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Original Research

Optimization of Service Process in Emergency Department Using Discrete Event Simulation and Machine Learning Algorithm

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Abstract: **Introduction:** Emergency departments are operating with limited resources and high levels of unexpected requests. This study aimed to minimize patients' waiting time and the percentage of units' engagement to improve the emergency department (ED) efficiency. **Methods:** A comprehensive combination method involving Discrete Event Simulation (DES), Artificial Neural Network (ANN) algorithm, and finally solving the model by use of Genetic Algorithm (GA) was used in this study. After simulating the case and making sure about the validity of the model, experiments were designed to study the effects of change in individuals and equipment on the average time that patients wait, as well as units' engagement in ED. Objective functions determined using Artificial Neural Network algorithm and MATLAB software were used to train it. Finally, after estimating objective functions and adding related constraints to the problem, a fractional Genetic Algorithm was used to solve the model. **Results:** According to the model optimization result, it was determined that the hospitalization unit, as well as the hospitalization units' doctors, were in an optimized condition, but the triage unit, as well as the fast track units' doctors, should be optimized. After experiments in which the average waiting time in the triage section reached near zero, the average waiting time in the screening section was reduced to 158.97 minutes and also the coefficient of units' engagement in both sections were 69% and 84%, respectively. **Conclusion:** Using the service optimization method creates a significant improvement in patient's waiting time and stream at emergency departments, which is made possible through appropriate allocation of the human and material resources.

Keywords: Efficiency; Emergency Service, Hospital; Operations Research; Patients

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1. Introduction

Hospital is one of the most important sectors of healthcare and the emergency department (ED) is considered as one of the most critical and crowded departments of hospitals (1). Hospitals' managers are constantly trying to control rising costs, while responding to the growing demand for health care. As a result, they need to regularly review the efficiency of EDs to find opportunities for improvement (2). High referral rate and limited resources (physician, nurse, etc.) have clarified the importance of optimization methods in the process of evaluation and resource utilization in the health system, and specifically in EDs (3).

The number of patients who refer to EDs has a steadily growing trend. There was a 30% growth in ED visits in France from 2002 to 2012. EDs were one of the most crowded departments of a hospital during the COVID-19 pandemic and played a very important role in therapeutic response to the COVID-19 pandemic (4, 5). The elderly, limited access to medical care from other resources, and the high rate of use of EDs for non-emergency care are the main factors leading to the growing number of patients in the EDs (6).

The development of health infrastructures and appropriate

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allocation of resources will play a very important role in the implementation of general health policies (7). In the case of healthcare organizations, the improvement efforts, and thus the decisions, are concentrated on a system that aims to provide high-quality care, appropriate service times, and is also efficient in the use of resources. However, designing and operating these systems, especially EDs, are extremely complicated, mainly due to the high number of different resources involved in the activities of providing care, the uncertainty resulting from these activities happening at different moments, and the distinguished probability of simultaneously requiring resources (8). As a result, long patient waiting times and overcrowding are common problems in EDs all over the world. Optimization of patients' stream and bottleneck elimination in the ED could provide a solution that lessens the cost and raises the quality of care (4). Designing an appropriate allocation plan for human and material resources should be considered as one of the most important tasks in EDs.

In this context, simulation and optimization techniques have been used to address the described management problems in a complicated healthcare system (10)(11)(12). Most of these works do not pay attention to all stages of a patient stream in the ED. In order to respond to this gap, this study aimed to simulate an optimal patient stream in ED to reduce patient waiting time as well as raise the percentage of resource employment to an optimal level.

2. Methods

2.1. Study design and setting

The present study was a longitudinal and simulation study conducted from 21 March 2019 to 19 February 2020. The optimization method used in this research is a combination of comprehensive methods involving Discrete event simulation (DES), Artificial Neural Network (ANN) algorithm, and finally solving the model by use of Genetic Algorithm (GA).

The main objectives of the model include reducing the patients' waiting time and increasing the percentage of resources deployed to make optimal use of them. These two objectives will be modeled as two objective functions. The number of physicians, nurses, hospital beds, and triage space were considered as variables in the objective function.

The research steps of work, as shown in figure 1, were data collection, simulating the systems' current status using DES, validation of the simulated model, implementation of experiment design, ANN training and achieving system changes, modelling the problem, solving the model, and studying the outcome.

2.2. Data gathering

Data needed for workflow simulation were collected through observation by 2 researchers during 11 months. All the patients (74,796 patients) who referred to ED from 21 March 2019 to 19 February 2020 (11 months) were recorded and investigated by researchers using the census method. A summary of the number of studied patients in each part of ED is presented in (Table 1).

2.3. Developing the model

The relation between different parts in the emergency department was registered through observation of ED workflow. After collecting information and data regarding processes using Enterprise Dynamics software, the model was simulated. Enterprise Dynamics software is an objective-oriented simulation, which is combined with an event-driven method. First, using an auto-fit menu, the probability distribution of data related to patients' entry rate and service entry was determined. After determining the probable functions, the simulation model was designed. The next stage in simulation was to make sure about the accuracy and validity of the simulated model.

2.4. Validation of model

In the validation process, the average of the real and simulated data was studied through an independent T-test at the confidence level of 95%. In the next step, the current status of the service system regarding the queue length criterion was examined to identify the crowded sections that need improvement. Finally, machine learning experiments were designed to examine the effect of changes in individuals and equipment on average patient waiting time as well as the engagement rate of the units. In this regard, the complete factorial method was utilized by considering the central and axis points as well as 3 replications in MINITAB software. After designing the experiments and implementing them on the simulated model, as well as determining the queue length and the percentage of the units' engagement, Artificial Neural Network (ANN) and fractional genetic algorithm (GA) were used for simulation using MATLAB 2016 software. In this article, we have omitted the details and writing of mathematical models and syntax of the algorithms used and tried to clarify its management results for the reader. It should be noted that for ease of reading, the table of columns related to the minitab executive operation and its prioritization has been omitted.

2.5. Designing the model

The effect of 4 factors or resources on the system output were measured: the number of triage operators (triage), fast track physicians, ED physicians, and the number of inpatient beds (hospitalization) . All 4 factors have a queue and need to be examined in more detail. After designing the experiments, each of the experiments had been simulated and the related information was recorded in table 3.

Table 1: Number of patients in each part of the studied emergency department during the study period

Number	Month										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Non-hospitalized											
Futile cases	3	1	6	2	2	4	3	3	1	5	2
Outpatients	4154	4578	4268	4065	3935	4085	4603	4450	4382	4431	4925
Hospitalized cases											
ED	2465	2660	2518	2481	2524	2490	2485	2430	2287	2298	2250
General ward	516	509	600	810	899	803	799	844	748	730	670
Special ward	132	114	136	116	125	146	121	137	124	154	151
Others											
DAMA	146	169	172	147	147	156	147	159	138	102	119
Dispatched[1]	4	3	5	4	3	5	4	3	4	3	9
Died (first 24 h)	9	11	8	7	9	9	8	7	8	4	5
Discharged[2] (%6 h)	74	71	66	66	68	67	66	67	65	67	65
Discharged[3] (%12 h)	14	10	12	13	11	11	13	11	17	12	9
Total	6622	7239	6792	6548	6461	6579	7091	6883	6670	6734	7177

ED: emergency department; DAMA: discharged against medical advice; h: hour. [1]: to other hospitals;
[2]: percentage of discharged cases within 6 hours. [3]: percentage of discharged cases within 12 hours.

Table 2: The mean waiting times of patients in different sections of the studied emergency department (ED)

Waiting time (hours)	Mean ± SD	Min	Max	95% CI
Triage unit	139.72 ± 56.14	103.87	351.69	124.16- 155.29
Fast track unit	5158.57 ±1747.36	2486.89	10349.52	4673.98 - 5643.16
ED specialist	458.21 ±61.96	366.13	634.32	441.02 -475.39
Hospitalization	57.03 ±41.35	3.35	166	45.56 -68.5

SD: standard deviation. CI: Confidence interval. Min: minimum, Max: maximum.

2.6. Validation

Checking the validity of the model shows that the simulated model was not statistically different from the real data (p = 0.356). After ensuring the validity of the model, experiments were designed to investigate the effects of changes in the number of personnel and equipment in the emergency department on the average waiting time of patients and the percentage of bed occupancy.

2.7. Optimization

According to the model optimization result, it was determined that the hospitalization unit, as well as the hospitalization units' doctors, were in an optimized condition, but the triage unit, as well as the fast track units' doctors, should be optimized. According to the resulting optimized answer, the changes in patients' average waiting time, as well as units' efficiency coefficient were as follows (Table 4). The average waiting time in the triage unit was reduced to almost zero, also, the average waiting time in the fast track section was reduced to 158.97 minute. Units' engagement percentage in the two mentioned sections was 69% and 84%, respectively. Although the unit engagement percentage was reduced, this slight reduction can be overlooked due to the significant improvement in patients' waiting time.

3. Results

The studied ED's workflow is presented in figure 2. The studied ED included different parts. ED physician was in charge of patients who needed critical cares. Fast track phycisian was in charge of patients who needed fewer emergency services. After entering the ED, patients go to the triage section to be categorized into 5 levels based on their medical conditions. In this section, patients who are considered as level 1 and 2 are handed over to the ED physician. The ED physician sends them to recovery, hospitalization, or outpatient service parts. Level 3 patients are assigned to both ED and fast track physicians. Levels 4 and 5 patients are assigned to the fast track physician. The mean waiting times in different sections of the ED were calculated and presented in table 2.

4. Discussion

The decision-making process is extremely challenging for ED managers. Therefore, offering them the possibility to acquire more knowledge and evidence to ease this process is extremely valuable, especially in EDs where poor decisions may lead to critical situations for patients.
In this research, in contrast to traditional methods like regression, to estimate the objective function, trained networks

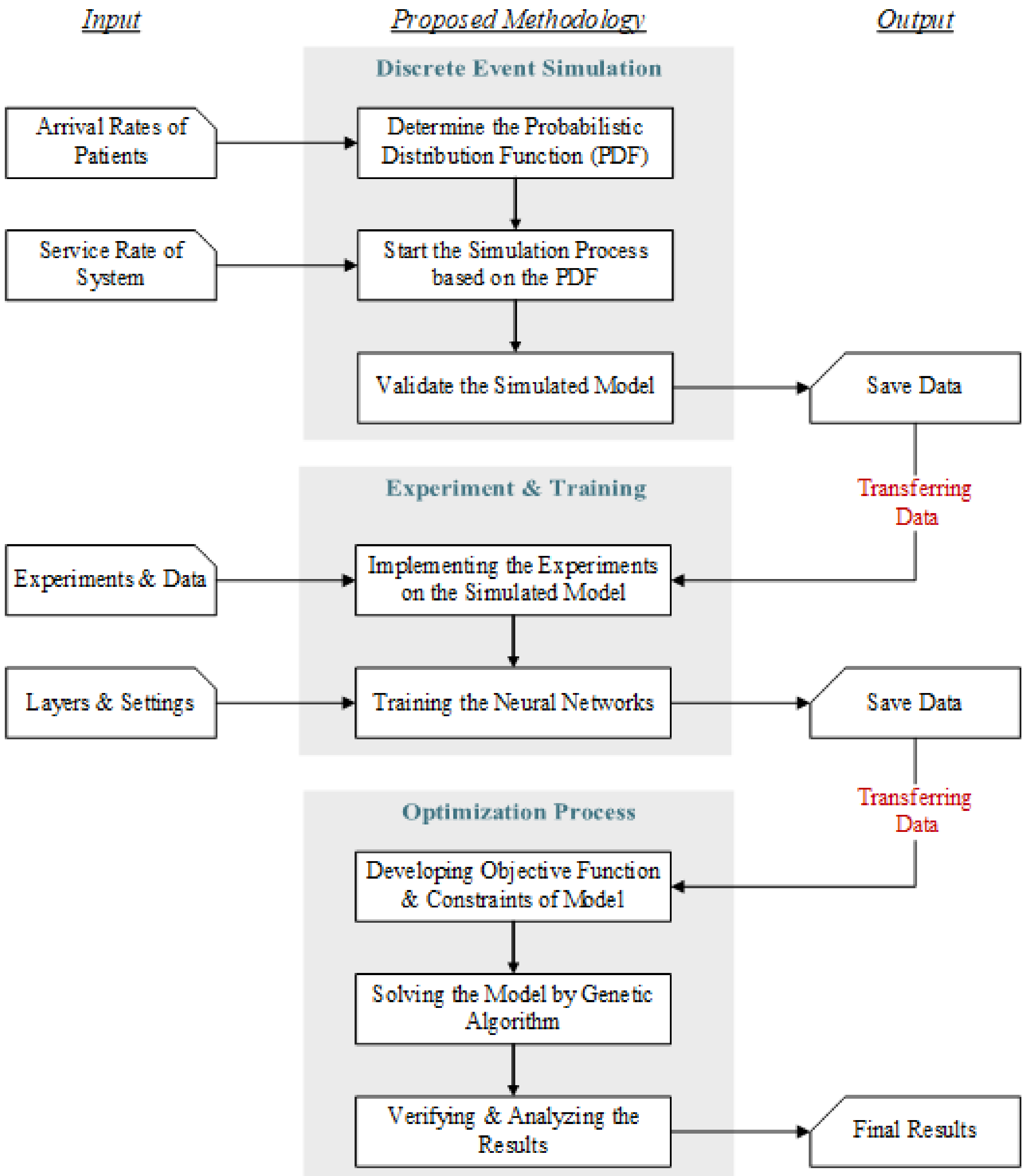

Figure 1: Research implementation steps.

were utilized. The results show the good performance of the proposed method in the analysis and optimization of the system. The major goals of this research are reducing the patients' waiting time as well as increasing the units' engagement percentage for optimal usage, which are modeled as the two objective functions. After collecting the information and processes by use of ED software, the model was simulated to include the system complexities in the model. After making sure about the model validity, the experiments were designed to examine the effects of changes in sectors' individuals and equipment on the average patient waiting time as well as the units' engagement percentage.

In the study by Duguay et al. (13), some alternatives, based on adding resources, have been investigated to reduce pa-

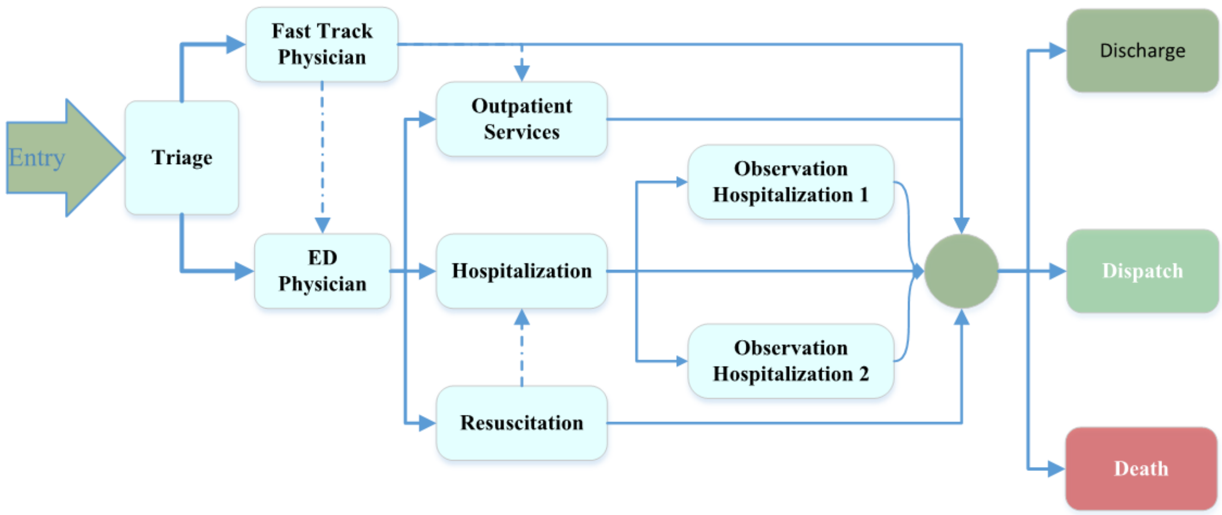

Figure 2: The relation between different parts in the emergency department.

tient waiting times and to improve overall service delivery and system's throughput. Additionally, Thorwarth et al. (14), examined the impact of staff scheduling on overall utilization and burnout issues related to overutilized staff. Considering the reviewed literature, some important performance measures such as resource utilization, productivity, and lay-out efficiency have not been analyzed completely, also there is a lack of a link between these indicators and international standards. Kırış et al. (15), developed a knowledge-based reactive scheduling system for emergency departments. To minimize patient waiting time, they considered patients' priorities, arrival time, flow time, and physician's workload.

In a similar study Azadeh et al. (16) proposed a genetic algorithm (GA) for solving the problem of scheduling prioritized patients in emergency department laboratories. A Response Surface Methodology (RSM) is applied for tuning the GA parameters. The algorithm can significantly improve the efficiency of the emergency department by reducing the total waiting time of prioritized patients. Granja et al. (17) proposed a simulation-based optimization approach to the patient admission scheduling problem to minimize patients' length of stay, while reducing the costs and increasing (or at least maintaining) the quality of care.

The number of studies applying simulation for the improvement of healthcare systems has increased since the early 1990s, (18). Simulation studies within EDs have been used to improve the performance and reduce patients' waiting time by studying multiple scenarios such as growing the number of physicians, staff, and medical devices (12). Gunal et al. (19), analyzed how to increase emergency department performance through Discrete-Event simulation. In a similar study, Al-Refaie et al. (12), took advantage of simulation in a Jordanian hospital's ED to decrease the average patient waiting time, increase the number of served patients, and improve nurses' productivity. Finally, they claimed that flexibility in cellular service systems such as hospitals has played an important role in improving the performance of ED. Zeng et al. (20) have done a study to increase the quality of services in a hospital's ED in Kentucky, using computer simulation. They considered the length of stay, waiting times, and patient elopement as the most important parameters.

According to our study results, the optimization of the patient stream at ED is possible through appropriate allocation of the human and material resources. Azadeh et al. (1) also optimized the process of work in the ED of a hospital in Iran by taking advantage of simulation optimization and modeling human errors. Repeated venipuncture, unsafe transportation, and sampling errors were considered in that study. Norouzzadeh et al. (21), developed a modular discrete event simulation in a hospital's ED to simplify the process of patient flow to inpatient wards. Finally, the result showed that in order to make sure about better efficiency in ED, all of the improvements should be accomplished at the same time.

5. Limitations

The present study, like other studies, had limitations that we like to mention here. First, multi-criterion decision-making methods about system optimization policies were not considered in the present study, but can be included in the model in future studies. Second, the study result is based on the studied patients' features and circumstance; therefore, the effect of COVID-19 pandemic on the ED had not been considered in this study, the consideration of which in future studies will be helpful.

Since ED waiting time and other indicator data were not

Table 3: Results of the designed experiments (Different modes of resource utilization)

Row	Number of sources				Waiting times (minute)				Resource efficiency (%)			
	Triage	Fast track	ED physician	Hospita-lization	Triage	Fast track	ED physician	Hospita-lization	Triage	Fast track	ED physician	Hospita-lization
1	2	2	2	14	122.92	4634	446	55	0.74	0.98	0.84	0.9
2	4	2	2	14	10.56	4780	458	56	0.68	0.98	0.84	0.9
3	2	2	4	14	126.48	4842	4.8	61.6	0.74	0.98	0.79	0.9
4	2	2	2	14	124.74	4899	467	65	0.74	0.99	0.85	0.89
5	2	2	4	14	134.13	5217	4.99	80.1	0.74	0.98	0.79	0.9
6	2	2	2	14	123.82	4998	463	76	0.74	0.98	0.84	0.9
7	2	2	2	14	143.7	5513	461	69	0.74	0.98	0.84	0.9
8	2	2	1	14	397.41	12743	12026	0.03	0.68	0.92	1	0.99
9	2	2	2	14	130.29	4943	462	63	0.74	0.98	0.84	0.9
10	4	2	2	14	18.46	5143	459	70	0.68	0.98	0.84	0.9
11	2	4	2	14	115	4	662	63.25	0.74	0.88	0.83	0.92
12	2	2	2	14	122.54	4618	459	64	0.74	0.98	0.84	0.9
13	1	2	2	14	3389	37	212.5	9.39	0.99	0.98	0.78	0.96
14	2	1	2	14	6836	44381	42	0	0.02	1	0.57	0.99
15	2	2	2	14	136.78	5053	447	60	0.74	0.98	0.84	0.9
16	2	1	2	14	6831	44380	43.3	0	0.02	1	0.57	0.99
17	2	2	2	14	123.18	4622	457	64	0.74	0.98	0.84	0.9
18	2	2	2	14	134.45	4795	468	48	0.74	0.98	0.84	0.9
19	4	2	2	14	12.34	4777	450	49	0.68	0.98	0.84	0.91
20	2	2	2	14	127.23	4814	457	79	0.74	0.98	0.84	0.9
21	1	2	2	14	3407	37	208.8	11.73	1	0.98	0.78	0.96
22	2	2	2	14	136.48	5053	447	60	0.74	0.98	0.84	0.9
23	2	2	2	14	140.7	5513	461	67	0.74	0.98	0.84	0.9
24	2	2	0.5	14	461.76	13825	12023	0.2	0.67	0.92	1	0.99
25	2	2	2	14	122.58	4638	451	56	0.74	0.98	0.84	0.89
26	2	2	2	14	124.3	4814	462	67	0.74	0.98	0.85	0.9
27	2	2	2	14	136.78	4943	446	60	0.74	0.98	0.84	0.9
28	2	2	2	14	128.6	4634	451	53	0.74	0.98	0.84	0.9
29	2	1	2	14	6830	44360	42.3	0	0.02	1	0.57	0.99
30	2	2	0.5	14	481.64	14060	12063	0.14	0.67	0.92	1	0.99
31	2	2	2	14	123.82	5513	462	60	0.74	0.99	0.84	0.9
32	2	2	2	14	130.29	5425	461	76	0.74	0.98	0.84	0.9
33	2	4	2	14	114	3.9	689	58.9	0.74	0.88	0.83	0.92
34	2	2	2	14	123.2	4899	463	65	0.74	0.98	0.84	0.9
35	1	2	2	14	3385	37.29	208	8	0.99	0.98	0.78	0.97
36	2	2	2	14	128.6	4888	448	63	0.74	0.98	0.84	0.9
37	2	2	2	14	134.45	5017	450	63	0.74	0.98	0.84	0.9
38	2	4	2	14	114	3.95	691	59.4	0.74	0.88	0.83	0.92
39	2	2	4	14	121.29	4711	4.54	84.1	0.74	0.98	0.79	0.89

Table 4: The results of optimization study of 4 studied factors or resources in the emergency department (ED)

Item	Triage	Fast track	ED physician	Hospitalization
Patients' waiting time				
Optimum	3.22	158.97	458.21	57.03
Real (before experiment)	139.72	5158.57	458.21	57.03
Units' efficiency coefficient (%)				
Optimum	0.69	0.84	0.84	0.9
Real	0.74	0.98	0.84	0.9

Times are presented as minute.

comprehensively integrated in the hospital information system (HIS), for ensuring reliability and completing the data, the researcher simultaneously used two ways: attending the emergency department and HIS data.

6. Conclusion

Using the studied optimization method creates a significant improvement in patient waiting time and the optimization of patient stream in the ED is possible through appropriate allocation of the human and material resources. It is suggested to study the optimization of patient stream through machine learning methodology for improving the other sections of hospital departments.

7. Declarations

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7.2. Authors’ contributions

Concept and design: KM, MY, SMHS. Acquisition, analysis, or interpretation of data: KM & MA. Drafting of the manuscript: KM & MY. Critical revision of the manuscript:SMHS & MY. Administrative, technical, or material support:MY, SMHS. Supervision: MY & SMHS. All authors read and approved the final version.

7.3. Funding and supports

None.

7.4. Competing interests

The authors declare that they have no competing interests.

7.5. Ethics approval and consent to participate

The Medical Research Ethics Committee of Iran reviewed the study protocol and concluded that the research is not subject to the Iran Medical Research Involving Human Subjects Act, and therefore, ethics approval was waived. The necessity for obtaining informed consent was waived by the medical research ethics committee of Iran, due to the complete anonymity of the study data. Therefore, study data was in no way traceable to individuals.

7.6. Consent for publication

Not applicable.

7.7. Availability of data and materials

Original data remain available and access may be provided upon reasonable request.

7.8. Availability of data and materials

Original data remain available and access may be provided upon reasonable request.

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