.43	0.29	0.33	1.00		
H	-0.27	0.19	0.18	0.20	0.44	0.52	0.48	0.17	0.10	0.49	1.00	
IB	-0.33	0.13	0.12	0.13	0.29	0.35	0.21	0.29	0.08	0.34	0.39	1.00

The correlation analysis among the selected input and output variables reveals several meaningful relationships that align with theoretical expectations regarding healthcare service delivery and hospital efficiency. As anticipated, Rural Population (RP) shows consistently negative correlations with all other variables, particularly with Urban Population (UP) ($r = -0.36$), Non-Specialists (NNS) ($r = -0.29$), Nurses and Midwives (NM) ($r = -0.32$), and Total Visits (V) ($r = -0.34$), reflecting the expected inverse relationship between rural demographics and healthcare service availability. Urban Population (UP) displays weak positive correlations with healthcare personnel variables such as NNS ($r = 0.28$) and NM ($r = 0.19$), supporting the notion that urbanization correlates with greater healthcare workforce density. Healthcare service volume indicators, notably Visits (V) and Inpatients (I), are moderately correlated ($r = 0.48$), suggesting that provinces with higher outpatient activity also experience higher hospitalization rates. Surgical activity (S) is moderately correlated with Inpatients (I) ($r = 0.43$) and Hospitals (H) ($r = 0.49$), indicating a logical link between the number of operations, patient load, and hospital infrastructure. Hospital Number (H) demonstrates moderate positive associations with Specialists (NS) ($r = 0.52$) and Visits (V) ($r = 0.44$), suggesting that larger hospital capacity is associated with both higher specialization and greater service volume. Interestingly, Beds per 10,000 People (B/10000) exhibits relatively weak correlations with other variables (e.g., NNS $r = 0.34$, S $r = 0.33$), indicating that this variable may vary independently across provinces. Intensive Care Beds (IB) show moderate positive correlations with Hospitals (H) ($r = 0.39$) and Surgical Activity (S) ($r = 0.34$), underscoring the relationship between critical care infrastructure and surgical service provision. Overall, the correlation structure is coherent with theoretical assumptions and suggests that urbanization, hospital capacity, and critical care infrastructure are key dimensions associated with hospital service volume and technical efficiency.

Overall, the correlation structure is coherent with theoretical expectations, reflecting logical relationships between healthcare inputs and outputs. This matrix supports the internal consistency and appropriateness of the selected variables for efficiency analysis.

The descriptive statistics presented (Table 3) for the input and output variables reveal substantial variation across provinces, indicating the presence of notable outliers. In particular, variables such as Rural Population (RP) and Urban Population (UP) show considerable dispersion. While the mean rural population is approximately 132,204, the maximum value exceeds 1.4 million, suggesting that a few provinces with exceptionally high rural populations, possibly due to large agricultural regions or under-urbanized areas, may skew the distribution. Similarly, the urban population ranges from approximately 23,000 to over 15 million, reflecting the dominance of megacities like Istanbul, which substantially inflates the average and highlights a right-skewed distribution. The massive urban concentration in a few provinces is largely a result of migration trends, economic centralization, and historical patterns of urbanization. Healthcare personnel indicators, including the Number of Non-Specialists (NNS), Nurses and Midwives (NM), and Specialists (NS), also display significant disparities. The maximum values for these variables are disproportionately high compared to their means, implying the dominance of highly urbanized and healthcare-intensive provinces. Provinces hosting major healthcare hubs, university hospitals, and specialized medical centers naturally have a much larger number of healthcare personnel. For instance, while the mean number of non-specialists is around 1,111, the maximum reaches nearly 18,778, driven by population density and the concentration of medical services. Infrastructure-related variables such as the Number of Qualified Beds (QB), Beds per 10,000 people (B/10000), Number of Hospitals (H), and Number of Intensive Care Beds (IB) further confirm the existence of significant outliers. The extremely high values for Qualified Beds and Hospitals are largely associated with provinces where healthcare infrastructure is heavily centralized, typically in economically advanced urban areas. Furthermore, national health policies favoring investment in metropolitan healthcare capacities also contribute to such imbalances. Notably, Beds per 10,000 people (B/10000) exhibits a relatively more balanced distribution, as minimum healthcare service standards are uniformly mandated across the country.

Examining the output variables, extreme values are even more pronounced. The Number of Specialists (NS), Number of Inpatients (I), and Number of Visits (V) display extremely high maximum values relative to their means. For example, while the average number of visits is around 8.3 million, the maximum reaches nearly 120 million, illustrating the overwhelming service burden borne by major metropolitan hospitals. These patterns are primarily driven by internal migration towards large cities, referral system structures that prioritize metropolitan hospitals for complex cases, and regional disparities in healthcare accessibility. Urbanization, centralization of healthcare services, socioeconomic inequalities, and differential rates of health infrastructure development are the major underlying causes of these high values.

Table 3. Descriptive statistics of input and output variables (N=81)

Input	Minimum	Maximum	Mean	Std. Deviation
RP	10652	1412236	132204	18039.55
UP	22973.54	15825059	931233	1940929.62
NNS	83.00	18778	1111	2401.03
NM	345	48689	3584	6147.30
QB	124	30558	2024	3682.74
B/10000	13	54	29	8.30
S	68	23490	1154	2897.70
H	1	234	19	27.57
IB	25	9587	601	1166.68
Output				
NS	674	921840	58075.23	115954.57
I	2771	2045691	145499.90	253493.28
V	562195.00	119744208,00	8341385.06	14633431.91

According to the findings obtained through DEA, the technical efficiency levels of the examined provinces in healthcare service delivery vary between 0.810 and 0.990. These results quantitatively assess the degree of efficiency between resource utilization and output production. In the DEA literature (Charnes et al., 1978; Banker et al., 1984), units with efficiency scores approaching 1 are considered to exhibit high performance, whereas units further from 1 indicate operational shortcomings that require improvement.

Provinces such as Bingöl (0.940) have drawn support from efficient units like Amasya (0.111), Sakarya (0.052), Şanlıurfa (0.012), Bayburt (0.109), and Iğdır (0.594). This reflects Bingöl's effort to enhance service delivery efficiency despite a dispersed rural population and limited resources. In Bitlis (0.967), reliance on Siirt (λ=0.789) as a major reference highlights the influence of regional socioeconomic similarities on efficiency. In western provinces such as Burdur (0.946) and Çanakkale (0.977), the use of diverse reference structures (e.g., Rize, Osmaniye, Afyonkarahisar) demonstrates that, despite regional differences in healthcare infrastructure, a relative balance in efficiency has been achieved. These provinces optimize their efficiency by adopting structures similar to those balancing population density and resource diversity. Larger and more heterogeneous provinces such as Diyarbakır (0.965) and Van (0.912) referenced developed healthcare centers like Gaziantep, Hatay, and Izmir, affirming the impact of regional developmental disparities on service delivery efficiency. In these provinces demographic structure, and socioeconomic indicators play a significant role in determining efficiency scores. Provinces with relatively lower scores, such as Hakkari (0.826) and Kars (0.810), primarily referenced provinces like Ağrı, Tunceli, and Rize, underlining how geographic isolation, infrastructural deficiencies, and low hospital bed density adversely affect operational efficiency. Highly efficient provinces like Kütahya (0.976) and Manisa (0.988) have constructed robust and flexible healthcare service delivery models by benefiting from multiple reference units such as Adana, Balıkesir, and Sakarya. This supports the notion that advanced healthcare policies in western regions significantly contribute to achieving higher technical efficiency levels. According to the analysis of the table, provinces with an efficiency score of 1, such as Ankara, Adana, Afyonkarahisar, Amasya, Denizli, Erzincan, and Osmaniye, have been identified as fully efficient units. These provinces, achieving perfect technical efficiency, demonstrate optimal utilization of healthcare resources relative to their outputs without needing to refer to other units. Their positioning on the efficiency frontier indicates exemplary practices in balancing healthcare service delivery with available resources.

In general, it can be stated that socioeconomic and political differences across regions significantly influence the technical efficiency scores of provinces. Provinces located in Eastern and Southeastern Anatolia tend to rely on more fragmented and less efficient reference structures, reflecting infrastructural deficits and service delivery challenges. In contrast, provinces in regions such as the Aegean and Marmara achieve higher technical efficiency levels by utilizing more diverse and advanced reference structures.

Table 4. CCR-I Scores of the Provincies

Provinces	Score	Reference (Lambda)
Bingöl	0.94	Amasya (0.111), Sakarya (0.052), Şanlıurfa (0.012), Bayburt (0.109), Iğdır (0.594)
Bitlis	0.967	Artvin (0.028), Elazığ (0.028), Giresun (0.044), Siirt (0.789), Bartın (0.095)
Burdur	0.946	Amasya (0.194), Isparta (0.004), Nevşehir (0.079), Rize (0.184), Bartın (0.085), Osmaniye (0.119)
Çanakkale	0.977	Adana (0.018), Adıyaman (0.002), Afyonkarahisar (0.347), Balıkesir (0.031), Rize (0.338), Bartın (0.427)
Çorum	0.899	Adana (0.007), Elazığ (0.137), Gaziantep (0.029), Hatay (0.007), Isparta (0.090), Niğde (0.771)
Diyarbakır	0.965	Gaziantep (0.462), Hatay (0.080), İzmir (0.018), Şanlıurfa (0.146)
Gümüşhane	0.953	Amasya (0.078), Denizli (0.005), Muğla (0.010), Rize (0.044), Tunceli (0.451), Bartın (0.102)
Hakkari	0.826	Ağrı (0.359), Sakarya (0.005), Tunceli (0.045), Bayburt (0.171), Yalova (0.059)
Kars	0.81	Isparta (0.042), Rize (0.335), Sakarya (0.018), Tunceli (0.533), Bartın (0.057)
Kütahya	0.976	Adana (0.009), Adıyaman (0.160), Amasya (0.758), Rize (0.282), Şanlıurfa (0.026), Osmaniye (0.070)
Manisa	0.988	Adana (0.177), Balıkesir (0.307), Rize (0.059), Sakarya (0.499), Tekirdağ (0.111)
Sinop	0.941	Artvin (0.233), Elazığ (0.066), Giresun (0.024), Isparta (0.001), Bartın (0.502)
Sivas	0.926	Adana (0.057), Artvin (0.653), Elazığ (0.031), Isparta (0.222), Rize (0.555), Şanlıurfa (0.028)
Van	0.912	Elazığ (0.065), Gaziantep (0.152), Malatya (0.143), Şanlıurfa (0.196), Bayburt (0.241)
Yozgat	0.897	Rize (0.673), Tunceli (0.161), Şanlıurfa (0.014), Bayburt (0.017), Iğdır (0.115), Osmaniye (0.080)
Kırıkkale	0.845	Adana (0.093), Isparta (0.021), Sakarya (0.008)
Batman	0.884	Gaziantep (0.045), Isparta (0.069), Niğde (0.197), Şanlıurfa (0.108), Uşak (0.014), Yalova (0.464)
Karabük	0.99	Elazığ (0.007), Ordu (0.098), Rize (0.208), Şanlıurfa (0.013), Bayburt (0.067), Iğdır (0.037), Yalova (0.196)

Then, k-means clustering analysis was applied to classify provinces based on their technical efficiency levels. In the analysis, efficiency scores were utilized, and Euclidean distances between observations were considered as the basis for clustering. The number of clusters (k) was predetermined as 2. Accordingly, the provinces were divided into two distinct groups: the first group included fully efficient provinces (Efficiency Score = 1), while the second group comprised provinces with an efficiency score below 1, indicating potential for improvement. The k-means algorithm assigned each province to a cluster by minimizing the distance to the cluster centroids based on their efficiency scores. According to the clustering results, 17.3% of the provinces were found to be not fully efficient, while the remaining provinces achieved full input and output efficiency (Figure 1).

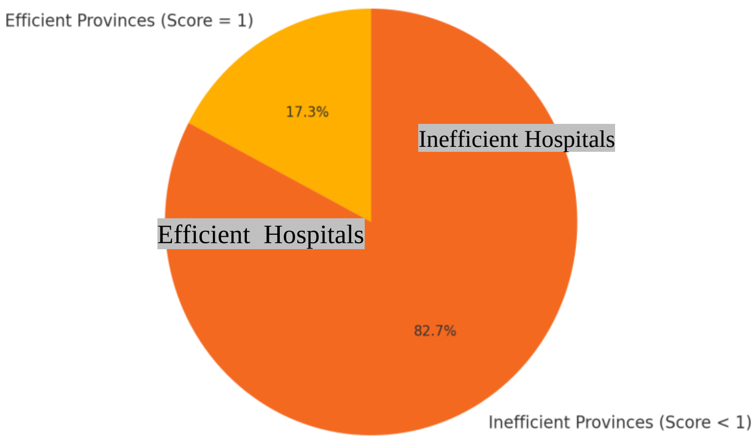

Figure 1. K-Means Clusters of Provinces' DEA Score

After conducting the Data Envelopment Analysis and analyzing the efficiency scores of hospitals, multivariate linear regression analysis was deemed the most suitable method to identify the independent variables that may influence technical efficiency. The regression analysis (Table 5) revealed the key factors that significantly impact hospital efficiency. The model explains 38% of the variance in efficiency scores ($R^2 = 0.380$, Adjusted $R^2 = 0.237$), and the results are statistically significant overall ($F = 2.653$, $p = 0.003$). Specifically, the number of qualified beds (QB) shows a significant negative relationship with technical efficiency ($\beta = 0.001$, $p = 0.037$), suggesting that an excessive number of beds, when not supported by adequate optimization of service processes and resources, may reduce overall efficiency. In contrast, the number of beds per 10,000 people (B/10000) has a positive and significant effect ($\beta = 0.001$, $p = 0.041$), indicating that a well-balanced distribution of beds relative to the population contributes positively to hospital efficiency. The number of intensive care beds (IB) also has a strong and significant negative effect on efficiency ($\beta = 0.005$, $p = 0.001$). This finding may reflect the higher operational and financial demands of critical care services, which can limit overall technical efficiency when not adequately managed. The number of non-specialist physicians (NNS) appears to have a weak but potentially positive contribution ($p = 0.074$), though this does not meet conventional significance thresholds. Other variables, including rural population (RP), urban population (UP), number of nurses and midwives (NM), surgeries (S), number of hospitals (H), number of specialists (NS), number of inpatients (I), and number of total visits (V), were not found to be statistically significant predictors of efficiency. In summary, the regression results suggest that hospital efficiency is primarily shaped by structural healthcare capacity factors particularly bed distribution and critical care infrastructure and that managing these effectively is crucial for improving performance across public hospitals.

Table 5. Regression Findings that Affecting the Efficiency Status

	β	**Std. Err.**	**S.β,**	**t**	**p**
(Constant)	0.002	0.000	-0.095	-0.645	0.521
RP	0.002	0.000	3.571	0.975	0.333
UP	-0.014	0.020	-0.839	-0.722	0.473
NNS	0.001	0.000	7.947	1.814	0.074
NM	0.008	0.011	0.149	0.791	0.432
QB	0.001	0.000	-3.683	-2.130	**0.037**
B/10000	0.001	0.001	3.631	2.082	**0.041**
S	0.003	0.000	-2.468	-1.053	0.296
H	0.002	0.000	2.933	0.990	0.326
IB	0.005	0.000	-7.082	-3.428	**0.001**
NS	0.003	0.000	-1.534	-0.775	0.441
I	0.001	0.000	0.127	0.053	0.958
V	0.001	0.000	-0.095	-0.645	0.521

R:0.616 R Square:0.380 Adjusted R Square:0.237 Durbin-Watson:1.950 F: 2.653 p:0.003

IV. CONCLUSION

This study assessed the technical efficiency of public hospitals across Turkey using Data Envelopment Analysis and explored the underlying factors influencing efficiency through multivariate regression. The results indicate that a higher number of beds per 10,000 people is positively associated with technical efficiency, while the number of qualified beds and intensive care bed capacity are negatively related. The latter findings suggest that excess physical capacity particularly in resource-intensive services like intensive care may diminish efficiency when not paired with operational optimization.

These results align with earlier evidence. In the study by Bal and Bilge (2013), the technical efficiency of 35 training and research hospitals in Turkey was evaluated using DEA, revealing that only a limited number of hospitals were fully efficient. The main causes of inefficiency were identified as idle bed capacity, insufficient staffing, and low levels of service output. Çınaroğlu (2021) emphasized the significance of hospital size that hospitals which expanded in size showed notable increases in efficiency scores. This suggests that, when properly planned, hospital size can provide a productivity advantage. Medin et al. (2011) conducted a cross-country analysis to evaluate the cost efficiency of university hospitals in Nordic countries. The study found significant variation in efficiency levels across hospitals, even after adjusting for differences in research and teaching functions. These academic roles were shown to increase overall hospital costs, partly explaining inefficiency compared to non-university hospitals. Moreover, the analysis identified geographic location and the share of high case-weight discharges as important determinants of efficiency. However, a considerable portion of the variation remained unexplained, suggesting the influence of additional contextual or institutional factors.

Brancalion and Lima (2022) explore how implementing a process-based management approach can simultaneously enhance healthcare delivery quality and financial performance. Drawing from case studies and quantitative metrics, they demonstrate that aligning clinical workflows with financial controls leads to both cost containment and service optimization. Their findings underline that infrastructure investment alone is insufficient; it is the marriage of operational efficiency and process standardization that drives improved outcomes across healthcare settings. Similarly, Kim & Oh (2024) emphasized that unmanaged expansion in intensive care capacity can result in operational inefficiencies. International datasets (Statista, 2025) also confirm the positive correlation between bed-to-population ratios and improved care access, while Song et al. (2025) highlighted regional disparities in healthcare efficiency in China, underscoring the relevance of equitable planning.

These patterns are evident in the Turkish context as well. Provinces in the Eastern and Southeastern Anatolia regions displayed lower efficiency scores than those in the Aegean and Marmara regions, reaffirming the impact of regional development gaps on healthcare outcomes (Worthington, 2004; Hollingsworth, 2008). Although the Health Transformation Program (HTP) led to improvements in access and infrastructure (Ministry of Health, 2023), the study's results suggest that physical investments alone have not translated into proportional efficiency gains.

In parallel, the WHO's *Working for Health 2022–2030 Action Plan* emphasizes that investments in workforce capacity, training, and motivation are essential for supporting innovation and sustaining productivity. It cautions that overstretched and underqualified healthcare personnel can undermine both service quality and institutional performance (WHO, 2022).

In light of the findings of this study, it is essential for health administrators and policymakers in Turkey to adopt a multidimensional and locally responsive approach to improving the technical efficiency of public hospitals. High-cost infrastructure investments—particularly in intensive care units—should be re-evaluated in accordance with each province's disease burden, demographic characteristics, and referral patterns. Units with low utilization rates should be considered for repurposing. Given the positive association between hospital bed density (per 10,000 population) and efficiency, this metric should be used as a central planning indicator to address interprovincial disparities. Imbalances in human resource distribution must be mitigated through targeted incentives such as preferential assignments, financial supplements, and career advancement opportunities for healthcare professionals serving in underserved regions. Underutilized hospital capacity, including specialized beds and facility space, can be converted into palliative care units, outpatient clinics, or home healthcare services to enhance system functionality. The development of digital performance dashboards at the provincial level would allow for regular feedback to administrators and support both local and national decision-making processes. Expanding process-oriented management practices particularly those related to patient flow, clinical pathways, and quality improvement could generate substantial gains in operational efficiency. Furthermore, high-cost hospital investments should be subject to a centralized approval mechanism based on prior efficiency assessments to ensure optimal resource allocation. To facilitate systematic performance monitoring, efficiency measurement tools such as DEA should be integrated into hospital information systems, enabling administrators to apply them in day-to-day decision-making.

Limitations

The data used in this study were obtained from the Turkey Statistical Yearbook published by the Ministry of Health (2023). Official datasets, although comprehensive, may be subject to delays in annual updates, changes in variable definitions over time, or variations in data reporting standards across provinces. For example, the classification of surgeries or the counting of intensive care beds might differ based on evolving national health policies. In addition, although the data provided by the Ministry of Health is considered reliable, possible underreporting or regional discrepancies cannot be entirely ruled out.

It is important that the limited number of input and output variables used in this study was a deliberate methodological choice. Given the nature of the Data Envelopment Analysis (DEA) method, increasing the number of variables disproportionately reduces the number of observations per decision-making unit, potentially leading to distortions in the analysis. As noted in the literature (Dyson et al., 2001), an excessive number of variables can artificially make all decision-making units appear efficient and obscure real differences in performance. Therefore, careful optimization of the number of variables enhances the discriminative power of the model and preserves the reliability of the efficiency scores. In this study, fundamental input and output variables that reflect the structural characteristics of healthcare services and support the statistical validity of the model were selected. This approach ensured both methodological rigor and increased the reliability of the results obtained. Nevertheless, in future studies, the inclusion of additional input and output variables could expand the scope of the analysis and further enhance the generalizability of the findings.

Ethical Statement: This study was conducted using publicly available, institutionally collected statistical data that does not contain any personal information. Therefore, ethical approval was not required. The author(s) contributed to all stages of the study including literature review, data analysis, interpretation of findings, and manuscript preparation and actively participated throughout the research process.

REFERENCES

Applanaidu, S. D., Samsudin, S., Ali, J., Dash, U., & Chik, A. R. (2014). Technical and scale efficiency of public district hospitals in Kedah, Malaysia: A data envelopment analysis (DEA). *Journal of Health Management, 16*(3), 327-335.

Bal, V., & Bilge, H. (2013). Eğitim ve araştırma hastanelerinde veri zarflama analizi ile etkinlik ölçümü. *Manas Sosyal Araştırmalar Dergisi, 2*(2), 1-14.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*(9), 1074-1092.

Brancalion, F. N. M, Lima, A. F. C. (2022). Process-based management aimed at improving health care and financial results. *Revista Latino-Americana de Enfermagem,* 56:e20210333.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444.

Çınaroğlu, S. (2021). Changes in hospital efficiency and size: An integrated propensity score matching with data envelopment analysis. *Socio-Economic Planning Sciences, 76*, 100960.

Dyson, R. G., Allen, R., Camanho, A. S., Podinovski, V. V., Sarrico, C. S., & Shale, E. A. (2001). Pitfalls and protocols in DEA. *European Journal of Operational Research, 132*(2), 245-259.

Hofmarcher, M. M., Paterson, I. & Riedel, M. (2002). Measuring hospital efficiency in Austria: A DEA approach. *Health Care Management Science, 5*(1), 7-14.

Hollingsworth, B. (2008). The measurement of efficiency and productivity of health care delivery. *Health Economics, 17*(10), 1107-1128.

Imani, A., Alibabayee, R., Golestani, M., & Dalal, K. (2022). Key indicators affecting hospital efficiency: A systematic review. *Frontiers in Public Health, 10*, 830102.

Kakeman E., Rahimi Forushani A. & Dargahi H. (2016). Technical efficiency of hospitals in Tehran, Iran. *Iran Journal of Public Health*. 45(4):494-502.

Kalhor, R., Amini, S., Torabi, F., Ziapour, A., & Kakemam, E. (2016). Factors affecting the technical efficiency of general hospitals in Iran: Data envelopment analysis. *Electronic Physician, 8*(10), 3049–3056.

Kamel, M. A., & Mousa, M. E. (2021). Measuring operational efficiency of isolation hospitals during COVID-19 pandemic using data envelopment analysis: A case of Egypt. *Benchmarking: An International Journal, 28*(7), 2178-2201.

Kim J-N & Oh I-H. (2024). Optimizing hospital bed capacity and resource allocation using inflow and outflow indices for effective healthcare management. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*. Jan-Dec;61:469580241304244.

Mark, B. A., Harless, D. W., & Spetz, J. (2009). California's minimum nurse staffing legislation: Results from a natural experiment. *Policy, Politics, & Nursing Practice, 10*(3), 180–186.

Medin, E., Anthun, K. S., Hakkinen, U., Kittelsen, S. A., Linna, M., Magnussen, J., Olsen, K., & Rehnberg, C. (2011). Cost efficiency of university hospitals in Nordic countries: A cross-country analysis. *European Journal of Health Economics, 12*(6), 509-519.

Ministry of Health. (2023). *Turkey Health Statistics Yearbook 2021*. Ankara: Republic of Turkey Ministry of Health.

OECD. (2024). *Rethinking health system performance assessment: A renewed framework*. Retrieved from: https://www.oecd.org/en/publications/rethinking-health-system-performance-assessment_107182c8-en.html (Accessed 06.10.2024).

O'Neill, L., Rauner, M., Heidenberger, K., & Kraus, M. (2008). A cross-national comparison and taxonomy of DEA-based hospital efficiency studies. *Socio-Economic Planning Sciences, 42*(3), 158–189.

Ravaghi, H., Afshari, M., Isfahani, P., & Bélorgeot, V. D. (2019). A systematic review on hospital inefficiency in the Eastern Mediterranean Region: Sources and solutions. *BMC Health Services Research, 19*, 1-20.

Rosko, M. D., & Mutter, R. L. (2008). Stochastic frontier analysis of hospital inefficiency: A review of empirical issues and an assessment of robustness. *Medical Care Research and Review, 65*(2), 131–166.

Song, Q., Ye, A., Zhou, M., Chen, T., & Jiang, W. (2025). Based on regional heterogeneity: measurement of hospital service efficiency and analysis of spatial effects. *Frontiers in Public Health, 13*, 1556737.

Statista. (2025). Hospital bed density in the U.S. by state. Retrieved from https://www.statista.com/statistics/1474768/hospital-bed-density-in-the-us-by-state/(Accessed 01.06.2025).

Varabyova, Y., & Schreyögg, J. (2013). International comparisons of the technical efficiency of the hospital sector: Panel data analysis of OECD countries using parametric and non-parametric approaches. *Health Policy, 112*(1-2), 70-79.

Waldman, D. (1997). *Measuring Efficiency and Productivity in Health Care Systems*. Ann Arbor: Health Administration Press. ISBN: 9781567930476.

WHO. (2021). *Health systems performance assessment: A framework for policy analysis*. Retrieved from: https://www.who.int/publications/i/item/9789240042476/ (Accessed 05.11.2024).

WHO, (2022). *Working for Health 2022-2030 Action Plan: planning and financing*. Retrieved from: https://www.who.int/publications/i/item/9789240063389, (Accessed 05.11.2024).

Worthington, A. C. (2004). Frontier efficiency measurement in health care: A review of empirical techniques and selected applications. *Medical Care Research and Review, 61*(2), 135–170.

Yildirim, C., Kacak, H., Yildirim, S., & Kavuncubaşı, Ş. (2019). Comprehensive efficiency assessment of Turkish teaching hospitals: Technical, pure technical and scale efficiencies with data envelopment analysis. *Journal of Applied Business and Economics, 21*(3), 47–62.

Zere, E., Mbeeli, T., Shangula, K. *et al.* (2006). Technical efficiency of district hospitals: Evidence from Namibia using Data Envelopment Analysis. *Cost Effectiveness and Resource Allocation*, 4(5): 1-9.