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Province-Level Efficiency Analysis of Public Hospitals in Turkey: A Data Envelopment Analysis and Self-Organizing Maps (SOMDEA) Approach

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ABSTRACT

In today's Turkey, the healthcare sector holds a critically important position, as it affects numerous aspects of society. Among the key units that must utilize their investment capacity and available resources most efficiently, hospitals serve as the central service providers within the healthcare system. In a sector involving a wide range of stakeholders, evaluating hospital performance at the provincial level through Data Envelopment Analysis (DEA) offers significant advantages in promoting efficiency within the public sector. This study aims to analyze the operational effectiveness of public hospitals and guide them toward optimal performance levels, thereby contributing to national welfare and the sustainability of quality of life. Unlike previous studies, this research not only employs DEA for provincial-level efficiency analysis but also incorporates Self-Organizing Maps (SOM), an unsupervised learning method from artificial neural networks, to identify and explain the underlying factors contributing to variations in efficiency. This combined approach has named SOMDEA, enables a more interpretable and comprehensive understanding of performance differences among provinces.

Türkiye'de Kamu Hastanelerinin İl Bazlı Verimlilik Analizi: Veri Zarflama Analizi ve Öz-Düzenleyen Haritalar (SOMDEA) Yaklaşımı

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Anahtar Kelimeler

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ÖZ

Günümüz Türkiye'sinde sağlık sektörü, toplumun birçok yönünü etkileyen hayati bir konumda yer almaktadır. Yatırım kapasitesini ve mevcut kaynaklarını en verimli şekilde kullanması gereken temel birimlerin başında gelen hastaneler, sağlık sisteminin merkezî hizmet sağlayıcılarıdır. Pek çok paydaşı içeren bu sektörde, iller düzeyinde hastane performansının Veri Zarflama Analizi (VZA) ile değerlendirilmesi, kamu sektöründe verimliliğin artırılması açısından önemli avantajlar sunmaktadır. Bu çalışma, kamu hastanelerinin operasyonel etkinliğini analiz etmeyi ve onları optimum performans düzeylerine yönlendirmeyi amaçlamakta; böylece ulusal refaha ve yaşam kalitesinin sürdürülebilirliğine katkı sağlamayı hedeflemektedir. Önceki çalışmalardan farklı olarak, bu araştırma yalnızca VZA ile iller düzeyinde verimlilik analizi yapmakla kalmayıp, yapay sinir ağlarının denetimsiz öğrenme yöntemlerinden biri olan Özdüzenleyici Haritalar (SOM) yöntemini de sürece dâhil ederek, verimlilikteki farklılıkları etkileyen temel faktörleri ortaya koymayı ve açıklamayı amaçlamaktadır. SOMDEA olarak adlandırılan bu bütünleşik yaklaşım, iller arasındaki performans farklılıklarının daha anlaşılır ve kapsamlı bir şekilde değerlendirilmesine olanak sağlamaktadır.

1. INTRODUCTION

The healthcare sector is one of the most strategic components of public service, directly influencing a country's economic development, social welfare, and overall quality of life [1]. In developing countries such as Turkey, a considerable share of public expenditure is allocated to healthcare. Therefore, the efficient use of limited resources has become a national priority to ensure the sustainability of health policies and equitable access to services [2]. Public hospitals, as the main service providers, constitute the backbone of the healthcare system both in terms of cost and service delivery. Accordingly, assessing their performance regularly and accurately is essential for policy improvement and effective resource allocation [3].

In Turkey, the healthcare system has experienced significant growth and development over the past decades, with improvements in infrastructure, service coverage, and health outcomes. Despite this progress, inter-provincial disparities remain a concern, making it crucial to evaluate hospital performance at the provincial level to inform targeted policy interventions.

Hospitals are complex institutions where multiple inputs—such as medical personnel, hospital beds, equipment, and pharmaceuticals—are transformed into outputs like outpatient services, inpatient treatments, recovery rates, patient satisfaction, and surgical procedures. Due to this complexity, traditional performance evaluation techniques often fall short in capturing overall efficiency. For this reason, quantitative and multi-criteria methods such as Data Envelopment Analysis (DEA) have gained prominence. DEA is a non-parametric frontier method that enables the measurement of the relative efficiency of Decision-Making Units (DMUs) using multiple inputs and outputs without requiring a predefined production function [4,5]. In Turkey, numerous studies have employed DEA to analyze hospital efficiency and to highlight inter-provincial differences in healthcare performance [6,7].

However, while DEA provides an efficiency score, it does not explain the underlying reasons for efficiency or inefficiency, nor how socio-economic, demographic, or environmental factors influence performance across regions. This represents a gap in the current literature: the reasons for inter-provincial differences in hospital performance in Turkey are not sufficiently explained. To address this limitation, recent studies have started integrating artificial intelligence and machine learning techniques with DEA outputs [8]. Among these, Self-Organizing Maps (SOM) offer a powerful unsupervised learning approach that enables the visualization of high-dimensional data, clustering of similar units, and detection of structural patterns affecting efficiency scores [9,10].

In this study, the fundamental research question is therefore defined as follows:

"What are the underlying demographic, socio-economic, and environmental factors that explain inter-provincial differences in the efficiency of public hospitals in Turkey?" To answer this question, this study first measures provincial hospital efficiency using the Charnes–Cooper–Rhodes (CCR) model of DEA. Subsequently, efficiency scores are combined with demographic and socio-economic indicators—such as population density, education level, per capita income, elderly and child population ratios, regional development level, and climatic conditions—and analyzed using Self-Organizing Maps (SOM). This integrated approach, termed SOMDEA, not only measures efficiency but also provides a deeper understanding of why efficiency varies across provinces. This methodological combination is rarely applied in the Turkish health policy literature and therefore constitutes the innovative contribution of this study.

2. LITERATURE REVIEW

2.1. Research Background for Data Envelopment Analysis

Hayami and Ruttan evaluated agricultural productivity in 38 countries using the Cobb-Douglas production function. Although DEA or the Malmquist Index were not applied, this study became a foundational reference for subsequent productivity analyses [11]. Capobianco and Fernandes [12] examined capital structure in the global airline industry using DEA and ratio analysis, highlighting efficient capital utilization and the importance of managerial decisions over national contexts. Luh et al. [13] and Fulginiti and Perrin [14] applied the Malmquist Productivity Index to assess cross-country productivity, demonstrating its flexibility in international comparisons. Stepanyan [15], Dao [16], and Teker et al. [17] analyzed airline financial performance using ratio analysis and DEA, showing the effects of operational and managerial factors on efficiency. Rosini and Gunawan [18] combined DEA with TOPSIS and correlation analysis for a multi-method perspective on airline performance evaluation.

Ray and Kim [19] applied DEA to the U.S. steel industry, identifying technical and allocative inefficiencies and emphasizing regulatory compliance in operational efficiency. Yolalan [20] and Çingi and Tarım [21] evaluated Turkish banks' efficiency using DEA, revealing higher efficiency in private and foreign banks compared to public banks. Bayrak et al. [22] applied DEA to 25 textile firms in Istanbul, identifying efficient practices.

Doğan and Tanç [23] evaluated 18 accommodation businesses in Cappadocia, identifying efficient firms and suggesting improvements for others. Ayan and Perçin [24] compared standard, constrained, and fuzzy DEA for Turkish automotive firms, finding fuzzy DEA more realistic. Saranga [25] examined Indian auto parts firms, highlighting working capital management's impact on operational efficiency. Apearing and Thollander [26] studied industrial energy efficiency barriers, emphasizing organizational factors. Debnath and Sebastian [27] assessed India's iron and steel industry productivity with DEA, noting inefficiencies in public enterprises. Özcan and Anıl [28] analyzed Turkey's top 500 steel firms with DEA and the Malmquist Index, illustrating differences in sensitivity between methods. Şengül [29] evaluated efficiency trends of basic metal firms in BIST 100 using DEA.

Mukherjee et al. [30] assessed public banking efficiency by combining service quality and DEA, finding high-quality services linked to better resource-to-performance transformation. Kayalıdere and Kargın [31] evaluated textile and cement firms on ISE using DEA, identifying efficient and inefficient firms. Önal and Sevimeser [32] applied DEA to Turkish banks (1980–2004), showing efficiency differences among foreign, state-owned, and private banks. Lo and Lu [33] implemented a two-stage DEA for Taiwanese holding companies, finding larger firms generally more efficient. Kula and Özdemir [34] assessed cement companies with input-oriented DEA, identifying efficient firms and improvement targets. Ertuğrul and Işık [35] evaluated basic metals firms using output-oriented CCR DEA, suggesting benchmarks for inefficient companies. Behdioğlu and Özcan [36] applied DEA to 29 Turkish banks (1999–2005), reporting average efficiency scores and identifying efficient groups under CCR and BCC models. Erik and Kuvvetli [37] applied the input-oriented CCR model to evaluate the Industry 4.0 integration efficiency of 24 manufacturing firms in the Adana region of Turkey, using 39 inputs covering IT infrastructure, ERP module usage, R&D activities, and quality management. They found that 13 of the firms achieved an efficiency score of 1, indicating relative efficiency in Industry 4.0 readiness.

2.2. DEA in Healthcare Institutions

Efficiency in hospitals, as key components of the healthcare sector, is crucial for effective resource management and quality service delivery. Accordingly, Data Envelopment Analysis (DEA) has been widely employed to evaluate hospital performance, treating healthcare providers as decision-making units (DMUs) and using various inputs and outputs.

Kirigia et al. [38] assessed 32 healthcare facilities in Kenya, using six input variables (clinical staff, allied health personnel, laboratory staff, administrative personnel, non-salary expenditures, and beds) and four output measures, including outpatient visits, antenatal/family planning services, vaccinations, and general consultations. Steinmann et al. [39] analyzed hospitals in Germany and Switzerland, using staff, expenses, and beds as inputs and patient bed-days as output. Spinks and Hollingsworth [40] conducted a cross-country OECD comparison with GDP, education, health expenditure, and unemployment as inputs and life expectancy as output.

Nayar and Ozcan [41] examined 53 hospitals to investigate the effect of quality indicators on efficiency. They used technical inputs (beds, expenditures, assets, staff expenses), technical outputs (discharges, outpatient visits, educational expenditures), and quality outputs (patients receiving antibiotics, oxygen, and pneumococcal vaccines), and found that quality measures significantly affected efficiency.

In Turkey, Ayanoğlu et al. [42] analyzed 16 hospitals using financial inputs (material, personnel, outsourced services, other expenditures, depreciation) and service revenue as output. Yiğit [43] evaluated all hospitals under Public Hospital Unions with three inputs (specialist physicians, general practitioners, hospital beds) and six outputs, including outpatient visits, inpatient admissions, surgeries (A, B, C), and bed occupancy rate. Bardakçı and Filiz [44] assessed six public hospitals in Artvin, Turkey, using beds, doctors, and nurses as inputs and surgeries, outpatient visits, and inpatient admissions as outputs.

Asandului et al. [45] and Cetin and Bahce [46] applied DEA to public healthcare systems in European and OECD countries, examining inputs such as physicians, hospital beds, and healthcare expenditures, with outputs including life expectancy, disability-free life expectancy, and infant mortality.

Digital hospital efficiency has also been studied in Turkey. Kılıç [47] demonstrated that digital hospitals improved workflow efficiency, reduced paper-related costs, and enhanced service quality. Tüfekçi et al. [48] reviewed the HIMSS EMRAM model and Turkey's digital healthcare progress, while Bayer et al. [49] highlighted practical advantages of digital hospitals, such as faster patient tracking, improved safety, and reduced administrative costs.

Some DEA applications in the healthcare sector, including authors, year, institutions, and input-output variables, is presented in Table 1.

Table 1. DEA studies applied in the public sector in the literature

Author and year	Public institution applied	Inputs	Outputs
Güçlü [50] - 1999	35 military hospitals under the Turkish Armed Forces	Number of physicians, beds, and other healthcare staff	Number of inpatients, outpatient visits, surgeries, tests, and medical board decisions
Özdemir [51] – 2015	Black Sea Economic Cooperation (BSEC) countries	Health expenditure per capita, doctors per capita, and the number of hospital beds	Population, healthy life expectancy
Şenol and Gençtürk [52] - 2017	Public Hospitals in Turkey	Number of beds, number of physicians, the number of nurses and midwives	Outpatient clinic examination, number of emergency examinations, number of operations in group A, number of operations in group B, number of operations in group C, number of hospitalized patients

2.3. Study Motivation

Overall, the literature demonstrates that DEA has been widely applied across different sectors including agriculture, banking, manufacturing, and transportation. These studies collectively highlight the flexibility of DEA in evaluating relative efficiency under multiple input–output conditions. However, although DEA has been extensively used for productivity measurement, relatively fewer studies integrate DEA with machine learning techniques to explore the structural determinants of efficiency. This gap provides motivation for the present study, which combines DEA with Self-Organizing Maps (SOM) to uncover underlying demographic and socio-economic factors affecting healthcare efficiency across provinces in Turkey.

3. MATERIAL AND METHOD

3.1. Study Framework

This study is structured in three main stages, as illustrated in Figure 1. First, data required for the Data Envelopment Analysis (DEA) were collected. Second, DEA was applied to measure the relative efficiency of decision-making units (DMUs). Third, efficiency scores were analyzed using Kohonen Self-Organizing Maps (SOM) to identify key factors influencing efficiency levels. In Figure 1, orange colors show input variables, blue colors show Output Variables and purple colors show city demographic variables.

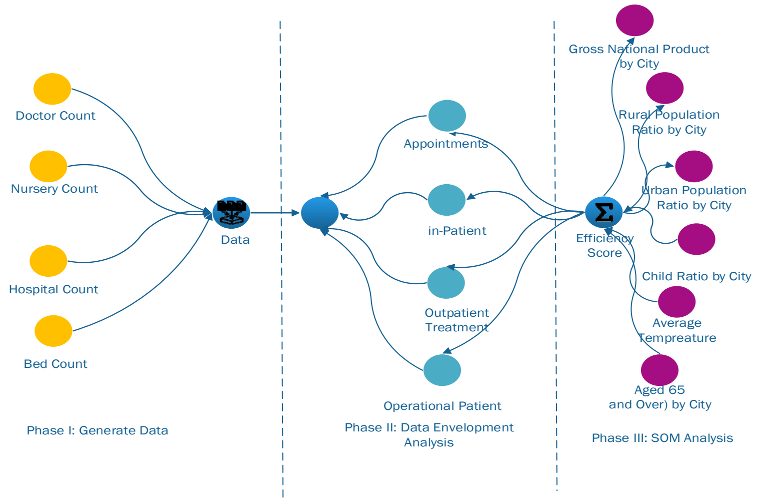

Figure 1. Study framework

3.2. Material

The study utilizes provincial-level data from the *Health Statistics Yearbook 2023* [53], published by the Ministry of Health of Turkey. In the DEA, all hospitals within each province were considered as DMUs.

Inputs were selected based on common indicators in the literature [50-52], including:

- *Number of hospitals*
- *Number of beds*
- *Number of physicians*
- *Number of nurses and midwives*

Outputs included:

- *Number of outpatient visits*
- *Number of inpatients*
- *Total inpatient days*
- *Number of surgeries*
- *Bed turnover rate*

After computing efficiency scores at the provincial level, demographic characteristics were incorporated to analyze their relationship with efficiency indices using SOM.

3.3. Method

3.3.1. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a linear programming approach developed to evaluate the relative efficiency of DMUs producing similar goods or services, especially when multiple inputs and outputs exist. The method, initially introduced by Charnes et al. [54], has been widely applied in healthcare, education, banking, and manufacturing.

Key features of DEA include:

- Handling multiple inputs and outputs simultaneously,
- No requirement for a predefined functional relationship between inputs and outputs,
- Efficiency comparison against reference DMUs or peers,
- Flexibility in measurement units,

Input selection criterion: To ensure the robustness of DEA results, the number of DMUs (n) and the number of inputs (m) and outputs (s) were determined according to the commonly used rule in DEA studies [55]:

$$n \geq \max\{m * s, 3(m + s)\} \quad (1)$$

This criterion ensures sufficient DMUs to avoid overestimation of efficiency scores. In this study, 81 provinces in Turkey were considered as Decision Making Units (DMUs). The model includes four input variables and five output indicators. According to Equation (1), the number of DMUs satisfies the recommended rule for DEA applications, ensuring the robustness of the efficiency estimation.

3.3.2. DEA Models

The study applies the input-oriented Charnes–Cooper–Rhodes (CCR) model under constant returns to scale (CRS). Input-oriented models are appropriate when outputs are difficult to control directly, focusing on minimizing inputs for a given level of output. The CCR efficiency of DMU k is defined as:

$$\text{CCR Efficiency} = \frac{\sum_{r=1}^{s} u_r * y_r}{\sum_{i=1}^{m} v_i * x_i} \quad (2)$$

where y_r and x_i denote outputs and inputs, u_r and v_i are weights, s is the number of outputs, and m is the number of inputs. For comparison, the Banker–Charnes–Cooper (BCC) model allows variable returns to scale (VRS) by adding the convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$ separating scale efficiency from technical efficiency [56].

The fractional programming form of the CCR model can be transformed into a linear programming problem for computational purposes. The input-oriented CCR model can therefore be expressed as the following linear programming formulation (3):

$$\begin{aligned} &min\theta \text{s.t.} \\ &\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ik} \\ &\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk} \\ &\lambda_j \geq 0 \end{aligned} \quad (3)$$

where θ represents the efficiency score of the evaluated DMU k, x_{ij} and y_{rj} denote the input and output values of DMU j, x_{ik} and y_{rk} denote the inputs and outputs of the evaluated DMU k, and λ_j are intensity variables defining the reference frontier. This linear programming problem is solved for each DMU to obtain its relative efficiency score with respect to the efficient frontier constructed by the observed units.

3.3.3. Computational Environment and Software

All analyses in this study were performed using Python 3.10 on a Windows 10 environment. The following libraries were given at Table 2. The computational environment relied on several widely used scientific computing libraries in Python. Pandas was used for data manipulation and preprocessing [57]. NumPy for numerical computation [58], and SciPy for linear programming optimization [59]. Data normalization was performed using the MinMaxScaler function from the scikit-learn machine learning [60]. Self-Organizing Maps were implemented using the MiniSom library [61].

Table 2. Using software packages with Python

Component	Library	Version	Purpose
Linear programming	SciPy (linprog, HiGHS)	1.12	CCR/BCC DEA solution
Data processing	pandas	2.2	IO & preprocessing
Numerical computation	numpy	1.26	Matrix operations
Normalization	scikit-learn (MinMaxScaler)	1.4	Input–output scaling
Visualization	matplotlib	3.8	Figures
SOM	MiniSom	2.3	Clustering & topology visualization

The DEA models (CCR under CRS and BCC under VRS) were implemented by directly solving the corresponding linear programs using the HiGHS interior-point solver in SciPy. No external DEA package was employed, allowing full control over constraints and model structure. For validation, bootstrap DEA (Simar–Wilson), super-efficiency (Andersen–Petersen), slack analysis, and ±5% sensitivity analysis were computed to evaluate the robustness of efficiency scores and frontier stability.

3.3.4. Validation and Robustness Checks

Because DEA is a deterministic, non-parametric method and is sensitive to sampling variation, several statistical and robustness procedures were implemented following Simar and Wilson [62] and Andersen and Petersen [63].

Bootstrap DEA (Simar–Wilson): To obtain bias-corrected efficiency estimates and confidence intervals, 200 bootstrap replications were performed for both CCR and BCC models. The bootstrap-corrected scores were computed as $\theta_{BC} = \theta - Bias(\theta)$, and 95% confidence intervals were derived from the empirical distribution of bootstrap samples.

Super-Efficiency (Andersen–Petersen): Outlier detection and frontier stability were assessed using the super-efficiency model, where each DMU is excluded from the reference set. Super-efficiency values greater than 1 indicate that the DMU remains efficient even when evaluated against all others, serving as a strong indicator of robustness.

Slack-Based Measures: Input slacks were calculated to verify the presence of weak efficiency and to determine whether DMUs require non-proportional adjustments after the radial contraction. Slack analysis complements θ-scores by identifying excess resources not captured by proportional reduction.

Sensitivity Analysis (±5%): To evaluate stability, inputs were perturbed by ±5% and efficiencies recalculated:

+5% inputs → decreased efficiency
–5% inputs → increased efficiency

Sensitivity results confirmed (or contradicted) the robustness of the frontier and the relative ranking of DMUs. In addition, feasibility and degeneracy control were examined during the DEA computations. All linear programming problems satisfied feasibility conditions, ensuring that each DMU could be evaluated against a valid reference set. Degeneracy issues, which may occur when multiple optimal solutions exist, were mitigated through the use of the HiGHS interior-point solver implemented in SciPy, which provides stable and numerically robust solutions for large-scale linear programming problems.

3.3.5. Self-Organizing Maps

Self-Organizing Maps (SOM), also known as Kohonen maps, are an unsupervised neural network method introduced by Teuvo Kohonen [9]. SOM is widely used for clustering, dimensionality reduction, and data visualization tasks, particularly when dealing with high-dimensional datasets. It projects complex data onto a lower-dimensional (typically two-dimensional) grid while preserving the topological properties of the input space.

In this study, SOM is applied to analyze the relationship between the DEA-based efficiency indices of Turkish provinces and various demographic variables such as population density, age structure, and education level. The main goal is to identify clusters of provinces with similar efficiency-demographic patterns and to reveal potential regional structures or disparities.

The SOM algorithm operates through the following steps:

1. **Initialization:** A grid of neurons (typically 2D) is initialized with random weight vectors of the same dimension as the input data.
2. **Best Matching Unit (BMU) Selection:** For each input vector, the neuron with the smallest Euclidean distance to the input (the BMU) is identified.

3. **Weight Update:** The weights of the BMU and its neighboring neurons are updated to become more similar to the input vector.
4. **Iteration and Convergence:** This process is repeated over several iterations, with a decreasing learning rate and shrinking neighborhood radius to ensure convergence.

SOM's ability to produce an interpretable two-dimensional map makes it particularly effective for visualizing the distribution of multidimensional provincial data. This method has been successfully applied in several socio-economic and regional development studies [64,65], demonstrating its strength in uncovering hidden patterns and clustering structures.

In this context, SOM allows the identification of provinces that share similar DEA performance scores and demographic characteristics. Such clustering results offer valuable insights into regional inequalities and can inform data-driven policy recommendations. SOM transforms complex multidimensional data into an interpretable 2D layout where topologically similar items cluster together. It has been demonstrated to effectively detect spatial and socio-economic structures even in complex systems. For example, it has been successfully applied to air quality station characterization [66] and landscape–demographic correlations via explainable SOM frameworks [67].

A recent survey of methodological improvements also highlights enhanced SOM robustness and usability in socio-economic data modeling [68].

- **DEA indices and demographic variables** are standardized and input into the SOM.
- **Topology preservation** ensures provinces with comparable profiles reside nearby on the map.
- **Post-clustering interpretation** involves analyzing neuron regions to interpret groupings—for example, identifying provinces where DEA efficiency correlates with higher education or lower population density.
- **Validation** through silhouette analysis, U-matrix visualizations, and cluster stability testing.

This mapping facilitates a nuanced understanding of how demographic patterns link with performance outcomes, providing a data-driven basis for targeting regional policy interventions.

3.3.6. Healthcare Industry in Turkey

Turkey's healthcare system operates within a mixed model, integrating public provision through universal health insurance with a growing private sector. Since the launch of the Health Transformation Program in 2003, significant progress has been made in access, coverage, and key health indicators. As of 2024, over 99% of the population is covered by the Social Security Institution (SGK), yet healthcare expenditure remains relatively low—approximately 6.3% of GDP—compared to the OECD average [69].

Despite broad insurance coverage, the Turkish healthcare system continues to face challenges such as regional inequalities in service provision, workforce shortages in rural areas, and increasing pressure due to population aging. Moreover, the growing demand for private services has amplified debates around healthcare equity and efficiency [70].

Recent studies have emphasized emerging trends in Turkey's health sector, including the rapid development of digital health technologies such as telemedicine, which gained momentum during and after the COVID-19 pandemic. For example, recent findings show that telecardiology systems in Istanbul have contributed to reducing both patient costs and carbon emissions [71].

Turkey has also positioned itself as a global player in medical tourism, supported by state-backed initiatives and competitive pricing. In 2024, the sector was valued at approximately $3.9 billion and is expected to grow steadily over the next decade [72].

In Turkey, the healthcare sector is one of the areas with the highest concentration of public expenditures, and these expenditures have been increasing steadily over the years. Figure 2 presents a graph illustrating public health expenditures and non-interest expenditures, summarizing the trend in healthcare spending.

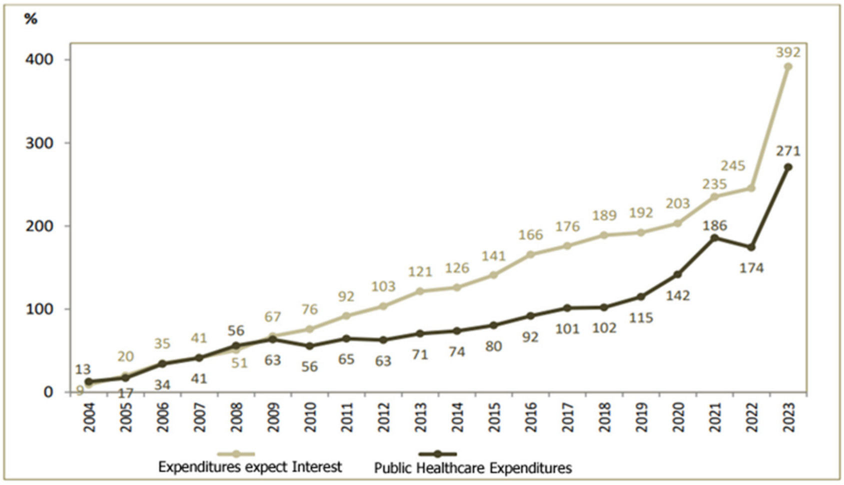

Figure 2. Change in public health expenditures over the years [73]

As can be seen in Figure 2, healthcare spending is constantly increasing, with a 392% increase, exceeding normal levels, in 2023 compared to the previous year. This undoubtedly has a significant impact on households. Figure 2 shows that per capita healthcare spending for 2023 is ₺2,589.

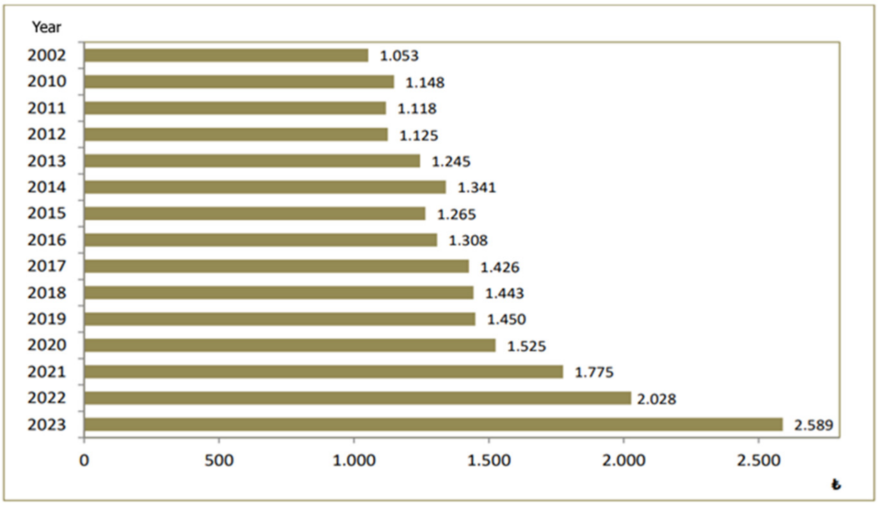

Figure 3. Out-of-pocket healthcare expenditures per capita, Real, ₺, 2023 [73]

As can be seen in Figure 3, per capita healthcare spending has generally increased by around 250%. When we correlate this figure with annual population growth, we see that it has increased at a higher rate. Consequently, we believe that considering the Turkish healthcare sector as a significant system utilizing such a large amount of expenditure and input, evaluating it, and analyzing inefficiencies will create significant added value. Numerous studies conducted using DEA can be found in the literature focusing on this sector. Therefore, comparing the recently published 2023 indicators with past studies on productivity is crucial. This allows us to assess how the healthcare sector in Turkey has evolved in terms of productivity.

4. FINDINGS

4.1. DEA Findings

In analyses conducted using Python 3.1, efficiency analyses were performed on a provincial basis using both the BCC and CCR methods. During the DEA, provinces were selected as DMUs, and the number of beds, doctors, hospitals, nurses, and midwives were used as input variables for the year 2023, while the number of examinations, inpatients, surgeries, days in bed, and bed turnover were used as output variables. The graph showing efficiency scores using the CCR and BCC methods is shown in Figure 4.

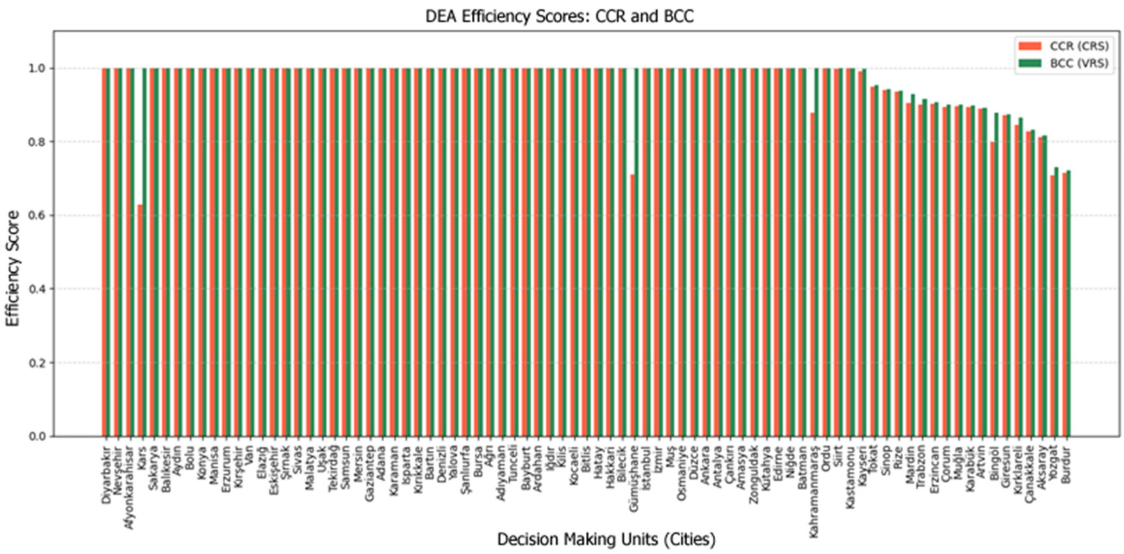

Figure 4. Efficiency scores by province using the CCR and BCC results for every city in Turkey

Analysis of the findings reveals that 22 cities had poor efficiency scores according to the CCR method, with Kars having the lowest score at 0.628610. Eighteen provinces also had low efficiency scores according to the BCC method, with Burdur having the lowest efficiency score at 0.720798.

4.2. Self-Organizing Maps (SOMDEA) Findings

After obtaining productivity scores by province, the aim was to investigate the impact of demographic characteristics on these productivity scores. For this purpose, the Self-Organizing Maps method, a frequently used unsupervised learning method in the literature, was chosen. The dataset used in this phase consisted of CRS values obtained through DEA, along with demographic data for each province, including population, rural population ratio, child ratio, elderly ratio, GDP, and average years of schooling. Using python script implements a Self-Organizing Map (SOM) based Data Envelopment Analysis (SOMDEA) approach to evaluate the efficiency of public hospitals in Turkey at the regional level. The data is first loaded and managed using pandas, a standard library for scientific data manipulation in Python. Pandas enables efficient reading of Excel files, handling missing values, and extracting relevant features, which is essential for preprocessing in operations research and efficiency studies.

Before training the SOM, the input data is normalized using MinMaxScaler from scikit-learn. Normalization scales all features to a common range [0,1], ensuring that variables with larger magnitudes do not dominate the training process. This step is critical because SOMs are sensitive to the relative scale of input variables, and proper normalization preserves the contribution of each feature in clustering and pattern recognition.

The core of the analysis is performed using MiniSom, a lightweight Python library for Self-Organizing Maps. SOMs are unsupervised neural networks that map high-dimensional input data onto a lower-dimensional grid while preserving the topological structure. In this code, a 9×9 SOM grid is trained with 500 iterations, using a learning rate of 0.5 and a neighborhood radius (sigma) of 1.0. During training, each hospital (Decision Making Unit, DMU) is associated with a “winning neuron” that represents its position on the SOM, allowing similar hospitals to cluster together.

Finally, the regional analysis is conducted by mapping each province to its corresponding SOM neuron and averaging the weight vectors within each region. The results are visualized using matplotlib as radar charts, showing the characteristic feature patterns for each Turkish region. This combination of SOM and DEA (SOMDEA) provides a robust framework for uncovering latent efficiency patterns among hospitals, combining the clustering capability of SOMs with the benchmarking perspective of DEA. Figure 5 shows the Self Organizing Maps of our study.

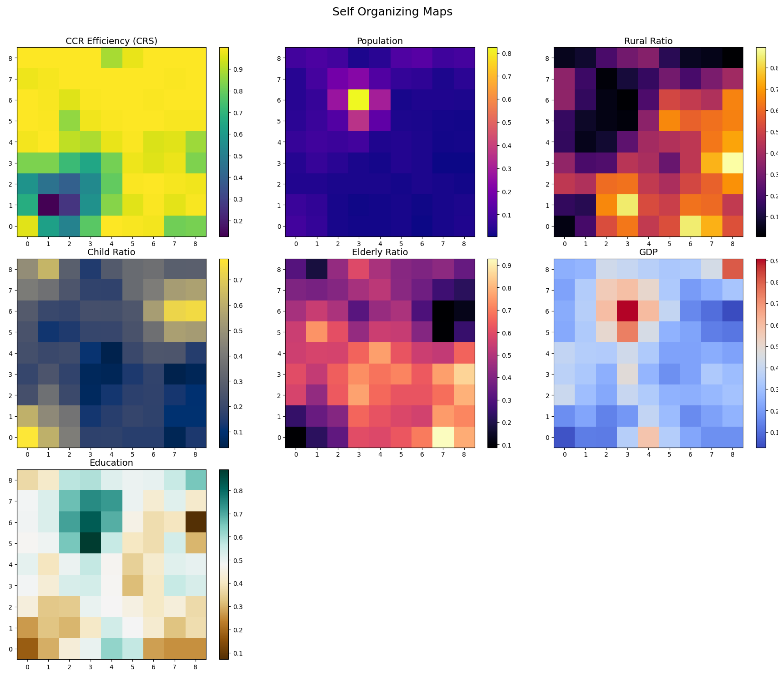

Figure 5. SOMDEA maps

As shown in Figure 5, a dataset consisting of 7 variables was used in the analysis. Training was performed using a 9×9 Kohonen map. In the resulting visualizations, lighter colors represent higher values, whereas darker colors represent lower values. The interpretation was conducted by analyzing the demographic variables and their effects, specifically on CRS (Constant Returns to Scale) efficiency. The findings obtained from Figure 5 are as follows:

- The region with the highest population is also the one with the lowest proportion of rural population. However, some provinces with relatively low populations also exhibit low rural population ratios.
- The region with the highest population is also among the provinces with the highest CRS efficiency.
- In provinces with the lowest CRS efficiency, it is observed that these regions tend to have low GDP, the shortest average years of schooling, and an above-average elderly population. Additionally, the proportion of children is also high in these areas.
- In regions where the rural population ratio is high and the elderly population is also high, CRS efficiency appears to be at a good level.
- In provinces with the highest average years of schooling, CRS efficiency is also high, indicating that as the average education level increases, the efficiency of institutions (i.e., hospitals) in those regions improves.
- In provinces with high GDP levels, CRS efficiency is generally high. However, in some low-GDP provinces, CRS efficiency was still found to be high, likely due to lower elderly population ratios.
- Provinces with the highest child population also tend to have the lowest elderly population, and low education levels and low GDP characterize these regions. Despite this, CRS efficiency is still high, suggesting that a high child population may positively influence efficiency.
- Provinces with higher average years of schooling also tend to have higher GDP values, suggesting a positive correlation between education level and income.
- There is a single point of extreme population density (shown in yellow), likely representing a highly populated city like Istanbul, while other regions are sparsely populated. This indicates a clear imbalance in population distribution across Turkey, which is reflected in the SOM map.
- No systematic effect of population on VRS efficiency was observed. Both highly populated and sparsely populated areas can be efficient.
- The rural population ratio does not directly align with CCR efficiency. Being rural or urban alone is not a decisive factor.

- The child population ratio is not negatively correlated with CCR efficiency. Some areas with high child populations fall into efficient categories.
- As the elderly population increases, CCR efficiency tends to decrease. In other words, regions with a predominantly elderly population are more likely to be classified as less efficient.
- As GDP increases, CCR efficiency also tends to rise, suggesting that economic strength is associated with higher efficiency. There is a clear and positive relationship between education level and CCR efficiency.

The provinces identified as efficient according to the CCR model generally exhibit strong performance in several key input categories. Specifically, efficient provinces tend to have a higher number of physicians and nurses per capita, a well-distributed bed capacity, and higher bed turnover rates, indicating optimized use of hospital infrastructure. In addition, provinces with larger hospital networks (measured by total hospital count) and greater specialization capabilities tend to reach or approach the efficiency frontier. These results suggest that human resource density, rather than physical capacity alone, plays a critical role in driving efficiency. The SOM analysis further supports this finding by clustering efficient provinces together with those possessing higher education levels, higher GDP, and lower elderly dependency ratios, indicating that favorable socio-economic conditions indirectly enhance hospital input utilization.

For provinces classified as inefficient, the SOM clusters reveal several shared demographic and socio-economic characteristics. Inefficient provinces generally fall into clusters with low GDP, low average years of schooling, and high elderly population ratios, suggesting a structural disadvantage in both the availability and utilization of healthcare resources. In addition, these regions commonly exhibit a higher rural population ratio, which may contribute to reduced accessibility to centralized healthcare services and increased logistical burden on hospitals. The SOM clusters also show that inefficient provinces often have high child dependency ratios combined with low population density, a pattern associated with higher demand pressure but limited service delivery capacity. This complementary analysis highlights that inefficiency is not solely caused by hospital-level operational issues, but is systematically related to regional socio-economic constraints. Incorporating SOM findings into the interpretation therefore strengthens the explanatory depth of the DEA results.

5. DISCUSSION

The results of the Data Envelopment Analysis (DEA) indicate that significant inter-provincial disparities in efficiency persist within Turkey's healthcare system. According to the CCR model, 22 provinces exhibited low efficiency scores, while the BCC model identified 18 provinces with low efficiency. This finding suggests that, although efficiency has improved in some regions compared to previous years, regional imbalances remain a continuing issue.

For instance, Yiğit [43], in a study based on 2013 data, found that 25 provinces were technically inefficient under the CCR model. Similarly, Bardakçı and Filiz [44], in their study based on 2016–2017 data, reported that among hospitals in the province of Artvin, four were efficient while two were found to be inefficient. The findings of the present study indicate that although some provinces have shown relative improvement over time, there is still a pressing need for comprehensive, region-specific strategies to enhance overall efficiency across the country.

The fact that provinces such as Kars and Burdur stand out with low efficiency scores suggests an imbalance between resource utilization and service outputs in those areas. The literature frequently highlights that low GDP and low levels of education negatively affect efficiency [40,46]. In this context, the findings from the Self-Organizing Maps (SOM) analysis in this study—which show that areas with shorter average years of schooling, low GDP, and a high elderly population tend to have low CRS scores—are consistent with previous research.

The positive relationship between education level and CRS efficiency aligns with earlier studies. For example, Spinks and Hollingsworth [40], in a comparative analysis among OECD countries, found that countries with higher average years of schooling tend to have more efficient healthcare systems. Similar findings were observed in this study concerning Turkey.

Another notable point is that some provinces with low GDP still exhibited high CRS scores. This may indicate that in regions with a younger population and consequently lower elderly care costs, hospital services operate more efficiently and at a lower cost. For such regions, health policies prioritizing child health may further support overall system efficiency.

In general, this study based on 2023 data demonstrates that while there has been some improvement in efficiency levels in Turkey's healthcare sector over time, regional inequalities in efficiency remain a challenge yet to be resolved. The increasing use of AI-assisted methods, such as Self-Organizing Maps (SOM), in the literature allows not only for measuring efficiency levels but also for modeling and explaining the underlying causes of inefficiency [8,9]. Regional based SOM results an also evaluated at Figure 5.

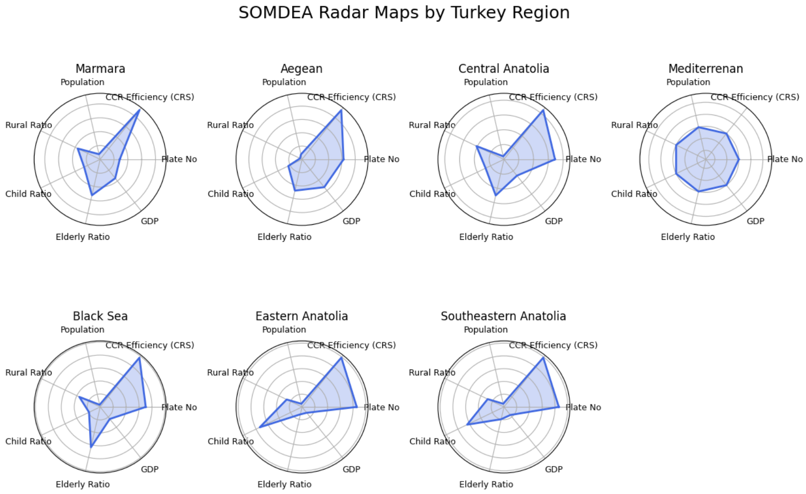

Figure 6. SOMDEA radar maps

At Figure 6, the radar charts provide a comparative visualization of the normalized socioeconomic and demographic indicators across Turkey's seven geographical regions. Each chart integrates multiple variables—Population, CCR Efficiency (CRS), Plate Number, GDP, Elderly Ratio, Child Ratio, and Rural Ratio allowing a multidimensional assessment of regional characteristics within the SOMDEA framework. This structure supports an understanding of how demographic composition and economic capacity interact with measured efficiency across regions.

The Marmara Region demonstrates a distinct profile characterized by high CCR efficiency and balanced performance across other indicators. As Turkey's most industrialized and urbanized region, Marmara's moderate-to-high values in population and GDP align with its developed economic structure. Similarly, the Aegean Region reflects high efficiency levels combined with stable demographic ratios, suggesting a mature socioeconomic environment with moderate administrative and economic loads.

Central Anatolia exhibits efficiency levels comparable to Marmara and the Aegean, supported by a relatively balanced distribution in rural, child, and elderly ratios. This pattern indicates a diversified demographic composition and consistent economic performance across the region's provinces. In contrast, the Mediterranean Region presents more moderate and evenly distributed values across all indicators, reflecting a region that maintains demographic balance while demonstrating slightly lower efficiency compared to western regions.

The Black Sea Region displays a unique structure with a notably high rural population ratio. While its efficiency level remains strong, the region's demographic pattern is characterized by a higher proportion of rural settlements and moderate elderly and child ratios. Eastern Anatolia, on the other hand, reveals a demographic profile marked by high rural and child ratios alongside lower population and GDP values. Despite these structural challenges, the region maintains a high efficiency score, suggesting effective resource utilization within its contextual constraints.

Finally, Southeastern Anatolia demonstrates a prominently high child ratio and relatively low elderly ratio, indicative of a younger population structure. Although the region's GDP levels are modest, its CCR efficiency remains strong, pointing to potential advantages in demographic dynamism. Overall, the comparative analysis of the radar charts reveals that western regions generally exhibit more balanced socioeconomic indicators and consistently high efficiency, while eastern regions are characterized by younger populations, higher rurality, and lower economic output, yet maintain considerable efficiency within the SOMDEA assessment.

6. CONCLUSIONS

This study adopts an integrated approach by employing Data Envelopment Analysis (DEA) and Self-Organizing Maps (SOM) to measure the efficiency of public hospitals in Turkey at the provincial level. Initially, the relative efficiency levels of hospitals were calculated using the Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models. Then, the relationships between efficiency scores and various demographic and socio-economic variables were visualized and analyzed through the SOM method.

Based on 2023 data, the study found that, according to the CCR model, 22 provinces and, according to the BCC model, 18 provinces exhibited low performance in terms of efficiency. Compared to previous years, these figures indicate a modest improvement. For example, Yiğit [43] reported that 25 provinces were inefficient based on 2013 data.

The findings reveal that the healthcare infrastructure does not solely determine hospital efficiency but is also closely related to a wide range of factors such as population structure, economic development, rural/urban ratios, education levels, and age distribution of the provinces. Notably, provinces with higher education levels and per capita income tend to exhibit higher efficiency, while those with a larger elderly population generally display lower efficiency scores.
In this context, policies aimed at improving efficiency in healthcare services should not be limited to the healthcare delivery system but should also be integrated with regional development initiatives, investments in education, and broader social policies.

Overall, the integrated SOMDEA approach presented in this study offers a methodological advancement by not only identifying efficiency levels but also uncovering the underlying socio-economic patterns associated with provincial disparities. The complementary use of SOM enhances traditional DEA interpretations by illustrating the structural factors that shape efficiency outcomes. Implementing the recommended revisions such as incorporating more detailed SOM-based interpretations and refining the presentation of efficient and inefficient groups will significantly enhance the analytical depth and policy relevance of the study. By strengthening these elements, the manuscript will provide clearer guidance for regional healthcare planning and contribute more effectively to the ongoing academic discussion on public-sector efficiency measurement.

For Future studies, conducting similar analyses over multiple years, incorporating time series and trend analyses, and performing comparative assessments between public and private hospitals will contribute to a more in-depth understanding of the healthcare system.

In conclusion, although there has been a partial increase in efficiency in Turkey's healthcare system, regional disparities remain a significant issue. In this regard, the proposed SOMDEA method provides more comprehensive and actionable insights than traditional efficiency analyses, enriching the academic literature. Future studies may focus on expanding the model to include time series and private sector comparisons to enhance its explanatory power further.

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