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Enhancing Emergency Department Efficiency Through Simulation and Fuzzy Multi-Criteria Decision-Making Integration

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Abstract: An innovative framework is introduced for the enhancement of efficiency within emergency departments (EDs), utilizing an integration of simulation and fuzzy Multi-Criteria Decision-Making (MCDM). A discrete event simulation (DES) model was developed, capturing the intricate dynamics characteristic of ED operations with high fidelity. This model's integration with the Analytic Hierarchy Process (AHP) and the Elimination and Choice Expressing Reality (ELECTRE) method, within a fuzzy context, facilitated a critical evaluation and optimization of the decision-making processes inherent in EDs. The incorporation of these methodologies yielded significant improvements in patient flow and service quality, highlighting the substantial potential of marrying simulation with fuzzy MCDM to achieve operational excellence in healthcare settings. The study stands as a contribution to the enhancement of ED operations, offering a versatile methodology with potential for adaptation across diverse healthcare environments. This approach underscores the imperative of employing a nuanced, integrated strategy to navigate the complexities of healthcare service delivery, ensuring an equilibrium between operational efficiency and the quality of patient care.

Keywords: Emergency department (ED); Discrete event simulation; Multi-criteria decision-making (MCDM); Fuzzy environment; Analytic hierarchy process (AHP); Elimination and choice expressing reality method

1 Introduction

Effectively allocating resources in a medical center characterized by high complexity poses a considerable challenge [1, 2]. Even with a well-established database, decision-making concerning resource allocation remains intricate, where minor errors can lead to significant crises or irreversible damage [3]. The paramount imperative within hospital EDs is the sustained delivery of services [4–6]. This includes the timely provision of services to patients and the prioritization of those with more severe conditions. Adding to the complexity, the influx of non-emergency patients contributes to prolonged queues, adversely impacting both patients and departmental staff.

The influx of patients with varying degrees of urgency necessitates innovative approaches to enhance operational efficiency and decision-making processes within EDs. To address these challenges, this study proposes the integration of advanced simulation models and MCDM frameworks. These integrated solutions aim to optimize resource allocation and improve patient flow, thereby enhancing the overall performance of EDs.

Simulation, as a versatile and practical method, offers significant advantages in modeling and evaluating healthcare service systems. It allows for the exploration of various operational configurations and "what-if" scenarios without the risks associated with real-world changes. The increasing adoption of simulation in healthcare decision-making is supported by its documented success in the literature and the continuous advancements in simulation technologies [7–9].

Recent literature highlights the growing application of simulation models in healthcare to analyze and improve patient flow and resource allocation. Simulation provides a risk-free environment to evaluate the impact of operational changes on ED performance [10]. Konrad et al. [11] leveraged discrete-event simulation modeling to assess the impact of a split-flow process in an ED, aimed at reducing wait times and congestion. Implementing the split-flow process at Saint Vincent Hospital demonstrated significant improvements in patient throughput and reduced length-of-stay, offering a practical solution to ED overcrowding. Sobolev et al. [12] conducted a systematic review on the use of computer simulation modeling in surgical patient flow, analyzing literature over five decades and identifying 34 publications. They found a high percentage of studies detailed simulation approaches and data requirements, but fewer addressed policy-makers' needs directly or involved them in the study, highlighting a gap in engaging stakeholders and variability in reporting simulation outcomes for surgical care improvement. Nasser et al. [13] explored the enhancement of private hospital performance in Egypt, focusing on reducing patient waiting times in the ED through the implementation of the Performance Acceleration Tool (PATH). This approach involves structural and organizational changes, including the formation of quality committees, multidisciplinary teams, and technology investments, leading to improved overall hospital efficiency. Bhattacharjee and Ray [14] reviewed and critically appraised patient flow modeling and performance analysis in hospital healthcare delivery processes, classifying existing approaches and highlighting recent advancements. They proposed a generic framework aimed at guiding healthcare managers in decisions related to resource allocation, capacity planning, and process improvement, underscoring the importance of patient flow modeling in enhancing hospital efficiency and healthcare delivery. Kovalchuk et al. [15] introduced a hybrid simulation of patient flow across healthcare units, using a combination of data-driven methods for model automation. They developed a framework and methodology that blend data, text, and process mining with machine learning to analyze electronic health records, specifically focusing on acute coronary syndrome (ACS) patients. This approach enabled the realistic simulation of patient flows, improving the accuracy of predicting patient length of stay based on clinical pathways identified in the records, and aimed at enhancing healthcare decision-making and management optimization. A smart healthcare reward model was proposed by Oueida et al. [16] for improving resource allocation in smart cities. This model, leveraging mobile and fog computing technologies, was designed to tackle the challenges of mobility, scalability, efficiency, and reliability in smart healthcare systems. Through the development and application of a Maximum Reward Algorithm (MRA), the model was demonstrated to significantly enhance the delivery and utilization of healthcare resources, achieving a performance improvement ranging from 50.1% to 77.2% in various simulations. Heshmati [17] reviews the integration of healthcare and crisis supply chains in the context of natural disasters, highlighting the crucial role this integration plays in reducing fatalities and saving lives. The paper analyzes existing studies, identifies challenges, and proposes research opportunities for improving supply chain resilience, focusing on transportation disruptions, inventory models, supply chain integration, and the use of information technology during crises. Ordu et al. [18] introduced a decision support tool for healthcare resource allocation using a forecasting-simulation-optimization framework. This tool models the interconnectedness of hospital services, including emergency, outpatient, and inpatient sectors, to forecast demand, simulate patient pathways with uncertainties, and optimize bed capacity and staff needs for strategic planning in a mid-size English hospital. The approach underscores the benefits of hybrid models in enhancing resource allocation decisions. Wang [19] presents a Petri net approach for optimizing patient flow and staffing in EDs. This method focuses on addressing patient congestion by determining optimal staffing levels, considering the high costs associated with emergency medicine staffing. The study develops a hierarchical modeling process using stochastic timed Petri nets to analyze patient flow, resource requirements, and service durations, supported by a software tool for ED performance evaluation and staffing optimization. Tyler et al. [20] addressed the gap in the widespread adoption of simulation tools in healthcare for patient flow modeling. They developed PathSimR, an open-source, user-driven tool, by identifying end-user requirements through surveys and existing literature. PathSimR models outpatient and inpatient pathways with features capturing variability in patient arrivals, length of stay, and dynamic delays in discharge and transfer, offering a blueprint for deploying simulation models in healthcare settings. Duma and Aringhieri [21] investigated real-time resource allocation in an ED through a case study, employing an online allocation algorithm with lookahead capabilities. This algorithm, supported by a process mining model, aimed to improve ED performance by efficiently managing resources based on the prediction of patient pathways and resource behavior. Their approach, validated via a detailed simulation, highlighted the potential to enhance ED operational metrics such as door-to-doctor time, length of stay, and resource utilization by considering probable subsequent activities in allocation decisions. Eslamipoor and Nobari [22] proposed a multi-objective model for a sustainable and reliable blood supply chain design in healthcare, considering donor centers, distribution, and hospitals. The model focuses on ensuring blood demand fulfillment, minimizing costs, and reducing environmental impacts under uncertainty. An improved ε-constraint method and an imperialist competitive algorithm are applied for solving the model, with effectiveness validated through test cases and comparisons using CPLEX.

Fuzzy MCDM methods have been recognized for their ability to handle uncertainty and ambiguity in decision-making processes [23–28]. These methods facilitate the evaluation of multiple, often conflicting criteria, which is essential in the complex ED setting where decisions must balance various factors such as treatment urgency, resource availability, and patient outcomes. Zhang et al. [29] developed a model and a fuzzy multi-criteria group decision support system (FMCGDSS) for emergency management evaluation. This system addresses both subjective and objective criteria across multiple levels through group evaluation, specifically aimed at enhancing the evaluation of emergency operating centers/systems by incorporating extended fuzzy multi-criteria group evaluation methods to assess and improve emergency risk management. Amaral and Costa [30] applied the Preference Ranking

Organization METHod for Enrichment Evaluations (PROMETHEE) II method to enhance decision-making and resource management in an ED, particularly addressing the challenge of patient throughput in a Brazilian public hospital. This technique, chosen for its suitability in complex healthcare decision contexts, successfully identified and implemented solutions to reduce overcrowding wait times by approximately 70%, demonstrating its effectiveness as a decision support tool in hospital resource management. Ebrahimi and Modam [31] developed a novel algorithm using a hybrid fuzzy Multi-Attribute Decision Making (MADM) approach, combining fuzzy Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) and AHP methods, to select optimal zones for new emergency services in Tehran. This method accounts for various criteria, including population, traffic, and proximity to fault lines, to optimize emergency service response times in both non-disaster and earthquake scenarios, effectively ranking the city's 22 zones for emergency service placement. Gul [32] introduced a two-stage methodology incorporating a fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) and an ergonomic checklist for evaluating the design of EDs. This approach, applied in a case study at a training and research hospital in Istanbul, assesses the ED's ergonomic design, focusing on accessibility, space, equipment, and accommodations for patients and staff. The study emphasizes the importance of ergonomic considerations in improving ED productivity and service quality, offering targeted recommendations to enhance patient and personnel experiences. Ortiz-Barrios and Alfaro-Saiz [33] developed a hybrid fuzzy MCDM model to assess the performance of public EDs through integrating fuzzy AHP (FAHP), fuzzy DEMATEL (FDEMATEL), and the TOPSIS. This comprehensive approach, applied to a case study involving three EDs, highlighted infrastructure as a critical factor and identified specific areas for performance improvement, showcasing the model's utility in managing healthcare quality and efficiency. Clemente-Suárez et al. [34] critically reviewed the application of fuzzy multi-criteria decision analysis in managing emergency systems during the COVID-19 pandemic. This method, valuable for healthcare workers and first responders, addresses the pandemic's challenges by handling uncertainty and risk. The review, synthesizing various sources, underscores the methodology's significance in crisis response, highlighting its potential for future emergencies. Etu et al. [35] developed a consensus-based modified fuzzy Delphi approach to identify critical indicators for ED performance enhancement during medical surges. This methodology, through a literature review, expert interviews, and a systematic ranking process, pinpointed twenty key indicators across five performance factors, emphasizing the significance of ED beds, nurse staffing ratios, and patient length of stay as pivotal to ED efficiency in surge situations [36–40].

Despite the recognized potential of simulation and fuzzy MCDM, limited research has explored their integrated application in healthcare settings. This study responds to this gap by developing an integrated simulation and fuzzy MCDM framework aimed at optimizing ED operations. The approach proposed in this study leverages the strengths of DES to model the dynamic nature of EDs and applies FAHP and ELECTRE methods to evaluate and optimize decision-making processes under uncertainty. The objective is to demonstrate how such an integrated approach can lead to significant improvements in patient flow and service quality, contributing to the operational excellence of healthcare facilities. This integration is poised to offer significant improvements in ED efficiency, patient flow, and overall service quality.

2 Proposed Methodology

This section elaborates on the research methodology adopted to identify the most effective scenario for improving the performance of EDs. This methodology encompasses the integration of computer simulation, the AHP within a fuzzy environment, and the ELECTRE method. While the fusion of MCDM methods with computer simulation is relatively novel in this context, it offers significant advantages. Particularly, it enables the application of "what if" analysis or rapid scenario assessment within the MCDM framework, thereby aiming to elevate the efficiency and service quality of EDs. A detailed, systematic procedure has been devised to pinpoint the optimal scenario, as depicted in Figure 1 and further described below.

In the initial phase, essential data from the ED, including patient arrival rates and service times, are systematically gathered. Subsequently, these data undergo statistical analysis to determine their probability distribution, making them suitable for integration into the simulation. Utilizing Arena software for simulation, the model is meticulously scrutinized. To validate the output data derived from simulation, a thorough comparison is conducted with empirical, real-world data. Moving forward, the subsequent phase involves presenting existing criteria to the decision-making group, based on the available data and a comprehensive review of previous research. The selection of the most relevant criteria follows, with their interrelationships delineated. During this stage, the weights assigned to each criterion are computed within a fuzzy environment, employing the AHP method. In the final phase, the optimal scenario is identified through the application of the ELECTRE method. This results in a thorough and judicious selection process, aligning simulation outputs, decision criteria, and fuzzy weighting to determine the scenario that optimally enhances the ED's performance.

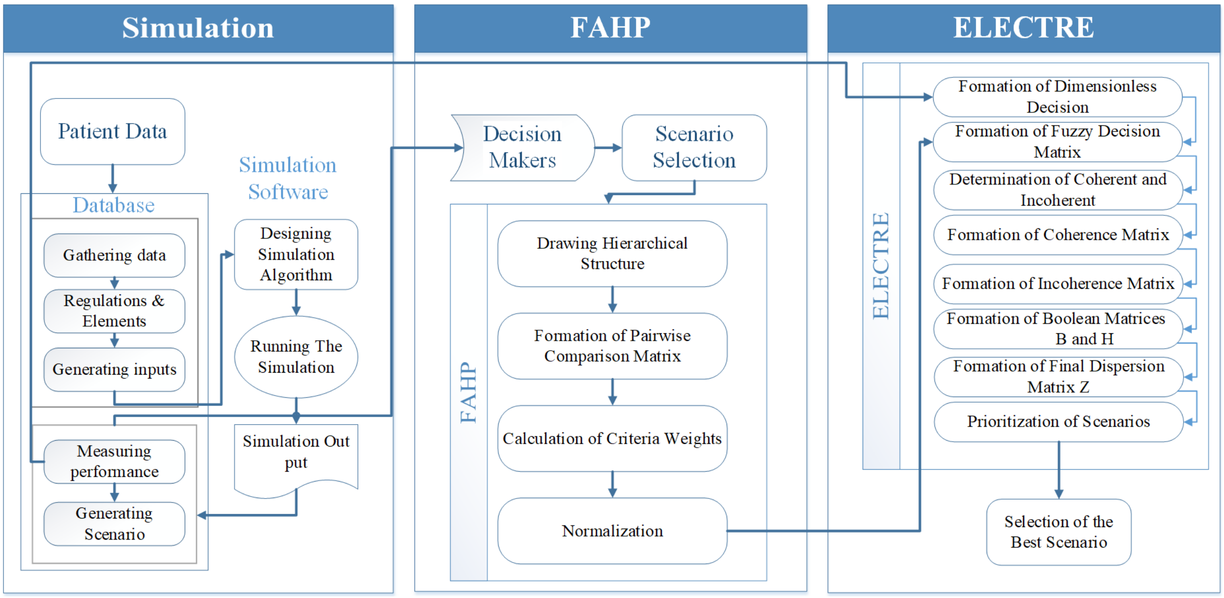

Figure 1. Proposed research method

2.1 Simulation

Simulation is a systematic process that entails creating a model replicating a real system, followed by conducting experiments within this model to comprehend the system's behavior or evaluate different strategies for its operational functionalities. Particularly in the domain of complex multi-criteria systems like EDs, computer simulation emerges as a potent and versatile tool. The growing popularity of simulation can also be attributed to the improved performance-to-price ratio of computer hardware, making simulation more cost-effective than in previous periods. The utility of computer simulation lies in its capacity to assess performance variables across various dimensions, specifically chosen for evaluating service delivery within the ED. The rapid pace of simulation not only facilitates ease of measurement, but also empowers users to adeptly evaluate different scenarios using the "what if" method.

2.2 AHP Method in a Fuzzy Environment

Prior to delving into the elucidation of the AHP method in the fuzzy environment (FAHP), it is pertinent to provide a concise overview of the fuzzy environment. If X denotes a set of objects, then a fuzzy set $\bar{A}$ in X is defined as a set of ordered pairs in the following manner:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in X\}$$

The membership function, symbolized as $\mu_{\tilde{A}}(x)$, characterizes the membership degree of an element x within the fuzzy set $\tilde{A}$. This function, operative over the set X, allocates a real-valued parameter within the interval $[0, 1]$ to each individual element, thereby capturing the degree of inclusion within the fuzzy set [41]. A fuzzy number $\tilde{M}$ is designated as LR type if and only if:

$$\mu_{\tilde{M}}(x) = \begin{cases} L\left(\frac{m-x}{m-1}\right) & l \leq x \leq m \\ R\left(\frac{x-m}{u-m}\right) & m < x \leq u \\ 0 & \text{O.W.} \end{cases}$$

As for $\tilde{M} = (l, m, u)\_LR$, it signifies that L and R represent two arbitrary functions [42]. For a given fuzzy number $\tilde{M}$, the α-cut set of the fuzzy number $\tilde{M}$ for $\alpha \in [0, 1]$ is defined as follows [43]:

$$[\tilde{M}]_{\propto} = \{x \in R \mid \mu_{\tilde{M}}(x) \geq \propto\}$$

In the realm of AHP, while domain experts draw upon their competencies and cognitive prowess to execute comparisons, it is imperative to acknowledge that the conventional AHP methodology incompletely encapsulates the nuances of human thought processes. The incorporation of fuzzy numbers, owing to their enhanced alignment with linguistic expressions and occasional ambiguity in human sentiments, emerges as a judicious approach for decision-making in real-world scenarios [44–46].

To operationalize this, the use of linguistic (qualitative) variables in surveys becomes imperative, aiming to enhance participant engagement and achieve more nuanced outcomes. The conversion of fuzzy data into linguistic terms is facilitated through the utilization of the tabular representation (Table 1) outlined in Figure 1, as explained subsequently.

Table 1. Fuzzy spectrum equivalent to the nine-point scale in the AHP technique

Superiority State i over j	Fuzzy Equivalent	Weakness State i over j	Fuzzy Equivalent
Equally superior (E)	(1,1,1)	Equally weak (E)	(1,1,1)
Intermediate (E-SS)	(1,2,3)	Intermediate (E-SS)	(0.33,0.5,1)
Slightly superior (SS)	(2,3,4)	Slightly weak (SS)	(0.25,0.33,0.5)
Intermediate (SS-FS)	(3,4,5)	Intermediate (SS-FS)	(0.2,0.25,0.33)
Fairly superior (FS)	(4,5,6)	Fairly weak (FS)	(0.166,0.2,0.25)
Intermediate (FS-VS)	(5,6,7)	Intermediate (FS-VS)	(0.142,0.166,0.2)
Very superior (VS)	(6,7,8)	Very weak (VS)	(0.125,0.142,0.166)
Intermediate (VS-AS)	(7,8,9)	Intermediate (VS-AS)	(0.111,0.125,0.142)
Absolutely superior (AS)	(9,9,9)	Absolutely weak (AS)	(0.111,0.111,0.111)

The AHP method is used to determine the weights of preference criteria due to its compatibility in a fuzzy environment. This method ensures a unique final solution in the pairwise comparison matrix.

2.3 ELECTRE Method

In this method, when the decision-maker faces more than five criteria in examining their options, it yields satisfactory performance, and even with 12 to 13 criteria, it maintains its effectiveness. In pairwise comparisons, the degree of agreement comes from the weights, denoted as Wj, and the preference values as a matrix V_{ij}. All these steps are based on a set of concordant and a set of discordant bases, which is why this method is known as a universal analysis. Assumptions required for using this method are:

- The criteria must be quantitative or convertible to quantitative.
- The criteria must be entirely heterogeneous.

The primary objective of the ELECTRE method is to discern and segregate options that are favored in the evaluation, particularly with respect to the majority of criteria.

3 Research Scope

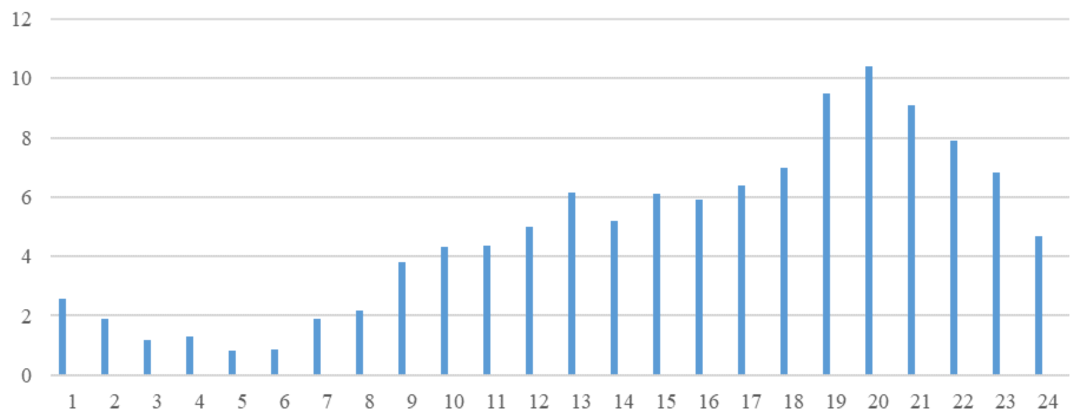

Figure 2. The average count of patients attending the ED within a 24-hour period

The research centers on the geographic scope of the emergency unit at Imam Sajjad Hospital (ISH) in Ramsar. This medical facility holds a pivotal position as the primary and essential treatment center in the city, primarily due to its central location within the county. With the observed population growth in the region and a consistent influx of settlers into the city, particularly during specific periods, the strategic significance of this medical unit is further emphasized. The temporal scope of this research spans forty-two days, specifically from September 23rd to November 23rd, 2023. The emergency unit of ISH serves as a crucial entry point to the main sections of the hospital. Therefore, the majority of patients initially seek assistance within this department. Following initial assessments, individuals in need of extended care are directed to other specialized sections within the hospital or referred to alternative medical centers as necessary.

The operational timeframe within this medical unit is divided into three distinct shifts: the morning shift (first) from 07:00 to 15:00, the afternoon shift (second) from 15:00 to 23:00, and the night shift (third) from 23:00 to 07:00. The suitability of this shift schedule is supported by the data collected in this section, as illustrated in Figure 2.

The inquiry focuses on the afternoon shift, as highlighted in Figure 2, which shows the highest influx of visitors. Consequently, anticipating an extended waiting queue during this shift is reasonable. Given this scenario, the prudent allocation of resources becomes imperative to efficiently manage demand during the afternoon shift.

The allocated human resources for the afternoon shift are outlined as follows:

Nurses (five personnel): responsible for providing medical services and care within the unit.

Physicians (two personnel): engaged in conducting initial examinations, diagnosing diseases, administering tests, scrutinizing test results, and prescribing medications.

Receptionists (two personnel): responsible for registering visitor information, maintaining data archives, managing financial transactions, and overseeing patient discharges.

3.1 Simulation Model

Before formulating an algorithm within the simulation software, it is crucial to gain a comprehensive understanding of the sections and pathways traversed by visitors. The overall perspective of these elements is encapsulated in Figure 3.

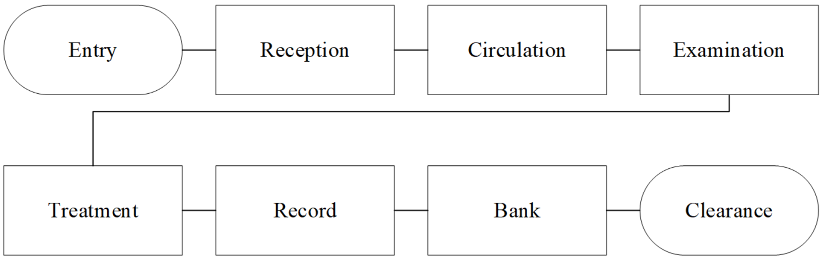

Figure 3. Overview of a patient's path

After assimilating this general view, the subsequent phase involves meticulous data collection and recording intricate details pertaining to various sections and their interrelationships. Within the simulation software, two fundamental elements facilitate the execution of simulations: time and entities.

In the context of this research, time encompasses the duration of diagnostic and therapeutic activities, thereby influencing the performance of the ED staff. This temporal element is further broken down into three criteria, contributing to the research metrics. Entities, on the other hand, represent the patients. The synergy between time and entities gives rise to critical metrics, namely waiting time and service time, constituting foundational aspects of the problem under investigation. Following the delineation of the timing of activities and services within the ED and discerning the volume of visitors during the afternoon shift, the research proceeds to calculate data and establish the probability distribution for entry, patient movement paths, and service time. Figure 4 provides a graphical representation of the average influx of patients on different days of the week.

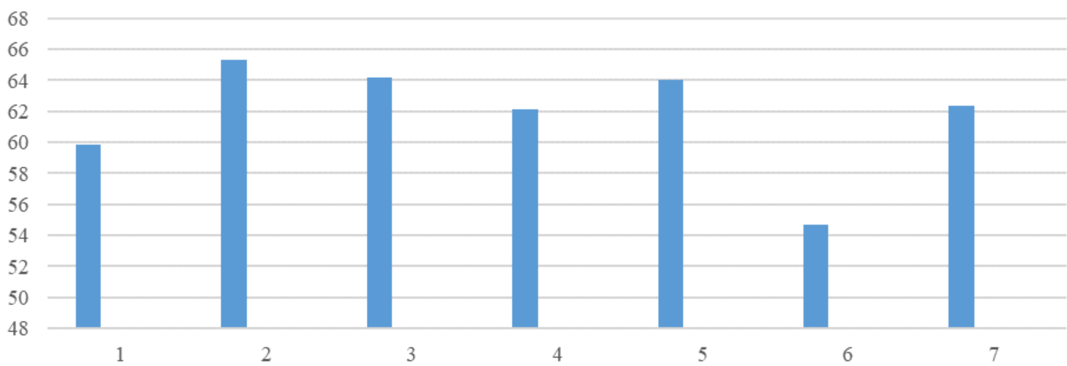

Figure 4. Average patient admission during the evening shift throughout the week

The dataset undergoes normality testing using the Kolmogorov-Smirnov method within the SPSS software. The underlying assumptions for this statistical test are defined as follows:

Null hypothesis (H0): The distribution of data for each variable adheres to a normal distribution.

Alternative hypothesis (H1): The distribution of data for each variable deviates from normality.

This testing framework enables the evaluation of whether the data follows a normal distribution, a critical consideration in various statistical analyses and hypothesis testing procedures.

After entering the data related to the second shift into the SPSS software and performing the Kolmogorov-Smirnov test, the obtained result is displayed in Figure 5.

Tests of Normality

	Kolmogorov-Smirnov^{a}			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
VAR00001	.087	42	.200*	.975	42	.466

Figure 5. Result of the Kolmogorov-Smirnov test in SPSS software

Given that the significance level, denoted by *sig*. in Figure 5, is equal to 0.2, and this value is greater than the conventional threshold of 0.05, the null hypothesis (H0) is not rejected. Consequently, it is inferred that the collected data conform to a normal distribution.

3.2 Generating Scenarios

After compiling the requisite data and inputting it into the simulation software, Arena, the desired model is finalized and poised for execution. The simulation yields the results presented in Table 2, encompassing outcomes derived from seven distinct scenarios. These scenarios collectively represent the spectrum of executions conducted by the decision-making group. The process of ranking and selecting the optimal scenario is facilitated through decision-making methods. It is noteworthy that Scenario Seven aligns with the existing configuration currently operational in the ED.

The description of the selected scenarios is as follows:

Scenario 1: Adding one nurse and one admission officer.

Scenario 2: Adding one physician.

Scenario 3: Adding one physician and reducing one nurse.

Scenario 4: Adding one physician and one admission officer.

Scenario 5: Adding one nurse.

Scenario 6: Adding one physician, one nurse, and one admission officer.

Scenario 7: Maintaining the current situation.

Table 2. Performance of scenarios based on the current situation

Row		Presence Time	Utilization of Receptions	Utilization of Nurses	Utilization of Doctors	Waiting Time in the MBA	Waiting Time in the BA
Scenario 1	Performance	1.1729	0.5751	0.6991	0.9257	0.207	5.646
	Improvement	197.8	-32.52	-3.78	3.42	455	-11
Scenario 2	Performance	1.9488	0.834	0.8798	0.6435	0.2	2.15
	Improvement	79.23	8.62	17.54	-38.93	475	132.03
Scenario 3	Performance	2.7088	0.6927	0.922	0.5642	0.507	8.01
	Improvement	28.95	-10.02	21.31	-58.45	126.82	-37.72
Scenario 4	Performance	2.2258	0.6063	0.9067	0.6921	0.66	4.29
	Improvement	56.93	-25.7	19.98	-29.17	74.24	16.29
Scenario 5	Performance	2.899	0.9526	0.6013	0.9302	0.814	6.922
	Improvement	20.49	20	-20.66	3.89	41.28	-27.93
Scenario 6	Performance	1.0626	0.6466	0.7272	0.7551	0.101	0.309
	Improvement	228.71	-17.86	0.23	-18.39	1038.61	1514.5
Scenario 7	Performance	3.4929	0.7621	0.7255	0.894	1.15	4.9887

3.3 Execution of AHP

In this section, to better understand the problem, the hierarchical structure of criteria and various scenarios is illustrated. Figure 6 presents the main criteria along with their sub-criteria.

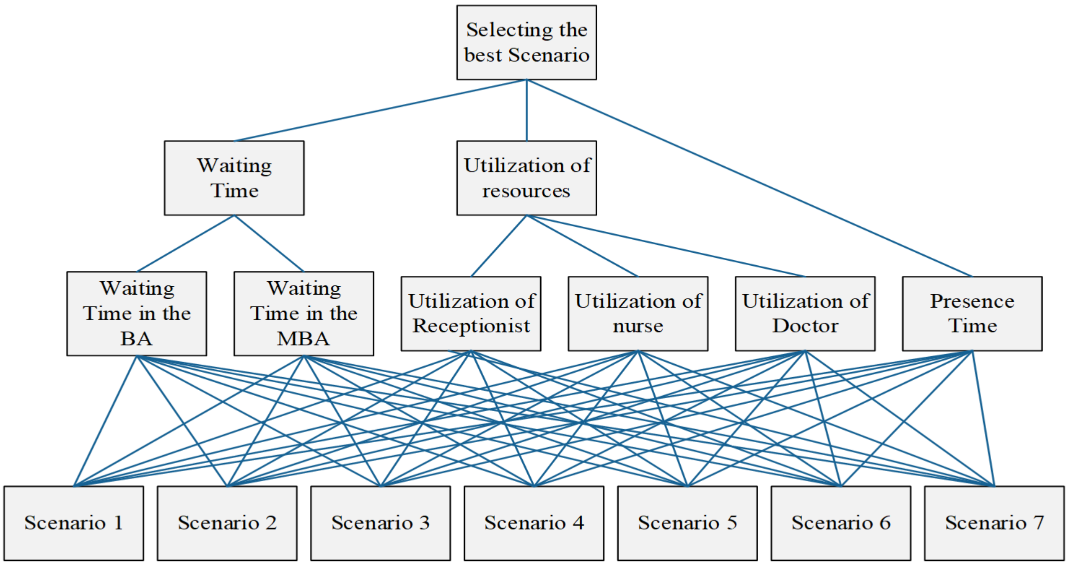

Figure 6. Hierarchical structure of criteria and scenarios

After determining the criteria, the decision team was asked to express their opinions about the importance of the three selected criteria. For this purpose, the AHP method was utilized. Table 3 displays the result of this survey. It should be noted that in this survey, the decision team used qualitative variables for feedback.

Table 3. Pairwise comparison matrix of criteria

Criteria	**Waiting Time in the MBA**	**Waiting Time in the BA**	**Utilization of Doctors**	**Utilization of Nurses**	**Utilization of Receptionists**	**Presence Time**
Waiting time in the MBA	E	E_SS	FS	VS	SS	SW
Waiting time in the BA	E_SW	E	FS_SS	SS	SS	SW_E
Utilization of doctors	FW	SS_FS	E	SS_FS	VS_AS	FS
Utilization of nurses	VW	SS	FW_SW	E	FS_VS	FS_VS
Utilization of receptionists	SW	VW_FW	AW_VW	VW_FW	E	VS
Presence time	SS	FS_VS	FW	VW_FW	VW	E

The above data is transformed into fuzzy data using Table 1. The result is presented in Table 4.

Following the encoding of fuzzy data in the pairwise comparison matrix and applying the AHP method, the Si values are computed for each criterion (Tables 5 and 6). The outcomes of these computations are systematically detailed and presented in the ensuing tables.

Upon determining the S_i values for each criterion, the subsequent step involves computing the magnitude degree for each S_i value (Table 7).

The final step in the FAHP method involves determining the final weight and normalized weight of the criteria. The conclusive outcome of this process is presented in Table 8.

Consequently, the analysis reveals that the criterion "utilization of doctors" holds the highest degree of importance relative to the other criteria. Furthermore, Table 8 illustrates that the criteria "waiting time in BA," "presence time," and "utilization of nurses" are of equivalent significance in the overall hierarchy.

Table 4. Fuzzy hierarchical comparison matrix of criteria

Criteria	**Waiting Time in the MBA**	**Waiting Time in the BA**	**Utilization of Doctors**
Waiting time in the MBA	(1,1,1)	(1,2,3)	(1,2,3)
Waiting time in the BA	(0.33,0.5,1)	(1,1,1)	(0.25,0.33,0.5)
Utilization of doctors	(1,2,3)	(2,3,4)	(1,1,1)
Utilization of nurses	(1,2,3)	(0.33,0.5,1)	(0.33,0.5,1)
Utilization of receptionists	(0.25,0.33,0.5)	(2,3,4)	(0.2,0.25,0.33)
Presence time	(0.25,0.33,0.5)	(0.33,0.5,1)	(1,2,3)
Criteria	**Utilization of Nurses**	**Utilization of Receptionists**	**Presence Time**
Waiting time in the MBA	(0.33,0.5,1)	(2,3,4)	(2,3,4)
Waiting time in the BA	(1,2,3)	(0.33,0.5,1)	(1,2,3)
Utilization of doctors	(2,3,4)	(3,4,5)	(0.33,0.5,1)
Utilization of nurses	(1,1,1)	(1,2,3)	(0.25,0.33,0.5)
Utilization of receptionists	(0.33,0.5,1)	(1,1,1)	(1,2,3)
Presence time	(1,2,3)	(0.33,0.5,1)	(1,1,1)

Table 5. Row sum of the data in the pairwise comparison matrix

Row	$\sum_{i=1}^{6} L_i$	$\sum_{i=1}^{6} M_i$	$\sum_{i=1}^{6} U_i$
Waiting time in the MBA	7.33	11.5	16
Waiting time in the BA	3.91	6.33	9.5
Utilization of doctors	9.33	13.5	18
Utilization of nurses	3.91	6.33	9.5
Utilization of receptionists	4.78	5.58	11.83
Presence time	3.91	6.33	9.5
Sum	33.17	49.57	74.33

Table 6. Calculating S_i for each criterion

Row	**S**
Waiting time in the MBA	(0.0986,0.232,0.4824)
Waiting time in the BA	(0.0526,0.1277,0.2864)
Utilization of doctors	(0.1255,0.2723,0.5427)
Utilization of nurses	(0.0526,0.1277,0.2864)
Utilization of receptionists	(0.0643,0.1126,0.3566)
Presence time	(0.0526,0.1277,0.2864)

Table 7. Magnitude of Si

Row	S_1	S_2	S_3	S_4	S_5	S_6
V $(S_1 \geq S_i)$	-	1	0.8984	1	1	1
V $(S_2 \geq S_i)$	0.6429	-	0.5266	1	1	1
V $(S_3 \geq S_i)$	1	1	-	1	1	1
V $(S_4 \geq S_i)$	0.6429	1	0.5266	-	1	1
V $(S_5 \geq S_i)$	0.6836	0.9526	0.5913	0.9526	-	0.9526
V $(S_6 \geq S_i)$	0.6429	1	0.5266	1	1	-

3.4 Execution of the ELECTRE Algorithm

After calculating the weights for each criterion, the next step is ranking the scenarios using the ELECTRE method. Therefore, the data from Tables 2 and 8 is needed. The steps are given below.

The normalization process involves squaring the data in Table 2, summing the squared data for each criterion,

Table 8. Weight of criteria

Row	Unnormalized Weight	Normalized Weigh	Order
Waiting time in the MBA	0.8984	0.220764	2
Waiting time in the BA	0.5266	0.129402	4
Utilization of doctors	1	0.24573	1
Utilization of nurses	0.5266	0.129402	4
Utilization of receptionists	0.5913	0.1453	3
Presence time	0.5266	0.129402	4

and subsequently taking the square root of the result. The resultant values are then used to divide the data for each scenario. The normalized outcomes are illustrated in Table 9, while Table 10, presented below, encapsulates the fully normalized dataset.

Table 9. Prerequisites for normalization

Row	Waiting Time in the MBA	Waiting Time in the BA	Utilization of Doctors	Utilization of Nurses	Utilization of Receptionists	Presence Time
Scenario 1	0.042849	31.87732	0.85692	0.488741	0.33074	1.375694
Scenario 2	0.04	4.6225	0.414092	0.774048	0.695556	3.797821
Scenario 3	0.257049	64.1601	0.318322	0.850084	0.479833	7.337597
Scenario 4	0.4356	18.4041	0.479002	0.822105	0.3676	4.954186
Scenario 5	0.662596	47.91408	0.865272	0.361562	0.907447	8.404201
Scenario 6	0.010201	0.095481	0.570176	0.52882	0.418092	1.129119
Scenario 7	1.3225	24.88713	0.799236	0.52635	0.580796	12.20035
Sum	**2.770795**	**191.9607**	**4.303021**	**4.35171**	**3.780064**	**39.19897**
Square root	**1.664571**	**13.85499**	**2.074372**	**2.086075**	**1.944239**	**6.260908**

Table 10. Normalized data

Row	Waiting time in the MBA	Waiting Time in the BA	Utilization of Doctors	Utilization of Nurses	Utilization of Receptionists	Presence Time
Scenario 1	0.124356	0.407507	0.446255	0.335127	0.295797	0.187337
Scenario 2	0.120151	0.155179	0.310214	0.421749	0.42896	0.311265
Scenario 3	0.304583	0.578131	0.271986	0.441978	0.356283	0.432653
Scenario 4	0.396499	0.309636	0.333643	0.434644	0.311844	0.355508
Scenario 5	0.489015	0.499603	0.448425	0.288245	0.48996	0.463032
Scenario 6	0.060676	0.022302	0.364014	0.348597	0.332572	0.16972
Scenario 7	0.690869	0.360065	0.430974	0.347782	0.391979	0.55789

By utilizing the weights derived from Table 8, a concordance matrix is formulated by multiplying each criterion's weight with its corresponding data in Table 10. In this process, positive criteria are visually emphasized in green, while negative criteria are distinctly marked in red. The resultant concordance matrix is presented in Table 11.

Table 11. Weighted data

Row	Waiting Time in the MBA	Waiting Time in the BA	Utilization of Doctors	Utilization of Nurses	Utilization of Receptionists	Presence Time
Scenario 1	0.016092	0.089963	0.064841	0.043366	0.072686	0.024242
Scenario 2	0.015548	0.034258	0.045074	0.054575	0.105408	0.040278
Scenario 3	0.039414	0.127631	0.03952	0.057193	0.08755	0.055986
Scenario 4	0.051308	0.068356	0.048478	0.056244	0.07663	0.046003
Scenario 5	0.063279	0.110295	0.065156	0.037299	0.120398	0.059917
Scenario 6	0.007852	0.004924	0.052891	0.045109	0.081723	0.021962
Scenario 7	0.0894	0.07949	0.062621	0.045004	0.096321	0.072192

In the subsequent step, pairwise comparisons are conducted across various scenarios, giving rise to the generation of two matrices: a harmony matrix and a disharmony matrix. These matrices are obtained by following distinct pathways.

Upon examination of Table 12, it is clear that favorable criteria are bolded for emphasis, whereas unfavorable criteria are presented in regular typeface. This visual distinction expedites the process of crafting both the harmony and disharmony matrices.

Table 12. Detection of coherence and incoherence

Row	Waiting Time in the MBA	Waiting Time in the BA	Utilization of Doctors	Utilization of Nurses	Utilization of Receptionists	Presence Time
1-2	0.000544	0.055705	**0.019767**	0.011209	0.032722	**0.016036**
1-3	**0.023322**	**0.037668**	**0.025321**	0.013827	0.014863	**0.031744**
1-4	**0.035216**	0.021606	**0.016363**	0.012878	0.003943	**0.021762**
1-5	**0.047187**	**0.020332**	0.000315	**0.006067**	0.047712	**0.035675**
1-6	0.00824	0.085039	**0.01195**	0.001743	0.009037	0.00228
1-7	**0.073308**	0.010473	**0.00222**	0.001638	0.023635	**0.04795**
2-1	**0.000544**	**0.055705**	0.019767	**0.011209**	**0.032722**	0.016036
2-3	**0.023866**	**0.093373**	**0.005555**	0.002618	**0.017859**	**0.015708**
2-4	**0.03576**	**0.034099**	0.003404	0.001669	**0.028779**	**0.005725**
2-5	**0.047732**	**0.076037**	0.020082	**0.017276**	0.01499	**0.019639**
2-6	0.007696	0.029334	0.007817	**0.009466**	**0.023685**	0.018316
2-7	**0.073852**	**0.045232**	0.017546	**0.009571**	**0.009087**	**0.031914**
3-1	0.023322	0.037668	0.025321	**0.013827**	**0.014863**	0.031744
3-2	0.023866	0.093373	0.005555	**0.002618**	0.017859	0.015708
3-4	**0.011894**	0.059274	0.008959	**0.000949**	**0.01092**	0.009983
3-5	**0.023866**	0.017336	0.025637	**0.019893**	0.032849	**0.003931**
3-6	0.031562	0.122707	0.013372	**0.012084**	**0.005827**	0.034024
3-7	**0.049986**	0.048141	0.023101	**0.012189**	0.008771	**0.016206**
4-1	0.035216	**0.021606**	0.016363	**0.012878**	**0.003943**	0.021762
4-2	0.03576	0.034099	**0.003404**	**0.001669**	0.028779	0.005725
4-3	0.011894	**0.059274**	**0.008959**	0.000949	0.01092	**0.009983**
4-5	**0.011972**	**0.041938**	0.016678	**0.018944**	0.043769	**0.013914**
4-6	0.043456	0.063433	0.004413	**0.011135**	0.005093	0.024041
4-7	**0.038092**	**0.011133**	0.014142	**0.01124**	0.019691	**0.026189**
5-1	0.047187	0.020332	**0.000315**	0.006067	**0.047712**	0.035675
5-2	0.047732	0.076037	**0.020082**	0.017276	**0.01499**	0.019639
5-3	0.023866	**0.017336**	**0.025637**	0.019893	**0.032849**	0.003931
5-4	0.011972	0.041938	**0.016678**	0.018944	**0.043769**	0.013914
5-6	0.055428	0.105371	**0.012265**	0.00781	**0.038675**	0.037955
5-7	**0.02612**	0.030805	**0.002536**	0.007704	**0.024077**	**0.012275**
6-1	**0.00824**	**0.085039**	0.01195	**0.001743**	**0.009037**	**0.00228**
6-2	**0.007696**	**0.029334**	**0.007817**	0.009466	0.023685	**0.018316**
6-3	**0.031562**	**0.122707**	**0.013372**	0.012084	0.005827	**0.034024**
6-4	**0.043456**	**0.063433**	0.004413	**0.011135**	**0.005093**	**0.024041**
6-5	**0.055428**	**0.105371**	0.012265	**0.00781**	0.038675	**0.037955**
6-7	**0.081548**	**0.074566**	0.009729	**0.000105**	0.014598	**0.05023**
7-1	0.073308	**0.010473**	0.00222	**0.001638**	**0.023635**	0.04795
7-2	0.073852	0.045232	**0.017546**	0.009571	0.009087	0.031914
7-3	0.049986	**0.048141**	**0.023101**	0.012189	**0.008771**	0.016206
7-4	0.038092	0.011133	**0.014142**	0.01124	**0.019691**	0.026189
7-5	0.02612	**0.030805**	0.002536	**0.007704**	0.024077	0.012275
7-6	0.081548	0.074566	**0.009729**	0.000105	**0.014598**	0.05023
Weight	0.2208	0.1294	0.2457	0.1294	0.1453	0.1294

The generation of the harmony matrix involves the summation of the weighted values corresponding to harmonious elements (indicated in green) for each row. The outcome of these computations is encapsulated in the harmony matrix, as depicted in Table 13.

The discordance matrix is crafted by dividing the largest discordant element (identified in red) in each row by the largest element within the same row. The resultant values from these calculations constitute the discordance matrix, as illustrated in Table 14.

Table 13. Coherence matrix

Row	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Scenario 1	-	0.3751	0.7253	0.5959	0.609	0.1294	0.5959
Scenario 2	0.6249	-	0.8706	0.6249	0.609	0.2747	0.7543
Scenario 3	0.2747	0.1294	-	0.4955	0.4796	0.2747	0.4796
Scenario 4	0.4041	0.3751	0.5045	-	0.609	0.1294	0.609
Scenario 5	0.391	0.391	0.5204	0.391	-	0.391	0.7412
Scenario 6	0.7543	0.7253	0.7253	0.8706	0.609	-	0.609
Scenario 7	0.4041	0.2457	0.5204	0.391	0.2588	0.394	-

Table 14. Incoherence matrix

Row	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Scenario 1	-	1	0.3946	0.6135	1	1	0.3224
Scenario 2	0.3548	-	0.0280	0.0952	0.2641	1	0.2376
Scenario 3	1	1	-	1	1	1	0.9631
Scenario 4	1	1	0.2007	-	1	1	0.5169
Scenario 5	0.9890	1	0.7265	0.9582	-	1	1
Scenario 6	0.1405	0.8074	0.0985	0.1755	0.3670	-	0.1790
Scenario 7	1	1	1	1	0.8479	1	-

Following the acquisition of the concordance and discordance matrices, the next step involves transforming the data within these matrices into Boolean values (0 and 1). The Boolean concordance matrix is denoted by the symbol B, and the discordance matrix is represented by H. To elaborate, at this stage, the data is subjected to averaging, where entries equal to or greater than the computed average are set to one, while values below the average are designated as zero (Tables 15 and 16).

Table 15. Boolean matrix B

Row	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Scenario 1	-	0	1	1	1	0	1
Scenario 2	1	-	1	1	1	0	1
Scenario 3	0	0	-	0	0	0	0
Scenario 4	0	0	1	-	1	0	1
Scenario 5	0	0	1	0	-	0	1
Scenario 6	1	1	1	1	1	-	1
Scenario 7	0	0	1	0	0	0	-

Table 16. Boolean matrix H

Row	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Scenario 1	-	0	1	1	0	0	1
Scenario 2	1	-	1	1	1	0	1
Scenario 3	0	0	-	0	0	0	0
Scenario 4	0	0	1	-	1	1	0
Scenario 5	0	0	0	0	-	0	0
Scenario 6	1	0	0	1	1	-	1
Scenario 7	0	0	0	0	0	0	-

In this segment, the matrices B and H are subjected to multiplication, yielding the final coherence matrix denoted as Z (Table 17). This multiplication process combines the Boolean concordance matrix (B) and the discordance matrix (H), culminating in the generation of the coherence matrix that encapsulates the integrated information from both matrices.

The number of wins, losses, and the final outcome are determined using Table 17.

Table 17. Final tearing matrix

Row	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Scenario 1	-	0	1	1	0	0	1
Scenario 2	1	-	1	1	1	0	1
Scenario 3	0	0	-	0	0	0	0
Scenario 4	0	0	1	-	1	0	0
Scenario 5	0	0	0	0	-	0	0
Scenario 6	1	0	0	1	1	-	1
Scenario 7	0	0	0	0	0	0	-

Table 18. Win-loss table of options

Row	Win	Loss	Outcome
Scenario 1	3	1	2
Scenario 2	5	0	5
Scenario 3	0	3	-3
Scenario 4	2	3	-1
Scenario 5	0	3	-3
Scenario 6	4	0	4
Scenario 7	0	3	-3

Table 18 indicates that Scenario 2 has been identified as the optimal scenario. The prioritization order among scenarios is visually represented in Figure 7, highlighting the comparative rankings.

Figure 7. Prioritization of scenarios

Therefore, Scenario 2, involving the "utilization of doctors," emerges as the most favorable option for enhancing performance and augmenting patient satisfaction within the ED at ISH. Drawing insights from the study, the following practical recommendations are proposed for the healthcare unit:

1. Swiftly implement Scenario 2 in the ED at Sajjad Hospital to expedite performance improvement and elevate patient satisfaction.
2. Extend similar studies to other shifts within the healthcare unit to mitigate waiting times, enhance patient presence, and optimize resource utilization comprehensively.
3. In light of escalating medical service costs and the multifaceted factors influencing decision-making in healthcare centers, conduct parallel research in other EDs. This facilitates a pre-implementation evaluation of proposed changes and a thorough assessment of outcomes.
4. Given the increasing prominence of management discussions and industrial engineering concepts, particularly simulation and MCDM in healthcare, consider establishing specialized units with cross-disciplinary specialists to ensure efficient resource utilization.
5. Recognize the significance of system management and control based on inputs and outputs, particularly in service-oriented organizations like healthcare centers. The study underscores the necessity for heightened attention to this aspect and a reevaluation and control of implemented systems.
6. Acknowledge the pivotal role of operational efficiency and patient waiting and presence times in healthcare settings. Organizations should strive for a balanced and optimized approach to these criteria, steering clear of disproportionate emphasis on a singular factor. This strategy ensures the avoidance of erroneous decisions and encourages the adoption of comprehensive strategies to optimize all three criteria.

4 Conclusion

This study successfully demonstrated the effectiveness of integrating simulation and fuzzy MCDM techniques to enhance performance and patient satisfaction within EDs. Scenario 2, which involves the addition of a physician, emerged as the optimal solution for improving ED operations at Sajjad Hospital. This scenario not only expedited patient processing times but also significantly increased patient satisfaction levels. The implementation of this integrated approach provides a comprehensive framework for addressing the complexities inherent in ED operations. By leveraging DES, the intricate dynamics of patient flow and resource allocation were modeled in a risk-free environment. The inclusion of fuzzy MCDM, specifically the AHP and ELECTRE methods, allowed for a nuanced evaluation and prioritization of decision-making criteria under uncertainty. The findings suggest that the proposed framework can serve as a valuable tool for healthcare administrators and decision-makers. It facilitates informed decision-making by providing a detailed analysis of the potential outcomes of various operational strategies. Moreover, this study contributes to the body of knowledge by highlighting the utility of combining simulation with fuzzy MCDM techniques in healthcare settings, which has been relatively unexplored. While this study focused on a specific ED at Sajjad Hospital, future research could explore the applicability of the proposed framework in other healthcare settings or departments. Additionally, further investigation into the integration of other simulation models or decision-making techniques could offer deeper insights into optimizing healthcare operations. The impact of such interventions on other key performance indicators, such as healthcare costs and staff satisfaction, also warrants exploration.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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