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RESEARCH

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Optimizing emergency department efficiency: a comparative analysis of process mining and simulation models to mitigate overcrowding and waiting times

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Abstract

Objective Overcrowding and extended waiting times in emergency departments are a pervasive issue, leading to patient dissatisfaction. This study aims to compare the efficacy of two process mining and simulation models in identifying bottlenecks and optimizing patient flow in the emergency department of Al-Zahra Hospital in Isfahan. The ultimate goal is to reduce patient waiting times and alleviate population density, ultimately enhancing the overall patient experience.

Methods This study employed a descriptive, applied, cross-sectional, and retrospective design. The study population consisted of 39,264 individuals referred to Al-Zahra Hospital, with a sample size of at least 1,275 participants, selected using systematic random sampling at a confidence level of 99%. Data were collected through a questionnaire and the Hospital Information System (HIS). Statistical analysis was conducted using Excel software, with a focus on time-averaged data. Two methods of simulation and process mining were utilized to analyze the data. First, the model was run 1000 times using ARENA software, with simulation techniques. In the second step, the emergency process model was discovered using process mining techniques through Access software, and statistical analysis was performed on the event log. The relationships between the data were identified, and the discovered model was analyzed using the Fuzzy Miner algorithm and Disco tool. Finally, the results of the two models were compared, and proposed scenarios to reduce patient waiting times were examined using simulation techniques.

Results The analysis of the current emergency process at Al-Zahra Hospital revealed that the major bottlenecks in the process are related to waiting times, inefficient implementation of doctor's orders, delays in recording patient test results, and congestion at the discharge station. Notably, the process mining exercise corroborated the findings from the simulation, providing a comprehensive understanding of the inefficiencies in the emergency process. Next, 34 potential solutions were proposed to reduce waiting times and alleviate these bottlenecks. These solutions were simulated using Arena software, allowing for a comprehensive evaluation of their effectiveness. The results were then compared to identify the most promising strategies for improving the emergency process.

Conclusion In conclusion, the results of this research demonstrate the effectiveness of using simulation techniques and process mining in making informed, data-driven decisions that align with available resources and conditions. By leveraging these tools, unnecessary waste and additional expenses can be significantly reduced. The comparative

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analysis of the 34 proposed scenarios revealed that two solutions stood out as the most effective in improving the emergency process. Scenario 19, which involves dedicating two personnel to jointly referring patients to the ward, and scenario 34, which creates a dedicated discharge hall, have the potential to create a more favorable situation.

Keywords Comparison, Simulation, Process mining, Process management, Emergency department management

Introduction and literature review

The emergency department (ED) plays a critical role in the healthcare system, serving as the primary point of entry for patients with acute, life-threatening, and complex medical conditions. It is the most voluminous, versatile, and sensitive area of a hospital and its effective operation is essential for providing timely and high-quality care to patients [1]. A hospital without an active emergency department cannot be considered an ideal treatment center [2].

The ED is also considered one of the most complex operational clinical units in hospitals, requiring a high level of coordination and efficiency to manage a large volume of patients requiring diagnostic and therapeutic measures [3]. The speed and timeliness of service provision in emergency care centers are critical in reducing mortality and disability, as every minute counts in saving lives [4, 5].

Despite its importance, the ED is often plagued by issues such as overcrowding, long waiting times, and delays in treatment [6]. These issues can lead to patient dissatisfaction, decreased quality of care, and increased risk of adverse outcomes [3]. Emergency congestion can be caused by a range of factors, including delayed treatment, prolonged waiting times, patient length of stay, limited staff and resources, and reduced operational capacity [7, 8].

The main challenge faced by emergency departments is the bottleneck caused by a mismatch between the demand for emergency services and the available resources [9]. To address this issue, it's essential to optimize the workflow in order to reduce the length of stay for patients in the emergency department [10]. This can be achieved by implementing strategies that aim to reduce waiting times for patients in hospitals [11].

In recent years, organizations have shifted from data-oriented to process-oriented systems [12] to improve their efficiency and better support their governing processes. Process mining is a new field of research that has emerged as a result of this shift. By extracting knowledge from event logs stored in information systems, process mining seeks to analyze and improve enterprise processes. This field encompasses three categories: process discovery methods, process compliance checking methods, and business process improvement methods [13].

Process mining algorithms are categorized into three types: alpha algorithm, fuzzy mining, and heuristic mining. The alpha algorithm is used to determine the order of existing events by analyzing event reports [14]. This algorithm serves as a foundation for examining challenges related to process discovery and introducing more practical algorithms. The fuzzy exploration algorithm is suitable for exploring less developed processes and simplifying models [13]. The innovative exploration algorithm uses a causal network representation and considers the repetition of events and sequences to create a process model [14].

Process mining is a technique used to simplify complex processes, including structured and unstructured ones. In recent studies, reducing complexity is a major topic of focus. Process mining is applied to discover various processes, including structured lasagna processes and unstructured spaghetti processes [15].

One study, led by Badakhshan (2016), analyzed data using fuzzy algorithm and DISCO process mining tool to discover the process of developing and improving Iran's Emergency Medical Services, known as 115 [16]. Another study, conducted by Manz et al., explored the application of process-oriented healthcare and process management in health systems, highlighting the importance of organizational, performance, and flow control [17].

Delias et al. (2014) and Amissah & Lahiri (2022) analyzed the emergency function and proposed ways to reduce waiting times in the emergency department, presenting solutions to improve patient flow [9, 18].

Roohani et al. [19] conducted a study titled "Application of Process-mining in healthcare", which found that hospitals should simplify their processes to provide high-quality services while reducing costs. Additionally, they highlighted that patients with the same diagnosis may not receive the same treatment, a problem that needs to be addressed [19].

Falahatgar and Sepehri's research aimed to improve patient flow in the operating room using process mining. The study employed innovative techniques, social network analysis, and classification algorithms to develop strategies for increasing patient capacity and tracking patient flow using RFID sensors. The research focused on improving the processes of the women's operating room at Baqiyatullah Al-Azam Hospital [20].

Sepehri et al. conducted a study titled "Knowledge Discovery and Improvement of Hospital Processes Using by Process Mining", which described different frameworks for data analysis in hospitals [21].

Homayounfar conducted a research on "Process mining challenges in hospital information systems", which identified the most significant challenges in process extraction as special measures and process changes, lack of proper data collection and data entry, and incorrect and inadequate data recording [22].

Rojas et al. emphasized the importance of using process mining to improve quality in healthcare systems in their review article titled "Process Mining in Healthcare" [23].

Salimifard et al. used the discrete simulation method with ARENA software to propose a scenario for improving the performance of an emergency department at one of Bushehr hospitals. The scenario, which involved three inpatient beds and one nurse, aimed to reduce waiting times for patient admission and decrease high bed occupancy rates [24].

Davari et al. conducted a research on "Process Management Model in the Emergency Department of a University Hospital" which suggested using simulation methods to reduce patient waiting times by making changes to human resources. The study focused on improving the emergency department's processes to reduce patient waiting times [1].

The emergency room of Al-Zahra Medical Education Hospital, one of the most prominent in the country due to its specialized and super-specialized facilities, is a major referral center for patients from Isfahan province and surrounding regions. As a result, it is essential to address the issue of lengthy waiting times for patients and their companions. This research aims to investigate the effectiveness of applying simulation models and process mining in discovering and extracting the real emergency process, analyzing the process, and identifying bottlenecks in order to reduce patient waiting times, population density, and improve patient satisfaction.

This qualitative research has no hypothesis or assumptions and seeks to answer four key questions: What are the bottlenecks in patient waiting times in the emergency department of this hospital?, What are the actual emergency procedures at Al-Zahra Hospital?, Do the results obtained from the simulation model match those obtained from process mining?, and What are the effective ways to improve processes?

This study is groundbreaking in the Middle East and Iran as it is the first to apply simulation models and process mining techniques to optimize the emergency department process in a hospital setting. The unique combination of these methodologies has not been explored in this region before, making this research a pioneering effort.

The use of simulation models allows for the creation of a virtual representation of the emergency department, enabling researchers to analyze and improve the process in a controlled and flexible environment. Process mining, on the other hand, provides a data-driven approach to identify bottlenecks and inefficiencies in the process. By combining these two methodologies, this study offers a comprehensive and innovative approach to improving patient care and reducing waiting times in emergency departments.

Furthermore, this research is significant because it addresses a pressing issue in healthcare in Iran, where emergency departments are often overwhelmed with patients, leading to long waiting times and decreased patient satisfaction. The findings of this study will provide valuable insights for healthcare policymakers and hospital administrators, enabling them to develop evidence-based strategies to improve the efficiency and effectiveness of emergency departments.

Methods

Study design

This study was conducted as a cross-sectional and retrospective study, using a sample size of 1275 subjects from a population of 39,264 people. The population consisted of individuals who referred to the emergency department of Al-Zahra Hospital between November 2021 and October 2022. The sample was selected using systematic random sampling with a confidence level of 99%. In this study, as the researchers only had access to anonymous data that did not permit the identification of individuals, the Research Ethics Committee of Isfahan University of Medical Sciences approved the utilization of such data without requiring patient consent. (Approval No.: IR.MUI.REC.1394.1.004).

Data collection

The data collection instrument is a comprehensive questionnaire (Appendix 1) comprising 24 questions that gather information on various aspects of patient care. The questionnaire covers a range of details, including patient identification details such as file number, age, and sex, as well as patient arrival information, including whether they came in person or were referred from another center. The questionnaire also collects data on the date and time of visit, triage level, and the patient's initial consultation with the emergency medicine specialist. Additionally, it captures the timing of the nurse's implementation of the first order from the emergency medicine specialist, initial radiology and laboratory test requests, as well as sample collection and test result delivery times. Furthermore, the questionnaire inquires about patient counseling and ECG procedure request and completion times, physician-ordered ECGs, patient transfers to wards, and discharge decisions, including leave against medical advice (LAMA). Finally, it captures the final discharge and bed clearing times.

Data validation

The questionnaire was refined through collaboration with experts, including officials and specialists from Al-Zahra Hospital's Emergency Department. The validity of the data was subsequently confirmed by reviewing patients' medical charts at the hospital's medical records unit. To minimize potential bias, the medical record abstractors were assigned to abstract and collect data from medical records over a period of six months, and were not hospital personnel, thereby ensuring that they were not influenced by the hospital's internal dynamics or protocols.

The questionnaire was further modified and content validated through a multi-stage process involving expert opinions (officials and emergency medicine specialists from Al-Zahra Hospital) and a review of patients' files in the medical records unit. The reliability of the research was calculated using the alpha coefficient Cronbach, which was determined using SPSS software.

All information related to the variables in the questionnaire was documented in the medical charts at the medical records unit of Al-Zahra Hospital, with the exception of laboratory and some radiology results, which were accessible via the hospital's information system (HIS).

Data analysis

Subsequently, statistical analysis was conducted using Excel software. The research employed a time average method, which was also utilized to compare two models. This study was conducted in three stages. The first stage involved a simulation-based approach, focusing on the long patient waiting times in the emergency department (ED) and the importance of reducing these times using a cost-effective and efficient approach.

In our study, we employed the following statistical tests to compare the two models: For continuous outcome variables, we employed ANOVA and/or t-test to compare the means of the two models. For categorical outcome variables, we utilized the Chi-squared test and/or Fisher's exact test to compare the proportions of the two models. For categorical outcome variables with binary outcomes, we utilized logistic regression to estimate the odds ratios and compare the models.

Simulation-based approach

A physical model of the real system was designed using ARENA software, and then the flow of patients in Al-Zahra Hospital was observed through graphics and animations on the screen. The distribution function of the model was $0.001 + \text{EXPO}\ (13.2)$ and Input Analyzer software was used to detect the input distribution function of the model. The distribution function represents the probability density of a random variable, specifically the time it takes for patients to arrive at the emergency department, with an average time of approximately 13.2 min. The function was estimated by combining statistical methods and simulation techniques, including collecting data, analyzing it, simulating the arrival process, and defining the distribution function using simulation software.

A three-point distribution was used for all process functions, and the model was run 1000 times using ARENA software. Finally, data analysis was performed using statistical methods, and process bottlenecks were determined.

Process mining

The second stage of the research involved process mining: a technique that leverages artificial intelligence to automate data analysis and uncover hidden patterns that may be difficult for humans to identify. Machine learning algorithms processed the data, revealing insights and opportunities for improvement. One of the key techniques used in process mining was automatic process discovery, which enables the design of a process and provides a visual representation of each step, allowing for the identification of bottlenecks. This technique examines all possible paths and suggests ways to automate them, ultimately helping to create efficient workflows and deploy automated processes. Using process mining, the data was cleansed by removing duplicate data, noise, and records with missing values. The data was then analyzed using statistical methods, and process bottlenecks were identified. The event report file was imported into Access software, and the relationships between the data were identified. The discovered model was then analyzed using the Fuzzy Miner algorithm and Disco tool. This step involved assigning time tags and naming conventions for each event to ensure that each activity in the event report could be accurately identified.

We clarified the essential information needed for process mining by asking: 'Is all event report data necessary?' Our answer was informed by the research goals and the specific data-mining algorithms employed in our study.

Scenario evaluation

The third stage of our research involved a thorough examination of 34 proposed scenarios to reduce patient waiting times, which were generated using simulation modeling and focused on average time reduction. These scenarios were evaluated based on a combination of quantitative data from the questionnaire and qualitative insights provided by experts.

Results

1-findings from the simulation

The first finding from the simulation phase is that it revealed the waiting bottlenecks for patients in the emergency department of Al-Zahra Hospital. The output of the Input Analyzer Software showed an exponential function with a mean time of 13.2 min, indicating that patients, on average, wait for approximately 13.2 min after visiting the emergency department. The triage process classifies patients into three levels: Level 1, Level 2, and Level 3, based on their condition. Level 1 patients, who are in a more critical condition, are prioritized and receive services faster, while Level 2 and Level 3 patients receive services at a slower rate. The simulation also revealed that the maximum admission capacity is 163 patients, with 12 being Level 1 patients, 56 being Level 2 patients, and 95 being Level 3 patients.

According to the simulation results, the average number of patients in the emergency department is 109. The breakdown of patients by level is as follows: 4 patients are classified as Level 1, 35 patients are classified as Level 2, and 70 patients are classified as Level 3. Notably, 9% of Level 2 patients and 11% of Level 3 patients leave the hospital before completing their treatment with their personal consent. Table 1 presents the current emergency situation at Al-Zahra Hospital in Isfahan, highlighting the number of personnel available. The simulation model was run 1000 times, and as a results the average waiting time for patients to receive emergency services, as well as the number of patients in line at each station, were determined. Furthermore, the simulation identified key bottlenecks that impact the emergency department's operations.

The results of the simulation phase of the research revealed that the waiting bottlenecks for patients in the emergency department of Al-Zahra Hospital are primarily located at the following stations: the first examination station, where nurses implement doctor's orders, the registration of patient tests in the Hospital Information System (HIS) and ECG, and the discharge hall station. These bottlenecks appear to be the main areas where patients are experiencing delays and wait times in the emergency department.

2- findings from the process mining

The purpose of this phase was to investigate and validate the emergency procedures of Al-Zahra Hospital. The research aimed to uncover the actual processes in place, rather than relying on simulated results. However, the treatment processes proved to be complex and difficult to comprehend, making it challenging to

Table 1 Baseline waiting times and queues

Service stations	Level 2		Level 3	
	The average patient waiting time (minutes)	**Queue**	**The average patient waiting time (minutes)**	**Queue**
Triage	0.0982	0	0.0982	0
Admission	138.46	3	274.37	44
First examination by a specialist and writing orders	67.9820	2	341.15	3
Run physician's orders by a nurse	146.49	7	277.27	9
Perform radiology	210.66	3	284.61	3
Perform ECG	337.54	7	319.68	3
Lab exams registry by nurse	48.8092	6	56.3218	4
Transfer of the sample to the laboratory by sample carrier	4.1038	3	3.9020	3
Test results prepared	179.42	3	38.7190	1
Consultation	212.60	3	254.61	2
Leave Against Medical Advice (LAMA)	80.2757	1	67.4585	1
Discharge of patients who have been discharged by physician	102.99	3	74.0511	2
The patient's discharge with the personal consent after completing the treatment process	56.4063	0	14.5931	0
Referral to the ward and the release of the bed	60.0722	3	47.6461	2

Table 2 Process model with different percentages

Raw	Actions (%)	Directions (%)
1	100	100
2	100	50
3	100	0

analyze and improve them. Additionally, the extracted data was found to be incomplete, prone to human errors, and contained low-occurrence events or noise. To overcome these challenges, process mining techniques were employed to identify patterns and trends in the data. By analyzing the frequency and distribution of activities, as well as the routes taken through the process, the research aimed to confirm the results obtained from simulation and provide a more accurate understanding of the emergency procedures at Al-Zahra Hospital.

By adjusting the percentage of activities and routes, we can identify the most frequent and dominant patterns in the process. For example, reducing the percentage of activities to a certain threshold will allow us to focus on the most common activities, while reducing the percentage of routes will reveal the most frequently traveled routes. However, it's essential to note that over-reducing the percentage can lead to an inaccurate analysis of the process.

It's also important to understand that the percentage refers to the minimum and maximum values, rather than a strict cutoff. This means that a 0% reduction, for instance, does not mean omitting all activities or routes, but rather identifying the most important and prominent ones.

The emergency process models of Al-Zahra Hospital were created using different percentages, as outlined in Table 2. The Fuzzy Miner algorithm and Disco tool were utilized to discover these process models. The process model for emergency patients was visualized by depicting all activities and routes (100% of routes and activities), as shown in Fig. 1.

As depicted in Fig. 2, the process model is extremely complex, with 100% of activities and paths, resulting in a "spaghetti-like" diagram that is both busy and intricate. This level of complexity makes it challenging to analyze and examine the treatment process. To address this issue, the percentage of paths has been reduced and the most frequent and important paths have been highlighted. Figure 2 illustrates the various paths that are patient-specific and tailored to the conditions of each individual in the hospital's emergency room. According to Fig. 2, the dominant path in this model is shown below:

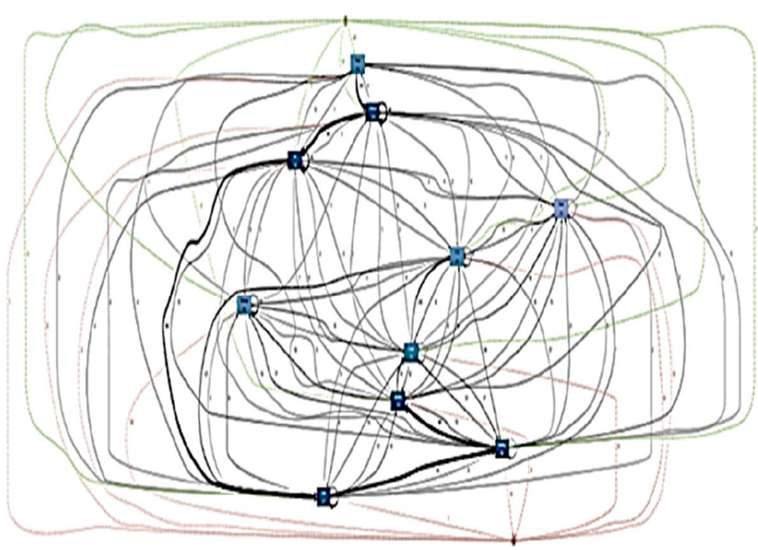

Fig. 1 Process model of emergency patients by drawing all activities and paths

Triage → Admission → Visit → Radiology → Laboratory → Consult → Discharge

Other dominant path is:

Triage → Admission → Visit → Order → Laboratory → Consult → Discharge

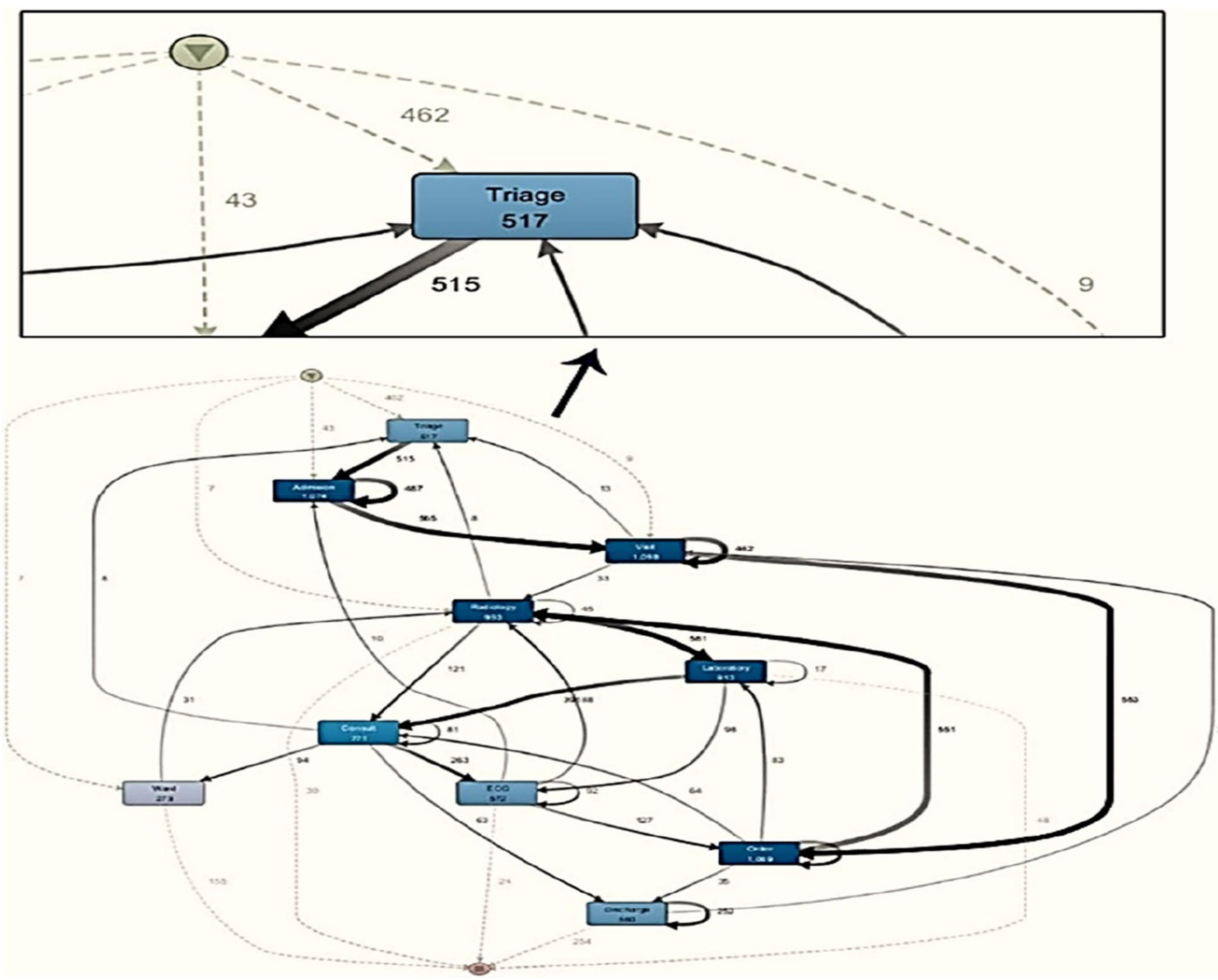

Fig. 2 Emergency process model with 50% of paths and 100% of activities

Table 3 Time of treatment activities in the ED

Action	MIN	Median	Mean	Max(hours)
Admission	Instant	6	31	11
Visit	Instant	19	23.6	2.3
Radiology	Instant	15	29.1	7.2
Laboratory	Instant	59	70.6	3.4
Consult	Instant	20	41.8	10
ECG	Instant	16.5	33.3	12.3
Order	Instant	Instant	46.8 s	1
Discharge	instant	36	73.4	17.5

The loops in certain activities represent the duration of the activity, signifying that the start and end times of each activity are connected, indicating a specific time spent within that activity. Additionally, the numerical value (515) displayed on the transition from triage to admission indicates the number of patients who have been transferred from the triage activity to the admission stage.

To facilitate the analysis of performance, Table 3 provides the average, median, and maximum times for each activity.

The analysis results as shown in Table 3, reveal that the discharge stations, laboratory, and implementation of doctor's orders by the nurse are the key bottlenecks in the emergency department of Al-Zahra Hospital.

Table 4 The simulated scenarios

Row	Scenario	Row	Scenario
1	Adding one nurse to level 2	18	Assign one person for patient hand over to ward instead of a nurse for each level
2	Adding one resident to level 2	19	Assign two persons for patient hand over to ward Jointly instead of a nurse for each level
3	Adding two nurses to level 2	20	Assign one person for ECG in level 2 and two persons for ECG level 3
4	Adding two residents to level 2	21	Adding one person to ECG jointly for both levels
5	Adding one nurse and one resident to level 2	22	Assign a person as a test registry staff instead of nurse for two levels
6	Adding two nurses and one resident to level 2	23	Assign a person as a test registry staff instead of nurse for each level
7	Adding one nurse and two residents to level 2	24	Adding one nurse and one resident to each level
8	Adding two nurses and two residents to level 2	25	Adding two nurses and one resident to each level
9	Adding one nurse to level 3	26	Adding two nurses and two residents to each level
10	Adding one resident to level 3	27	Adding one nurse and two residents to each level
11	Adding two nurses to level 3	28	Assign one person for ECG in level 3 and two persons for ECG level 2
12	Adding two residents to level 3	29	Adding one person to radiology unit
13	Adding one nurse and one resident to level 3	30	Adding 2 beds to level 3
14	Adding two nurses and one resident to level 3	33	Adding 4 beds to level 3
15	Adding one nurse and two residents to level 3	32	Reduction of two beds from level 2 (from 44 to 42)
16	Adding two nurses and two residents to level 3	33	Reduction of four beds from level 2 (from 44 to 40)
17	Adding someone as discharge personnel for each level	34	Creating a discharge unit

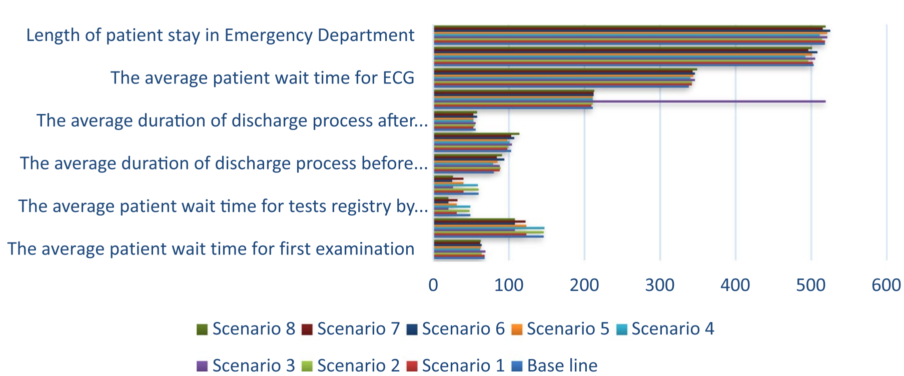

Fig. 3 The results of level 2 scenarios

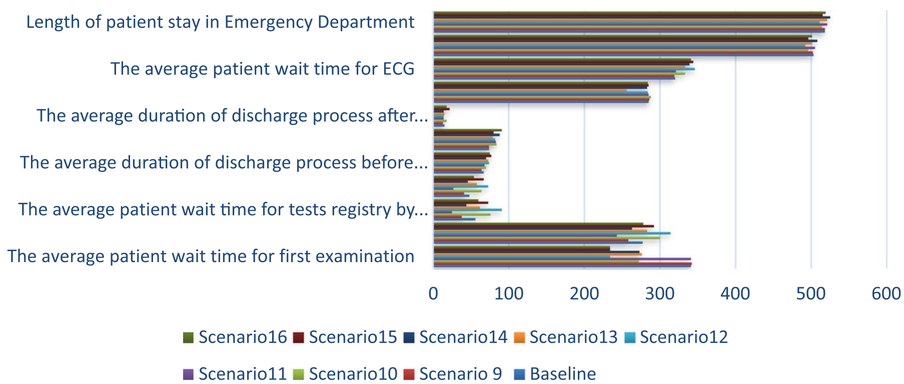

Fig. 4 The results of level 3 scenarios

Additionally, the simulation model identifies the implementation of doctor's orders by the nurse and registration of patient tests in HIS and ECG as the primary bottlenecks for patients waiting at the first examination stations.

3- proposing solutions and simulating scenarios to reduce patient waiting time

During the analysis phase, we aimed to answer the question: "What are the effective ways to improve processes?". In this step, we identified 34 potential solutions to address the bottlenecks in patient waiting times. These solutions were based on expert opinions and can be categorized into three main groups: 29 scenarios for changes in human resources, 4 scenarios for changes in the number of beds, and 1 scenario for creating a discharge unit.

The Table 4 lists the proposed simulated scenarios. Next, we used ARENA software to simulate each scenario and measure the impact of each scenario on patient waiting times at each service station. This allowed us to evaluate the effectiveness of each proposed solution and identify the most promising strategies for improving processes.

The results of scenario implementation

The outcomes of implementing eight scenarios related to Level 2 are depicted in Fig. 3.

Level 2 scenarios

Among the 8 scenarios related to Level 2, which involve changes in human resources, scenario number 4 (increasing one resident to Level 2) stands out as the most effective in improving both the total waiting time and length of stay for patients.

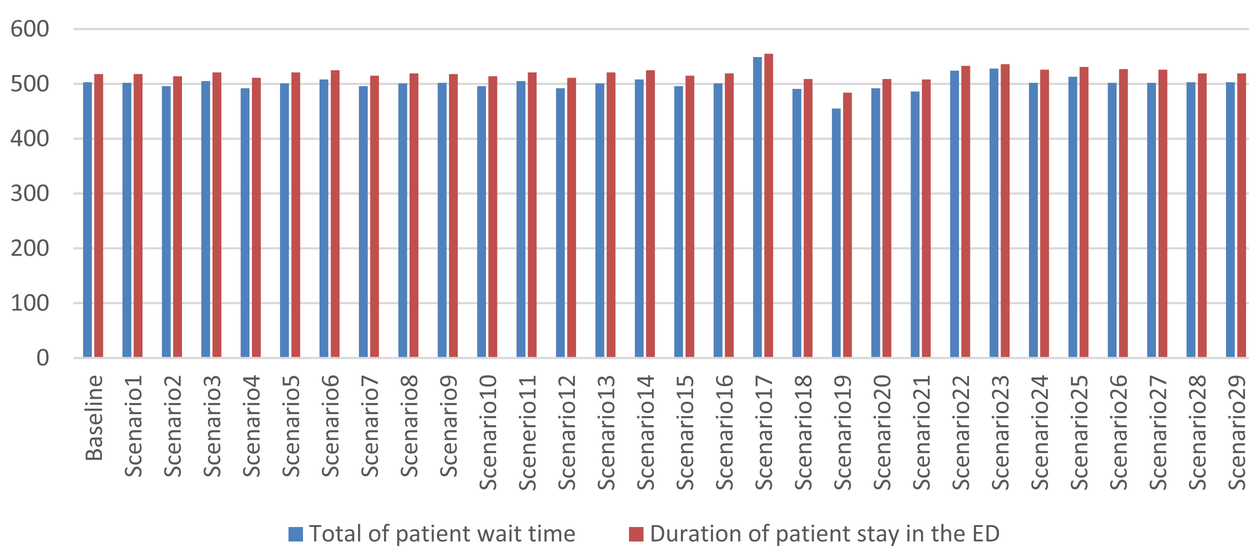

Fig. 5 The results of the simulation of 29 scenarios

Figure 4 presents the results of implementing the Level 3 scenarios, which involve changes to the number of beds. The findings show that scenario 12 (adding two residents to the Level 3 emergency room) is the most effective in reducing both the total waiting time and length of stay for patients.

The results of the simulation of 29 scenarios: human resource changes

The results of the simulation scenarios are presented in Fig. 5, which shows the total waiting times for patients resulting from implementing scenarios 1, 2, 4, 5, 7, 8, 9, 10, 12, 13, 15, 16, 18, 19, 20, and 21. The waiting times have decreased by 0.198%, 1.391%, 2.186%, and so on.

The length of stay for patients in the emergency room has also been affected by the implementation of these scenarios. Specifically, scenarios 2, 4, 7, 10, 12, 15, 18, and 19 have resulted in a reduction in length of stay compared to the base situation. The percentage reductions in length of stay are: 0.772%, 1.351%, 0.579%, and so on.

Notably, scenarios 18 (assignment of one person as referral personnel to the department instead of a nurse for each level), 19 (assignment of two people as referral personnel to the department jointly instead of a nurse for each level), and 21 (adding one person to the common ECG staff for both levels) have demonstrated the most significant reductions in waiting times and length of stay.

Scenario number 19 stands out as the most effective scenario, reducing patient waiting time by a significant 9.542% and length of stay by 6.563%. This scenario suggests that instead of having one nurse in each level, two staff members dedicated to referring patients to the ward will play a joint role between the two levels.

These results indicate that Scenario number 19 is the most favorable scenario for reducing waiting times and length of stay for patients.

The results of scenario implementation: adding four beds to level 3

The implementation of the scenario involving the addition of four beds to Level 3 has resulted in a significant improvement in the admission process. Specifically, the average patient waiting time in the bed allocation process has decreased from 274 min to 268 min, representing a reduction of 6 min.

In addition to the decrease in waiting time, the Total Time and Waiting Time have also decreased compared to the current situation. This indicates that the addition of four beds to Level 3 has optimized the bed allocation process, leading to faster patient processing and reduced congestion.

Moreover, the number of patients receiving services at the reception station (bed allocation) has increased from 26 people in the current situation to 30 people in

Table 5 Comparison of the existing status with the implementation of the "Discharge Unit" scenario

Row	Scenario	Row	Scenario
1	Adding one nurse to level 2	18	Assign one person for patient hand over to ward instead of a nurse for each level
2	Adding one resident to level 2	19	Assign two persons for patient hand over to ward Jointly instead of a nurse for each level
3	Adding two nurses to level 2	20	Assign one person for ECG in level 2 and two persons for ECG level 3
4	Adding two residents to level 2	21	Adding one person to ECG jointly for both levels
5	Adding one nurse and one resident to level 2	22	Assign a person as a test registry staff instead of nurse for two levels
6	Adding two nurses and one resident to level 2	23	Assign a person as a test registry staff instead of nurse for each level
7	Adding one nurse and two residents to level 2	24	Adding one nurse and one resident to each level
8	Adding two nurses and two residents to level 2	25	Adding two nurses and one resident to each level
9	Adding one nurse to level 3	26	Adding two nurses and two residents to each level
10	Adding one resident to level 3	27	Adding one nurse and two residents to each level
11	Adding two nurses to level 3	28	Assign one person for ECG in level 3 and two persons for ECG level 2
12	Adding two residents to level 3	29	Adding one person to radiology unit
13	Adding one nurse and one resident to level 3	30	Adding 2 beds to level 3
14	Adding two nurses and one resident to level 3	33	Adding 4 beds to level 3
15	Adding one nurse and two residents to level 3	32	Reduction of two beds from level 2 (from 44 to 42)
16	Adding two nurses and two residents to level 3	33	Reduction of four beds from level 2 (from 44 to 40)
17	Adding someone as discharge personnel for each level	34	Creating a discharge unit

this scenario. This suggests that the added capacity has enabled the hospital to accommodate more patients, improving patient flow and overall efficiency.

The results of scenario implementation: Reducing beds and "discharge unit" scenarios

The research findings indicate that the implementation of scenarios involving the reduction of beds from the second level (from 44 to 42) and from 44 to 40 resulted in a reduction in the average waiting time of patients and the state of queues.

The next step involved simulating the "discharge unit" scenario. Table 5 provides a comparison of the existing emergency situation at Al-Zahra Hospital in terms of waiting times of patients at the discharge station between the baseline situation and the implementation of the "discharge hall" scenario.

The "discharge hall" scenario involves changes made to improve patient flow and reduce waiting times.

Results of "discharge unit" scenario implementation

The simulation of the "discharge hall" scenario has yielded significant improvements in patient flow and satisfaction. The key findings are:

1. Reduced waiting times: The average waiting time for Level 2 patients at the discharge station has decreased from 56 min to 44 min, while the average waiting time for Level 3 patients has decreased from 15 min to 13 min.
2. Improved patient satisfaction: The average waiting time for Level 2 patients to be discharged with personal satisfaction when their treatment process has not yet been completed has decreased from 80 min to 50 min, while the average waiting time for Level 3 patients has decreased from 67 min to 41 min.
3. Reduced congestion in the emergency room: The number of Level 2 patients waiting to be discharged from the emergency room who have been discharged by a doctor has decreased from 3 to 2 people, and the number of Level 3 patients has decreased from 2 to 1 person.
4. Increased capacity at the reception station: The number of Level 3 patients waiting at the reception station (bed allocation) has decreased from 44 to 39.
5. Increased exits: The average number of exits has increased from 7 to 12 people.

These improvements demonstrate that the "discharge hall" scenario has effectively streamlined the discharge process, reducing wait times and increasing patient satisfaction. Additionally, the scenario has helped to alleviate congestion in the emergency room and increase capacity at the reception station.

Comparison of the existing situation and scenario implementation

As shown in Fig. 6, the comparison between the existing situation at the clearance station and the implementation of the "discharge unit" scenario reveals a significant decrease in waiting times for patients at both emergency triage levels as 2, and 3.

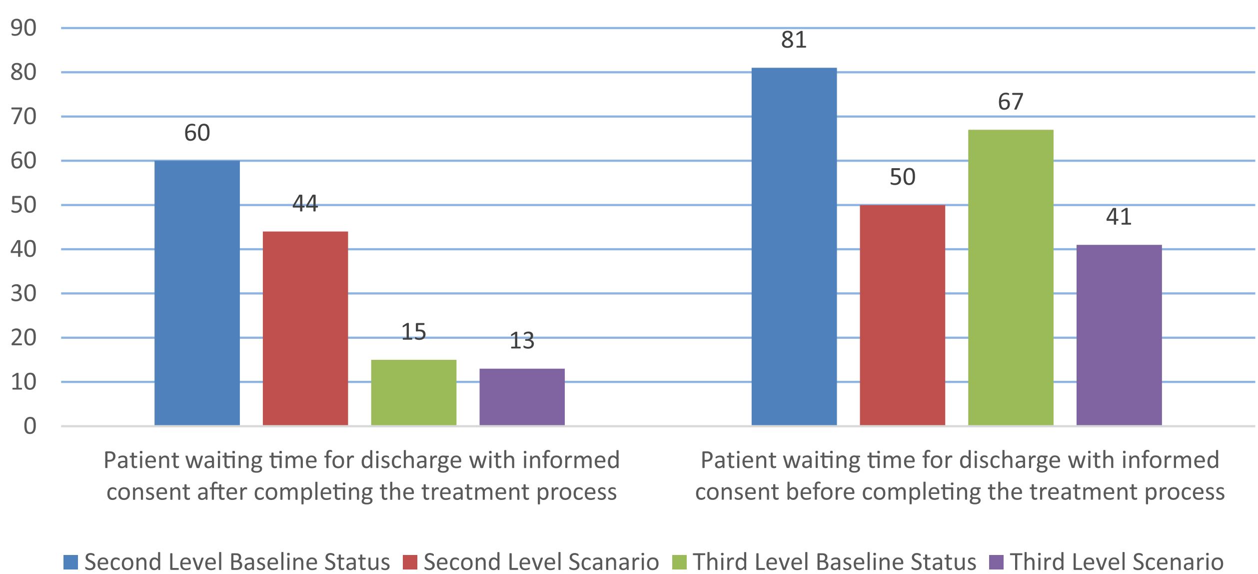

Fig. 6 Comparison of patient waiting times in two situations (Baseline & Discharge unit scenarios)

Comparison results

Waiting Time for patients in the discharge scenario at:

Emergency triage level 2: decreased from baseline situation.
Emergency triage level 3: decreased from baseline situation.

This indicates that the implementation of the "discharge hall" scenario has resulted in a reduction in waiting times for patients at both levels, improving the overall patient experience and flow.

Discussion

The emergency department's primary objective is to deliver timely and effective medical care, with prolonged delays potentially leading to patient dissatisfaction and adverse outcomes. The study's findings demonstrate that leveraging operations research and its various techniques, including simulation, can facilitate informed decision-making that minimizes waste and reduces expenses.

In this study, we utilized the simulation technique to analyze the service delivery processes and design the actual system performance in the emergency department of Al-Zahra Hospital in Isfahan. The results of the first phase revealed that the key bottlenecks affecting patient waiting times are: Initial examination stations, Nurses' execution of doctor's orders, Registration of patient test results in HIS and ECG systems, and Discharge hall processes.

These findings highlight the importance of addressing these bottlenecks to optimize the emergency department's performance and reduce patient wait times. By leveraging simulation and operations research, healthcare providers can develop targeted solutions to improve patient flow, enhance overall patient satisfaction, and reduce the risk of adverse outcomes.

The findings of this study are consistent with those of previous research studies, including those of Paul and Lin [8], and Amissah and Lahiri [9], which identified bottlenecks in the emergency department, such as waiting for specialist input, tests outside the ED, awaiting transportation, bed search, and inpatient handover. Similarly, the study by Tabibi et al. [25], found that radiology and laboratory stations, as well as EKG stations, are expected bottlenecks. Additionally, the research conducted by Beyranvand et al. [26], identified laboratory, discharge, and radiology ultrasound processes as patient waiting bottlenecks.

These findings suggest that the bottlenecks observed in this study are not unique and are consistent with previous research, highlighting the importance of addressing these bottlenecks to improve patient flow and reduce waiting times in emergency departments.

The primary objective of an emergency department is to provide timely and effective medical services, with speed of service delivery being a crucial factor. Prolonged patient length of stay can lead to dissatisfaction and increased risk of adverse outcomes. In contrast, the medical field is inherently complex, with diverse processes involving various stakeholders, including patients, doctors, nurses, managers, and technicians. This complexity cannot be replicated in other business organizations.

The results of the second phase demonstrate that the integration of process mining and simulation techniques enables the development of informed and logical decisions, minimizing waste and additional costs. This study utilizes real-life clinical data and process mining techniques to uncover role interaction models, providing valuable insights into how healthcare professionals collaborate and identify opportunities for process improvement. By gaining this knowledge, organizations can optimize ER processes from a strategic perspective, ultimately improving patient care and outcomes.

In the next phase, expert interviews were conducted to identify strategies for reducing waiting times and improving the current situation. One solution proposed was to equip the emergency department with a dedicated laboratory unit, increase laboratory staff, and utilize young, energetic, and committed staff to transport patient samples from the emergency department to the laboratory. This recommendation is consistent with the findings of Amissah & Lahiri's study [9], "Modelling Granular Process Flow Information to Reduce Bottlenecks in the Emergency Department," which also suggested adding laboratory staff to reduce waiting times.

Another strategy proposed was to establish a discharge lounge, a safe and comfortable space for patients, relatives, and caregivers. This lounge facilitates the discharge process, allowing patients to leave the emergency department more efficiently, freeing up emergency beds, and preparing them for subsequent patients. This concept is also supported by Hernandez et al.'s study [27], "A reimagined discharge lounge as a way to an efficient discharge process," which aimed to improve patient flow and disposition.

Conclusion

In conclusion, our study utilized event reports from Al-Zahra Hospital's emergency department in Isfahan to develop a process model, identify bottlenecks, and propose solutions to improve patient flow and reduce waiting times. Notably, the time-consuming and costly sampling process presented a significant research challenge.

For future research, we recommend considering the following areas: optimizing efficiency and reducing costs, enhancing patient service, minimizing errors, and increasing the reliability of medical organization processes. Additionally, we suggest simulating each emergency procedure before implementation and conducting similar research in other departments, particularly those closely related to the emergency department.

Abbreviations

ED Emergency Department
HIS Hospital Information System

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

M.N.I. and F.D. contributed to the conception and design of the work, data interpretation, drafting, and critical revision of the paper. A.A., M.N.I., F.D. and E.GH. helped with data collection. All authors read and approved the final version of the article.

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Availability of data and materials

The data that support the findings of this study are available on reasonable request from the corresponding author. The data are not publicly available due to their containing information that could compromise the privacy of research participants.

Declarations

Ethics approval and consent to participate

The study is conducted in accordance with the Declaration of Helsinki in its current version (World Medical Association [WMA], 2013). In this study, as the researchers only had access to anonymous data that did not permit the identification of individuals, the Research Ethics Committee of Isfahan University of Medical Sciences approved the utilization of such data without requiring patient consent. (Approval No.: IR.MUI.REC.1394.1.004).

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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