Optimizing Emergency Department Triage with Priority Algorithms: A Study on Prioritizing Severe Patients for Improved Outcomes

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Abstract: Emergency rooms must quickly identify and treat patients who are in severe condition while making the best possible use of their finite supply of medical supplies. The growing number of patients in emergency rooms might cause delays in triage and treatment, which could have a negative impact on patient health. In response, priority algorithms can be used to rank patients according to a variety of criteria, including the urgency of the medical situation, the severity of the sickness, and the availability of resources. This makes it possible for medical professionals to immediately recognize and prioritize patients who are in a critical state, and to allocate resources accordingly. Healthcare providers can also use automation and artificial intelligence to help with the triage process with the incorporation of robotic healthcare physicians, further optimizing patient care. In this study, the effectiveness of priority algorithms in emergency department triage will be assessed, along with how they can benefit seriously ill patients' health outcomes. The project is also investigating the advantages of including robotic medical professionals in the triage procedure. The findings of this study are assisting in the creation of emergency department triage systems that are more effective and efficient, resulting in better patient care and outcomes. The employment of priority algorithms and robotic healthcare physicians will undoubtedly increase the quality of care while making the best possible use of the available resources, which has important implications for healthcare providers, legislators, and patients alike.

Keywords: *Emergency Department Triage, Priority Algorithms, Robotic Healthcare Physicians, Patient Health Outcomes, Healthcare Resource Optimization*

1 Introduction

Emergency rooms are essential for giving patients with serious and life-threatening diseases prompt care. However, rapid triage and treatment of patients while maximizing the use of scarce healthcare resources is frequently a difficulty faced by emergency departments. Patient volume growth can cause delays in triage and treatment, which can have a negative impact on patient outcomes. The lack of qualified healthcare workers makes this problem worse, hence it is critical to implement cutting-edge technologies to boost emergency departments' effectiveness and efficiency.

A particular factor of technology is priority algorithms, which can be used in emergency rooms to rank patients according to their need for medical attention, the severity of their disease, and the resources that are available. With the use of these algorithms, healthcare professionals can immediately identify and prioritize patients who are in severe condition, allocating resources as necessary. Priority algorithms can shorten wait times and lower the chance of negative outcomes by identifying patients who require immediate attention, improving patient outcomes in terms of their health.

The incorporation of robotic medical doctors can improve the triage procedure in the relevant department in addition to priority algorithms. Robots or automated systems with artificial intelligence that can help with patient evaluation and medical decision-making are referred to as robotic healthcare physicians. Healthcare professionals can improve the precision, effectiveness, and consistency of patient assessments by utilizing artificial intelligence and automation. Additionally, by managing their workload, these technologies can assist healthcare professionals in lowering their risk of burnout.

This study intends to assess the effectiveness of triage priority algorithms in the emergency department and how they can enhance patient outcomes for serious conditions. The study also considers the advantages of incorporating robotic healthcare doctors into the triage procedure.

Ultimately, the utilization of priority algorithms and robotic healthcare physicians can significantly improve the quality of care provided in Emergency departments while optimizing the use of limited resources. These technologies can help healthcare providers make informed decisions and allocate resources efficiently, leading to improved health outcomes for patients. The outcomes of this study have broader implications for healthcare providers, policymakers, and patients alike, highlighting the potential benefits of innovative technologies in improving the Emergency department's efficiency and effectiveness.

2 **Literature Review**

Most of the researchers have worked on multiple approaches in order to prioritize severe patients using priority algorithms. Every research has its own pons and cons. A few of the research works are analyzed here:

In this research [1], the researchers presented a review on triage and prioritization of large-scale telemedicine patients with big data analysis. Several techniques for triaging and prioritizing patients have been presented and evaluated. The weak points were also determined, and possible solutions were discussed and recommended. The results highlighted unresolved problems and difficulties in the process of prioritizing and triaging patients. We advise choosing the appropriate technique, method, or approach because different decision-making techniques showed different configurations and contexts (such as individual decision-making group decision context experimentally as a methodological approach to cover this gap.

According to the research [2], the researchers this review explores the combination of wireless sensor technology and IoT-based human health monitoring terminals. The study demonstrates the system's stability, accurate data collection, real-time monitoring, and alarming capabilities. Test results for temperature and pulse rate show consistent and accurate readings. The IoT-based system successfully collects vital sign data and suggests further exploration of risk prediction factors for expanding its application in preventing and controlling chronic high-risk diseases.

In [3], the researcher's Wireless BSN technology is emerging as a significant element of next-generation healthcare services. In this paper, we proposed a mobile physiological monitoring system, which is able to continuously monitor the patient's heartbeat, blood pressure, and other critical parameters in the hospital. the entire system consists of a coordinator node to acquire the patient's physiological data, a WMHRN to forward the data, and BS to collect the data. This system is able to carry out long-term monitoring of a patient's condition and is equipped with an emergency rescue mechanism using SMS/E-mail.

The researchers in [4], have provided an overview of existing research on prioritizing severe patients in emergency departments (EDs) using priority algorithms. It explores the limitations of current triage systems and protocols, examines different approaches to prioritization, analyzes algorithm development methodologies and their predictive factors, and evaluates the impact of priority algorithms on patient outcomes and resource utilization. The review identifies gaps in the literature and highlights the significance of the study in optimizing ED triage and improving outcomes for severe patients.

According to this research [5], the development of a triaging and prioritizing model, called TPM, in order to decrease the waiting time of the patients in an e-medicine system while taking into consideration patients admitted to the hospital. In the article a simulation of patients who were 580 in number, having various indications, and were at different stages of risk, triage, and prioritized founded on the proposed algorithms. Results showed that TPM had superior performance in reducing waiting time, and a larger patient capacity while taking into account the range of prioritized stages. Future work should focus on developing a flexible policy that responds to various illnesses and a sophisticated telehealth measuring system that uses machine-learning methods.

In [6], **the researchers** TBI is a significant cause of mortality, especially among the elderly, leading to higher mortality rates, longer hospital stays, and long-term disability. Early identification of severe intracranial injuries is crucial, but under-triage of elderly TBI patients is observed due to subtle changes in consciousness. This study examines RETTS-A triage in isolated TBI cases, considering age-related differences in acute management. The research aims to improve triage strategies and optimize outcomes for elderly TBI patients.

In this research [7], **the researchers** focus on addressing the issue of crowding in hospitals and its impact on emergency departments (ED) and patients. The objective is to present an approach called the "floating patients" method, which aims to optimize the scheduling of patients' ED examinations. This approach involves redirecting patients, when possible, to receive treatment in other hospital departments instead of the ED, with the aim of reducing their waiting time for examinations and treatment. The paper begins by solving a basic problem where the ED physician and triage have complete information about patients' conditions and expected evaluation times. It then extends this problem to account for real-life uncertainty, where the physician conducts initial examinations to gather information and decides whether to continue examining patients or redirect them based on a "halting rule." The physician also determines the optimal schedule for the full evaluations of examined patients. The proposed algorithms are demonstrated through a simulation using real-life data.

In this article [8], **the researchers** have pointed out that Hospital managers face the challenge of allocating resources optimally in emergency departments to balance waiting time and service costs. Allocating excessive resources incurs costs without reducing waiting time, while insufficient resources increase waiting time. To address this, the article proposes a methodology that integrates data-mining techniques and mathematical formulations to determine the optimal number of servers and service rate to minimize waiting and service costs. The methodology involves classifying and prioritizing patients using data mining algorithms and determining the optimal number of servers and service rate using a mathematical model. The article presents a real-life case study and recommends future research on server breakdowns and patient data censorship. The methodology can be applied to other medical institutions to enhance productivity, and researchers can consider other priority models or queuing systems for triage stations. The article suggests uploading patient records electronically to prevent patient data censorship and shorten data gathering time.

In [9], **the researchers,** compare APQ-h and APQ policies in an emergency department (ED) setting, considering stochastic patient arrivals and multiple treatment stages. Results show that both policies outperform other priorities, effectively managing ED patient flow. APQ-h aligns with certain hospitals' queue discipline and performs well in congested and non-stationary environments. In less congested scenarios, simple priority disciplines are recommended. The analysis includes various performance indicators for patient treatment and waiting times. Further research is needed to explore policy differences and non-linear rates for priority accumulation. Efficient optimization algorithms are necessary for ED management.

In this research [10], **the researchers** have pointed out that the laboratory-based simulation study evaluated a new electronic display designed for use in emergency medicine, using work-centered usability methods. Participants rated the display and its components favorably on scales measuring usability, usefulness, and clinical support. The display's overall usability score, as measured by the SUS tool, was rated as acceptable or marginally acceptable. However, the performance of clinicians using the display on scenario-based tasks varied depending on the type of task or question. The study results highlight the importance of work-centered usability testing for electronic systems produced using user-centered design processes and provide valuable insights for improving the display's design. Qualitative feedback collected from participants also generated insights for improvement. The findings from this study will inform the design improvements of the current display, with implications for improving health IT design in the emergency department on a broader scale.

In [11] the researchers, managers frequently consult ED patients as a performance indicator. There are two categories of patients: admitted patients and non-admitted patients. A simulation using DOE demonstrates that the variable's influence is ranked differently. The hospital's capability for admitting patients has the greatest impact on the ED LOS. An increase in beds or the establishment of a separate unit for patients under observation and short-stay patients could be used to boost this capability.

The improvement change with the greatest impact on non-admitted patients is extending the time spent treating patients who are being observed. Lean thinking appears to be a remarkable tool for reviewing and improving the process for patients who are being observed.

Limitations of previously published works:

Reference	The large scale of patients	Model	Addressing Triage	Addressing Priority	Medical Case study	Place of patients		Consider waiting time for large-scale patients.
						Hospital Emergency Department EDs	E-medicine	
[1]	√	Real-time remote health monitoring systems (RTRHMSs)	√	X	Chronic diseases	X	√	X
[2]	√	IOT	√	√	All Diseases	√	X	X
[3]	√	Wireless Body Sensor Network (WBSN)	√	X	All Diseases	X	√	X
[4]	√	Length of Stay (LOS)	√	X	All Diseases	√	√	X

[5]	√	**TPM**	√	√	**Heart Chronic Disease**	√	**X**	**X**
[6]	√	**Rapid Emergency Triage and Treatment System–Adult (RETTS-A)**	√	√	**Traumatic brain injury (TBI)**	√	**X**	**X**
[7]	√	**Floating Patients Model (FPM)**	√	**X**	**All Diseases**	√	**X**	**X**
[8]	√	**Data Mining Model**	√	√	**COVID-19**	√	**X**	**X**
[9]	√	**Accumulative Priority Queue (APQ)**	√	√	**All Diseases**	√	**X**	**X**
[10]	√	**Patient-Focused Display (PFD)**	√	**X**	**All Diseases**	**X**	**X**	**X**
[11]	√	**Dynamic nature**	√	**X**	**Chronic diseases**	√	**X**	**X**
Proposed Model	√	**Triaging and Prioritizing Model TPM**	√	√	**All Diseases**	√	√	√

Table-1: Comparison of Previous Published Works with Proposed Model

Proposed model: 3-4 lines generic where first highlight concerns, then possible solutions, in this research…, the proposed model is given in figure 1.

Showing all the limitations of previous work such as some techniques working for specific diseases and some for all diseases as a whole.

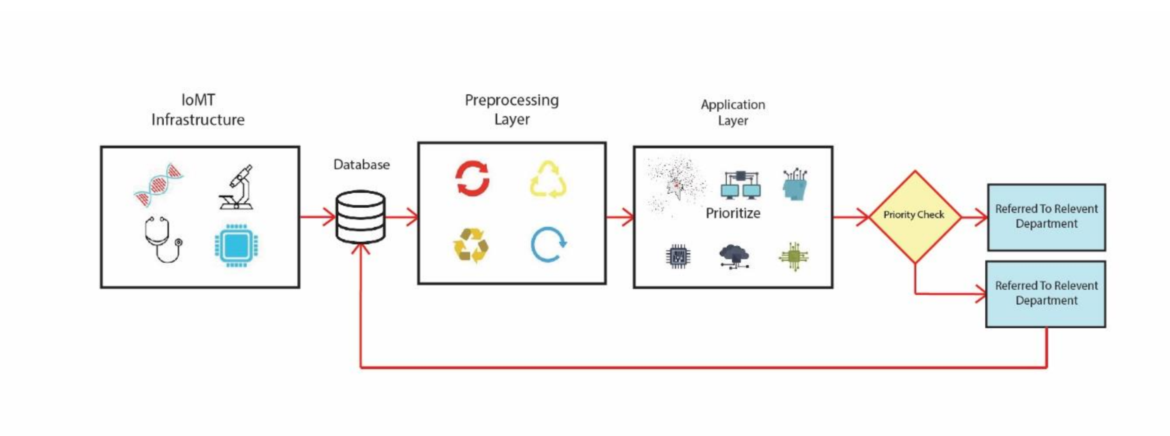

Figure 1: Triaging and prioritizing patients in one queue without considering treated emergency department (EDs) patients:

This approach focuses on triaging and prioritizing patients within a single queue, without taking into account the patients already treated in the emergency department (ED). The system aims to efficiently manage the patient flow by assessing their condition and assigning priority levels. By utilizing a single queue, the system can streamline the triage process and allocate resources based on the urgency and severity of each patient's condition. This method disregards the status of patients who have already received treatment in the ED, ensuring that patients are assessed and prioritized solely based on their current condition and needs.

Following is an explanation of the relationship between a priority algorithm, an ImOT (Internet of Moving Things) database, a preprocessing layer, and an application layer:

1. ImOT: ImOT is an acronym for Internet of Things (IoT) and mobility integration, which enables connectivity and interaction between moving objects and devices. ImOT entails the installation of IoT devices on moving items like automobiles, drones, or wearable tech so that they can produce and exchange data in real-time.

2. Database: In order to store and manage the data produced by ImOT devices, the database is essential. It acts as a storage location for the gathered sensor data, device metadata, and other pertinent data. Depending on what the application needs, the database might be distributed or centralized.

3. Preprocessing Layer: After the raw data gathered from ImOT devices are placed in the database, the preprocessing layer is in charge of cleaning, modifying, and organizing it. It could entail operations like feature extraction, data aggregation, data normalization, and filtering. The preparation layer makes sure the data is formatted properly for additional analysis and use.

4. Priority Algorithm: Based on predetermined criteria, a priority algorithm is a computational approach or methodology used to rank or assign priority levels to various objects or occurrences. A priority algorithm can be used in the context of ImOT to examine the data gathered and assess the importance or priority of particular events, objects, or actions. The algorithm may take into account elements like criticality, importance, and urgency.

Pseudocode from the proposed priority algorithm

function triagePriorityAlgorithm(patients)	The main function is to prioritize patients based on severity and score
patients.sortBySeverity()	Sorts the patients based on the severity of their condition
for the patient in patients:	Loop through each patient in the list
patient.priorityScore = calculatePriorityScore(patient)	Assigns a priority score to each patient based on their condition
patients.sortByPriorityScore()	Sorts the patients based on their priority score
return patients	Returns the prioritized list of patients
function calculatePriorityScore(patient)	Calculates the priority score for a given patient
score = 0	Initializes the score variable to 0
if patient.isCritical():	Checks if the patient's condition is critical
score += 5	Increases the score by 5 if the condition is critical
if patient.hasLifeThreateningCondition():	Checks if the patient has a life-threatening condition
score += 4	Increases the score by 4 if the patient has a life-threatening condition

if patient.requiresImmediateIntervention():	Checks if the patient requires immediate intervention
score += 3	Increases the score by 3 if the patient requires immediate intervention
if patient.hasSignificantPain():	Checks if the patient has significant pain
score += 2	Increases the score by 2 if the patient has significant pain
if patient.isUnstable():	Checks if the patient is unstable
score += 1	Increases the score by 1 if the patient is unstable
return score	Returns the calculated priority score

Table 2.
Represents pseudo code of priority algorithm with a description

5. Application Layer: The ImOT architecture's highest layer, the application layer is where the data gathered from sensors is used to create software or deliver services. The application layer can use the outputs of the priority algorithm, which are obtained from the preprocessing and database layers, to drive intelligent decision-making, resource allocation, or real-time actions based on the prioritized information.

In **conclusion**, the data gathered from ImOT devices, which is processed in the preprocessing layer, saved in the database, and made accessible for use by applications in the application layer, is used by the priority algorithm. The priority algorithm assists in assigning events or objects a priority or ranking, allowing programmers to base their judgments or actions on the information that has been assigned a priority.

Simulations:

To create a simulation for optimizing emergency department triage, you would typically need to consider the following components:

1. Patient Arrival Process: Simulate the arrival of patients to the emergency department based on realistic patterns and distributions. This can include factors such as arrival rates, patient demographics, and severity levels.

2. Triage Algorithm: Implement the priority algorithm or algorithms being studied. This could involve assigning priority levels to patients based on their presenting symptoms, vital signs, or other relevant criteria.

3. Resource Allocation: Simulate the allocation of resources such as medical staff, examination rooms, diagnostic equipment, and treatment facilities. This could include considering the availability and utilization of resources based on patient priorities.

4. Patient Flow: Model the flow of patients through the emergency department, including the waiting time for triage, diagnostic tests, and treatment. Consider the impact of prioritization on patient flow and the potential for resource bottlenecks.

5. Outcome Measures: Define the outcome measures you wish to evaluate, such as patient outcomes (e.g., mortality rates, length of stay), resource utilization (e.g., utilization rates, waiting times), or system-level performance metrics (e.g., throughput, efficiency).

6. Data Analysis: Collect and analyze the simulation data to assess the performance of the priority algorithms and their impact on the specified outcome measures. Compare different algorithms or variations to determine their effectiveness in improving outcomes.

By simulating the triage process with priority algorithms, you can gain insights into how different algorithms perform in terms of patient outcomes, resource utilization, and overall system efficiency. This can help inform decision-making and identify opportunities for optimizing emergency department triage.

Recent time challenges, and different approaches used in various studies related to emergency department optimization. It covers topics such as real-time remote health monitoring systems, IoT, wireless body sensor networks, length of stay (LOS), rapid emergency triage and treatment systems, data mining models, COVID-19, patient-focused displays, and a proposed triaging and prioritizing model.

This research utilizes a retrospective cohort design to develop and evaluate a priority algorithm for prioritizing severe patients in emergency departments (EDs). The methodology consists of several key steps: data collection, preprocessing, algorithm development, integration into the triage workflow, and evaluation of outcomes.

Data Collection: Historical patient data from ED visits will be collected, including demographics, vital signs, chief complaints, diagnostic codes, treatments, and outcomes. This dataset will serve as the foundation for algorithm development and analysis.

Preprocessing: After collecting all patient data. Convert the unsorted data of patients into preprocessed data for further processes.

Algorithm Development: Machine learning techniques will be employed to develop the priority algorithm. The dataset will be preprocessed to clean and normalize the data, and relevant features will be selected based on their predictive value for patient acuity and resource needs. Various machine learning algorithms, such as decision trees, logistic regression, or neural networks, will be trained and tested using appropriate evaluation metrics. The algorithm will undergo multiple iterations and refinements based on feedback from healthcare professionals and stakeholders to ensure its accuracy and clinical relevance.

Integration into Triage Workflow: Once the algorithm is developed, it will be integrated into the existing ED triage workflow. A user-friendly interface will be designed to facilitate data input by triage nurses or providers. Real-time decision support will be provided by the algorithm, assisting in the identification and prioritization of severe cases. The interface will display the algorithm's recommendations to aid triage personnel in making timely and informed decisions.

Evaluation of Outcomes: The algorithm's performance will be evaluated using various metrics, including sensitivity, specificity, positive predictive value, and negative predictive value. These measures will assess the algorithm's accuracy in identifying severe cases. Additionally, the impact of the algorithm on patient outcomes, such as mortality rates, length of stay, and resource utilization, will be analyzed. Waiting times for severe patients will be compared before and after the implementation of the algorithm. Surveys or interviews may also be conducted with healthcare providers to assess their satisfaction and perceived benefits of the algorithm.

Ethical considerations, such as bias mitigation and transparency, will be integrated throughout the methodology to ensure the fairness and reliability of the algorithm. Collaboration with healthcare professionals and stakeholders will be ongoing, allowing for their input and feedback at various stages of the study. The methodology aims to provide a comprehensive evaluation of the priority algorithm and its potential to improve outcomes for severe patients in E.Ds.

Sr. No	Proposed model pseudocode	
1.	**Start**	Begin the triage and prioritization process.
2.	**Initializing Data**	Data of patients arrive at the emergency department and join a single queue.

3.	**Data Collection**	A healthcare professional collects data and initializes the assessment of each patient's condition upon arrival.
4.	**Urgency Determination**	The healthcare professional assigns an urgency level to each patient based on the severity of their condition.
5.	**Data Prioritization**	Patients are prioritized based on their urgency level, with the most critical cases receiving higher priority.
6.	**Queue Management**	Patients are organized in a single queue based on their assigned priority.
7.	**Treatment Process**	Patients are called in order of priority for further examination and treatment by medical staff.
8.	**Ongoing Monitoring**	Patients who are waiting for treatment are continuously monitored to ensure their condition does not deteriorate.
9.	**Treatment Completion**	Patients receive appropriate medical care and treatment based on their prioritization.
10.	**Discharge or Transfer**	Patients are either discharged from the emergency department or transferred to other departments or facilities for specialized care if needed.
11.	**End**	The triage and prioritization process concludes.

Table 2

Table 2 is showing the steps that are involved in the simulation of Optimizing Emergency Department Triage with Priority Algorithms

Pseudo Code of Optimizing Emergency Department Triage with Priority Algorithms: A Study on Prioritizing Severe Patients for Improved Outcomes

START

1. Initialize Data
    - Initializing data for the emergency department.
2. Data Collection:
    - Get the list of patients in the emergency department.
3. Data preprocessing
    - Convert the unsorted data of patients into preprocessed data.
4. Data prioritization
    - Calculate the ate priority score of the patients based on their severity
    - Add the patient into the priority queue with their high priority score.
        - For each patient in the sorted list referred to the relevant department.
5. Condition
    - If(patient==high priority)
      {
      Referred to ED.
      }
    - If(patient!=high priority)
      {
      Repeat step 4.

}
- Else
{
The entered value is invalid.
}
6. Return the prioritized patient list.

END

Patient No.	Triage Level based on (RETTS-A) triaging algorithm	Waiting Time-based on Benchmark [9] (Mins)	Waiting Time Benchmark [10] (Mins)	Waiting for Time-based on TPM Algorithm (Mins)	Δ 1 (Mins)	Δ 2 (Mins)
1	Danger	5	5	5	0	0
2	Danger	10	10	10	0	0
3	Danger	15	15	15	0	0
4	Danger	20	20	20	0	0
5	Critical	25	25	5	-20	-20
6	Critical	30	30	10	-20	-20
7	Critical	35	35	15	-20	-20
8	Critical	40	40	20	-20	-20
9	Critical	45	45	25	-20	-20
10	Critical	50	50	30	-20	-20
11	Critical	50	55	35	-20	-20
12	Ailing	65	60	5	-55	-55
13	Ailing	65	65	10	-55	-55
14	Ailing	70	70	15	-55	-55
15	Ailing	75	75	20	-55	-55
16	Ailing	80	80	25	-55	-55
17	Low Priority	85	85	30	-55	-55
18	Low Priority	90	90	2	-88	-88
19	Danger	100	95	2	-99	-99
20	Danger	95	100	4	-96	-96
21	Ailing	105	105	35	-70	-70
22	Ailing	110	110	40	-70	-70
23	Ailing	115	115	45	-70	-70
24	Critical	120	120	40	-80	-80
			Last 24 patients			
556	Low Priority	2499	2502	134	-2368	-2365
557	Ailing	2501	2504	1170	-1334	-1331

558	Ailing	2503	2506	1175	-1331	-1328
559	Low Priority	2505	2508	136	-2372	-2369
560	Low Priority	2507	2510	138	-2372	-2443
561	Average	2509	2512	66	-2446	-2443
562	Average	2511	2514	68	-2446	-2443
563	Average	2513	2516	70	-2446	-2443
564	Average	2515	2518	72	-2446	-2443
565	Average	2517	2520	74	-2446	-1339
566	Ailing	2519	2522	1180	-1342	-1766
567	Critical	2521	2524	755	-1769	-2143
568	Danger	2523	2526	380	-2146	-2449
569	Average	2525	2528	76	-2452	-2449
570	Average	2527	2530	78	-2452	-2449
571	Average	2529	2532	80	-2452	-2449
572	Average	2531	2534	82	-2452	-2449
573	Average	2533	2536	84	-2452	-2449
574	Average	2535	2538	86	-2452	-2449
575	Average	2537	2540	88	-2452	-2449
576	Average	2539	2542	90	-2452	-2449
577	Average	2541	2544	1185	-1359	-1356
578	Ailing	2543	2546	760	-1786	-1783
579	Critical	2545	2548	385	-2163	-2160
580	Danger	2547	2550	256	-1586	-2160

Table 1

The outcomes of the Benchmark research and TPM factual computation of waiting times for the patients from 1-24.

Simulation Time (Mins)	**Benchmark [10]**						**Propose model TPM**					
	Danger	**Critical**	**Ailing**	**Low Priority**	**Average**	**Number of patients**	**Danger**	**Critical**	**Ailing**	**Low Priority**	**Average**	**Number of patients**
30	**4**	**2**	**0**	**0**	**0**	**6**	**4**	**6**	**0**	**0**	**0**	**10**
60	**4**	**7**	**1**	**0**	**0**	**12**	**4**	**10**	**11**	**2**	**1**	**28**
90	**4**	**7**	**6**	**0**	**1**	**18**	**8**	**14**	**16**	**3**	**4**	**45**
120	**4**	**8**	**9**	**2**	**1**	**24**	**9**	**19**	**22**	**5**	**5**	**60**
150	**4**	**10**	**13**	**2**	**1**	**30**	**11**	**23**	**28**	**5**	**6**	**73**
180	**7**	**12**	**13**	**2**	**3**	**36**	**11**	**25**	**34**	**6**	**7**	**83**
240	**8**	**14**	**18**	**3**	**4**	**48**	**13**	**32**	**46**	**8**	**7**	**106**
300	**9**	**19**	**23**	**4**	**5**	**60**	**25**	**51**	**58**	**8**	**7**	**140**

600	17	38	51	7	10	121	34	78	117	71	45	354
1185	31	71	115	19	26	264	60	143	279	52	46	580

Table 2

Comparison of the TPM's performance to the benchmark in terms of the patients served per unit of time.

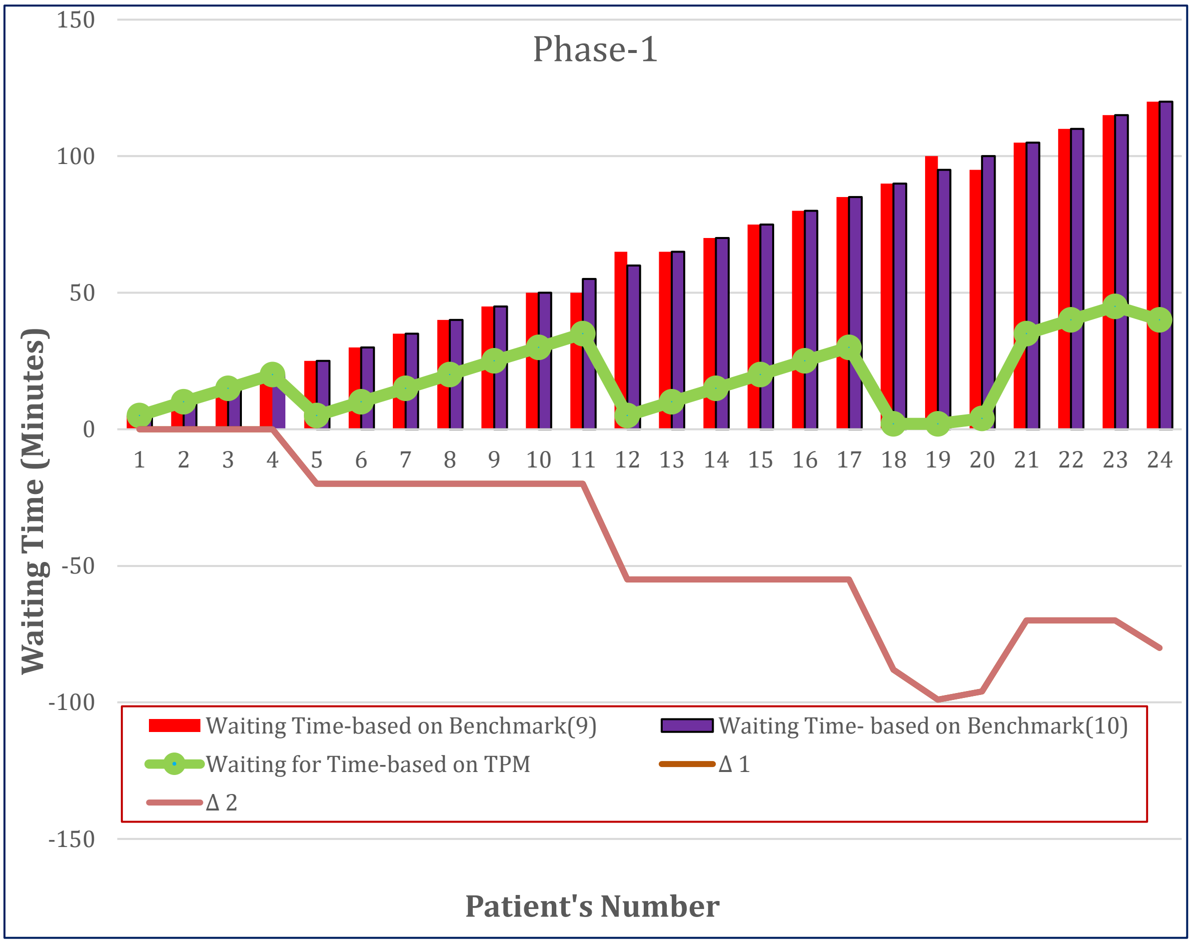

Fig. 2.

Differentiating the suggested algorithm's Waiting Time Rate (TPM) from the Benchmark algorithms [9] and [10].

The TPM results of the waiting time are compared with two benchmark studies in the graph in Fig. 2. The triage level based on (RETTS-A) prioritization algorithms rank the patients according to the Patient Condition value [10] whereas the decision matrix prioritizes the patients using a multi-criteria integrated decision-making algorithm [9]. The findings reveal a steadily rising waiting time that reaches statistically significant levels. For instance, patient number 19 must wait 100 minutes (nearly two hours) because he is a "Danger" (according to the triage level). The patients in the telemedicine system may pass away as a result of this prolonged waiting period. However, based on the TPM, the waiting time is only 2 min, as shown in Fig. 2, which demonstrates the results for the first 24 patients. In Table 1, the outcomes for all patients are presented.

TPM and benchmarks both have waiting time values of $\Delta 1$ and $\Delta 2$ that are zero for the first 4 patients before the values of 1 and 2 gradually start to rise. Higher 1, and 2 numbers signify more discrepancies between TPM and standards. The timing differences in (1 or 2) show how our server's scalability has improved when handling lots of requests (patients). As a result, Table 1 illustrates a sample of the results for the first 24 patients, including the patient's sequence, triage level (based on the RETTS-A triage algorithm), and levels 1, 2, and 3. The waiting time for the last patient (whose number is 580) exceeded 2550 minutes, according to the benchmarks' performance. As a result, this patient will have to wait approximately 41 hours to obtain the services, which is a serious problem regardless of the patient's location, whether they are in a remote area or an emergency department. The TPM data, on the other hand, indicate that the maximum response time is less than 800 minutes. The final patient will have to wait for 256 minutes or about 4.3 hours.

As a result, these data demonstrate that our suggested model TPM outperformed the benchmark [9, 10]. The waiting time values in the benchmarks [9, 10] are the same. As a result, neither benchmark significantly reduces the waiting time, nor does both have the same limitations. As depicted in Fig. 2, the TPM's implementation, in contrast, achieves a superior reduction in waiting time. All patients' waiting time values proved that the two benchmark approaches [9, 10] have the same values and patterns as those displayed in Fig. 2 and Table 1. This result is mathematical proof that neither algorithm specifically addresses patient prioritization as a process. They participate in a process that combines patient triaging with contributions to the prioritization algorithms. As a result, one of these pertinent methods might be chosen to serve as the standard for assessing the following results. Benchmark [10] was chosen because, based on specific considerations, the computational findings in this study demonstrated significantly better scalable performance than [9], but the patients' waiting time was not taken into account.

4 Conclusion

This systematic review has examined the use of Genetic Algorithm (GA) in enhancing educational performance prediction using machine learning algorithms. Through an extensive analysis of the literature, we have identified the key findings and limitations of existing studies in this field.

The findings indicate that GA has shown promising results in educational performance prediction by extracting patterns and relationships from large datasets of student records, demographic information, and academic performance indicators. Its ability to identify complex patterns and optimize the selection of input features and model parameters has contributed to improved accuracy, scalability, and efficiency in predicting student success and identifying at-risk students.

Overall, this review highlights the potential of Genetic Algorithm in enhancing educational performance prediction using machine learning algorithms. By leveraging the power of GA and considering its limitations, researchers and practitioners can make informed decisions in developing effective prediction models that contribute to student success and educational improvement.

The collective insights from the reviewed literature underscore the significance of Genetic Algorithm (GA) in enhancing educational performance prediction using machine learning algorithms. The diverse range of studies examined in this review demonstrates the widespread interest and research efforts dedicated to this field. The findings suggest that GA offers valuable opportunities for accurately predicting student performance, identifying at-risk students, and facilitating timely interventions to improve academic outcomes. The limitations identified in the literature highlight the need for further research, including investigations into different machine learning algorithms, educational contexts, and ethical considerations. By addressing these limitations and building upon the existing body of knowledge, educators and policymakers can harness the power of GA to create effective and tailored interventions that support student success and advance educational practices.

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