Healthcare Engineering 2 (2026) 87–100

Contents lists available at GrowingScience

Healthcare Engineering

homepage: www.GrowingScience.com/he

Comparative analysis of hospital efficiency in Iran: A multi-methodological study using DEA and TOPSIS techniques

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C H R O N I C L E

Article history:
Received: October 10, 2025
Received in revised format: January 15, 2025
Accepted: February 2, 2026
Available online:
February 2, 2026

Keywords:
Data Envelopment Analysis
TOPSIS
Hospital Efficiency
Performance Measurement
Healthcare Management
Iranian Hospitals
Multi-Criteria Decision Analysis
CCR Model
BCC Model
Additive DEA

A B S T R A C T

This study presents a comprehensive comparative analysis of hospital efficiency in Iran using Data Envelopment Analysis (DEA) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methodologies. With increasing pressure on healthcare systems to optimize resource utilization while maintaining quality standards, measuring hospital efficiency has become crucial for evidence-based decision-making. The research employs four distinct DEA models, Charnes, Cooper, and Rhodes (CCR), Banker, Charnes, and Cooper (BCC) input-oriented, BCC output-oriented, and Additive models, alongside TOPSIS to evaluate the relative efficiency of Iranian hospitals. By comparing these methodological approaches, this study aims to identify the most suitable framework for hospital performance assessment in the Iranian healthcare context. The analysis incorporates multiple input variables including number of physicians, nursing staff, available beds, and operational costs, against output variables such as patient discharges, outpatient visits, surgical procedures, and bed occupancy rates. The findings provide insights into the consistency and reliability of different efficiency measurement techniques, offering healthcare administrators and policymakers a robust analytical framework for performance evaluation. The comparative approach reveals methodological strengths and limitations in different contexts, contributing to the advancement of healthcare efficiency measurement literature while providing practical implications for hospital management in emerging economies.

1. Introduction

Healthcare system efficiency has emerged as a critical concern for policymakers and administrators worldwide, particularly in developing countries where resource constraints often limit healthcare delivery capacity. In Iran, the healthcare sector has undergone significant transformations over recent decades, with increasing emphasis on performance measurement and quality improvement initiatives. The assessment of hospital efficiency plays a pivotal role in identifying areas for improvement, optimizing resource allocation, and enhancing service delivery outcomes. This study addresses the methodological challenges in hospital efficiency measurement by comparing two prominent analytical techniques: Data Envelopment Analysis (DEA) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

1.1 Literature Review

The application of DEA in healthcare efficiency analysis has gained substantial attention since its initial introduction. In hospital settings, DEA has been extensively employed to evaluate technical efficiency by comparing multiple decision-making units (DMUs) with similar operational characteristics. Pioneering work by Banker, Conrad, and Strauss (1986) demonstrated DEA's superiority over traditional econometric methods for hospital production analysis, establishing it as a robust tool for handling multiple inputs and outputs. This foundational application has been followed by a vast expansion of DEA use in healthcare, as thoroughly cataloged in systematic reviews. Kohl et al. (2019) provided a comprehensive

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ISSN 3115-8269 (Online) - ISSN 3115-8250 (Print)

doi: 10.5267/j.he.2026.3.004

review focusing on hospital settings, while Pai, Pakdil, and Azadeh-Fard (2024) conducted an extensive systematic literature review of DEA applications in acute care hospitals from 1984 to 2022, confirming the methodology's enduring relevance and evolving sophistication. The selection of appropriate inputs and outputs is a critical step in DEA modeling. Azreena, Juni, and Rosliza (2018) conducted a systematic review to establish evidence-based recommendations, identifying common inputs like physician and nursing staff numbers, bed capacity, and equipment, alongside outputs such as patient discharges and surgical procedures. This guidance was further refined by Zubir et al. (2024) in their systematic review of input-output selection approaches. The fundamental structure of DEA models for classifying efficiency was elaborated by Charnes, Cooper, and Thrall (1991), providing the theoretical underpinning for many subsequent hospital studies. Early textbooks and guides, such as that by Bhat, Verma, and Reuben (2001), helped disseminate DEA methodology for health management applications. Recent methodological innovations have sought to address specific limitations and enhance DEA's applicability. Recognizing that hospitals must balance efficiency with quality, Khushalani and Ozcan (2017) developed a dynamic network DEA model that integrates both dimensions. Similarly, Ghahremanloo et al. (2020) proposed a novel model incorporating efficiency, effectiveness, and productivity. To tackle the issue of data uncertainty common in healthcare settings, Peykani and Pishvaee (2024) developed an uncertain common-weights DEA model. Other advanced applications include the use of window analysis to assess longitudinal efficiency changes, as demonstrated by Jia and Yuan (2017) in studying branched hospitals, and the measurement of scale efficiency in settings with non-substitutable inputs, as explored by Barnum et al. (2011). The context of emerging economies presents unique challenges, leading to tailored methodological developments. Hajiagha et al. (2023) proposed a three-stage DEA approach for public hospitals in such settings, incorporating contextual variables. Studies applying DEA in various countries highlight both the model's versatility and the contextual nature of efficiency. For instance, Gonçalves et al. (2007) evaluated public hospitals in Brazilian capitals, Jehu-Appiah et al. (2014) analyzed ownership and efficiency in Ghana, Silwal and Ashton (2017) measured productivity in Nepalese public hospitals, and Zere et al. (2006) assessed the technical efficiency of district hospitals in Namibia. In the Iranian context specifically, interest in hospital efficiency measurement has grown significantly. Bahadori et al. (2016) and Mahdiyan et al. (2019) conducted systematic reviews of hospital performance evaluation and efficiency studies in Iran, respectively, charting the field's evolution and noting the diversity of approaches. Specific applications include the evaluation of hospital productivity by Torabipour et al. (2014) and the development of an integrated DEA model for stroke care services by Mirmozaffari et al. (2021).

Alongside DEA, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has emerged as a vital multi-criteria decision-making (MCDM) tool for hospital performance evaluation, particularly effective in integrating diverse performance metrics. Its application in healthcare has been demonstrated in various forms. Shafii et al. (2015) employed a fuzzy AHP-TOPSIS approach to analyze hospital manager performance in Iran, addressing the inherent imprecision in managerial assessments. This integrated fuzzy approach was further advanced by Ozel, Topcu, and Oztaysi (2025) in a hospital performance measurement system. Beyond hospital management, Rađenović and Veselinović (2017) applied an integrated AHP-TOPSIS method to assess health management information systems efficiency, while Araujo, Wanke, and Siqueira (2018) combined TOPSIS with neural networks to analyze Brazilian public health performance. The true strength of these methodologies often lies in their combined or comparative application. Mujasi, Asbu, and Puig-Junoy (2016) applied both DEA and TOPSIS to evaluate referral hospitals in Uganda, highlighting how each method provides a different but complementary perspective on performance drivers. This synergy allows DEA's focus on technical efficiency frontiers to be augmented by TOPSIS's ability to incorporate multiple weighted criteria. Other integrated frameworks have been proposed to bridge strategic and operational views. Hatefi and Haeri (2019) combined a balanced scorecard with fuzzy DEA for hospital evaluation, and Al-Shammari (1999) developed a multi-criteria DEA model, both aiming for a more holistic assessment. The comparative value of these methods is also evident in studies like Nayar and Ozcan (2008), who used DEA to compare hospital efficiency and quality, and Sikka, Luke, and Ozcan (2009), who evaluated the efficiency of hospital-based clusters. Further regional applications underscore the global relevance of these techniques. Habib and Shahwan (2020) used Malmquist DEA to analyze operational and financial efficiency trends in Egyptian hospitals. Gok and Sezen (2011) focused on analyzing hospital efficiencies in Turkey, Peixoto, Musetti, and de Mendonça (2020) applied PCA and DEA to federal university hospitals in Brazil, and Ram Jat and San Sebastian (2013) measured the technical efficiency of public district hospitals in India. Chitnis and Mishra (2019) applied both standard and super-efficiency DEA to evaluate Indian private hospitals. This extensive body of literature demonstrates that while DEA and TOPSIS are well-established, their combined and contextually adapted application continues to yield valuable insights for healthcare management and policy. The evolution from simple efficiency measurement to integrated frameworks that account for quality, uncertainty, and multiple strategic objectives reflects the growing complexity of performance evaluation in healthcare systems worldwide.

This study builds upon this extensive literature by providing a comprehensive comparative analysis of multiple DEA models and TOPSIS methodology in the specific context of Iranian hospitals. By examining four distinct DEA approaches alongside TOPSIS, the research addresses methodological questions regarding technique selection, consistency of results, and practical applicability in healthcare settings. The following sections detail the methodological framework, present comparative results, and discuss implications for hospital efficiency measurement practice and policy development.

2. Methodological Framework

2.1 Data Envelopment Analysis (DEA) Models

Data Envelopment Analysis represents a non-parametric linear programming methodology for evaluating the relative efficiency of decision-making units (DMUs) that utilize multiple inputs to produce multiple outputs. Developed initially by Charnes, Cooper, and Rhodes (1978), DEA constructs an empirical production frontier based on observed best practices, against which all units are compared. In hospital efficiency analysis, each hospital serves as a DMU, with inputs typically including resources such as medical staff, beds, and equipment, while outputs encompass healthcare services delivered, including patient treatments, surgeries, and outpatient visits.

2.1.1 CCR Model (Constant Returns to Scale)

The CCR model, named after its developers Charnes, Cooper, and Rhodes, assumes constant returns to scale, meaning that proportional changes in inputs result in proportional changes in outputs. This model evaluates overall technical efficiency, combining both pure technical efficiency and scale efficiency. The mathematical formulation for the input-oriented CCR model is expressed as follows:

min θ subject to: $\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}$ for $i = 1,...,m$ $\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}$ for $r = 1,...,s$ $\lambda_j \geq 0$ for $j = 1,...,n$	where: θ = efficiency score of DMU_o (DMU under evaluation) x_{io} = amount of input i for $DMUo$ y_{ro} = amount of output r for $DMUo$ x_{ij} = amount of input i for DMU_j y_{rj} = amount of output r for DMU_j λ_j = intensity variable for DMU_j m = number of inputs s = number of outputs n = number of $DMUs$

The efficiency score θ ranges between 0 and 1, with 1 indicating full efficiency and values less than 1 indicating relative inefficiency. The dual formulation of the CCR model provides the multiplier form, which identifies optimal weights for inputs and outputs:

$\max \sum_{r=1}^{s} u_r y_{ro}$ subject to: $\sum_{i=1}^{m} v_i x_{io} = 1$ $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$ for $j = 1,...,n$ $u_r \geq \varepsilon > 0$ for $r = 1, 2, ..., s$ $v_i \geq \varepsilon > 0$ for $i = 1, 2, ..., m$	where: u_r = weight assigned to output r v_i = weight assigned to input i ε = a small positive non-Archimedean infinitesimal

2.1.2 BCC Model (Variable Returns to Scale)

The BCC model, developed by Banker, Charnes, and Cooper (1984), relaxes the constant returns to scale assumption of the CCR model by incorporating variable returns to scale. This model evaluates pure technical efficiency by eliminating the scale efficiency component. The BCC model exists in both input-oriented and output-oriented formulations, each addressing different managerial perspectives.

BCC Input-Oriented Model:	**BCC Output-Oriented Model:**
min θ	max φ
subject to:	subject to:

$\sum_{j=1}^{n}\lambda_j x_{ij} \le \theta x_{io}$ for i = $1,\ldots,m$ $\sum_{j=1}^{n}\lambda_j y_{rj} \ge y_{ro}$ for r = $1,\ldots,s$ $\sum_{j=1}^{n}\lambda_j = 1$ $\lambda_j \ge 0$ for j = 1, 2, ..., n The constraint $\sum_{j=1}^{n}\lambda_j = 1$ introduces convexity, allowing for variable returns to scale. This formulation identifies input reductions possible while maintaining current output levels.	$\sum_{j=1}^{n}\lambda_j x_{ij} \le x_{io}$ for i = $1,\ldots,m$ $\sum_{j=1}^{n}\lambda_j y_{rj} \ge \varphi y_{ro}$ for r = $1,\ldots,s$ $\sum_{j=1}^{n}\lambda_j = 1$ $\lambda_j \ge 0$ for j = 1, 2, ..., n where φ represents the efficiency score in output orientation, with values ≥ 1. The reciprocal $1/s$ provides a measure between 0 and 1 similar to input-oriented scores. This formulation identifies output expansions possible while maintaining current input levels.

2.1.3 Additive DEA Model

The additive DEA model, introduced by Charnes et al. (1985), simultaneously considers both input reduction and output augmentation possibilities. Unlike radial models that proportionally adjust inputs or outputs, the additive model identifies specific improvement potentials for each input and output variable. The formulation is expressed as:

$$\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$

subject to:

$$\sum_{i=1}^{n}\lambda_j x_{ij} + s_i^- = x_{io} \quad \text{for } i = 1,\ldots,m$$

$$\sum_{i=1}^{n}\lambda_j y_{rj} + s_r^+ = t_{ro} \quad \text{for } i = 1,\ldots,s$$

$$\sum_{j=1}^{n}\lambda_j = 1$$

$\lambda_j \ge 0$ for j = 1, 2, ..., n

$$s_i^- \ge 0 \quad \text{for } i = 1,\ldots,m$$
$$s_i^+ \ge 0 \quad \text{for } i = 1,\ldots,s$$

where:
s_i^- = input slack variables representing excess input utilization
s_i^+ = output slack variables representing output shortfalls

The additive model provides comprehensive information about specific inefficiencies in each input and output dimension, making it particularly valuable for identifying targeted improvement areas in hospital operations.

2.2 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The Technique for Order Preference by Similarity to Ideal Solution, developed by Hwang and Yoon (1981), represents a multi-criteria decision-making method that evaluates alternatives based on their geometric distance from ideal and anti-ideal solutions. The fundamental premise of TOPSIS is that the optimal alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS).

2.2.1 Mathematical Formulation of TOPSIS

The TOPSIS methodology involves six systematic steps:

Step 1: Construction of the Decision Matrix

The initial decision matrix D contains performance ratings of m alternatives (hospitals) with respect to n criteria:

$$D = \left[x_{ij} \right]_{m \times n}$$

where x_{ij} represents the performance rating of alternative i with respect to criterion j.

Step 2: Normalization of the Decision Matrix

To facilitate comparison across criteria with different measurement units, the decision matrix is normalized using vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \text{for } i = 1,..,m; j = 1,..,n$$

This results in the normalized decision matrix $R = \left[r_{ij} \right]_{m \times n}$.

Step 3: Construction of the Weighted Normalized Decision Matrix

The weighted normalized decision matrix V is obtained by multiplying the normalized ratings by their corresponding criterion weights:

$$v_{ij} = w_j \times r_{ij} \quad \text{for } i = 1,...,m; j = 1,...,n$$

Where w_j represents the weight assigned to criterion j, with $\sum_{j=1}^{n} w_j = 1$.

Step 4: Determination of Ideal and Anti-Ideal Solutions

The positive ideal solution A^+ and negative ideal solution A^- are determined as:

$$A^+ = \left\{ v_1^+,...,v_n^+ \right\} = \left\{ \left(\max_i v_{ij} \mid j \in J^+ \right), \left(\max_i v_{ij} \mid j \in J^- \right) \right\}$$
$$A^- = \left\{ v_1^-,...,v_n^- \right\} = \left\{ \left(\min_i v_{ij} \mid j \in J^+ \right), \left(\max_i v_{ij} \mid j \in J^- \right) \right\}$$

Where J^+ represents benefit criteria (higher values preferred) and J^- represents cost criteria (lower values preferred).

Step 5: Calculation of Separation Measures
The Euclidean distances of each alternative from the ideal and anti-ideal solutions are calculated as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+ \right)^2} \quad \text{for } i = 1,...,m$$
$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2} \quad \text{for } i = 1,...,m$$

Step 6: Calculation of Relative Closeness to Ideal Solution
The relative closeness coefficient for each alternative is computed as:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad \text{for } i = 1,...,m$$

where $0 \le C_i \le 1$, with higher values indicating better performance. Alternatives are ranked in descending order of C_i values.

2.2.2 Weight Determination Methods

The determination of criterion weights represents a critical component of TOPSIS implementation. Several approaches may be employed:

Equal Weighting: All criteria receive equal importance weights:

$w_j = 1/n$ for j = 1, 2, ..., n

Subjective Weighting: Weights are assigned based on expert judgment, often employing techniques such as:

- Analytic Hierarchy Process (AHP)
- Delphi method
- Direct rating by domain experts

Objective Weighting: Weights are derived mathematically from the decision matrix data:

- Entropy method: $w_j = \dfrac{1-E_j}{\sum_{k=1}^{n}(1-E_k)}$

  where $E_j = -k\sum_{i=1}^{m} p_{ij} \ln(p_{ij})$, with $p_{ij} = \dfrac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$ and $k = \dfrac{1}{\ln(m)}$
- Criteria Importance Through Intercriteria Correlation (CRITIC) method

Integrated Weighting: Combines subjective and objective approaches to balance expert judgment with data-driven insights.

2.3 Comparative Framework

The comparative analysis between DEA and TOPSIS methodologies examines several dimensions:

Methodological Foundations: DEA operates as a frontier-based efficiency measurement technique, identifying best-practice benchmarks and measuring deviations from this frontier. TOPSIS functions as a distance-based multi-criteria decision-making method, evaluating alternatives relative to ideal and anti-ideal reference points.

Assumption Structures: DEA requires minimal assumptions about the functional form of the production relationship but assumes convexity of the production possibility set. TOPSIS assumes criteria independence and linear additive utility, with preferences represented by Euclidean distance measures.

Information Requirements: DEA utilizes actual input and output quantities without requiring a priori weight assignments, deriving optimal weights through linear programming. TOPSIS requires explicit criterion weights, which may be determined subjectively, objectively, or through integrated approaches.

Output Interpretation: DEA provides efficiency scores (0 to 1) with diagnostic information about input excesses and output shortfalls. TOPSIS generates relative closeness coefficients (0 to 1) with ranking information but limited diagnostic insights into specific improvement areas.

Scale Properties: DEA models explicitly consider returns to scale properties through model specifications (CCR for constant returns, BCC for variable returns). TOPSIS does not inherently address scale properties, though these may be incorporated through appropriate criterion definitions.

Sensitivity to Extreme Values: DEA frontier estimation can be sensitive to outliers, which may disproportionately influence efficiency scores. TOPSIS distance calculations may also be affected by extreme values, though normalization procedures mitigate some of these effects.

The comparative application of these methodologies to Iranian hospital efficiency assessment provides insights into their complementary strengths and limitations, informing methodological selection decisions for healthcare performance evaluation.

3. Results

In this study, four input variables and three output variables are employed to evaluate the efficiency of hospitals. The raw data are given in the Appendix.

Inputs:	Outputs:
1. Number of hospital beds	1. Adjusted mortality rate (inverse indicator)
2. Number of physicians	2. Number of surgical procedures
3. Number of nurses	3. Number of admitted and discharged patients
4. Average length of patient stays (days)	

Analytical Method:

Two basic DEA models are applied in this analysis:

- Constant Returns to Scale (CRS): used to measure overall technical efficiency
- Variable Returns to Scale (VRS): used to measure pure managerial efficiency

In addition, the TOPSIS index is calculated to provide a more in-depth analysis and ranking of the hospitals. Table 1 shows the summary of some basic statistics.

Table 1

Summary of Efficiency Results

Number of Efficient Units (Score = 1)	Minimum	Maximum	Standard Deviation	Median	Mean	Efficiency Indicator
20 units (50%)	0.568	1.000	0.156	0.955	0.893	CCR Efficiency
26 units (65%)	0.569	1.000	0.132	1.000	0.921	BCC Efficiency
24 units (60%)	0.974	1.000	0.016	0.995	0.983	Scale Efficiency

Fig. 1 illustrates the frequency distribution of CCR efficiency scores. As shown, the highest concentration of efficiency scores falls within the range of 0.9 to 1.0 indicating relatively favorable performance for the majority of hospitals.

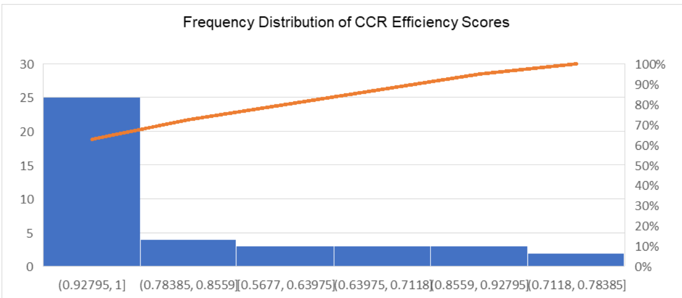

Fig. 1. Frequency Distribution of CCR Efficiency Scores

The efficiency distribution of 40 hospitals affiliated with Iranian universities of medical sciences, based on the CCR model, reveals a distinct pattern of performance dispersion, clearly observable in the histogram. The distribution exhibits a notable negative skewness, indicating a concentration of units in the higher efficiency range. The mean efficiency of 0.893 and median of 0.955 suggest that more than half of the hospitals perform above the average. This distribution deviates from normality and displays two distinct peaks, reflecting the existence of two separate performance groups among the evaluated units. Statistically, 50% of the hospitals fall within the efficiency range of 0.928 to 1.0, indicating favorable performance for half of the units. In contrast, 17.5% of the units (7 hospitals) are located in the low-efficiency range (below 0.712), requiring immediate attention and intervention. The intermediate range (0.712 to 0.928) comprises 32.5% of the units, highlighting considerable potential for performance improvement within this group. This distribution pattern underscores the necessity of adopting differentiated policies tailored to each performance group. Table 2 shows the results of the efficiency of different hospitals.

Table 2
Top 10 and Bottom 10 Hospitals Based on Efficiency

Hospital Name	Scale Efficiency	BCC Efficiency	CCR Efficiency	Rank
Tehran University of Medical Sciences	1.000	1.000	1.000	1
Shahid Beheshti University of Medical Sciences	1.000	1.000	1.000	1
Iran University of Medical Sciences	1.000	1.000	1.000	1
Isfahan University of Medical Sciences	1.000	1.000	1.000	1
Shiraz University of Medical Sciences	1.000	1.000	1.000	1
Tabriz University of Medical Sciences	1.000	1.000	1.000	6
Yazd University of Medical Sciences	1.000	1.000	1.000	7
Ardabil University of Medical Sciences	1.000	1.000	1.000	8
Guilan University of Medical Sciences	1.000	1.000	1.000	9
North Khorasan University of Medical Sciences	1.000	1.000	1.000	10
Bushehr University of Medical Sciences	1.000	1.000	1.000	11
Hamedan University of Medical Sciences	1.000	1.000	1.000	12
Lorestan University of Medical Sciences	1.000	1.000	1.000	13
Ilam University of Medical Sciences	0.912	1.000	0.912	14
Gonabad University of Medical Sciences	1.000	1.000	1.000	15
Kashan University of Medical Sciences	1.000	1.000	1.000	16
Jahrom University of Medical Sciences	0.995	0.982	0.973	17
Rafsanjan University of Medical Sciences	1.000	1.000	1.000	18
Sabzevar University of Medical Sciences	0.980	0.638	0.632	19
Shahroud University of Medical Sciences	1.000	1.000	1.000	20
Zabol University of Medical Sciences	1.000	1.000	1.000	21
Zahedan University of Medical Sciences	0.976	1.000	0.976	22
Fasa University of Medical Sciences	1.000	1.000	1.000	23
Bandar Abbas University of Medical Sciences	1.000	1.000	1.000	24
Dezful University of Medical Sciences	1.000	1.000	1.000	25
Nishabur University of Medical Sciences	1.000	1.000	1.000	26
Ahvaz University of Medical Sciences	0.995	0.865	0.865	27
Kerman University of Medical Sciences	0.789	1.000	0.789	28
Zanjan University of Medical Sciences	0.997	0.819	0.784	29
Qom University of Medical Sciences	0.989	0.873	0.872	30
Qazvin University of Medical Sciences	0.993	0.851	0.851	31
Arak University of Medical Sciences	0.990	0.968	0.963	32
Kohgiluyeh and Boyer-Ahmad University of Medical Sciences	0.979	0.727	0.720	33
Babol University of Medical Sciences	0.995	0.957	0.955	34
Mashhad University of Medical Sciences	0.993	0.668	0.667	35
Kermanshah University of Medical Sciences	0.974	0.569	0.568	36
Mazandaran University of Medical Sciences	0.986	0.615	0.613	37
Semnan University of Medical Sciences	0.990	0.675	0.657	38
Birjand University of Medical Sciences	0.990	0.727	0.725	39
Golestan University of Medical Sciences	0.983	0.698	0.695	40

The results indicate that 50% of hospitals are fully efficient under the CCR model, while 65% are fully efficient under the BCC model. This 15% difference highlights the impact of scale efficiency on unit performance. The mean CCR efficiency is calculated as 0.893, and the mean BCC efficiency as 0.921, indicating that, on average, hospitals perform better at the managerial level (BCC) compared to the overall technical level (CCR). Among the 40 hospitals examined, 20 hospitals were identified as fully efficient under both models. These units include Tehran, Shahid Beheshti, Iran, Isfahan, Shiraz Universities of Medical Sciences, among others. The efficiency of these units indicates that these centers have successfully converted available resources (beds, physicians, nurses) into desired outputs (reduced mortality, increased surgeries, higher patient discharges) in an optimal manner.

In TOPSIS, the performance of each decision-making unit is evaluated based on its distance from two reference points. The first reference point represents the best possible performance among all units, while the second represents the worst observed performance. The underlying principle is that an ideal option should be as close as possible to the positive ideal solution and as far as possible from the negative ideal solution. The combination of these two distances is expressed as the closeness coefficient to the ideal solution (CCIS). This coefficient ranges from zero to one, where values closer to one indicate better performance and closer alignment with the ideal scenario.

In this study, the closeness coefficient was calculated for each of the 40 hospitals, and based on these values, a complete ranking of hospitals from a multi-criteria performance perspective was established. Table 3 presents the closeness coefficient values and the final ranking of hospitals according to the TOPSIS method. In this table, all hospitals are sorted in descending order of their closeness coefficient, so that the highest-performing hospitals occupy the top ranks. Analysis of the results have indicated a significant difference between the top-ranked hospitals and those at the lower end of the ranking. The substantial gap in closeness coefficient values between these two groups reflects a noticeable performance disparity from a multi-criteria perspective. This gap demonstrates that some hospitals have simultaneously achieved high performance across multiple key performance indicators, while others exhibit weaknesses across most criteria.

Table 3
Closeness Coefficient (Ci) and Final Ranking of Hospitals Based on the TOPSIS Method

Rank	University Hospital	Closeness Coefficient (Ci)	Row
1	Isfahan University of Medical Sciences	0.6860	1
2	Shiraz University of Medical Sciences	0.6801	2
3	Guilan University of Medical Sciences	0.6628	3
4	Fasa University of Medical Sciences	0.6373	4
5	Bandar Abbas University of Medical Sciences	0.6329	5
6	Sabzevar University of Medical Sciences	0.6314	6
7	Nishabur University of Medical Sciences	0.6292	7
8	Shahid Beheshti University of Medical Sciences	0.6191	8
9	Iran University of Medical Sciences	0.6081	9
10	Tehran University of Medical Sciences	0.6068	10
11	Zabol University of Medical Sciences	0.6010	11
12	Tabriz University of Medical Sciences	0.5906	12
13	Qom University of Medical Sciences	0.5860	13
14	Babol University of Medical Sciences	0.5700	14
15	Kermanshah University of Medical Sciences	0.5563	15
16	Ahvaz University of Medical Sciences	0.5511	16
17	Kerman University of Medical Sciences	0.5510	17
18	Ilam University of Medical Sciences	0.5296	18
19	Kohgiluyeh and Boyer-Ahmad University of Medical Sciences	0.5169	19
20	Zanjan University of Medical Sciences	0.5096	20
21	Kashan University of Medical Sciences	0.4901	21
22	Bushehr University of Medical Sciences	0.4764	22
23	Qazvin University of Medical Sciences	0.4762	23
24	Jahrom University of Medical Sciences	0.4745	24
25	Golestan University of Medical Sciences	0.4706	25
26	Lorestan University of Medical Sciences	0.4691	26
27	Ardabil University of Medical Sciences	0.4686	27
28	Zahedan University of Medical Sciences	0.4534	28

Table 7 displays the closeness coefficient values for all hospitals, which range from 0.267 to 0.686, indicating substantial differences in multi-criteria performance among the hospitals studied.

The top-ranked hospital, Isfahan University of Medical Sciences, with a closeness coefficient of 0.686, demonstrates the closest proximity to the ideal solution and the highest overall performance across the applied criteria. In contrast, the 40th-ranked hospital, Birjand University of Medical Sciences, with a closeness coefficient of 0.267, exhibits the lowest proximity to the ideal solution, reflecting a significantly weaker performance compared to its peers.

From the perspective of rank distribution, the closeness coefficient values are relatively compressed among the top-ranked hospitals, while the decline becomes steeper among lower-ranked hospitals. This pattern indicates a clear performance gap among high-performing, average, and low-performing hospitals.

The mid-ranked hospitals mostly fall within a closeness coefficient range of 0.45 to 0.55. From a managerial decision-making standpoint, this group represents the greatest potential for performance improvement. Targeted adjustments in key performance indicators could elevate these hospitals closer to the high-performing group.

Notably, the TOPSIS-based ranking provides meaningful differentiation among hospitals that had identical efficiency scores (Ci = 1) in the DEA analysis. This demonstrates that employing TOPSIS alongside DEA is not merely complementary, but crucial for enhancing the accuracy of decision-making and prioritization in healthcare units.

Overall, the results in Table 4.7 indicate that TOPSIS, by enabling a complete multi-criteria ranking, offers a more comprehensive and precise assessment of hospital performance than relying solely on efficiency models. It can serve as an effective tool in planning, resource allocation, and performance improvement for healthcare institutions.

3.1 Integrated Summary of DEA and TOPSIS Results

In this subsection, the performance of 40 university hospitals across the country was evaluated using two complementary approaches: Data Envelopment Analysis (DEA) and the multi-criteria decision-making method TOPSIS. The combined application of these methods allowed for a dual-perspective assessment: DEA focused on technical, managerial, and scale efficiency, while TOPSIS enabled a comprehensive multi-criteria ranking and distinction among the hospitals. DEA results revealed that a significant proportion of hospitals were identified as fully efficient under both constant returns to scale (CCR) and variable returns to scale (BCC) models. This indicates that many university hospitals efficiently utilize available resources. However, the presence of numerous units with an efficiency score of one highlighted the inherent limitation of

DEA in generating a complete ranking and differentiating within-group performance. In this context, applying TOPSIS as a complementary tool played a pivotal role in completing the evaluation. The TOPSIS results, based on the closeness coefficient to the ideal solution, enabled full ranking of hospitals and revealed meaningful differences in multi-criteria performance. The closeness coefficient ranged from 0.267 to 0.686, indicating substantial performance gaps among hospitals from a combined metrics perspective. Comparative analysis of the two methods showed that hospitals identified as efficient by DEA generally ranked high in TOPSIS as well, reflecting stable and balanced performance. However, some hospitals with full DEA efficiency scores were ranked in the middle or lower tiers in TOPSIS, demonstrating that technical efficiency does not necessarily equate to superior multi-criteria performance. Factors such as qualitative indicators, the combination of multiple metrics, and the distribution of outputs play critical roles in overall performance assessment. Conversely, some hospitals classified as inefficient in DEA achieved mid-level ranks in TOPSIS, suggesting they possess potential capacity for performance improvement. Targeted management and process adjustments could rapidly enhance their rankings. Hospitals that were inefficient in both DEA and TOPSIS were identified as critical units, requiring priority in structural reforms, process optimization, and supportive policies. Overall, the integrated use of DEA and TOPSIS provides a comprehensive, precise, and reliable framework for hospital performance evaluation. This combined approach identifies strengths and weaknesses objectively and offers a scientific basis for managerial decision-making, prioritization of corrective actions, and optimal resource allocation in the healthcare system.

4. Conclusion

This study has demonstrated the complementary value of integrating Data Envelopment Analysis (DEA) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methodologies for comprehensive hospital performance evaluation in the Iranian healthcare context. The comparative analysis of 40 university hospitals reveals several critical insights with significant implications for healthcare management, policy formulation, and methodological practice. The application of multiple DEA modelsm including CCR, BCC input-oriented, BCC output-oriented, and Additive formulations, provided a nuanced understanding of hospital efficiency from various technical perspectives. The finding that a substantial proportion of hospitals achieved full efficiency scores under both constant and variable returns to scale models suggests commendable resource utilization practices within many Iranian university hospitals. However, the methodological limitation of DEA in differentiating among efficient units and generating complete rankings necessitated the complementary application of TOPSIS, which successfully addressed these constraints by providing a full ordinal ranking based on multi-criteria performance. The divergence between DEA efficiency scores and TOPSIS rankings offers particularly valuable insights for healthcare management. The observation that some hospitals identified as technically efficient by DEA ranked in middle or lower tiers according to TOPSIS underscores the multidimensional nature of hospital performance. This discrepancy highlights that technical efficiency in resource utilization does not necessarily translate to comprehensive excellence across all performance dimensions. Hospitals must balance operational efficiency with quality of care, patient satisfaction, service accessibility, and other relevant criteria to achieve holistic performance excellence. Conversely, the identification of DEA-inefficient hospitals achieving respectable TOPSIS rankings suggests that some institutions may possess latent capacity for rapid improvement with targeted interventions. These findings align with previous research by Chitnis and Mishra (2019), who noted that hospitals with moderate technical efficiency often demonstrate the greatest potential for performance enhancement through focused managerial interventions and process optimization. The integrated DEA-TOPSIS framework employed in this study addresses several methodological gaps identified in the literature review. By combining DEA's strength in technical efficiency measurement with TOPSIS's capability for comprehensive multi-criteria evaluation, this approach provides a more holistic assessment than either method could achieve independently. This methodological integration responds to the call by Hatefi and Haeri (2019) for more sophisticated performance measurement frameworks that bridge operational and strategic perspectives in healthcare management.

From a policy perspective, the findings suggest several actionable recommendations. First, hospitals classified as inefficient by both methodologies require prioritized attention, potentially through structural reforms, resource reallocation, or management restructuring. Second, the identification of performance gaps among DEA-efficient hospitals highlights the need for benchmarking practices that extend beyond technical efficiency to encompass broader quality and outcome measures. Third, the variation in hospital performance across different regions and contexts underscores the importance of tailored, context-sensitive improvement strategies rather than one-size-fits-all approaches. The methodological implications of this study extend beyond the Iranian context. The successful integration of DEA and TOPSIS provides a replicable framework for hospital performance evaluation in diverse healthcare settings. Future research could enhance this framework by incorporating dynamic efficiency measurement through Malmquist indices, addressing data uncertainty through fuzzy extensions, and integrating clinical outcome measures more explicitly into the evaluation criteria. In practical terms, healthcare administrators and policymakers can utilize the combined DEA-TOPSIS approach to inform evidence-based decision-making regarding resource allocation, quality improvement initiatives, and performance benchmarking. The methodology provides not only efficiency scores and rankings but also specific diagnostic information about input excesses and output shortfalls, enabling targeted improvement strategies. This study contributes to the growing body of literature on hospital performance measurement in emerging economies, addressing the research gap identified by Bahadori et al. (2016) regarding comprehensive, multi-methodological evaluations of Iranian hospital efficiency. The findings validate the applicability of both DEA and TOPSIS in healthcare settings while demonstrating their complementary strengths when applied in tandem. In conclusion, the integrated application of DEA and TOPSIS methodologies provides a robust, multidimensional framework for hospital performance evaluation that balances technical efficiency with comprehensive multi-criteria assessment. This approach offers healthcare managers, policymakers, and researchers a sophisticated tool for identifying performance variations, diagnosing inefficiencies, and formulating evidence-based improvement strategies. As healthcare systems worldwide face increasing pressure to optimize resource utilization while maintaining or enhancing service quality, such integrated performance measurement frameworks will become increasingly valuable for informed decision-making and sustainable healthcare system development.

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Appendix

Table A1
The input and output data

University Name	Number of Beds	Physicians	Nurses	Surgeries	Admitted & Discharged Patients	Mortality Rate (%)	Avg. Length of Stay (Days)
Tehran University of Medical Sciences	1285	369	666	31026	140037	2.52	4.2
Shahid Beheshti University of Medical Sciences	445	210	1500	22346	81153	1.64	3.4
Iran University of Medical Sciences	570	318	1329	13296	141106	2.66	4.7
Isfahan University of Medical Sciences	679	538	1571	42756	145377	1.18	3.5
Shiraz University of Medical Sciences	535	661	564	30266	139109	3.06	3.7
Mashhad University of Medical Sciences	1169	517	1775	23046	101603	2.71	4.5
Tabriz University of Medical Sciences	854	177	545	35060	31249	1.42	2.7
Ahvaz University of Medical Sciences	980	567	584	38782	38518	2.09	4.5
Kerman University of Medical Sciences	715	703	2305	44945	111002	3.42	3.9
Kermanshah University of Medical Sciences	855	711	2204	15499	48244	0.78	5.0
Yazd University of Medical Sciences	424	444	2183	13782	140536	1.48	4.9
Zanjan University of Medical Sciences	894	365	2336	28855	34760	3.01	3.6
Ardabil University of Medical Sciences	294	342	1735	6521	28787	1.79	3.0
Gilan University of Medical Sciences	487	410	812	33300	80870	0.65	4.2
Mazandaran University of Medical Sciences	1381	881	2306	28003	137399	1.67	5.0
Babol University of Medical Sciences	1015	201	988	31281	52241	1.45	3.5
Semnan University of Medical Sciences	1183	896	2387	9842	86995	2.38	4.2
Birjand University of Medical Sciences	823	297	1849	24469	12814	2.04	4.1
North Khorasan University of Medical Sciences	920	595	1281	16813	27306	0.80	2.6
Golestan University of Medical Sciences	1268	726	1219	6170	87301	1.73	4.1
Bushehr University of Medical Sciences	682	209	2336	15733	50032	1.19	2.7
Qom University of Medical Sciences	369	706	2254	17220	97540	1.46	4.1
Qazvin University of Medical Sciences	712	470	2193	42305	99054	2.23	3.7
Arak University of Medical Sciences	1086	226	1170	10498	68082	1.27	3.2
Hamadan University of Medical Sciences	278	533	2487	10029	28595	2.69	3.7
Lorestan University of Medical Sciences	299	332	561	8552	28428	0.80	3.0
Ilam University of Medical Sciences	540	734	1159	38044	49516	1.00	4.6
Kohgiluyeh & Boyer-Ahmad University of Medical Sciences	474	440	2012	6219	14735	3.27	3.2
Gonabad University of Medical Sciences	524	740	2309	8483	136084	2.27	4.3
Kashan University of Medical Sciences	1286	870	547	44245	76801	2.05	4.5
Jahrom University of Medical Sciences	987	877	1504	43732	65720	0.70	3.1
Rafsanjan University of Medical Sciences	329	672	456	42956	19178	2.47	3.4
Sabzevar University of Medical Sciences	980	513	2462	5981	88399	1.46	4.7
Shahroud University of Medical Sciences	367	208	2053	29426	91544	2.69	3.5
Zabol University of Medical Sciences	340	730	2031	43412	135311	1.33	2.8
Zahedan University of Medical Sciences	996	691	1120	24330	50943	2.88	2.8
Fasa University of Medical Sciences	907	638	1842	42886	15440	1.91	2.7
Bandar Abbas University of Medical Sciences	873	436	708	13583	137715	3.46	3.1
Dezful University of Medical Sciences	523	238	1752	44480	57922	3.19	3.0
Neyshabur University of Medical Sciences	392	296	1112	26727	80034	0.75	4.9