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Enhancing Decision-Making in Healthcare Systems: Lean, Agile, Resilient, Green, and Sustainable (LARGS) Paradigm for Performance Evaluation of Hospital Departments under Uncertainty

Salman Nazari-Shirkouhi [1✉], **and Reihane Zarei Babaarabi** [2]

1. Corresponding Author, Department of Industrial and Systems Engineering, Fouman Faculty of Engineering, College of Engineering, University of Tehran, Tehran, Iran. E-mail: snnazari@ut.ac.ir
2. Department of Industrial and Systems Engineering, Fouman Faculty of Engineering, College of Engineering, University of Tehran, Tehran, Iran. E-mail: reihane.zarei.ba@ut.ac.ir

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ABSTRACT

Objective: This research aims to propose a multi-criteria decision-making model for ranking hospital departments. The primary purpose of this model is to assist managers in the optimal allocation of limited resources, thereby reducing costs while increasing patient satisfaction. The ranking results help managers in decision-making processes such as equipment development, staff training, and addressing patient complaints.

Methods: This study evaluated the performance of five hospital departments (Emergency, Ophthalmology, Cardiovascular, Infectious, and Neurology) in Shiraz, Iran, using the fuzzy DEMATEL-MARCOS multi-criteria decision-making method. Firstly, criteria were prioritized using the fuzzy DEMATEL method, after which hospital departments were ranked using the fuzzy MARCOS method. A sensitivity analysis was conducted to validate the results.

Results: Performance metrics for the hospital departments were identified based on the Lean, Agile, Resilient, Green, and Sustainable (LARGS) paradigm. The results revealed that patient satisfaction and job satisfaction had the most substantial influence on performance, while reducing excess transportation and over-processing had the least impact. Utilizing the fuzzy MARCOS method, the hospital departments were ranked according to their overall desirability. The sensitivity of these rankings was assessed by adjusting the weights of the criteria. A comparative analysis with four other fuzzy methods (ARAS, COCOSO, EDAS, and WASPAS) confirmed that the fuzzy MARCOS method was the most effective tool for prioritizing hospital departments.

Conclusion: The fuzzy MARCOS results indicated that the "Infectious Department" performed well, while the "Ophthalmology Department" required improvement. Enhancing the "Infectious Department" hinged on better staff training, cost reduction, and safe waste management. This research introduces a novel approach using the fuzzy DEMATEL-MARCOS model, enabling hospitals to assess performance through modern methodologies, such as Lean, Agile, Resilient, Green, and Sustainable, even in uncertain conditions.

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Introduction

Given the critical importance of hospitals in the healthcare system and their substantial share of budget allocation, enhancing the performance of these institutions, especially in developing countries, has become a primary priority. Despite considerable advancements in the medical field, healthcare systems continue to encounter numerous challenges that impede achieving optimal performance. Performance evaluation serves as an effective tool for hospital managers to accurately assess and monitor hospital operations. Consequently, by utilizing this tool, managers can identify organizational strengths and weaknesses and take actions to enhance performance (Amiri et al., 2020).

In numerous studies, hybrid multi-criteria decision-making (MCDM) methods have been employed for evaluation, particularly during the criteria weighting phase. For instance, Nazari-Shirkouhi et al. (2023) assessed key suppliers' flexibility in achieving a resilient supply chain using a Data Envelopment Analysis (DEA) model with Z-numbers. Prabadevi et al. (2023) developed an MCDM model based on natural language processing for selecting the optimal higher education institution. Lin et al. (2023) and Nazari-Shirkouhi et al. (2020) applied the Balanced Scorecard approach for performance measurement. While this method evaluates various aspects of the supply chain, the innovative LARGS approach provides a more comprehensive perspective, incorporating economic, social, and environmental dimensions to elevate performance evaluation in healthcare supply chains.

Shortell et al. (2021) found that Lean methodologies have significant potential to enhance hospital performance, serving as a comprehensive approach to improving service quality, reducing costs, and increasing patient and staff satisfaction. Regragui et al. (2024) proposed a framework based on the fuzzy TOPSIS-MCDM method for evaluating and improving hospital performance across three sustainability dimensions: economic, social, and environmental. Eskandari et al. (2022) conducted a comprehensive evaluation of pharmaceutical companies, integrating lean production and sustainability dimensions to identify strengths and weaknesses and formulate improvement strategies.

Rahmani et al. (2023) introduced an innovative approach for integrated hospital performance assessment based on Green, Lean, and Agile (LARG) practices. Sahu et al. (2023) developed a comprehensive supplier selection model that combines Lean, Agility, Flexibility, and Sustainability principles, enabling organizations to select suppliers that meet current needs while enhancing supply chain performance and fostering sustainable development.

The initial set of criteria for this study was identified through a review of existing literature and discussions with healthcare experts. The following section presents the final set of identified criteria. Improving service quality, increasing safety, optimizing service processes, and enhancing staff satisfaction through the implementation of effective initiatives are achievable (Ortíz-Barrios et al., 2023). Many researchers have used performance indicators to evaluate hospital performance and improve healthcare management. Key performance indicators (KPIs) have been employed to evaluate institutions by setting objectives, supporting programs, monitoring results, and reporting the achievements and outcomes of hospitals (NAR et al., 2021). In most of the previously reviewed papers, researchers have considered healthcare KPIs without taking into account the relationships between them. Therefore, this study represents one of the first efforts to bridge this gap by providing a structured framework for analyzing the LARGS paradigm in healthcare to improve performance evaluation.

This research first classifies a set of LARGS paradigms based on a literature review, and then employs an integrated fuzzy MCDM approach for identifying and prioritizing efficient healthcare centers, helping managers make informed decisions and drive continuous improvement (Amiri et al., 2020). Furthermore, this study seeks to develop previous methods by considering the uncertainty in the environment and the interdependencies between the LARGS indicators simultaneously. The fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) method is used to eliminate additional interdependencies and provides potential interactions and the weight of KPIs (Tseng et al., 2022). In other words, this research highlights the relationships among KPIs in healthcare and proposes a causal framework to strengthen managerial insight within the healthcare industry. The questionnaire has been designed based on a survey with experts being informed about the format of the fuzzy DEMATEL questionnaire and the fuzzy Measurement of Alternatives and Ranking according to compromise Solution (MARCOS) method, as these differ from their traditional counterparts in the Likert scale. Data have been collected through a survey questionnaire and designed to prioritize the selected criteria. To minimize potential response bias, the survey has been conducted separately with experts. The hospital in this study, one of the most well-equipped and recognized medical centers in Shiraz, Iran, has played a pivotal role in reducing mortality, especially during the COVID-19 pandemic. Given the hospital's significance during the pandemic, a comprehensive performance evaluation, incorporating the perspectives of five expert specialists in emergency medicine, ophthalmology, cardiology, infectious and neurology, with over ten years of experience in their respective fields, can greatly contribute to improving services and reducing mortality.

The remainder of the paper is organized as follows. Section 2 is assigned to the Theoretical and empirical background of the research. Section 3 outlines the methodology, including the fuzzy DEMATEL method for analyzing KPIs and the fuzzy MARCOS method for ranking various hospital departments. The results are summarized and discussed in Section 4. The paper concludes with a summary of the results, a synthesis of the main findings, and recommendations for future research in Section 5.

Literature Background

The healthcare industry is experiencing rapid growth and continuous evolution, leading to heightened competition among service providers. To differentiate themselves and foster patient loyalty, healthcare organizations must prioritize the delivery of high-quality, personalized care. Within this competitive environment, modern management strategies such as lean, agile, resilient, green, and sustainable approaches present valuable opportunities for enhancing and adapting healthcare service delivery. These strategies contribute not only to operational efficiency but also to long-term organizational development and improved patient outcomes.

Lean production represents a systematic approach that focuses on eliminating non-value-added activities and optimizing processes to increase productivity, flexibility, and profitability in production. Implementing lean principles requires substantial organizational culture transformation, innovative leadership, and highly motivated healthcare personnel (Alsyani & Mohammed, 2023; Ilangakoon et al., 2022). Agility is the ability of an organization to quickly respond to unpredictable changes in the environment while still staying competitive in the market (Alsyani & Mohammed, 2023). The idea of an agile strategy comes from the need for businesses to stay flexible and adapt to changes in the market and shifting customer needs. On the other hand, resilience refers to the ability to identify, adapt to, and manage unexpected disruptions. disruptions such as equipment failures, shortages of raw materials, transportation delays, or shifts in demand can severely disrupt the flow of materials and goods, resulting in increased costs, lower quality, and delivery delays (Tortorella et al., 2022).

In the past two decades, organizations have shifted their focus toward environmental concerns due to increasing awareness about these issues (AlBrakat et al., 2023). Green practices can lead to significant reductions in waste, save energy and raw materials, and reduce the use of harmful substances, all of which help improve environmental sustainability (Al-Awamleh et al., 2022). Green hospitals contribute to sustainability by lowering energy use, and improving air quality (Norouzi et al., 2019). Sustainable development focuses on improving the quality of life for current and future generations through responsible economic growth, social fairness, and environmental protection, helping build a sustainable society (Cavagnaro & Curiel, 2022).

By combining green strategies with Lean, Agile, and Resilient approaches, organizations can boost their overall sustainability (Hosseini Dehshiri et al., 2024). This combination leads to better profits, more efficient use of time, and less environmental harm. Given the limited resources in hospitals and the rising demand for healthcare services, along with the need to improve hospital responsiveness, using LARGS methods is essential to evaluate healthcare performance. Each approach within LARGS offers unique benefits, and when combined, they can greatly improve the performance of the healthcare system.

Empirical Research Background

Numerous studies have been conducted in the field of organizational evaluation and ranking. In the research by Navas de Maya et al. (2022), data mining was utilized as a powerful tool for ranking companies. By employing machine learning algorithms, neural networks, and other methods, the KPIs of companies have been assessed. Another commonly used approach for ranking organizations and evaluating their performance has been DEA. This is a method that employs linear programming to numerically compare the relative efficiency of multiple similar units (Izadikhah & Farzipoor Saen, 2020). Most studies on organizational ranking have relied on MCDM methods to assess and compare organizational performance, taking into account multiple often conflicting criteria.

For instance, by Kesici & Duzdar (2025) used MCDM models to identify the most effective lean method for reducing waste in healthcare services. Güneri and Deveci (2023) utilized the EDAS method in a fuzzy setting to evaluate criteria for selecting suppliers active in the defense industry. Gai et al. (2023) employed a Z-number-based Multi-MOORA approach within a fuzzy environment to rank green suppliers, emphasizing sustainability considerations. Additionally, Nazari-Shirkouhi et al. (2023) integrated DEA with Artificial Neural Networks to enhance supplier selection processes in pharmaceutical companies.

Shao et al. (2023) proposed a combined entropy and TOPSIS approach to enhance decision accuracy. Tasa et al. (2023) introduced a fuzzy TOPSIS method specifically for risk response prioritization in construction projects, addressing uncertainties inherent in project management. Nejatnia et al. (2023) developed a dynamic MCDM model integrated with a fuzzy inference system to rank international transportation companies, facilitating more adaptable decision processes. Adabavazeh et al. (2023) presented a novel Best-Worst method for ranking healthcare system departments based on their resilience levels, highlighting the importance of robustness in healthcare decision-making.

Furthermore, Alamroshan et al. (2022) combined fuzzy logic with a green and agile approach to create a decision-making framework for supplier selection in the medical equipment industry. AmirSalami and Alaei (2023) applied a fuzzy DENP-TOPSIS method for selecting green suppliers, emphasizing sustainability considerations. Rahmani et al. (2024) utilized a fuzzy TOPSIS method to evaluate hospital departments' performance, integrating Lean, Agile, and Green approaches simultaneously to improve healthcare efficiency. In the pharmaceutical supply chain, Sheykhizadeh et al. (2024) employed an MCDM method based on the LARG approach for supplier selection, addressing the complexities of pharmaceutical procurement. Additionally, Amiri et al. (2018) used the SWARA-ARAS method to enhance supply chain management within the LARG framework.

Although these studies demonstrate the effectiveness of the LARG paradigm across various domains, there remains a notable gap in its application within the healthcare sector. Moreover, few studies have explicitly considered the impact of inter-criteria relationships within these models. A comprehensive comparison of the research methodologies and indices examined in this review with previous studies is summarized in Table 1, highlighting areas for future exploration.

Table 1. Comparison of the proposed method with previous studies

Study	Method	LARGS paradigm					Features										
		Lean	Agile	Resilient	Green	Sustainable	Comprehensive Literature Review	Structured Methodology	Pair-wise comparison	Handling Interdependencies	Using expert judgments	Handling uncertainties	Shortening the process	High accuracy in ranking	Top-down approach	Providing a final solution	Implementation in a case study
This study	Fuzzy DEMATEL-MARCOS	□	□	□	□	□	□	□	□	□	□	□	□	□	□	□	□
Alamroshan et al.,) (2022	Fuzzy DEMATEL-VICOR		□		□		□		□	□	□	□	□		□	□	□
Jamali et al.,) (2023	DEMATEL-ANP			□			□		□	□	□					□	□
(2024Liu et al.,)	Fuzzy DEMATEL-ISM			□			□		□	□	□	□	□		□		□
Kokkinos et al.,) (2024	DEMATEL-FCM			□		□	□		□	□	□	□				□	□
Rahmani et al.,) (2024	Fuzzy TOPSIS	□	□		□		□					□	□	□		□	□
Ahmad et al.,) (2024	Fuzzy DEMATEL-DELPHI						□		□	□	□	□			□	□	□
(2025Li & Lu,)	Fuzzy DEMATEL-ISM			□			□		□	□	□	□	□		□		□
(2024Niu et al.,)	Fuzzy DEMATEL-COCOSO						□		□	□	□	□				□	□
(2024Ramadhani,)	Fuzzy DEMATEL-ARAS						□		□	□	□	□	□			□	□
Kandemir et al.,) (2024	Fuzzy DEMATEL-WASPAS								□	□	□	□				□	□
(2023Lu et al.,)	Fuzzy DEMATEL-EDAS						□		□	□	□	□	□			□	□

The existing body of research indicates that previous studies in the field of ranking have primarily focused on unidimensional MCDM methods. Although various hybrid methods for ranking arepresented in Table 1, these approaches have largely concentrated on specific aspects, such as lean, agile, resilience, and green strategies. However, they have often neglected the intelligent integration of criteria, the consideration of interrelationships among them, top-down approaches, and the precision of rankings. This study addresses this gap by introducing, a hybrid fuzzy DEMATEL-MARCOS model for ranking hospital departments for the first time. This model allows for the simultaneous analysis of lean, agile, resilience, green, and sustainability criteria under conditions of uncertainty.

Materials and Methods

Fuzzy Set Theory

Uncertainty in a fuzzy environment serves as a crucial tool for modeling real-world systems, particularly in scenarios where precise and reliable information is unavailable.Fuzzy uncertainty allows for the modeling of complex systems that are accompanied by ambiguity and uncertainty, leading to better decision-making. The theory of fuzzy sets was first introduced by (Zadeh, 1965). The primary aim of this theory is the mathematical modeling of uncertainty and ambiguity.Additionally, it provides methods for analyzing uncertainty in decision-making structures. Based on the qualitative nature of expert opinions, which are often expressed linguistically (such as high, medium, etc.) and the limitations in the number of expert samples, this study employs fuzzy numbers instead of other uncertainty modeling methods like Z-numbers, D-numbers, and rough set theory. This choice stems from the fact that fuzzy numbers are particularly well-suited for modeling subjective ambiguity and qualitative data, whereas other methods require additional information or more complex structures that were not available in this research. The use of triangular fuzzy numbers (TFNs) is preferred in this study. These numbers are defined as a triplet (a_1, a_2, a_3).

Multi-Stage Model Based on Fuzzy DEMATEL and Fuzzy MARCOS

This study uses a combined model to evaluate the efficiency of hospital departments. In addition to identifying factors that influence performance, the model addresses the management of uncertainty and ambiguity in the data. In the first stage, the weights of the criteria has been determined using the fuzzy DEMATEL method, and the relationships between them has been identified. Then, the hospital departments has been ranked using the fuzzy MARCOS method.

Determination of Selection Criteria and Options

This study seeks to provide a comprehensive classification of modern management paradigms, emphasizing the significance of these paradigms—particularly LARGS—in enhancing performance and achieving a competitive advantage in the healthcare industry.The primary goal of this research is to develop a comprehensive and integrated model that combines the LARGS paradigm with the performance of healthcare departments. After clearly defining the problem, the next step is to formulate the criteria for evaluating and selecting the best healthcare department based on the specific needs of the hospital or the structure of the issue. In this regard, the criteria weighting process has carried out in three main stages using the fuzzy DEMATEL method: 1. Selecting Experts process: The experts have been chosen based on their experience and education. In this study, the opinions of five experts, each with at least ten years of experience in emergency medicine, ophthalmology, cardiology, infectious and neurology, have been used. 2. Determining Criteria: The main criteria for the research have been identified by reviewing existing studies. 3. Using the Fuzzy DEMATEL Model: In this step, fuzzy numbers and calculations have been used to determine the final weight for each criterion. This method provides a more accurate calculation by considering uncertainty and how the criteria are connected.

Calculation of Selection Criteria Weights

The relative importance of criteria can be measured through various methods, both objective and subjective. These methods allow researchers to gain a more comprehensive assessment of the performance of hospital departments from different aspects. Numerous methods have been developed to determine the weights of criteria in various studies. These include entropy methods (Zhou et al., 2019), linear programming (Wan & Li, 2013), threshold indifference-based feature ratio analysis (Hatefi, 2019), gray relational analysis (Luo et al., 2019), the analytic hierarchy process (Sirisawat & Kiatcharoenpol, 2018), DEA (Davoudabadi et al., 2021), the best-worst method (Maghsoodi et al., 2019), and DEMATEL (Gabus & Fontela, 1972).

A key feature of the DEMATEL method in hospital evaluations is the consideration of the relationships between various criteria. DEMATEL helps to improve decision-making quality by representing these relationships in the form of a network. A notable aspect of evaluating the performance of multiple hospital departments is the synergy and reciprocal influence of the criteria on one another. Several studies have shown that the DEMATEL method is a powerful tool for evaluating and analyzing complex systems in various fields, due to its ability to determine precise factor weights, and map the relationships between them. In this study, fuzzy DEMATEL has been used to determine the weight of indicators and analyze the relationships between them. Although many decision-making problems in the literature have been solved successfully by applying the DEMATEL method, the development of the fuzzy DEMATEL method has been necessary due to the uncertainty inherent in decision-making. The fuzzy DEMATEL method has been employed to calculate the weights of criteria in a fuzzy environment. Additionally, it is applicable to problems such as group decision-making. Due to its suitability for real-world case studies, the fuzzy DEMATEL method has been widely applied for various problems across different fields. A summary of the reviewed literature is presented in Table 2.

Table 2. Application of the proposed Method

Literature review	Method	Application
(Geng et al., 2017)	DEMATEL-DEA	Selection of medical devices in the healthcare sector
(Ecer, 2022)	MARCOS-EDAS-MAIRCA	Evaluation and selection of sustainable suppliers in healthcare
(Torkayesh, Malmir, et al., 2021)	GREY-MARCOS	Location selection for healthcare waste
)Mavi & Standing, (2018	DEMATEL-ANP	Identification of critical success factors in project management
(Kilic et al., 2020)	DEMATEL-ELECTRE	Qualitative attributes in healthcare personnel selection decisions
(Liu et al., 2020)	DEMATEL-ANP	Evaluation of Taiwanese airlines
(Liou et al., 2019)	DEMATEL, DANP and MOORA	Evaluation and selection of sustainable suppliers
This study	Fuzzy DEMATEL-MARCOS	Performance evaluation of five hospital departments using LARG paradigm

The stages in the fuzzy DEMATEL approach are as follows. DEMATEL, which is one of the decision-making methods based on pairwise comparisons, utilizes expert judgment and the principles of graph theory to create a hierarchical structure for the factors of a system. In this structure, causal relationships are quantitatively defined, and the impact of each factor on other factors is determined with a numerical score. The steps of the fuzzy DEMATEL method are presented below.

Step 1: Construction of Fuzzy Pairwise Comparison Matrix

To assess the criteria, the judgments of five experts are considered, and a pairwise comparison Matrix is created for each expert. In these matrices, the values are TFNs, and they are treated as fuzzy numbers.

Step 2: Aggregation of Comparison Matrix

To incorporate the opinions of all experts, the arithmetic mean of their assessments is calculated according to Formula 1.

$$\tilde{z} = (\tilde{x}^1 + \tilde{x}^2 + \tilde{x}^3 + \cdots + x^p) / p \tag{1}$$

In this formula, p represents the number of experts, and the matrices $\tilde{x}^1$ correspond $\tilde{x}^p$ ، $\tilde{x}^2$ ، to the pairwise comparison Matrix for expert 1,2,… and p, respectively. The triangular fuzzy number $\tilde{z}$ is represented as $\tilde{z}_{ij} = (l'_{ij}, m'_{ij}, u'_{ij})$.

Step 3: Normalization of the Direct Relationship Matrix

According to Equation 2, the average matrix is normalized, and this normalized matrix is referred to as matrix H. To normalize the resulting matrix, Equations 2 and 3 are used. The value r is obtained from Equation 3.

$$\tilde{H}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l'_{ij}}{r}, \frac{m'_{ij}}{r}, \frac{u'_{ij}}{r}\right) = \left(l''_{ij}, m''_{ij}, u''_{ij}\right) \tag{2}$$

$$\mathrm{r} = \max_{1 \le i \le n}\left(\sum_{j=1}^{n} u'_{ij}\right) \tag{3}$$

Step 4: Calculation of the Total Fuzzy Relation Matrix

After computing the above matrices, the Fuzzy Relation Matrix is obtained using Equations 4 through 7.

$$T = \lim_{k \to +\infty}\left(\tilde{H}^1 \oplus \tilde{H}^2 \oplus \ldots \oplus \tilde{H}^k\right) \tag{4}$$

Each element of $\tilde{t}_{ij} = \left(l^t_{ij}, m^t_{ij}, u^t_{ij}\right)$ is a fuzzy number, which is calculated as follows:

$$\left[l^{t}_{ij}\right] = \mathrm{H}_l \times \left(\mathrm{I} - \mathrm{H}_l\right)^{-1} \tag{5}$$

$$\left[\mathrm{m}^{t}_{ij}\right] = \mathrm{H}_m \times \left(\mathrm{I} - \mathrm{H}_m\right)^{-1} \tag{6}$$

$$\left[u^{t}_{ij}\right] = \mathrm{H}_u \times \left(\mathrm{I} - \mathrm{H}_u\right)^{-1} \tag{7}$$

In these equations, I represents the identity matrix and the elements H_l H_u و H_m ، correspond to the lower, middle, and upper bounds, respectively, of the TFNs in the matrix T. In this research, the fuzzy DEMATEL method involves 15 criteria, the names of which are presented in Table 3.

Table 3. Related criteria for the LARGS paradigm

Strategy	Code	Criterion	Description	Reference
Lean	C1	Reducing Excess Transportation	Staff walk long distances within departments to fetch items or take notes. Centralizing frequently used equipment can eliminate unnecessary travel.	(Found & Bicheno, 2016), (Hussain et al., 2016), (Radnor et al., 2012), (Robinson et al., 2012)
	C2	Reducing Waiting Time (Delays)	Patients waiting for prescriptions, medications, or discharge should experience minimal delays.	(Psychogios et al., 2012), (Hussain et al., 2016), (Al-Aomar & Hussain, 2018)
	C3	Reducing Over-Processing	Repeating patient information or asking for details multiple times is a form of over-processing that should be eliminated.	(Hussain et al., 2016), (Robinson et al., 2012), (Found & Bicheno, 2016),
Agile	C4	Leadership	Leadership builds trust and is crucial in improving overall healthcare performance.	(Moheimani et al., 2021), (Brennan Jr et al., 2012), (Vinodh et al., 2010)
	C5	Organizational Structure	Streamlined organization and effective team management reduce conflicts and eliminate non-value-adding tasks.	(Moheimani et al., 2021), (Jefferson & Harrald, 2007), (Sindhwani et al., 2019)
	C6	Outsourcing	Agile promotes outsourcing to access advanced healthcare technologies, often from global providers.	(Wang & Wagner, 2016), (Moheimani et al., 2021), (Machado Guimarães & Crespo de Carvalho, 2012)
Resilient	C7	Top Management Commitment	Strong commitment from senior management reduces the environmental impact of healthcare services.	(Rahmani et al., 2024), (Chías & Abad, 2017), (Rahiminezhad Galankashi & Helmi, 2016)
	C8	Eco-Friendly Transportation	Environmentally friendly transport methods help reduce overall operational costs.	(Rahmani et al., 2024), (Chías & Abad, 2017), (Rahiminezhad Galankashi & Helmi, 2016)
	C9	Hazardous Waste Management & Pollution Prevention	Minimizing hazardous materials and enforcing strict environmental standards for vendors helps prevent pollution.	(Rahmani et al., 2024), (Chías & Abad, 2017), (Rahiminezhad Galankashi & Helmi, 2016)
Green	C10	Visibility	A systemic view and operational transparency enable faster responses to disruptions and better future preparedness.	(Ganguly & Kumar, 2019), (Tukamuhabwa et al., 2015), (Cao et al., 2010)
	C11	Patient Satisfaction	Ensuring customer satisfaction through quality services is key to building a responsive and sustainable healthcare organization.	(Pickering et al., 2017), (Sheth et al., 2011), (Baalbaki et al., 2008),
	C12	Cost Optimization	Optimizing costs can significantly enhance service levels in flexible healthcare systems.	(Ganguly & Kumar, 2019), (Singh et al., 2016), (Hussain et al., 2020)
Sustainable	C13	Waste Minimization	Reducing waste through reuse, recycling, and waste management programs is vital to sustainability.	(Mehra & Sharma, 2021), (Sherman et al., 2020), (Chauhan & Singh, 2017)
	C14	Research and Innovation	Research and innovation drive transformational changes needed for sustainable healthcare systems.	(Greenhalgh et al., 2017), (Mehra & Sharma, 2021), (Aquino et al., 2018)
	C15	Employee Job Satisfaction	High job satisfaction is essential for staff retention and long-term workforce stability in healthcare.	(Mehra & Sharma, 2021), (Pinzone et al., 2012), (AlJaberi et al., 2020),

The research employs a 5-point Likert scale consisting of specific linguistic variables to facilitate pairwise comparison of criteria. The complete list of these verbal expressions and their corresponding fuzzy numerical equivalents are presented in Table 4.

Table 4. Linguistic variables and corresponding TFNs (Li et al., 2020)

Linguistic Variable	Abbreviation	Corresponding TFN (l, m, u)
No Influence	NI	(0, 0, 0.25)
Very Low Influence	VLI	(0, 0.25, 0.5)
Low Influence	LI	(0.25, 0.5, 0.75)
High Influence	HI	(0.5, 0.75, 1.0)
Very High Influence	VHI	(0.75, 1.0, 1.0)

$$\tilde{D} = (\tilde{D}_i)_{(n\times1)} = [\sum_{j=1}^{n} \tilde{T}_{ij}]_{(n\times1)} \tag{8}$$

$$\tilde{R} = (\tilde{R}_j)_{(1\times n)} = [\sum_{j=1}^{n} \tilde{T}_{ij}]_{(1\times n)} \tag{9}$$

Step 5: Determining the Degree of Influence and Dependence Values

The significance of each criterion is determined by the intensity of its interactions ($\tilde{\mathrm{D}}_{\mathrm{i}} + \tilde{\mathrm{R}}_j$), while the nature of the relationship between criteria is identified by the net effect value ($\tilde{\mathrm{D}}_{\mathrm{i}} - \tilde{\mathrm{R}}_j$). If ($\tilde{\mathrm{D}}_{\mathrm{i}} - \tilde{\mathrm{R}}_j$) > 0), the corresponding criterion is considered influential, if ($\tilde{\mathrm{D}}_{\mathrm{i}} - \tilde{\mathrm{R}}_j$) < 0, the criterion is considered influenced. Table 5 presents the values of ($\tilde{\mathrm{D}}_{\mathrm{i}} + \tilde{\mathrm{R}}_j$) and ($\tilde{\mathrm{D}}_{\mathrm{i}} - \tilde{\mathrm{R}}_j$).

Table 5. Cause and effect values

Code	Criterion	D+R	D−R	Causal Relationship
C1	Reducing Excess Transportation	4.15	0.45	Cause
C2	Reducing Waiting Time	4.67	–0.06	Effect
C3	Reducing Over-Processing	4.15	–0.01	Effect
C4	Leadership	4.71	–0.45	Effect
C5	Organizational Structure	4.84	–0.08	Effect
C6	Outsourcing	4.88	–0.34	Effect
C7	Top Management Commitment	4.91	0.39	Cause
C8	Eco-Friendly Transportation	4.76	–0.53	Effect
C9	Hazardous Waste Management	5.05	0.81	Cause
C10	Visibility	5.05	0.17	Cause
C11	Patient Satisfaction	5.52	0.39	Cause
C12	Cost Optimization	5.06	0.80	Cause
C13	Waste Minimization	4.41	–0.66	Effect
C14	Research and Innovation	4.88	–0.47	Effect
C15	Employee Job Satisfaction	5.39	–0.41	Effect

Results

According to the findings of the study, among the fifteen evaluated criteria, patient satisfaction (C11) with a weight of 5.52 and Employee job satisfaction (C15) with a weight of 5.39 were identified as the most significant influencing factors. In contrast, the criteria for Reducing Excess Transportation (C1) and Reducing Over-Processing (C3) had the least weight, 4.15 and 4.15, respectively, indicating the least importance among the criteria. These results highlighted the importance of focusing on improving the patient experience and enhancing the working conditions of staff in hospitals. Improving these factors can directly impact the quality of healthcare services and the overall efficiency of the system. On the other hand, reducing focus on factors with less influence could lead to better resource allocation and cost reduction. This strategic approach would help managers achieve better results with limited resources and increase overall satisfaction with healthcare services. Figure 1 illustrates the importance, impact, and effect among the criteria. To draw the causal relationship diagram, the degree of influence and Influenceability for each criterion has first been calculated using the relationship matrix. Then, by examining the sum of the rows and columns of the matrix, the main and subordinate variables have been identified, and the diagram has been plotted. The horizontal axis of the diagram ($D+R$) represents the importance of the identified criteria, while the vertical axis ($D-R$) shows the influence or Dependence of the criteria. This classification separates the parameters into two groups: causal and effect. If the value of ($D-R$) is negative, it means the parameter is part of the effect group and is influenced by other factors. On the other side, a positive value of ($D-R$) shows that the parameter is a causal factor, meaning it has a significant influence on other parameters.

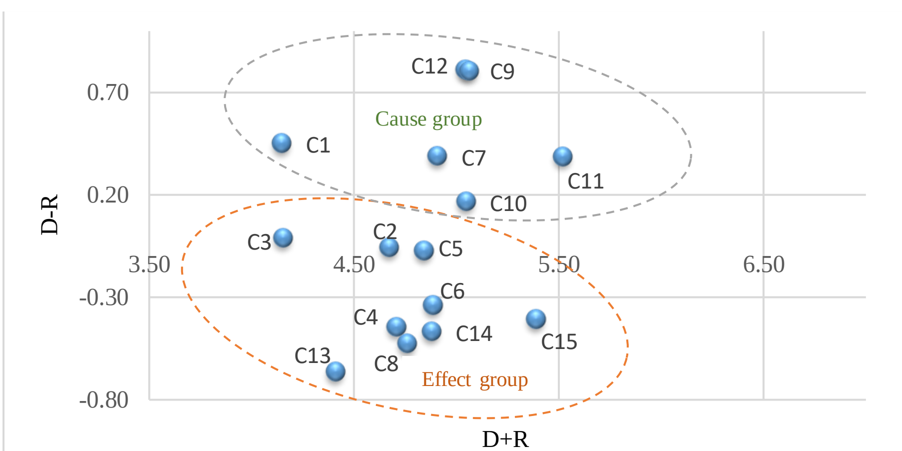

Figure 1. Cause-effect relationship diagram

Fuzzy MARCOS for Alternative Ranking

Achieving a comprehensive prioritization of the evaluated sectors necessitates precise identification and ranking, facilitated by MCDM techniques.The systematic integration of the DEMATEL method and MCDM techniques as a comprehensive framework provides a powerful tool for solving complex decision-making problems in various fields. Among MCDM methods, the MARCOS method, proposed by (Stanković et al., 2020), offers more realistic results by comparing Alternatives with an ideal state. , By calculating utility functions, this method increases the sensitivity of the approach to weight changes and helps prevent ranking errors. Additionally, it performs better in fuzzy environments and conditions of uncertaintydue to its stronger analytical structure, , distinguishing it from MCDM methods. The MARCOS method is a relatively new MCDM approach that is recognized as a practical and efficient solution for solving complex decision-making problems and is applicable in a wide range of situations, such as selecting sites for offshore wind farms (Deveci et al., 2021), and Healthcare waste landfill location determination (Torkayesh, Zolfani, et al., 2021). This method determines the priority of alternatives by considering the relationship between the alternatives and reference values.

In this study, the MARCOS-MCDM method was employed to select five hospital departments in Shiraz, Iran—Emergency, Ophthalmology, Cardiology, Infectious Diseases, and Neurology—as the primary options for evaluation.Decision-making preferences have been defined through utility functions. These functions indicate the position of a department relative to the positive and negative ideal solutions. The closest option to the positive ideal and farthest from the negative ideal option has been considered the best. Decision-makers have employed the linguistic variables, shown in Table 6, when evaluating the options based on the criteria. The steps of this method are as follows.

Step 1: Construction of the Fuzzy Decision Matrix

The fuzzy decision matrix, which includes fuzzy performance functions of different options based on various criteria, is formed with the assumption that the problem involves m Alternatives, Ai (i = 1, 2, ..., m), n criteria, Cj (j = 1, 2, ..., n) and K decision-makers, DM_K (K=1,2,...,K). The decision-makers utilize the linguistic variables presented in Table 6 to evaluate the options based on the specified criteria.

Table 6. linguistic variables for rating Alternatives and corresponding TFNs (Tian et al., 2018).

Linguistic Variable	Abbreviation	Corresponding TFN (l, m, u)
Very Low	VL	(0, 0, 1)
Low	L	(0, 1, 3)
Slightly Low	SL	(1, 3, 5)
Medium	M	(3, 5, 7)
Slightly High	SH	(5, 7, 9)
High	H	(7, 9, 10)
Very High	VH	(9, 10, 10)

Step 2: Aggregation of Fuzzy Decision Matrix

A fuzzy group decision-making matrix is formed using linguistic variables.

$$\tilde{X}_{ij} = \left[\tilde{x}_{ij}\right]_{m\times n} \quad \text{(i = 1,2…,m ; j = 1,2,…,n)} \tag{10}$$

Step 3: Determination of Positive and Negative Ideal Solutions

An extended fuzzy group decision matrix is developed by incorporating both the Positive Ideal Solution $\tilde{A}(ID)$ and Negative Ideal Solution $\tilde{A}(AID)$. The option that exhibits the most desirable characteristics is referred to as the Positive Ideal Solution, while the one with the least desirable characteristics is referred to as the Negative Ideal Solution. By simultaneously considering both the Positive and Negative Ideal Solution from the outset of the matrix construction, this method enables a comprehensive evaluation of multiple departments and ensures the reliability of the model (Gong et al., 2021).

$$\begin{aligned} \tilde{A}(ID) &= \underset{i}{Max}(\tilde{x}_{ij}) \\ \tilde{A}(AID) &= \underset{i}{Min}(\tilde{x}_{ij}) \end{aligned} \quad \text{For Maximization Criteria (Positive)} \tag{11}$$

$$\begin{aligned} \tilde{A}(ID) &= \underset{i}{Min}(\tilde{x}_{ij}) \\ \tilde{A}(AID) &= \underset{i}{Max}(\tilde{x}_{ij}) \end{aligned} \quad \text{For Minimization Criteria (Negative)} \tag{12}$$

Step 4: Normalized Fuzzy Decision Matrix

The criteria for maximization and minimization are normalized using equations 14a and 14b, respectively.

$$\tilde{N} = \left[\tilde{n}_{ij}\right]_{m\times n} \tag{13}$$

$$\tilde{n}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \tag{14a}$$

$$\tilde{n}_{ij} = \left(\frac{a^-{}_j}{c_{ij}}, \frac{a^-{}_j}{b_{ij}}, \frac{a^-{}_j}{a_{ij}}\right) \quad \text{(i = 1,2…,m; j = 1,2,…,n)} \tag{14b}$$

$$a^-{}_j = \underset{i}{Min}\, a_{ij} \tag{15}$$

$$c_j^* = \underset{i}{Max}\, c_{ij} \tag{16}$$

$\tilde{n}_{ij}$ represents the normalized fuzzy performance values. The normalization formulas in Equations (14a) and (14b) ensure that the normalized fuzzy numbers fall within the range of [0, 1].

Step 5: Weighted Normalized Fuzzy Decision Matrix

In the matrix $\tilde{R}$, the values $\tilde{r}_{ij}$ are calculated using Equation (18), where $\tilde{w}_j$ represents the weights of the criteria determined through the fuzzy DEMATEL method.

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m\times n} \tag{17}$$

$$\tilde{r}_{ij} = \tilde{W}_j \tilde{n}_{ij} \qquad 0 \langle \tilde{W}_j \langle 1 \tag{18}$$

Step 6: Calculation of the Matrix $\tilde{S}_i$

This step is performed to determine the desirability degree of the alternatives.

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{r}_{ij} \tag{19}$$

Step 7: Calculation of the Desirability Degree for Each Option

The desirability degree of each alternative is calculated using Equations 20a and 20b.

$$\tilde{K}_i^- = \frac{\tilde{S}_i}{\tilde{S}_{AID}} \tag{20a}$$

$$\tilde{K}_i^+ = \frac{\tilde{S}_i}{\tilde{S}_{ID}} \tag{20b}$$

Step 8: Calculation of the Overall Desirability Degree

This includes the Positive and Negative Ideal Solution for each option, which are computed using Equation (21).

$$\tilde{T}_i = \tilde{K}_i^+ + \tilde{K}_i^- \tag{21}$$

To proceed with the operations, a new fuzzy representative value of the overall desirability degrees is obtained as follows.

$$D = Max(\tilde{t}_{ij}) = (d^l, d^m, d^u) \tag{22}$$

Then, defuzzification is performed using Equation (23).

$$\text{dfCrisp} = \frac{l + 4m + u}{6} \tag{23}$$

Step 9: Desirability Functions for the Positive and Negative Ideal Solution

The desirability functions are calculated using Equations (24a) and (24b) for the Positive and Negative Ideal Solution, respectively. The computed values are presented in Table 6.

$$f(\tilde{K}_i^+) = \frac{\tilde{K}_i^-}{\text{dfCrisp}} \tag{24a}$$

$$f(\tilde{K}_i^-) = \frac{\tilde{K}_i^+}{\text{dfCrisp}} \tag{24b}$$

Step 10: Overall Desirability Degree of Each Option

The overall desirability degree of each alternative is calculated as follows.

$$f(K_i) = \frac{\tilde{K}_i^- + \tilde{K}_i^+}{1 + \frac{1 - f(\tilde{K}_i^+)}{f(\tilde{K}_i^+)} + \frac{1 - f(\tilde{K}_i^-)}{f(\tilde{K}_i^-)}} \tag{25}$$

Step 11: Ranking of Alternatives

The alternatives are ranked in descending order based on the obtained performance values. The results of the calculations are presented in Table 7.

Table 7. Results based on the fuzzy MARCOS method

Department	Department	Ki+	Ki-	f(K+)	f(K-)	f(Ki)	Rank
Department-1	Emergency	0.711	1.767	0.509	0.205	0.424	4
Department-2	Ophthalmology	0.690	1.719	0.495	0.199	0.398	5
Department-3	Cardiology	0.828	2.041	0.588	0.239	0.586	2
Department-4	Infectious	1.008	2.463	0.710	0.290	0.901	1
Department-5	Neurology	0.781	1.930	0.556	0.225	0.517	3

The fuzzy MARCOS analysis evaluated the performance of the infectious department as satisfactory, however, it revealed that the performance of the ophthalmology department requires improvement and enhancement. Senior management, while appreciating the evaluation conducted, concluded that many inadequate decisions and supervisory deficiencies stem from the organization's inefficient structure. To improve the performance of the ophthalmology department under conditions of limited human resources, a review of the organizational structure and staff duties would be essential. This requires actions such as educational planning, professional skill development for personnel, cost optimization, safe management of hazardous waste, outsourcing specialized activities, and encouraging research and innovation in this department. The systematic implementation of these strategies will not only enhance service quality but also boost patient and staff satisfaction, leading to an overall improvement in departmental performance. It is recommended that these programs be implemented in practice with the support of senior hospital management, ensuring alignment with available resources.

Sensitivity and Comparative Analyses

In this research, sensitivity analysis has been conducted in two stages to assess the reliability of the results and assist in making accurate decisions. Since the weight of the criteria significantly impacts the ranking, their variations have been evaluated in the first stage. The main objective of conducting a sensitivity analysis in this section is to identify the most sensitive variable to changes in the final ranking of the model. According to the research by (Kahraman, 2002), Equation 26 is defined as follows:

$$w_c = (1 - w_s) \times (w_c^o / W_c^o) = w_c^o - \Delta x \alpha_c \tag{26}$$

In the above equation, w_c represents changes in criterion weights, w_s denotes the weight of the most important criterion, w_c^o indicates the original values of the criterion weights and W_c^o represents the sum of the original values of the criteria weights that have changed. The parameter α_c is defined as the sensitivity coefficient, which is calculated using Equation (27).

$$\alpha_c = w_c^o / W_c^o \tag{27}$$

The change in the weight of the most important criterion must be limited. Otherwise, the weights may become negative. The changes in the weight of the most important criterion in both the negative and positive directions, based on the boundary values Δx, are defined using Equation (28).

$$-w_s^o \le \Delta x \le \min\left[w_c^o / \alpha_c \right] \tag{28}$$

After determining the limits, the new weights of the criteria are calculated based on Equations 29 and 30.

$$w_s = w_s^o + \alpha_s \Delta x \tag{29}$$

$$w_c = w_c^o - \alpha_c \Delta x \tag{30}$$

In this research, the C11 index (patient satisfaction) has been identified as the most influential criterion, as it has the highest weighted coefficient value. In the next step, the weight sensitivity coefficient has been determined according to Table 8, and the limits for the change in the weight coefficient of the most important index have been defined.

Table 8. Elasticity Coefficients values

Criterion	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
Elasticity Coefficient	0.620	0.0698	0.0620	0.0704	0.0723	0.0729	0.0734	0.0711	0.0755	0.0755	0.0825	0.0756	0.0659	0.0729	0.0806

The distance -0.0824 $\leq \Delta x \leq$ 1 has been divided into 12 scenarios. After determining the threshold values for the most influential criterion, the new weight coefficients for the 12 scenarios (12 distinct weight vectors) have been defined according to Table 9. The results obtained from implementing the MARCOS method based on the different weights of the criteria are illustrated in Figure 2. The consistent ranking of the best care department in the sensitivity analysis demonstrates the reliability of the results. Conversely, with only minor adjustments to the criteria weights, the rankings of different alternatives have exhibited a high degree of similarity across various scenarios, although some differences have been observed. This underscores the sensitivity of the MARCOS method to changes in criteria weighting. Modifying the assigned weights could significantly impact the final rankings. As shown in Figure 2, the correlation between results reached a minimum of 81%, indicating a strong level of consistency. Therefore, the MARCOS method would be regarded as a reliable and effective decision-making tool.

Table 9. Different scenarios of weight changes

Criterion	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12
C1	0.0621	0.0573	0.0530	0.0489	0.0452	0.0417	0.0385	0.0356	0.0329	0.0303	0.0280	0.0259
C2	0.0697	0.0644	0.0594	0.0549	0.0508	0.0468	0.0432	0.0399	0.0329	0.0341	0.0314	0.0290
C3	0.0621	0.0573	0.0530	0.0489	.0452	0.0417	0.0385	0.0356	0.0329	0.0303	0.0280	0.0259
C4	0.0704	0.0650	0.0600	0.0554	0.0515	0.0473	0.0438	0.0403	0.0379	0.0344	0.0318	0.0293
C5	0.0724	0.0669	0.0617	0.0570	0.0527	0.0486	0.0449	0.0415	0.0383	0.0354	0.0327	0.0302
C6	0.0731	0.0675	0.0623	0.0576	0.0523	0.491	0.0453	0.0419	0.0378	0.0357	0.0330	0.0305
C7	0.0734	0.0678	0.0626	0.0578	.0534	0.0493	0.0455	0.0420	0.0388	0.0359	0.0331	0.0306
C8	0.0711	.0657	0.0606	0.0560	0.0517	0.0478	0.0441	0.0407	0.0376	0.0357	0.0321	0.0296
C9	0.0754	0.0696	0.0643	0.0594	0.0548	0.0506	0.0468	0.0432	0.0399	0.0368	0.0340	0.0314
C10	0.0754	0.0696	0.0643	0.0594	0.0548	0.0506	0.0468	0.0432	0.0399	.0368	0.0340	0.0314
C11	0.0000	0.0765	0.0156	0.0299	0.0306	0.0382	0.0459	0.0535	0.0612	0.0688	0.0765	0.0706
C12	0.0756	0.0698	0.0645	0.0595	0.0550	0.0508	0.0469	0.0433	0.0400	0.0369	0.0341	0.0315
C13	0.0661	0.0610	0.0564	0.0521	0.0481	0.0444	0.0410	0.0379	0.0350	0.0323	0.0298	0.0275
C14	0.0731	0.0675	0.0623	0.0576	0.0532	0.0491	0.0453	0.0419	0.0387	0.0357	0.0330	0.0305
C15	0.0805	0.0743	0.0678	0.0634	0.0586	0.0541	0.0499	0.0461	0.0426	0.0393	0.0363	0.0325

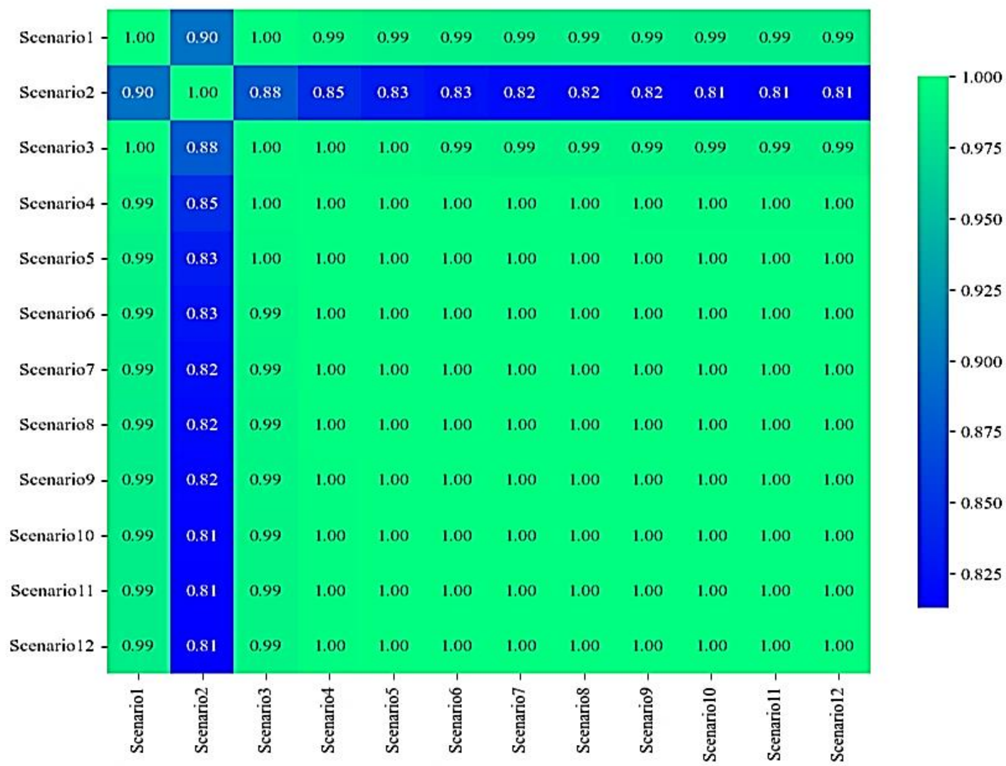

Figure 2. Heat map of correlation coefficients between different scenarios of weight change criteria

In the second stage of the sensitivity analysis, the proposed approach has been compared with several MCDM models, including fuzzy ARAS (Ramadhani, 2024), fuzzy COCOSO (Niu et al., 2024), fuzzy EDAS (Lu et al., 2023), and fuzzy WASPAS (Kandemir et al., 2024). The ranking of departments using all four methods is presented in Table 10. Notably, the best alternative has been the same across all approaches, which supports the findings of the fuzzy DEMATEL–MARCOS method. Generally speaking, all the employed decision-making methods produced consistent and aligned results, and the fuzzy (ARAS, COCOSO, EDAS, WASPAS, MARCOS) approaches demonstrated strong correlation, indicating the reliability and robustness of the analysis performed.

Table 10. Comparison between MCDM Method

Department		MARCOS Value	Rank	EDAS Value	Rank	VIKOR Value	Rank	ARAS Value	Rank	COCOSO Value	Rank
Department-1	Emergency	0.424	4	0.115	4	55.563	4	0.637	4	8.273	4
Department-2	Ophthalmology	0.398	5	0.075	5	53.869	5	0.613	5	7.471	5
Department-3	Cardiology	0.586	2	0.443	2	65.092	2	0.749	2	11.583	2
Department-4	Infectious	0.901	1	0.977	1	79.758	1	0.961	1	17.92	1
Department-5	Neurology	0.517	3	0.316	3	61.338	3	0.703	3	10.092	3

To evaluate the consistency and reliability of the results obtained from five MCDM methods MARCOS, ARAS, WASPAS, COCOSO, and EDAS, in assessing hospital performance, the Spearman Rank Correlation Coefficient (SRCC) test has been employed with equation 31.

$$\rho = 1 - \left(\frac{6 \times \sum d_i^2}{n \times (n-1)} \right) \tag{31}$$

In this context, the SRCC is denoted as (ρ) represents the degree of association, d_i denotes the difference between the ranks assigned by the two methods, and n indicates the number of alternatives. As shown in Table 11, the analysis revealed a strong correlation (greater than 0.75) among all the methods. This showed that the rankings produced by the different methods have been mostly consistent, indicating that the results are stable and trustworthy. The close alignment between these methods suggests that the research model is dependable and could be confidently used in different decision-making situations. This is especially valuable for hospital managers, as it demonstrates that these methods serve as powerful tools for evaluating hospital performance.

Table 11. Correlation type among MCDM Method

MCDM Method	SRCC Equation	SRCC Value	Correlation Type
Among MARCOS, ARAS, WASPAS, COCOSO and EDAS	$\rho = 1 - \left(\frac{6 \times 0}{5 \times (4)} \right)$	1	Very Strong

Policy Recommendations

Managerial decision-making is inherently complex and sensitive, given its multi-criteria nature and the discretionary authority managers hold in making final decisions.Performance evaluation requires a comprehensive and detailed assessment of various alternatives. It plays a crucial role in fostering a culture of continuous improvement within hospital departments, ensuring efficient resource utilization and minimizing waste.As evidenced by previous studies, multi-criteria models provide a valuable framework for assessing performance across various industries, including healthcare. Performance evaluation models used in healthcare possess distinct characteristics, each with its own advantages and limitations.

The application of fuzzy DEMATEL and fuzzy MARCOS in evaluating the factors influencing healthcare department performance has yielded valuable insights into their nature and prioritization. A key finding of the fuzzy DEMATEL method was its ability to identify relationships among these factors and determine their relative priority. The performance-shaping factors C1 (reduction excessive transportation), C7 (top management commitment), C9 (hazardous waste management), C10 (visibility), C11 (patient satisfaction), and C12 (cost optimization) have been categorized as causal factors. As shown in Table 5, the causal criteria indicated that these factors exert a certain influence on other criteria. Their pivotal role in enhancing hospital performance underscores the importance of prioritizing them, enabling decision-makers to drive further improvements.

In performance evaluation, various models offer distinct advantages and limitations, as highlighted in previous studies. Compared to fuzzy logic models, the MARCOS method excels in handling complex decision-making scenarios involving multiple criteria, thanks to its enhanced flexibility. A key strength of MARCOS is its ability to maintain algorithmic simplicity even when addressing intricate problems with numerous criteria and alternatives. This method follows three fundamental steps to support well-informed decisions: (I) Identifying reference points, including both positive and negative ideal solutions. (II) Establishing relationships between the alternatives and these ideal solutions. (III) Evaluating the usefulness of each alternative concerning the ideal solutions. By integrating relative approaches with reference point ranking, the MARCOS method delivers more comprehensive and well-reasoned results compared to one-dimensional models.

Sensitivity analysis of the fuzzy MARCOS method demonstrated that evaluation outcomes remain highly stable across various weight change scenarios. This stability highlighted the method’s ability to enhance decision-making accuracy and reliability. Subsequently, hospital department rankings have been compared using four other fuzzy MCDM methods: ARAS, WASPAS, COCOSO, and EDAS. SRCC analysis of these rankings revealed a significant correlation, indicating strong agreement among the results and confirming the validity of the methodology applied in this research.

Discussion and Conclusion

In this study, we evaluated the performance of five hospital departments—Emergency, Ophthalmology, Cardiology, Infectious Diseases, and Neurology. The evaluation criteria were selected through a comprehensive review of relevant literature, expert interviews, and content analysis, ensuring alignment with the hospital’s vision and values.

Grounded in the performance enhancement paradigm, five primary criteria and fifteen sub-criteria were identified at the macro level:

- Lean (three sub-criteria)
- Agile (three sub-criteria)
- Resilience (three sub-criteria)
- Green (three sub-criteria)
- Sustainability (three sub-criteria)

To collect data, five experts from different hospital departments provided input by completing structured questionnaires. The fuzzy DEMATEL method was used to assign weights to the criteria, utilizing linguistic variables and triangular fuzzy numbers (TFNs) to enhance evaluation accuracy. Given the inherent ambiguity of certain concepts, this approach enables more precise decision-making compared to traditional DEMATEL methods.

Subsequently, the hospital departments were ranked using the fuzzy MARCOS method, based on their overall desirability. The fuzzy MARCOS method offers several advantages over other decision-making techniques, as it incorporates both positive and negative ideal solutions as reference points, establishes them early in the decision process, and identifies the best alternative using utility functions.

In a case study conducted at a hospital in Shiraz, Iran, the proposed model was tested through a two-step sensitivity analysis. In the first step, the reliability of the fuzzy MARCOS method was examined under various conditions by analyzing results with different criteria weights. In the second step, the rankings generated by the fuzzy MARCOS method were compared with those from other fuzzy decision-making methods, including ARAS, WASPAS, COCOSO, and EDAS. To further evaluate the alignment between these rankings, correlation coefficients were calculated for all methods. The analysis demonstrated that the proposed model is reliable, with the fuzzy MARCOS method outperforming other decision-making approaches.

Additionally, fuzzy DEMATEL analysis identified patient satisfaction and employee job satisfaction as key factors in enhancing hospital performance. Historically, these areas appear to have been overlooked, and prioritizing them could significantly improve service quality and boost satisfaction for both patients and staff. Conversely, the lower priority assigned to aspects such as reducing excess transportation and minimizing over-processing suggests that the hospital may not have fully recognized their impact.

The fuzzy MARCOS method also revealed that the Infectious Diseases department performed better than other departments, potentially due to factors such as superior staff training, advanced equipment, or stronger management. By comparing the Infectious department's performance with that of other departments, key performance-driving factors can be identified to inform improvement strategies for the remaining units.

Despite the benefits of this study and its model, certain limitations must be considered. One significant challenge is the selection of qualified experts, as this greatly influences the model's outcomes. To ensure expert selection aligns with the study's goals, clear criteria—such as education and professional experience—should be established.

For future research, this study's framework can serve as a foundation for further investigations in the field. Researchers may refine and expand these models by integrating new concepts or combining existing methodologies with recent theoretical advancements. Additionally, exploring alternative decision-making techniques for determining criteria weights could improve model accuracy and adaptability.

Previous studies have often relied on deterministic methods with relatively small expert samples (Chowdhury & Paul, 2020; Mostafa, 2021). Given the fuzzy nature of the problem, future research should consider larger samples, incorporating broader expert panels and a wider range of hospitals to enhance model generalizability and validity. Furthermore, employing diverse fuzzy membership functions, including fuzzy Z and D numbers, could improve the representation of complex issues. The use of various defuzzification techniques may further enhance result accuracy and reliability. These approaches could contribute to the development of more sophisticated models for hospital management and decision-making systems.

Data Availability Statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Not applicable

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Conflict of interest

The authors declare no conflict of interest.

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