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Research Article

Synergizing IFTOPSIS and DEA for Enhanced Efficiency Analysis in Inpatient Units

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ABSTRACT

The pursuit of efficiency in the business sector is a multifaceted endeavor, extending beyond mere cost reduction to encompass a strategic optimization of operational performance. The enhancement of efficiency is not solely for the benefit of investors or proprietors but is also a concerted effort to maximize resource utilization and minimize waste. This study introduces an integrative approach combining IFTOPSIS and DEA methodologies to deliver a robust efficiency evaluation framework. The fusion of IFTOPSIS's qualitative analysis with DEA's quantitative assessments addresses the complexity of operational performance, providing a balanced evaluation that transcends subjective bias with data-driven insights. IFTOPSIS articulates decision-makers' preferences in uncertain scenarios, assigning weights to criteria, while DEA discriminates between efficient and inefficient operational units. This confluence of methods is applied to the assessment of inpatient healthcare units—a sector that has traditionally relied on patient-centric evaluations, neglecting the comprehensive review of resource deployment. The results of this amalgamated approach reveal dimensions of operational efficiency previously unexplored, offering stakeholders a data-enriched foundation for strategic decision-making. The study's findings have significant implications for the healthcare industry, providing a template for resource evaluation that could inform policy and drive improvements in patient care services.

Keywords: efficiency evaluation, operational performance, IFTOPSIS, DEA, inpatient unit

INTRODUCTION

In the crucible of healthcare, where the quality of services can be a matter of life and death, efficiency transcends mere fiscal prudence—it is a linchpin of healthcare delivery. Effective management that maximizes resource use and curtails waste is not only a policy imperative but also a clinical necessity [1], [2]. In both affluent and developing nations, the judicious allocation of finite resources directly impacts the health system's capacity to meet its objectives and ensure long-term financial health [3]. By optimizing operations, healthcare providers can enhance patient care, reduce waiting times, and increase the accessibility of services, thereby meeting the growing demands of a diverse patient population.

Performance measurement systems in healthcare are predicated on the capability of clinicians and administrators to use targeted information for enhanced decision-making [4]. Such systems use performance indicators as proxies for efficiency, assessing whether healthcare organizations are meeting their goals effectively and with the necessary precision [5]. In the complex environment of healthcare, where the efficacy of services directly correlates with patient well-being, consistently evaluating and comparing the performance of different units becomes indispensable [6]. Incorporating both qualitative and quantitative measures is essential, as this allows for a comprehensive appraisal that captures the multifaceted nature of healthcare delivery [7].

Within this context, the Multiple Attribute Decision-Making (MADM) method assumes a central role in healthcare, offering a structured approach for discerning the optimal course of action from a set of viable yet often conflicting

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alternatives. This systematic ranking of each option becomes particularly invaluable in the resource-constrained and ethically complex field of healthcare. Citing the pioneering application of MADM by Churchman et al. [8], Hwang and Yoon [9] further refined this methodology. Popular MADM methods include TOPSIS [9][10], AHP [11][12][13][14], ELECTRE [15][16][17], VIKOR [18][19][20], PROMITHEE [21], with different versions and modifications. Among the available MADM techniques, TOPSIS (Ordered Preference Technique by Similarity to Ideal Solution) developed by Hwang and Yoon [9] is undoubtedly easy to understand due to its straightforward approach and logic.

The core principle of the TOPSIS approach revolves around selecting the best-performing alternative based on a compromise solution. This compromise solution can be perceived as choosing an option closest to the positive ideal solution and farthest from the negative ideal solution. The positive ideal solution represents the most desired or maximum achievable outcome by any alternative, while the negative ideal solution depicts the least desired or minimum criteria by any given alternative. However, in real-world scenarios, attaining the positive ideal solution is rare. As such, the TOPSIS method operates under the foundational assumption that if the positive ideal solution remains unattained, decision-makers will seek an option as close as possible to it [22]. On the other hand, Data Envelopment Analysis (DEA) stands out as a widely embraced non-parametric, data-driven methodology explicitly designed for estimating performance metrics, with a particular emphasis on the efficiency of a Decision-Making Unit (DMU) [23]. In the context of DEA, a DMU encapsulates various units sharing similar operational characteristics, engaging in identical tasks, and pursuing common objectives [6]. Gharibdousti and Azadeh [24] conducted a performance evaluation of organizations by employing a combination of Fuzzy DEA and the TOPSIS method. Fuzzy DEA was utilized to analyze the most influential factors. Subsequently, the TOPSIS method was applied to rank organizations based on these identified crucial factors. In a similar vein, Ersoy [25] employed the DEA and TOPSIS methods to assess the performance of state university departments in Turkey. The DEA method played a pivotal role in determining the efficiency of decision-making units, identifying those performing optimally. Following this, the TOPSIS method was employed to conduct a comparative analysis and ranking of these units based on their efficiency levels.

Several studies have delved into the evaluation of performance efficiency, with notable examples such as Akkoç and Vatansever [26], who employed Fuzzy AHP and Fuzzy TOPSIS methodologies to assess the financial performance of twelve commercial banks. Their evaluation encompassed seventeen financial performance indicators, and intriguingly, the application of both fuzzy AHP and fuzzy TOPSIS models yielded consistent results. In a different context, Bhattacharyya and Chakraborty [27] undertook a performance evaluation of eight Indian Institutes of Technology (IITs) utilizing the DEA and TOPSIS methods. Here, DEA was initially employed to shortlist the efficient IITs based on stakeholders' preferences, and subsequently, the TOPSIS method was applied to rank these efficient IITs, identifying the best-performing institution in the process. Exploring yet another dimension, Yinghui and Wenlu [28] ventured into the evaluation of employee performance using the theory and method of intuitive fuzzy sets in conjunction with the TOPSIS method. Their research aimed to establish a TOPSIS method based on intuitive fuzzy sets, recognizing the inherent complexity of employee performance appraisal. The motivation for this approach stemmed from the acknowledgment that each performance appraisal method possesses its own set of advantages and disadvantages. However, Human resource appraisal, being a multi-level, multi-factor comprehensive evaluation, introduces numerous uncertainties, both objective and subjective. The challenges lie not only in quantifying objective factors, such as performance indices that defy easy quantification, but also in navigating subjective elements, including the experiences, knowledge, and values of human resource managers. Consequently, classical mathematical methods often fall short in analyzing many indicators of performance appraisal due to these inherent complexities.

IFTOPSIS refines the conventional TOPSIS method by integrating the Intuitionistic Fuzzy (IF) set theory, offering a sophisticated approach to evaluating healthcare efficiency where ambiguity and subjective assessments are prevalent. It acknowledges the complexities of clinical decisions, where rarely is a perfect solution achievable. This advanced technique not only seeks options that approximate the ideal outcome—maximizing patient benefits while minimizing costs and risks—but also provides a structured way to navigate the grey areas of healthcare practice,

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where data may be incomplete or inherently fuzzy. By doing so, IFTOPSIS offers a pragmatic approach to improving healthcare delivery by systematically aligning with the most favorable outcomes within the constraints of real-world clinical settings [22]. This aligns seamlessly with the term "alternative" within the IFTOPSIS method, denoting units whose performance undergoes evaluation. The harmonization of these terminologies accentuates the cohesive evaluation framework adopted by both methodologies, reinforcing their consistent application and interpretability. Central to both DEA and IFTOPSIS methodologies are assessments grounded in the implementation of resource measures (inputs) and the outcomes targeted (outputs). However, a distinctive hallmark of the DEA methodology is its notable capability to incorporate multiple outputs without imposing predefined assumptions on the production function [6]. This attribute enhances the adaptability of DEA in scenarios characterized by intricate and multifaceted processes. The parallel terminologies and shared evaluation principles between DEA and IFTOPSIS contribute to a unified and comprehensive understanding of their application in diverse contexts.

The integration of IFTOPSIS and DEA methods has been explored in previous research, particularly in the context of evaluating the retail industry [29]. However, despite this prior work, there is a notable gap in the literature as the combination of IFTOPSIS and DEA has not been applied to the evaluation of inpatient units. The units are the linchpins of hospital operations, integral to delivering comprehensive care that spans from routine treatments to emergency interventions [30]. The efficacy of these units is paramount, as their efficiency directly correlates with the overall hospital performance. This research seeks to fill this gap by proposing the integration of these two methods to achieve a more comprehensive assessment. The synergy between IFTOPSIS and DEA ensures a holistic evaluation, combining qualitative insights from IFTOPSIS with quantitative assessments from DEA. This integrated approach ensures that the assessment is not only subjective but also grounded in factual numerical data, making it more robust than using either IFTOPSIS or DEA alone.

To demonstrate the effectiveness of the proposed method, we applied it to evaluate the inpatient units of a hospital in Indonesia. The objective is to redefine efficiency parameters by broadening the evaluation criteria and establishing a model in which all inpatient units operate with optimal resource utilization. Ultimately, the aim of this research is to set a new benchmark for hospital efficiency. The outcomes not only classify inpatient units as efficient or inefficient but also determines the optimal input and output variable values necessary to render all units efficient. This innovative approach offers a more nuanced and insightful evaluation of inpatient units, contributing to the advancement of performance assessment methodologies in healthcare settings.

METHODS

This study discusses the integration of IFTOPSIS and DEA to evaluate performance evaluation of inpatient units at one of Indonesian hospital. Traditional performance evaluations at this hospital predominantly rely on patient and family service evaluation questionnaires, offering a limited perspective on operational performance. To overcome these limitations, this study seeks to expand the scope of assessment to encompass a more comprehensive range of performance indicators, with a specific emphasis on gauging the resource efficiency of inpatient services. The research framework shown in Figure 1, outlining the integration steps carried out.

Phase 1 begins by identifying the alternatives/DMU, criteria, and decision-makers involved in the IFTOPSIS method, as well as the input and output variables for the DEA method. In applying the DEA method, it is imperative that the chosen input and output variables adhere to specific criteria. The input variables should comprehensively cover the resources utilized, while the output variables must encompass both activity measurements and performance metrics, as outlined by [31]. Drawing on the research conducted by [31], this study adopts various input and output variables. To tailor the analysis to the unique parameters of the inpatient unit under investigation, this study made specific modifications to the output variables. Notably, surgery and outpatient visit cases were excluded, while inpatient unit performance was introduced as a new variable for evaluation. These adjustments were considered crucial to ensure the relevance of the variables to the research topic. In essence, the modifications were made to align the variables with the specific characteristics of the inpatient unit in Indonesia. Specifically, the chosen input variables include parameters such as the number of beds, healthcare professionals, and non-healthcare staff. Correspondingly, the

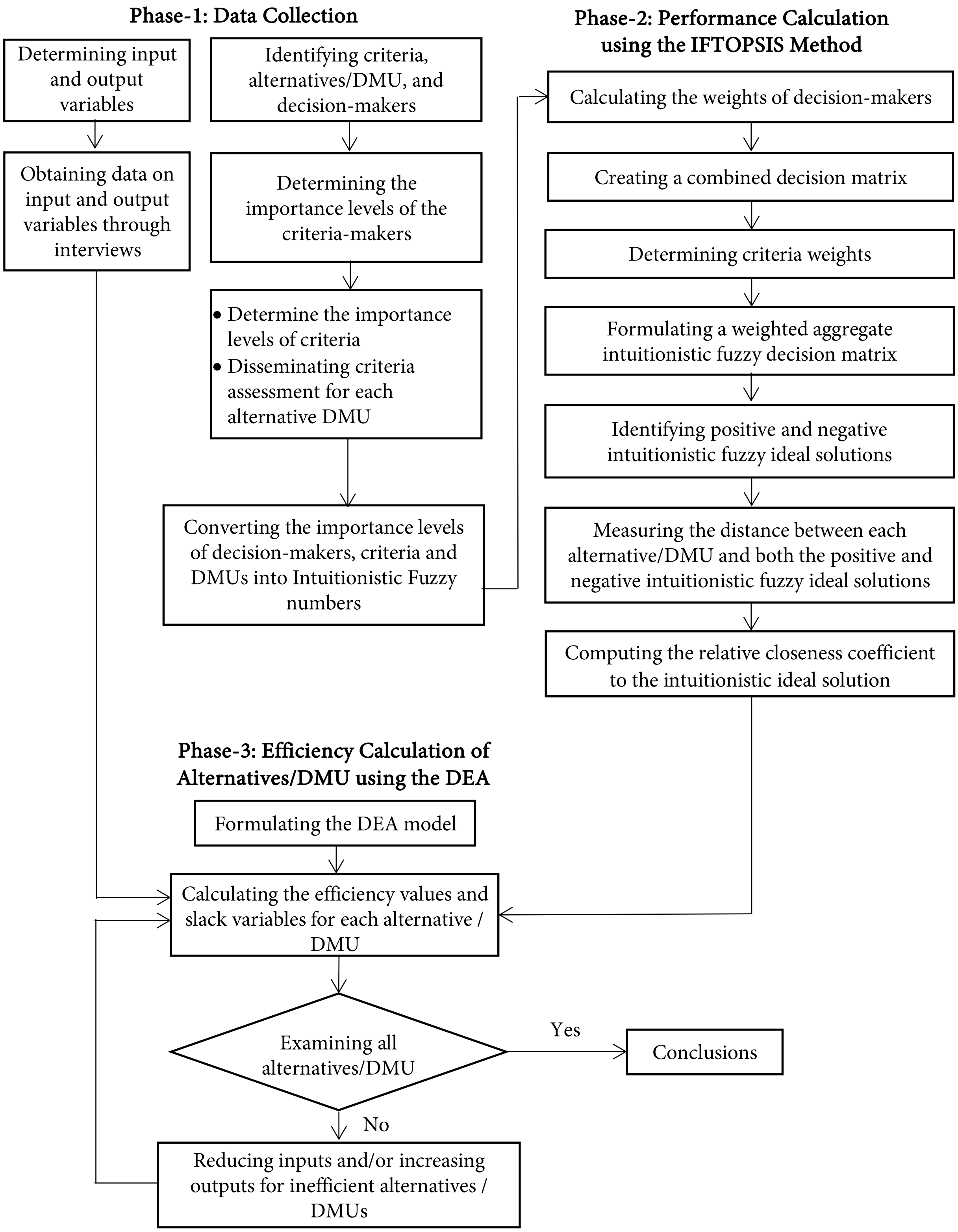

Figure 1. Flowchart of IFTOPSIS and DEA integration in evaluating the efficiency of inpatient units

selected output variables consist of inpatient cases, surgery cases, and outpatient visits [31]. This research involves two stakeholders involved in decision-making regarding inpatient unit services, namely the service unit manager (DM1) and the inpatient care coordinator (DM2). The important level of the DMs in this study was determined based on the nature and scope of the responsibility. Through interviews, all DMs conformed the selected input and output variables.

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Hospital infrastructure needs to follow health, safety, security, and accessibility guidelines [30]. Reducing service-related risks is the goal of these regulations. Physical risk factors were taken into consideration when identifying several assessment criteria [32]. Among these requirements are noise potential (the separation between the room and areas that might be noisy, C1), lighting (suitability of both artificial and natural light, C2), air movement (suitable ventilation, C3), room usage area (the arrangement of the building and the rooms, C4) , and position (outside view and convenient access to departments that are related, C5). Inpatient unit performance was evaluated using these criteria to guide this investigation. There are five alternative DMUs whose performance has been evaluated, namely A2, A3, A4 and A5. All criteria and DMUs were assessed by the DMs on its level of importance using pair-wise comparison questionnaires.

The data collected from the questionnaire is then converted into an intuitionistic fuzzy number (IFN). The IFN represents the decision maker's preference from three aspects: degree of membership, degree of non-membership and degree of uncertainty [33]. The IFN scale can be observed in Table 1 (Rating preferences for measuring the importance of criteria and decision makers) and Table 2 (Criteria scoring preferences for each alternative/DMU). The IFN scale in Table 1 is used to determine criterion weights and decision maker weights, while the IFN scale in Table 2 is used to convert qualitative data and criteria scores for each alternative/DMU into quantitative data [34].

During phase 2, the IFN data of criteria and DMUs is processed using the IFTOPSIS method. Let $A = \{A_1, A_2, \dots, A_m\}$ represent a set of alternatives, $C = \{C_1, C_2, \dots, C_n\}$ denote a set of criteria, dan l is the number of decision-makers. Once decision-makers, alternatives, and criteria were determined, the subsequent steps of the IFTOPSIS method are as follows [34],[35]:

1. Calculate the weights of the decision-makers based on Table 1 using the following equation (1).

$$\lambda_k = \frac{\left(\mu_k+\pi_k\left(\frac{\mu_k}{\mu_k+v_k}\right)\right)}{\sum_{k=1}^{l}\left(\mu_k+\pi_k\left(\frac{\mu_k}{\mu_k+v_k}\right)\right)} \tag{1}$$

with λ_k represents the weight of the k, $(k = 1,2, \dots, l)$, $\lambda_k \geq 0$, and $\sum_{k=1}^{l} \lambda_k = 1$.

Table 1. IFN scale for the importance levels of criteria and decision-makers

Evaluation Preferences	IFN (μ,v,π)
Very Important (VI)	(0,90; 0,10; 0,00)
Important (I)	(0,75; 0,20; 0,05)
Medium (M)	(0,50; 0,45; 0,05)
Unimportant (U)	(0,35; 0,60; 0,05)
Very Unimportant (VU)	(0,10; 0,90; 0,00)

Table 2. IFN scale for criteria evaluation for each alternative / DMU

Evaluation Preferences	IFN (μ,v,π)
Extremely Good (EG) / Extremely High (EH)	(1,00; 0,00; 0,00)
Very Very Good (VVG) / Very Very High (VVH)	(0,90; 0,10; 0,00)
Very Good (VG) / Very High (VH)	(0,80; 0,10; 0,10)
Good (G) / High (H)	(0,70; 0,20; 0,10)
Medium Good (MG) / Medium High (MH)	(0,60; 0,30; 0,10)
Fair (F) / Medium (M)	(0,50; 0,40; 0,10)
Medium Bad (MB) / Medium Low (ML)	(0,40; 0,50; 0,10)
Bad (B) / Low (L)	(0,25; 0,60; 0,15)
Very Bad (VB) / Very Low (VL)	(0,10; 0,75; 0,15)
Very Very Bad (VVB) / Very Very Low (VVL)	(0,10; 0,90; 0,00)

2. Construct a combined decision matrix (*R*) as described in Equation (2) by integrating the assessments about the criteria for each alternative provided by the decision-makers using Table 2.

$$\mathrm{R} = \begin{bmatrix} (\mu_{11}, v_{11}, \pi_{11}) & (\mu_{12}, v_{12}, \pi_{12}) & \dots & (\mu_{1n}, v_{1n}, \pi_{1n}) \\ (\mu_{21}, v_{21}, \pi_{21}) & (\mu_{22}, v_{22}, \pi_{22}) & \dots & (\mu_{2n}, v_{2n}, \pi_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (\mu_{m1}, v_{m1}, \pi_{m1}) & (\mu_{m2}, v_{m2}, \pi_{m2}) & \dots & (\mu_{mn}, v_{mn}, \pi_{mn}) \end{bmatrix}$$

$$= \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \tag{2}$$

$$\begin{aligned} r_{ij} &= \mathrm{IFWA}_\lambda\left(r_{ij}^{(1)}, r_{ij}^{(2)}, \dots, r_{ij}^{(l)}\right) \\ &= \lambda_1 r_{ij}^{(1)} \oplus \lambda_2 r_{ij}^{(2)} \oplus \dots \oplus \lambda_l r_{ij}^{(l)} \\ &= \left(1 - \prod_{k=1}^{l}\left(1 - \mu_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(v_{ij}^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(1 - \mu_{ij}^{(k)}\right)^{\lambda_k} - \prod_{k=1}^{l}\left(v_{ij}^{(k)}\right)^{\lambda_k}\right) \end{aligned} \tag{3}$$

where $r_{ij} = (\mu_{ij}, v_{ij}, \pi_{ij})$, $i = 1,2, \dots, m$ and $j = 1,2, \dots, n$. $r_{ij}^{(k)}$ represents the intuitionistic fuzzy value given by the k-th decision-maker for the i-th alternative and j-th criterion.

3. Calculate the weights of the criteria (*W*) by consolidating the intuitionistic fuzzy values provided for each criterion by each decision-maker based on Table 1 using the Equation (4)-(5) as follows.

$$W = (w_1, w_2, \dots, w_j) \tag{4}$$

$$\begin{aligned} w_j &= \mathrm{IFWA}_\lambda\left(w_j^{(1)}, w_j^{(2)}, \dots, w_j^{(l)}\right) \\ &= \lambda_1 w_j^{(1)} \oplus \lambda_2 w_j^{(2)} \oplus \dots \oplus \lambda_l w_j^{(l)} \\ &= \left(1 - \prod_{k=1}^{l}\left(1 - \mu_j^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(v_j^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(1 - \mu_j^{(k)}\right)^{\lambda_k} - \prod_{k=1}^{l}\left(v_j^{(k)}\right)^{\lambda_k}\right) \end{aligned} \tag{5}$$

where $w_j^{(k)} = \left(\mu_j^{(k)}, v_j^{(k)}, \pi_j^{(k)}\right)$ represents the intuitionistic fuzzy value given to the j-th criterion by the k-th decision-maker and $j = 1,2, \dots, \mathrm{n}$.

4. Formulate a weighted aggregate intuitionistic fuzzy decision matrix (R') as described in Equation (6) by merging the combined decision matrix (R) and criteria weights (W) using Equation (7) as follows.

$$R' = \begin{bmatrix} (\mu'_{11}, v'_{11}, \pi'_{11}) & (\mu'_{12}, v'_{12}, \pi'_{12}) & \dots & (\mu'_{1n}, v'_{1n}, \pi'_{1n}) \\ (\mu'_{21}, v'_{21}, \pi'_{21}) & (\mu'_{22}, v'_{22}, \pi'_{22}) & \dots & (\mu'_{2n}, v'_{2n}, \pi'_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (\mu'_{m1}, v'_{m1}, \pi'_{m1}) & (\mu'_{m2}, v'_{m2}, \pi'_{m2}) & \dots & (\mu'_{mn}, v'_{mn}, \pi'_{mn}) \end{bmatrix}$$

$$= \begin{bmatrix} r'_{11} & r'_{12} & \dots & r'_{1n} \\ r'_{21} & r'_{22} & \dots & r'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r'_{m1} & r'_{m2} & \dots & r'_{mn} \end{bmatrix} \tag{6}$$

with

$R' \;= R \otimes W$

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$$r'_{ij} = (\mu'_{ij}, v'_{ij}, \pi'_{ij}) \\ = (\mu_{ij} \cdot \mu_j, v_{ij} + v_j - v_{ij} \cdot v_j, 1 - v_{ij} - v_j - \mu_{ij} \cdot \mu_j + v_{ij} \cdot v_j) \quad (7)$$

where $r'_{ij} \in R'$, $i = 1,2, \dots, m$ and $j = 1,2, \dots, n$

5. Identify the positive intuitionistic fuzzy ideal solution (A^*) and negative (A^-). Initially, the type of criteria related to the decision alternative is determined. J_1 and J_2 represent benefit criteria (the higher the criterion assessment, the better the performance of the alternative) and cost criteria (the lower the criterion assessment, the better the performance of the alternative) respectively [35]. Subsequently (A^*) is derived using equation (8) and (A^-) is acquired using equation (9) as follows.

$$A^* = (r_1'^*; r_2'^*; \dots; r_n'^*) \quad (8)$$

$$A^- = (r_1'^-; r_2'^-; \dots; r_n'^-) \quad (9)$$

with

$$r_j'^* = (\mu_j'^*, v_j'^*, \pi_j'^*),\ j = 1,2, \dots, n \quad (10)$$

$$\mu_j'^* = \{(\max i \{\mu'_{ij}\} | j \in J_1), (\min i \{\mu'_{ij}\} | j \in J_2)\} \quad (11)$$

$$v_j'^* = \{(\min i \{v'_{ij}\} | j \in J_1), (\max i \{v'_{ij}\} | j \in J_2)\} \quad (12)$$

$$r_j'^- = (\mu_j'^-, v_j'^-, \pi_j'^-),\ j = 1,2, \dots, n \quad (13)$$

$$\mu_j'^- = \{(\min i \{\mu'_{ij}\} | j \in J_1), (\max i \{\mu'_{ij}\} | j \in J_2)\} \quad (14)$$

$$v_j'^- = \{(\max i \{v'_{ij}\} | j \in J_1), (\min i \{v'_{ij}\} | j \in J_2)\} \quad (15)$$

6. Measure the normalized distance by calculating the difference between each alternative and the positive intuitionistic fuzzy ideal solution (S_i^*) using Equation (16) and the negative intuitionistic fuzzy ideal solution (S_i^-) using Equation (17) as follows.

$$S_i^* = \frac{1}{2}\sum_{j=1}^{n}[|\mu'_{ij} - \mu_j'^*| + |v'_{ij} - v_j'^*| + |\pi'_{ij} - \pi_j'^*|] \quad (16)$$

$$S_i^- = \frac{1}{2}\sum_{j=1}^{n}[|\mu'_{ij} - \mu_j'^-| + |v'_{ij} - v_j'^-| + |\pi'_{ij} - \pi_j'^-|] \quad (17)$$

where $i = 1,2, \dots, m$.

7. Compute the relative closeness coefficient to the intuitionistic ideal solution (C_i^*) using Equation (18).

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-} \quad (18)$$

where $0 \le C_i^* \le 1$ and $i = 1,2, \dots, m$. The larger the C_i^* value, the better the performance of the alternative, with the optimal alternative having a C_i^* value closest to 1 [36]. This relates to the benefit and cost criteria. The higher the value associated with the benefit criterion, the better the C_i^* value.

In phase 3, the relative closeness coefficient from the IFTOPSIS method, hereafter referred to as the performance measure, is used as one of the output data for the DEA method. It's assumed that there are n DMUs to be evaluated. Each DMU utilizes several m distinct inputs and s distinct outputs. Specifically, DMU_j uses an amount of x_{ij} from input i and y_{rj} from output r. It's also assumed that $x_{ij} \ge 0$ and $y_{rj} \ge 0$, with each DMU having at least one input and one output. The DEA model for evaluating the efficiency of the DMU is described in Equation (19)-(26) as follows [37].

$$\text{Min } z = t - \frac{1}{m}\sum_{i=1}^{m}\frac{P_i^-}{x_i} \quad (19)$$

s.t.:

$$t + \frac{1}{s}\sum_{r=1}^{s}\frac{P_i^{+}}{y_r} = 1 \tag{20}$$

$$x_i = \sum_{j=1}^{n} x_{ij}\, L_j + P_i^{-} \tag{21}$$

$$ty_r = \sum_{j=1}^{n} y_{rj}\, L_j - P_r^{+} \tag{22}$$

$$L_j, P_i^{-}, P_r^{+}, t \geq 0 \tag{23}$$

with

$$s_i^{-*} = \frac{P_i^{-}}{t} \tag{24}$$

$$s_r^{+*} = \frac{P_r^{+}}{t} \tag{25}$$

$$\lambda_j = \frac{L_j}{t} \tag{26}$$

where z is efficiency value of the DMU, y_{rj} is the value of r output from the j-th DMU, x_{ij} is value of the i input from the the j-th DMU, s_i^{-*} is slack variable (input surplus), s_r^{+*} is slack variable (output deficit), t is positive scalar variable of the DMU, and λ_j is production weight.

DMU's performance is considered efficient if $z = 1$. This condition is equivalent to $s_i^{-*} = 0$ and $s_r^{+*} = 0$ indicating that there is neither an input surplus nor an output deficit. Conversely, a DMU is deemed inefficient if $0 < z < 1$. This implies the presence of an input surplus ($s_i^{-*} \neq 0$) and/or an output deficit ($s_r^{+*} \neq 0$) [37]. Inefficient DMUs can be improved and made efficient by reducing input values and/or increasing output values using Equations (27) and (28) respectively [37]:

$$x_i^* = x_i - s_i^{-*} \tag{27}$$

$$y_r^* = y_r + s_r^{+*} \tag{28}$$

where x_i^* and y_r^* denote new input and output value, respectively.

The basic steps in assessing efficiency using the DEA method are as follows [38].

1. Identify the DMU to be evaluated.
2. Determine input and output variables. Input and output variables are variables that influence DMUs efficiency.
3. Formulate a DEA model for each unit.
4. Calculate the efficiency value of each DMU. The efficiency value is an evaluation to obtain the ideal performance and number of resources.

RESULTS AND DISCUSSION

This section presents the results of the proposed methodology explained in the previous section. Due to the nature and scope of the responsibility, DM1 is believed to be more important than DM2. The importance levels and weight of each decision-maker are presented in Table 3. The importance weight of the criteria (W) is obtained from the results of the questionnaire regarding the level of importance of the criteria which is shown in Table 4. The weight calculations show that the criteria of noise potential (C1), lighting (C2) and location (C5) are deemed more critical with higher weights given by the decision-makers for evaluating the performance of inpatient units. These are followed in order by room usage area (C4) and air circulation (C3). The results of the questionnaire regarding the assessment criteria for each alternative/DMU in Table 5 are used to form a combined decision matrix (R).

This section presents the results of the proposed methodology explained in the previous section. Due to the nature and extent of the responsibility, DM1 is considered more important than DM2. The importance levels and weight of each decision maker are shown in Table 3. The importance weight of the criteria (W) was obtained from the results of the questionnaire on the importance level of the criteria, which is shown in Table 4. The weight calculations show

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Table 3. Importance levels and weight of decision-makers (DMs)

Decision-maker	Symbol	Importance Level	λ_k
Head of service unit	DM1	Very Important (VI)	0,5327
Inpatient care coordinator	DM2	Important (I)	0,4673

Table 4. Questionnaire results for the importance levels of criteria

Criteria	Decision-maker	
	DM1	DM2
C1	I	VI
C2	I	VI
C3	M	I
C4	M	VI
C5	I	VI

Table 5. Questionnaire results for criteria assessment for alternatives / DMU

Decision-maker	Criteria	A1	A2	A3	A4	A5
DM1	**C1**	VVG	VG	VVG	VG	G
	C2	VG	G	VVG	VG	VG
	C3	VG	VVG	VG	G	VG
	C4	VVG	VG	VG	VG	G
	C5	G	VVG	VG	VVG	VG
DM2	**C1**	MG	G	VG	MG	MG
	C2	G	MG	MG	G	MG
	C3	G	VG	G	MG	G
	C4	G	G	MG	MG	MG
	C5	MG	MG	G	G	MG

Table 6. Relative proximity coefficient (C_i^*)

Alternative	A1	A2	A3	A4	A5
C_i^*	0,5553	0,5909	0,7090	0,4739	0,2713

that the criteria noise potential (C1), lighting (C2) and location (C5) are deemed more critical with higher weights given by the decision-makers for evaluating the performance of inpatient units, followed in order by space utilization area (C4) and air circulation (C3). The results regarding the assessment of each alternative/DMU based on the evaluation criteria in Table 5 are used to form a combined decision matrix (R). Table 6 shows that the highest relative proximity coefficient (C_i^*) belongs to alternative A3 according to the decision-makers, which means that A3 has the best performance. Furthermore, the relative proximity coefficient (C_i^*) referred to as performance, serves as one of the output data for the DEA method.

In DEA method, the input variables utilized are beds (x_1), healthcare professionals (x_2), and non-healthcare staff (x_3). The output variables are inpatient cases (y_1) and performance (y_2). The initial input and output variable data are presented in Table 7. One of the output variables includes the number of inpatient unit cases over the past year (July 2022 – June 2023). The initial step of the DEA method involves forming a DEA model. Based on the information from Table 7, the DEA model was created for $A_1, A_2, A_3, A_4,$ dan A_5 using Equation (19)-(23). In the second step, the efficiency value of (z_o), $P_i^-, P_r^+,$ dan t_o were determined. Using Equations (24) and (25), slack

Table 7. Initial data on Input and Output Variables

Alternative/ DMU	Initial data				
	Input variable			Output variable	
	x_1	x_2	x_3	y_1	y_2
A1	16	19	4	2105	0,5553
A2	16	21	4	1895	0,5909
A3	10	17	2	1156	0,7090
A4	13	17	3	1566	0,4739
A5	11	17	3	1420	0,2713

Table 8. Input excess and output shortfall in the three iterations

DMUs	Iteration-1					Iteration-2					Iteration-3				
	s_1^{-*}	s_2^{-*}	s_3^{-*}	s_1^{+*}	s_2^{+*}	s_1^{-*}	s_2^{-*}	s_3^{-*}	s_1^{+*}	s_2^{+*}	s_1^{-*}	s_2^{-*}	s_3^{-*}	s_1^{+*}	s_2^{+*}
A1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A2	0,877	0	0,516	0	0,149	0	0	0	0	0	0	0	0	0	0
A3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A4	0,567	0	0,110	0	0,116	0	0	0	0	0	0	0	0	0	0
A5	0	3,061	0,335	0	0,172	0,026	0	0,484	0	0,004	0	0	0	0	0

variables (s_i^{-*}) and (s_r^{+*}) for each alternative/DMU were derived. The third step is to examine whether all units are efficient or not. After three iterations of the DEA method, all inpatient units were declared efficient ($z = 1$). This means that for the data from the third iteration of the DEA method, no excess inputs or deficient outputs are present, making it possible to obtain the ideal values for input and output variables for all units. Figure 2 shows the efficiency score results in the three iterations. Table 8 shows the input excess and output shortfall in the three iterations.

The evaluation using the DEA are summarized as follow:

a. Inpatient units A1 and A3 are the two most efficient units. This efficiency arises from the favorable state of their resources, the building's condition, and infrastructure, coupled with an ideal ratio between the number of beds, healthcare personnel, non-healthcare personnel, and the number of patients.
b. Inpatient units A2, A4 and A5 are deemed inefficient, hence requiring an evaluation of resource amounts (x_1, x_2, x_3), the number of patients (y_1), and performance metrics (y_2) to reach efficiency.
c. Inpatient unit A2 requires 15 beds, 3 non-healthcare staffs, and performance of 0,7396 to be declared efficient.
d. Inpatient unit A4 requires 12 beds and performance of 0,5894 to be declared efficient.
e. Inpatient unit A5 requires 14 healthcare professionals and performance of 0,4474 to be declared efficient.

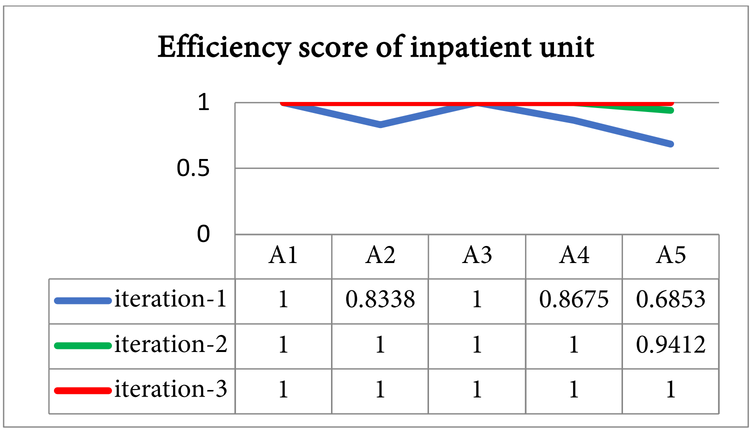

Figure 2. Efficiency score of inpatient unit

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The integration of IFTOPSIS and DEA in this study illuminates the multifaceted nature of healthcare efficiency, particularly in inpatient units. The rigorous evaluation through IFTOPSIS provided insight into qualitative aspects of healthcare delivery—such as the importance of room conditions on patient care—which are often overshadowed by quantitative measures. Conversely, DEA offered an objective analysis of resource utilization, presenting a clear picture of where and how resources could be optimized. Together, these methods paint a comprehensive picture of operational efficiency. They underscore the potential for significant improvements in patient care through better resource allocation. The results suggest that hospitals can achieve more with their existing resources, provided they are willing to embrace such innovative evaluative techniques.

This study's findings are poised to contribute to policy formulation by demonstrating a practical approach to measuring and improving efficiency. By adopting this integrated method, healthcare administrators can gain a deeper understanding of where inefficiencies lie and the most effective ways to address them. This could lead to the reallocation of resources, improved patient care, and ultimately, a more sustainable healthcare system. The methodology and findings of this research could serve as a benchmark for future studies, prompting a reevaluation of efficiency in other healthcare domains.

CONCLUSION

In conclusion, this study advances the application of IFTOPSIS and DEA methodologies, marking a significant leap in the evaluation of efficiency within healthcare inpatient units. The dual-pronged approach unites qualitative insights with quantitative rigor, offering a more rounded understanding of operational performance in healthcare settings. The research illuminates how inpatient units can leverage existing resources more effectively, pinpointing areas of improvement that could lead to enhanced patient outcomes and operational cost savings. The quantitative assessment through DEA highlighted the variability in resource utilization among different inpatient units, underscoring the potential for optimization. It provided an objective benchmark for performance, allowing for a clear identification of units operating at peak efficiency and those falling short. This aspect of the research is particularly valuable for healthcare administrators seeking to implement data-driven strategies for resource allocation.

Conversely, the qualitative analysis via IFTOPSIS offered a nuanced perspective on the factors contributing to efficiency, such as room conditions and infrastructure. This methodology allowed for the incorporation of decision-makers' preferences, adding a layer of depth to the understanding of what constitutes an effective healthcare environment from a stakeholder's viewpoint. By synthesizing the findings from both methods, this study presents a comprehensive model for assessing and enhancing efficiency. The implications for healthcare policy are far-reaching. Hospitals and healthcare systems can adopt this integrative approach to better assess their operations, leading to informed decisions that could reshape patient care protocols, resource management, and overall healthcare delivery. Additionally, the findings highlight the need for healthcare policies that prioritize efficient operations while maintaining or improving the quality of patient care. Policymakers can draw on the conclusions of this research to draft legislation or guidelines that encourage hospitals to adopt similar evaluative models, fostering a culture of continuous improvement. Furthermore, while this research focused on inpatient units, the methodologies employed have the potential for broader application. Future studies could adapt and apply the combined IFTOPSIS and DEA approach to other areas of healthcare, such as outpatient services or emergency care, where efficiency is equally crucial but presents different challenges.

The study also lays the groundwork for future research in this area. It opens up avenues for exploring the application of these methods across different healthcare systems, including comparisons between high-income and low- and middle-income countries. Such cross-sectional analyses could reveal broader insights into global healthcare efficiency dynamics. For future research, we suggest incorporating the Competitive Zone of Tolerance based Importance Performance Analysis (CZIPA) method. CZIPA is a method to measure the relationship between consumer perceptions and priorities for quality improvement [39]. The results from CZIPA are used to compare the quality of a product/service and to identify the factors causing consumers to switch from one product/service to another.

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CONFLICT OF INTEREST

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