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# Enhancing Patient Flow in Emergency Departments: A Machine Learning and Simulation-Based Resource Scheduling Approach

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**Abstract:** The efficient scheduling of resources within emergency departments (EDs) is crucial to minimizing patient length of stay (LoS) times and maximizing the utilization of limited resources. Reducing patient wait times can enhance the operation of emergency departments and improve patient satisfaction and the quality of medical care. This study develops a simulation model using Discrete Event Simulation (DES) methodology, examining six resource scheduling policies that consider different combinations of general and senior physicians. By leveraging six scheduling policies and machine learning techniques, this model dynamically identifies the most effective scheduling policy, based on a comprehensive dataset of ED visits in South Korea. The ED simulation achieves an accuracy rate of 90% and demonstrates that our proposed integrated machine learning approach reduces average length of stay (LoS) to approximately 322.91 min, compared to 327.10 min under traditional methods. This study underscores the potential of integrating DES and machine learning to enhance resource management in EDs.

**Keywords:** emergency department; resource scheduling; simulation; machine learning



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## 1. Introduction

Emergency Departments (EDs) play a pivotal role in enhancing the quality of healthcare services within hospitals [1,2]. However, effectively allocating essential resources such as doctors, nurses, and equipment in the unpredictable and often chaotic environment of overcrowded EDs remains a complex challenge [3]. Traditional mathematical approaches often fall short in dynamically describing the relationships among resources and adapting to changes, making them a major cause of extended patient resident time (length of stay: LoS) [4–6].

Patient wait time and LoS are critically important in urgent medical situations, such as surgeries [7,8], and are influenced by various factors including treatment time, hospitalization duration, and decision-making processes [9]. The LoS to receive treatment directly impacts the overall duration of their stay in the ED: the shorter the wait times, the shorter the total stay [10,11]. Thus, there is a demand for scheduling strategies that can effectively reduce LoS.

Simulation has proven to be an effective tool for improving complex systems such as medical processes and EDs, effectively addressing the challenges of resource management and irregular patient arrivals [12–14]. Research predominantly focuses on utilizing Discrete Event Simulation (DES) and advances in the field of data science [6,15–18]. Most studies aim to strategically determine how many additional resources are needed to alleviate the bottlenecks caused by patient congestion [19,20]. However, realistically, increasing resources is challenging due to financial constraints [21], necessitating research focused on optimizing existing personnel and equipment resources. Studies on constrained resource scenarios are increasingly focusing on personnel resource scheduling [22].

Research on scheduling medical staff in EDs remains limited. This study emphasizes utilizing existing physician resources to address scheduling challenges. Moreover, traditional resource scheduling often relies on seasonal or past data [23], which is insufficient due to the unpredictable nature of patient demand. Therefore, flexible research that considers real-time ED conditions is required. Differences in physicians' experience can influence treatment times, offering a potential to reduce wait times. Consequently, a resource scheduling approach based on the sudden influx of patients and the varying experience of physicians is needed. Moreover, optimizing scheduling requires machine learning-based strategies that utilize data from randomly arriving patients.

This research aims to develop a real-time resource utilization scheduling method based on admissions, patient, and physician information within the ED environment, and to build a simulation model that is applicable to various studies. The objectives include: developing an ED simulation using DES, providing six scheduling policies based on physician experience, and employing machine learning to select the most appropriate scheduling policy. This study aims to develop a generic simulation model that can be applied not just to specific hospitals but across various reusable systems [24]. Using comprehensive ED visit data from the Korean National Emergency Department Information System (NEDIS), we design and conduct experiments to validate our model, ultimately facilitating optimal scheduling policy that improves the LoS.

LoSs are a critical factor directly influencing the quality and efficiency of healthcare services. Shorter wait times are correlated with enhanced patient satisfaction and improved treatment outcomes, positively impacting key healthcare quality indicators. These indicators include patient satisfaction, treatment outcomes, and rates of readmission, all of which tend to improve as wait times decrease. Additionally, efficiency metrics such as medical staff productivity, patient processing time, and resource utilization also benefit from reduced wait times, thereby enhancing the overall operational efficiency of healthcare systems [7,9,10,14].

This analysis underscores the significant role that resource scheduling plays in reducing LoS and thereby improving healthcare quality and efficiency. By developing effective scheduling strategies that consider real-time conditions and physician expertise, this study aims to demonstrate how optimized resource allocation can directly contribute to improved healthcare outcomes.

The structure of this study is as follows: Section 2 describes the related works. Section 3 describes the materials and methods. Section 4 describes the results. Section 5 provides a discussion. Finally, Section 6 presents the conclusion.

## 2. Related Works

In this section, we explore existing literature on LoS and resource scheduling in EDs. Our analysis emphasizes how different studies approach performance metrics and crucial operational factors such as nonstationary demand, patient return visits, patient number control, and resource allocation scheduling. A summary of these studies is presented in Table 1, detailing their methodologies and focus areas.

**Table 1.** Related Works.

| Research | Performance Metrics | Nonstationary Demand | Patient Return | Patient Number Control | Allocation Scheduling |
|---|---|---|---|---|---|
| Green et al. (2006) [23] | Patient's abandonment ratio | N | N | N | N |
| Izady et al. (2012) [25] | Offered load | Y | N | N | Y |
| Ganguly et al. (2014) [26] | Service level of patients | N | N | N | Y |
| Ahmed et al. (2009) [27] | Average patient waiting time | Y | Y | N | N |
| Marchesi et al. (2020) [28] | Patient waiting time | Y | N | N | N |
| Lee et al. (2020) [29] | Patient waiting time | Y | N | Y | Y |
| Nidal et al. (2021) [24] | LoS | Y | N | Y | N |

**Table 1.** *Cont.*

| Research | Performance Metrics | Nonstationary Demand | Patient Return | Patient Number Control | Allocation Scheduling |
|---|---|---|---|---|---|
| Zaerpour et al. (2022) [30] | Divergence between the physician's service productivity and the patient's demands | Y | N | N | Y |
| Liu et al. (2023) [31] | Patient waiting time | Y | N | Y | Y |
| Wang et al. (2023) [32] | LoS | Y | Y | N | N |
| Ran et al. (2024) [33] | Patient queue length | Y | Y | Y | N |

Green et al. (2006) [23] examined the patient abandonment ratio without addressing nonstationary demand, patient returns, patient number control, or allocation scheduling. Their study focuses solely on how often patients leave the ED without being seen. Izady et al. (2012) [25] measured the offered load, acknowledging nonstationary demand and incorporating allocation scheduling, but did not consider patient returns or patient number control. Ganguly et al. (2014) [26] used service level of patients as their performance metric and included allocation scheduling, yet did not account for nonstationary demand, patient returns, or patient number control. Ahmed et al. (2009) [27] and Marchesi et al. (2020) [28] both used patient waiting time as their primary performance metric. Ahmed et al. considered both nonstationary demand and patient returns but did not include allocation scheduling or patient number control, whereas Marchesi et al. focused only on nonstationary demand without considering other factors. Lee et al. (2020) [29], Nidal et al. (2021) [24], and Liu et al. (2023) [31] all assessed patient waiting time, with Lee and Liu including nonstationary demand, patient returns, and allocation scheduling in their methodologies. Nidal et al. considered nonstationary demand and patient returns but did not integrate allocation scheduling. Zaerpour et al. (2022) [30] and Wang et al. (2023) [32] analyzed the divergence between the physician's service productivity and patient demands and total patient waiting time, respectively, with both acknowledging nonstationary demand. Zaerpour included allocation scheduling, but Wang did not, and neither study addressed patient returns or patient number control. Ran et al. (2024) [33] focused on patient queue length and was one of the few studies to address all indicators, including nonstationary demand, patient returns, and patient number control, although without incorporating allocation scheduling.

This comprehensive examination highlights the critical role of advanced scheduling techniques, especially online allocation scheduling, in adapting to fluctuating demands and optimizing resource allocation. Building on these findings, our research aims to address existing gaps by integrating machine learning to enhance responsiveness and operational efficiency in EDs, ultimately reducing LoS across varied demand scenarios.

## 3. Materials and Methods

### 3.1. Study Design

The study design for building an ED simulation system consists of several essential components: requirements analysis, hybrid simulation modeling, and experimental analysis, as illustrated in Figure 1. This study design is grounded in the concept of hybrid simulation, integrating different simulation methodologies to capture the complexities of ED operations [34].

- Designing Simulation Process

The initial phase involves tailoring the simulation process to meet the specific operational needs of the ED. This stage includes defining key concepts and identifying the main components of the ED system, such as patient intake, treatment processes, and resource allocation. By employing Discrete Event Simulation (DES) and Agent-Based Simulation (ABS), we can model the actual operations and patient flows within the ED with high accuracy, ensuring that the simulation reflects real-world conditions.

- Establishing Scheduling Policy

The second phase focuses on developing robust scheduling policies that are critical for optimizing ED operations. These policies consider real-time conditions such as patient influx and staff availability, and they are designed to be adaptable to dynamic changes within the ED. Our aim is to minimize LoS time by implementing effective and flexible scheduling strategies that can respond promptly to varying operational demands.

- Integrating Machine Learning Models

In the third phase, machine learning models are integrated into our scheduling strategies to handle the variability in patient influx and physician availability. We develop multiple strategies tailored to different scenarios, utilizing machine learning algorithms to optimize these strategies for enhanced operational efficiency and responsiveness in the ED setting.

- Experimentation and Evaluation

The final phase of our study involves experimentation and evaluation of the proposed scheduling strategies. By simulating various scenarios, we assess the impact of different strategies on reducing LoS, a critical issue in ED management. This iterative process not only refines our theoretical concepts but also supports the development of adaptable systems that can be implemented across various ED settings. Through continuous improvement and rigorous testing, our framework not only enhances the functionality of ED systems but also improves overall LoS and healthcare provider efficiency.

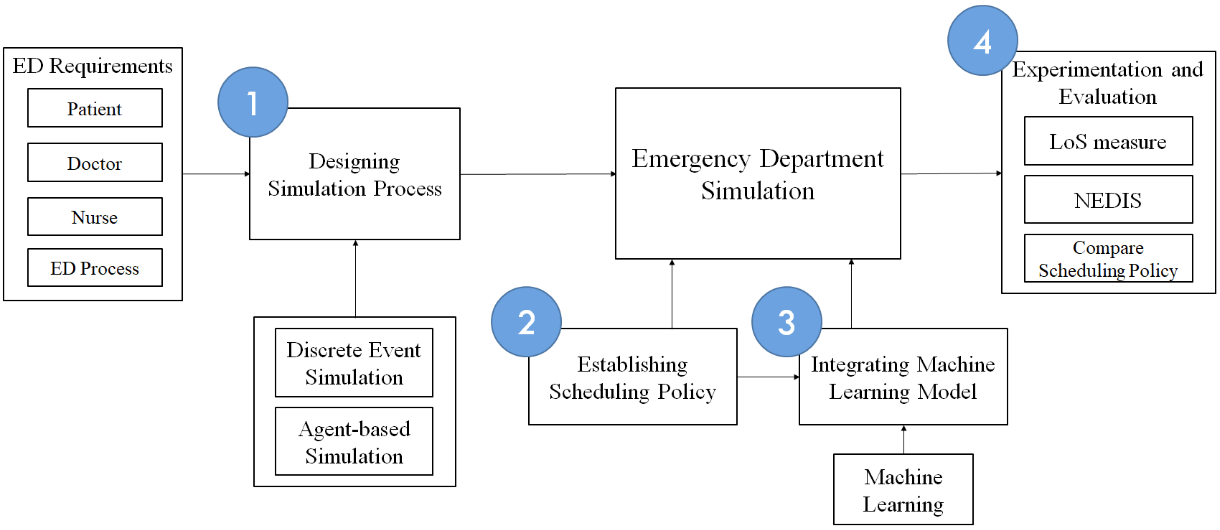


**Figure 1.** Study design.

### 3.2. Design Simulation Process

In this study, LoS includes patients admitted after emergency treatment and patients who were not hospitalized. LoS time includes not only the interval from patient arrival at the emergency department (ED) to receiving treatment but also additional time spent post-treatment. This definition allows for an extensive analysis of LoS times across various patient scenarios, facilitating a holistic understanding of resource scheduling and patient experiences in the ED.

- Patient Flow and Resource Utilization

The patient flow in the ED, as illustrated in Figure 2, involves a detailed analysis of the utilization of key resources such as nurses, technicians, physicians, beds, ultrasound, X-ray, and treatment rooms. This process is based on general ED processes that have been previously researched and refined rather than being specific to the scheduling for any particular emergency department [24,31].

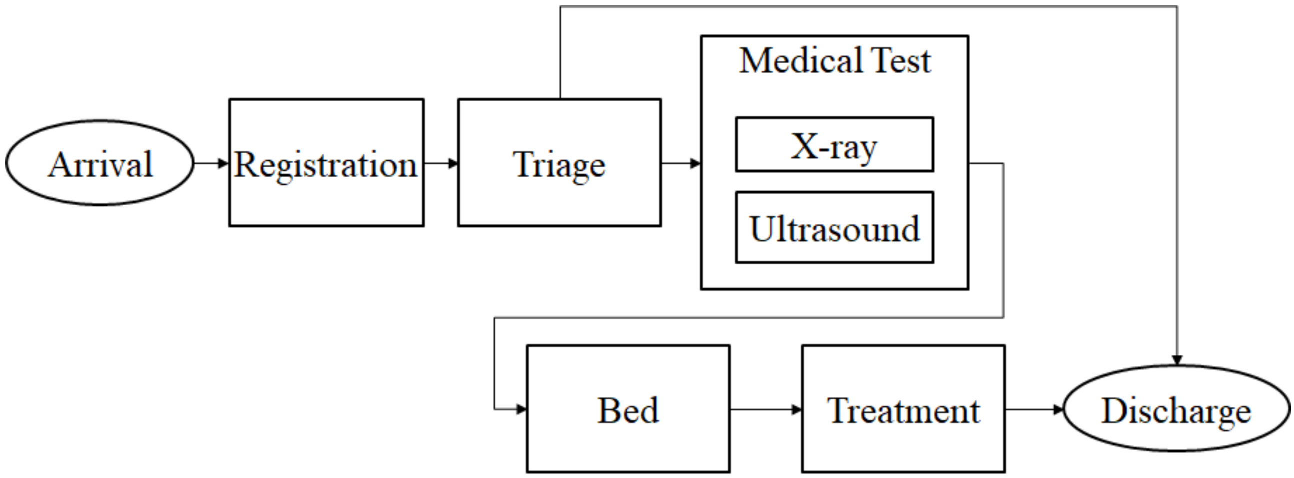


**Figure 2.** Patient flow in the ED.

- Simulation Scenario

Upon arrival at the hospital, patients are registered. Their arrival methods can vary, including direct walk-ins, ambulance transport, and others. As the initial step, nurses conduct triage based on the severity of the patients' conditions, as referenced in [35]. After classification, patients are divided into three groups according to their severity levels. Those with more severe conditions require longer treatment times and are prioritized accordingly. Patients then wait in the waiting room until they are called. The physicians are categorized into two types: regular and senior, each associated with different treatment times. This classification aids in aligning treatment capabilities with patient needs. The treatment process requires various resources, including medical personnel and equipment within the treatment room. Each resource is designated for specific tasks, reflecting the operational complexities of the ED. This simulation acknowledges the challenge of accurately modeling every aspect of the ED due to the inherent differences between theoretical models and real-world conditions.

- Simulation Modeling

We employ both Agent-Based Simulation (ABS) and Discrete Event Simulation (DES) to model the operations of the ED. The detailed components of the processes and agents constituting the simulation are presented in Table 2. DES analyzes the orderly operational flows such as patient arrivals, registration, triage, and treatment from a management perspective, allowing for an efficient layout of ED processes. ABS, on the other hand, captures the behaviors and interactions of individual agents (patients, medical staff) within the system. This dual approach enables us to address the dynamics of ED operations comprehensively.

**Table 2.** Simulation process and agent.

| Type | Entity | Script |
|---|---|---|
| Process (Block) | Arrivals | Patients randomly visit the ED |
| | Registration | Patient registration |
| | Triage | Classification by KTAS level according to patient severity |
| | Wait | Patient waiting after registration. After triage, the patient waits before receiving treatment. |
| | Medical test | Medical tests such as X-ray and ultrasound are performed. |
| | Bed | A bed for patients to receive treatment. Time required varies depending on severity. |
| | Treatment | A doctor provides treatment to a patient. Treatment time varies depending on the doctor's experience. |
| | Discharge | Patient leaves the ED |

**Table 2.** *Cont.*

| Type | Entity | Script |
| --- | --- | --- |
| Agent (Actor) | Patient | Patients using the ED |
| | Nurse | Registration, triage, and guiding the patient to the bed |
| | General and Senior Doctor | Treating the patient. Treatment time varies depending on the doctor's experience. |

### 3.3. Establishing Scheduling Policy

In EDs, the scheduling policy is designed to allocate physicians based on the patients' condition severity, reflecting the current dynamics within the ED. The primary goal of these policies is to minimize LoS times. Severity assessment is conducted using the Korean Triage and Acuity Scale (KTAS), which is an adaptation of the Canadian Triage and Acuity Scale (CTAS) specifically tailored to fit the healthcare context in Korea. KTAS categorizes patients into five levels based on their symptoms, where a higher severity score indicates a need for longer treatment times and prioritizes patients with more severe conditions.

- Resource Scheduling Policy

Scheduling in EDs is structured around six scenarios, differentiated by three scheduling methods that distinguish between general physicians and senior physicians [31]. These scenarios are designed to ensure that physicians are matched with patients according to the severity of the medical cases they are best equipped to handle. Treatment durations are adjusted based on the capacity and specialty of the physicians. The main scheduling strategies include:

1. First In First Out (FIFO): Patients are attended to on a first-come, first-served basis.
2. Shortest Remaining Processing Time (SRPT): Prioritizes patients based on the estimated time remaining for their treatment. This strategy aims to reduce waiting times by managing treatment flows more efficiently.
3. Critical Ratio (CR): This approach prioritizes patients based on the criticality of their conditions.

- Detailed Scheduling Policy

The resource scheduling policies in our EDs are designed to optimize the allocation of physicians and manage patient flows efficiently. These strategies are implemented through a structured approach that considers both the severity of the patient's condition and the specific expertise of our medical staff. Here is a detailed breakdown of the six scenarios under our three main scheduling strategies:

4. FIFO (Random): Under this strategy, patients are seen as they arrive, regardless of their condition severity. This scenario uses a random assignment where any available doctor, whether general or senior, may attend to the patient. This method is simple and ensures that everyone is treated without unnecessary delay.
5. FIFO (Centroid): This variation refines the FIFO approach by assigning patients based on the severity of their conditions. General physicians handle less severe cases, optimizing their quicker treatment times, while senior physicians take on more severe cases, leveraging their advanced expertise.
6. SRPT (General First): This strategy focuses on reducing overall waiting times by assigning general physicians to patients whose treatments can be completed quickly, thus clearing cases efficiently.
7. SRPT (Senior First): Similarly, senior physicians are assigned to less severe cases that can be quickly resolved, ensuring that their skills are used effectively to minimize the impact on the ED's flow.
8. CR (General First): General physicians are prioritized to treat the most severe cases they are qualified to handle, ensuring that critical patients receive immediate care.
9. CR (Senior First): The most critical patients are reserved for senior physicians, who are most capable of addressing complex and urgent medical needs quickly.

To better illustrate how each of these strategies is applied within our ED, Table 3 provides a clear, structured overview of the process and priorities assigned to each scheduling method:

**Table 3.** Resource Scheduling Policy.

| No. | Strategy | Priority | Script |
|---|---|---|---|
| 1 | FIFO (Random) | Random | Any available doctor can be assigned to incoming patients. |
| 2 | FIFO (Centroid) | Severity-based | General doctors for less severe, senior doctors for more severe cases. |
| 3 | SRPT (General First) | Efficiency | General doctors handle cases that can be completed quickly. |
| 4 | SRPT (Senior First) | Efficiency | Senior doctors handle quickly resolvable, less severe cases. |
| 5 | CR (General First) | Criticality | General physicians are first assigned to the most severe cases they can manage. |
| 6 | CR (Senior First) | Criticality | Senior doctors prioritize the most critical patients. |

*3.4. Integrating Machine Learning Model*

In EDs, the dynamic nature of patient influx and medical conditions requires a flexible and responsive scheduling policy. Traditional scheduling policies, while effective under consistent conditions, often struggle to adapt in real time to sudden changes in patient severity and volume. To address these limitations, we integrate ML models that analyze real-time data to select the most effective scheduling strategy dynamically. Figure 3 illustrates the workflow of our ML model, detailing how data flow from collection through to decision-making.

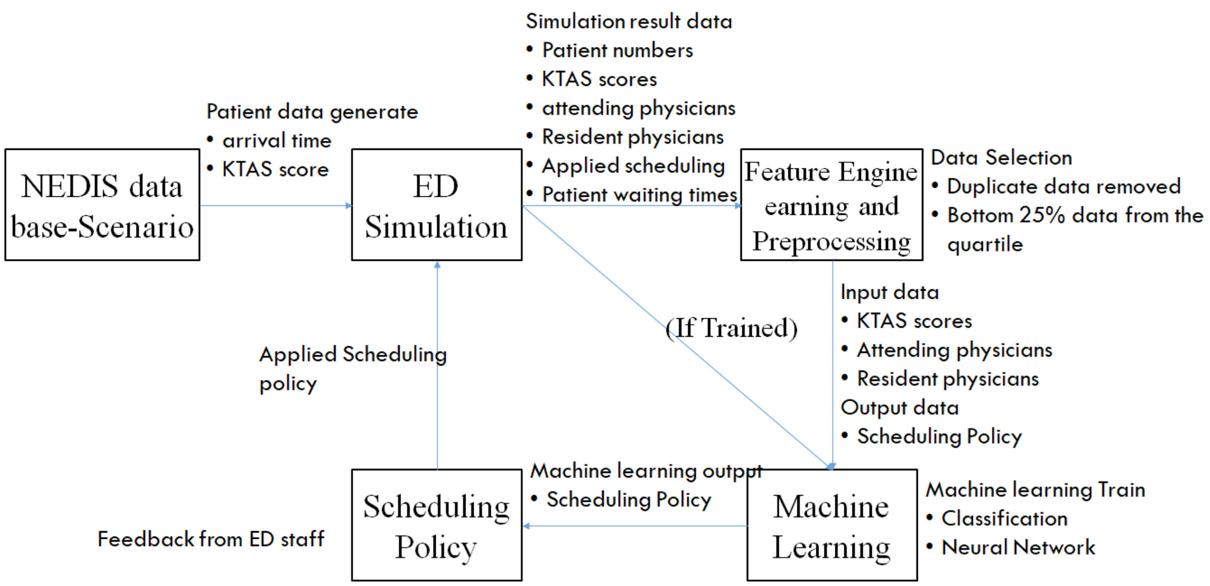


**Figure 3.** Machine Learning Workflow.

- Data generation and collection

The data are based on the National Emergency Department Information System (NEDIS) Emergency Medical Statistics Yearbook [35]. Data on visit records by hour and patient classification by KTAS are used for tree regions. A total of 9 scenarios are determined, each with different ED entry times, KTAS scores, and compositions of attending and resident physicians. Data are generated when a scenario is entered into ED simulation. Through simulation results, a model is created to provide scheduling strategies tailored to the situation. Data generated from ED simulation results are used at three-hour intervals out of 24 h. They utilize the number of patients waiting after triage and the number of attending and resident physicians. Scheduling is applied to data for each scenario, and data with minimal waiting times are utilized. Input data include the total number of patients waiting, the number of queues by severity, and the current availability of interns and attending physicians, while output data represent the respective scheduling strategy.

- Feature Engineering and Preprocessing

We enhance our model's accuracy by developing features that capture the complexities of ED operations, such as peak times, common types of emergencies during specific periods, and average wait times per severity level. These features help the model to predict scheduling needs more precisely. Data include the total number of patients, the number of queues by severity, and the current availability of interns and attending physicians, while output data represent the respective scheduling policy. Only data with low waiting times are used for training. Low waiting times comprise the bottom 25% of data from the quartile. Duplicate data are removed.

- Model Selection and Training

We employ the Backpropagation Algorithm within an Artificial Neural Network due to its efficacy in handling nonlinear data and its ability to learn from complex patterns. This model is trained on historical data from NEDIS, focusing on scenarios that align with current operational challenges. We choose models based on their performance metrics, including accuracy, precision, and recall, ensuring that they meet the high standards required for medical applications.

- Model Application

The trained model runs continuously, analyzing data every three hours to adjust scheduling policies accordingly. It considers various factors such as current patient queues, severity distributions, and available medical staff. By doing so, it dynamically selects from six predefined scheduling policies (e.g., FIFO, SRPT, CR) the one that best fits the current situation.

- Future Enhancements

We regularly assess the model's impact on ED operations by monitoring changes in patient wait times, resident times, and staff utilization rates. This is a process to check whether LoS has been reduced by measuring the resident time after the patient leaves the room, and through this, the database is reconstructed.

This adaptive approach ensures that our ED operates efficiently, with reduced waiting times and improved patient outcomes, demonstrating the practical benefits of machine learning in critical healthcare settings.

## 4. Results

EDs are challenging environments that must rapidly address a variety of patient conditions and urgent medical needs. This study evaluates the impact of patient KTAS levels and physician experience on the efficiency of medical treatment and LoS and proposes effective scheduling policies based on these findings. When implemented in actual ED settings, these policies can optimize the use of medical resources and reduce patient LoS times, thereby improving the quality of emergency medical services [7,8]. We describe the scenario, the results of the proposed machine learning model, and finally, the simulation results.

The purpose of the experiment is twofold. The first objective is to evaluate whether the ED simulation can measure LoS. The second objective is to assess whether a machine learning-based scheduling policy model can reduce LoS.

The experiments execution utilizes Anylogic 8.8.4 software. The desktop employed for the experiments features an AMD Ryzen 9 3900X 3.80 GHz processor and 32.0 GB of RAM. Data preprocessing and machine learning tasks utilize the Classification model in SPSS Clementine 11.1. Simulation and machine learning tasks are performed using separate software, and the approach involves checking data during simulation execution and inputting inferred values from machine learning into the simulation.

### 4.1. Scenario Discription

- Simulation flow and parameters

The scenario is as follows: Patients of varying severity levels visit the ED for treatment. Nurses classify the patients' condition into three levels based on the KTAS (1, 2; 3; 4, 5). All patients undergo a similar treatment process. Depending on their severity, patients receive medical tests (ultrasound/X-ray) before seeing a doctor. There are three treatment rooms tailored to the severity of the patients' conditions. After triage, nurses transfer patients to the appropriate beds, and doctors provide the necessary treatment. Patients are discharged upon completion of their treatment. Parameters used in the simulation of the ED research are listed in Table 4, with settings based on average durations and references from existing studies.

**Table 4.** Simulation experiments parameters (T: Triangular) [36–39].

| Process | Actor | Duration (min) |
|---|---|---|
| Registration | Nurse | Triangular (3, 5, 10) |
| Triage | Nurse | Triangular (3, 7, 10) |
| Medical Test (X-ray, Ultrasound) | Technician | Normal (3, 15, 30) |
| Diagnosis | General Doctor | KTAS 1, 2: Triangular (8, 20, 30) |
| | | KTAS 3: Triangular (10, 25, 35) |
| | | KTAS 4, 5: Triangular (20, 35, 45) |
| | Senior Doctor | KTAS 1, 2: Triangular (5, 15, 25) |
| | | KTAS 3: Triangular (5, 20, 30) |
| | | KTAS 4, 5: Triangular (15, 30, 40) |
| Bed | Patient | KTAS 1, 2: Triangular (480, 600, 720) |
| | | KTAS 3: Triangular (240, 360, 480) |
| | | KTAS 4, 5: Triangular (60, 120, 240) |

- Patient arrival scenario

Experimental analysis is based on the 2022 NEDIS Emergency Medical Statistics Yearbook, utilizing emergency department (ED) data from three regions within South Korea. NEDIS provides comprehensive statistical information on ED facilities, equipment, personnel, and training. It offers hourly patient admission times categorized by the Korean Triage and Acuity Scale (KTAS) and provides a year's worth of statistical data. However, simulating a full year would be too extensive, so daily admission rates are calculated instead. For each region, statistics for a single facility including medical staff, equipment, and facility capacity are used to estimate daily patient admissions. This approach allows for general application across various emergency departments, not just specific ones. Therefore, daily data from three regional EDs are used to construct the scenarios. These scenarios incorporate differences in patient arrival times, KTAS ratings, patient residence time, and medical staff availability across regions.

Ethical approval is not required for this study because the statistical data is publicly available.

The actual patient arrival data for the three regions of NEDIS are shown in Table 5. This is the average daily visit of patients recorded for one regional emergency center.

**Table 5.** Patient arrival data for the three regions of NEDIS (calculated for one day).

| Scenario | KTAS and Discharge | Patient Arrival (Number of Patient) | | | | | | | | | Resource | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Total | 0~3 | 3~6 | 6~9 | 9~12 | 12~15 | 15~18 | 18~21 | 21~24 | General Doctor | Senior Doctor | Nurse |
| A | Total | 105 | 10 | 6 | 9 | 17 | 16 | 16 | 16 | 15 | 7 | 6 | 32 |
| | KTAS 1, 2 | 8 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | | | |
| | KTAS 3 | 45 | 4 | 3 | 4 | 8 | 8 | 7 | 6 | 6 | | | |
| | KTAS 4, 5 | 52 | 5 | 3 | 4 | 7 | 7 | 7 | 9 | 9 | | | |
| B | Total | 99 | 8 | 5 | 8 | 17 | 16 | 16 | 15 | 14 | 5 | 4 | 23 |
| | KTAS 1, 2 | 11 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 1 | | | |
| | KTAS 3 | 60 | 4 | 3 | 5 | 11 | 11 | 10 | 9 | 7 | | | |
| | KTAS 4, 5 | 28 | 3 | 2 | 2 | 4 | 3 | 4 | 5 | 5 | | | |
| C | Total | 97 | 9 | 6 | 8 | 15 | 13 | 14 | 16 | 15 | 7 | 6 | 23 |
| | KTAS 1, 2 | 7 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | | | |
| | KTAS 3 | 41 | 4 | 3 | 4 | 7 | 6 | 6 | 6 | 6 | | | |
| | KTAS 4, 5 | 49 | 5 | 3 | 4 | 7 | 6 | 7 | 9 | 9 | | | |

### *4.2. Machine Learning Model Performance*

First, we generated simulation result data. For training, we obtained data by applying 6 scheduling algorithms to a total of 9 scenarios. Out of a total of 768 data generated from the simulation, we selected a final dataset of 192 with the lowest waiting times, which represents the top 25%. Some of the input and output data used for training are shown in Table 6.

**Table 6.** Learning dataset (simulation output data).

| Record | Queue | | | | | Doctor | | Scheduling Strategies |
|---|---|---|---|---|---|---|---|---|
| | | | | | | General | Senior | |
| 1 | 1 | 2 | 3 | 4 | 5 | 5 | 5 | 1 |
| 2 | 2 | 3 | 1 | 1 | 1 | 5 | 5 | 3 |
| 3 | 1 | 2 | 2 | 2 | 1 | 5 | 5 | 3 |
| | | | | ... | | | | |
| 192 | 2 | 2 | 2 | 1 | 3 | 4 | 6 | 6 |

Next, we proceed with training using a classification model. The algorithm employed is Backpropagation of the Neural Network (NN). The input layer consists of 7 nodes, with 1 hidden node and 1 output node. The training was executed 200 times, utilizing the sigmoid function as the activation function. For comparison of machine learning algorithms, we used Logistic Regression, C 5.0, and Naïve Bayesian. Machine learning performance evaluation was conducted using a 3-fold method on 192 data. The experimental results for the 4 machine learning algorithms and 192 data are shown in Figure 4. Performance evaluation was based on Sensitivity, Specificity, and Accuracy.

Sensitivity, Specificity, and Accuracy values recorded were above 93. While differences among experimental groups were not significant, the Neural Network exhibited the highest accuracy at 93.98%. The reason for insignificant differences among algorithms can be interpreted as most of the training data being biased toward specific scheduling policies, leading to the predominant usage of scheduling policies with superior performance. The most frequently used policy was CR (Senior First), followed by SRPT (General First) and CR (General First). In contrast, policies FIFO (Random), FIFO (Centroid), and SRPT (Senior First) were rarely used. Thus, it can be inferred that the performance of specific scheduling policies is better than using all policies.

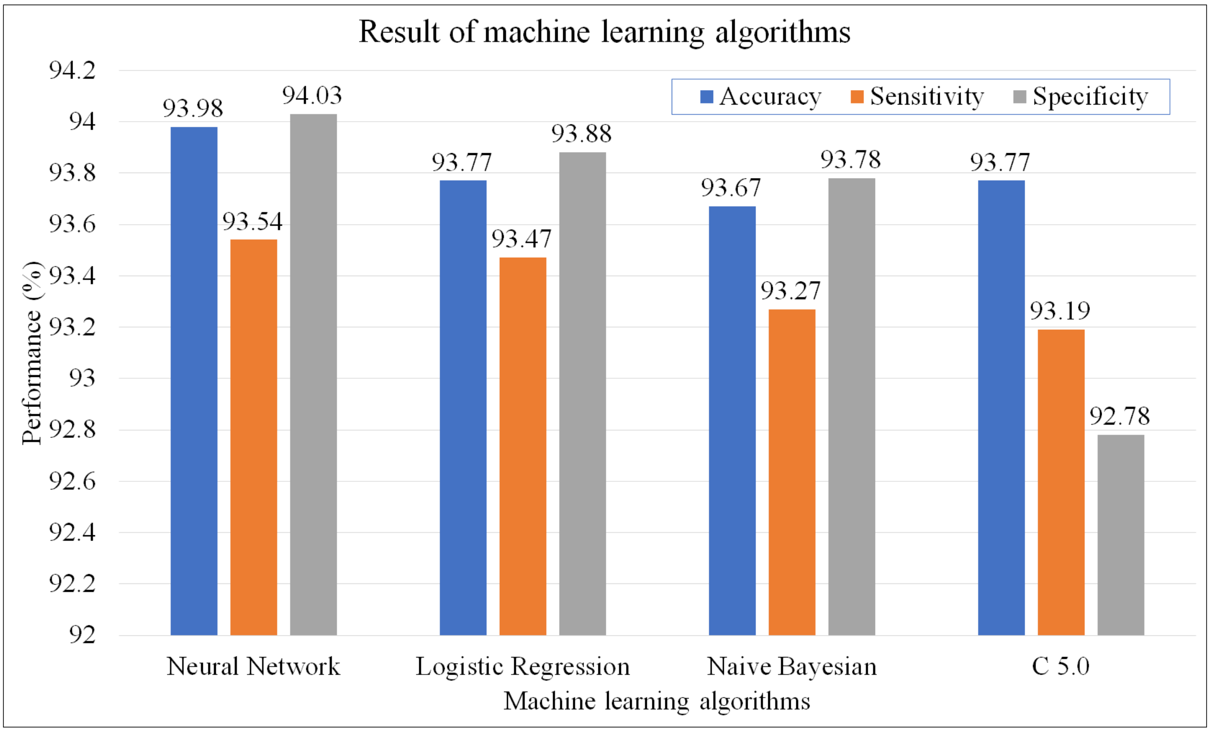


**Figure 4.** Result of machine learning algorithms (%).

### 4.3. Experimental Result

The experimental results aim to validate the effectiveness of the proposed machine learning-based scheduling policy in reducing LoS and improving the efficiency of ED operations. The experiments were conducted using real-world data obtained from the NEDIS and simulated scenarios based on different patient arrival patterns and severity levels (Table 5). The simulation was conducted 30 times for each region. The average of 30 results is used to reflect the results. Because the amplitude of LoS can be large depending on the individual patient, accurate measurement is difficult, so many measurements were performed.

#### 4.3.1. Comparison between Real Data and Simulation

The first experiment conducted assesses the difference in length of stay (LoS) between real operational data and simulated results across three distinct emergency department scenarios. The comparative analysis focuses on understanding how well different scheduling strategies perform in aligning simulated outcomes with real-world data. The experimental results are shown in Figure 5.

The current scenario includes all KTAS levels, thus showing a lower LoS. The real data show an average of 295.93 min, while the simulation results show a duration of 330.35 min. The final error is observed as an average of 10.41%, indicating an accuracy of 89.59%. Since the ED simulation shows a similarity of about 90%, it can be considered useful for simulations. In the case of Scenario A, the error rate is 9.46%, and because there are many low-severity patients and a large staff, the accuracy is higher. For Scenarios B and C, the error rates are 10.83% and 10.41%, respectively, showing that accuracy decreases when there are more high-severity patients.

The second experiment compares the results of the simulation with the actual data according to the KTAS of the actual data. It shows the results according to each KTAS in the three regions. The experimental results are shown in Table 7. This experiment inputs patients with the same severity. ED simulation measures the performance of predictions for each severity level.

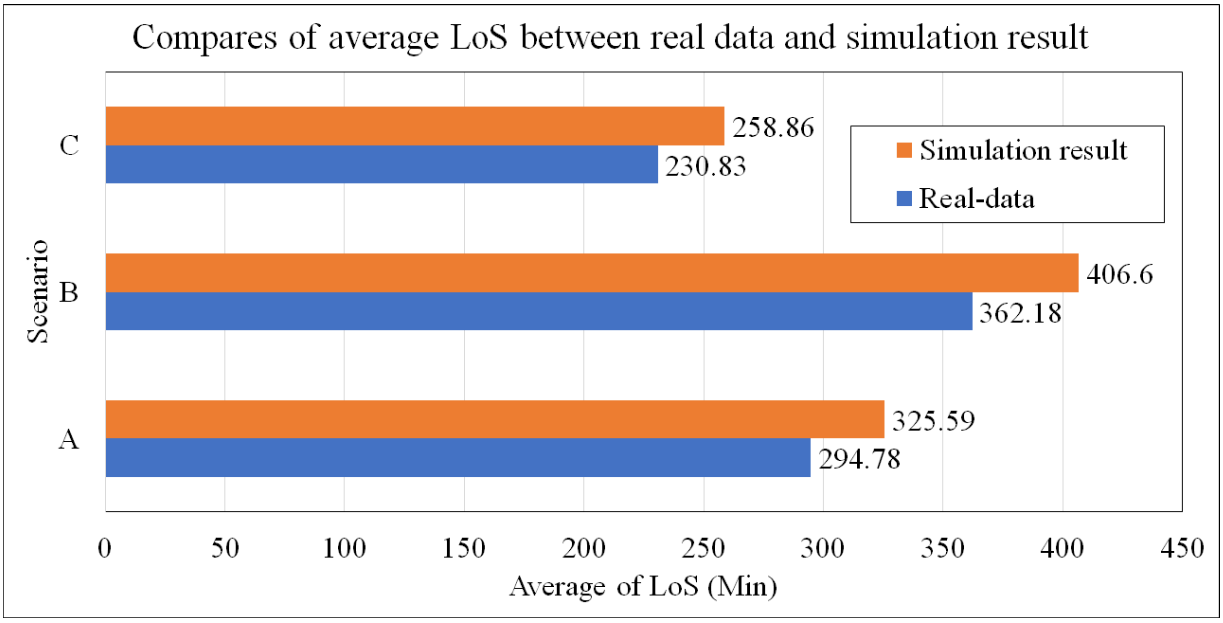


**Figure 5.** Compares of average LoS between real data and simulation result (min).

**Table 7.** Comparison of actual data and simulation data of KTAS.

| Scenario | KTAS Level | Real Data | Simulation Result | Accuracy |
|---|---|---|---|---|
| A | KTAS1 + 2 | 417.45 | 453.08 | 92.14% |
| | KTAS3 | 353.81 | 388.02 | 91.18% |
| | KTAS4 + 5 | 225.49 | 237.99 | 94.75% |
| B | KTAS1 + 2 | 463.62 | 498.30 | 93.04% |
| | KTAS3 | 404.75 | 439.40 | 92.11% |
| | KTAS4 + 5 | 231.02 | 244.32 | 94.56% |
| C | KTAS1 + 2 | 350.93 | 386.20 | 90.87% |
| | KTAS3 | 278.43 | 313.18 | 88.90% |
| | KTAS4 + 5 | 175.7 | 188.37 | 93.28% |

The experimental results showed a high accuracy of 92.31% overall. This is because patients with the same severity were entered. Scenario A: Revealed an accuracy ranging from 92.14% for KTAS levels 1 and 2, decreasing slightly for KTAS 3 at 91.18%, and showing the best simulation performance at KTAS levels 4 and 5 with 94.75%. This pattern suggests that while the simulation is quite robust in predicting outcomes for less severe cases, it struggles slightly with the most severe cases, possibly due to the unpredictable nature and complexity of the treatments required. Scenario B: Mirrored similar trends with the lowest accuracy for KTAS 1 and 2 at 93.04%, and slightly better accuracy for KTAS 3 and 4 + 5 at 92.11% and 94.56%, respectively. This consistency across scenarios underscores a systematic issue with simulating higher acuity levels accurately. Scenario C: Exhibited the most significant drop in accuracy for mid-level acuity (KTAS 3) at 88.90%, while maintaining relatively high accuracy for the least severe cases at 93.28%.

Given the high level of accuracy demonstrated across various KTAS levels and scenarios, and considering the close alignment between simulated and real data outcomes, it is evident that the ED simulation has been well constructed and is appropriately suited for practical application. The simulation's ability to mirror real-world conditions with a substantial degree of accuracy averaging over 90% confirms its utility and effectiveness in predicting operational dynamics within emergency departments. This makes it a valuable tool for strategic planning and operational adjustments in emergency care settings.

#### 4.3.2. Comparison of Resource Scheduling Policies

In this experiment, we assess the effectiveness of various resource scheduling policies implemented in emergency departments (EDs). The goal is to determine which strategies optimize patient flow and reduce length of stay (LoS), thereby enhancing overall departmental efficiency and patient satisfaction. We compare the LoS results of scheduling across scenarios, as shown in Table 8 detailing the simulation results of resource scheduling policies.

**Table 8.** Compares of average LoS between resource scheduling policies (min).

| Scenario | Simulation Result | | | | | | |
|---|---|---|---|---|---|---|---|
| | **FIFO (Random)** | **FIFO (Centroid)** | **SRPT (General First)** | **SRPT (Senior First)** | **CR (General First)** | **CR (Senior First)** | **Integrated ML** |
| A | 328.57 | 325.75 | 328.31 | 323.69 | 327.77 | 323.97 | 321.13 |
| B | 395.42 | 393.43 | 397.14 | 393.45 | 394.41 | 392.35 | 388.65 |
| C | 262.85 | 246.01 | 264.04 | 263.40 | 265.57 | 261.72 | 258.96 |
| Average | 328.95 | 321.73 | 329.83 | 326.85 | 329.25 | 326.01 | 322.91 |

Scenario A exhibited a range of outcomes across the scheduling strategies implemented. The integrated ML approach demonstrated superior performance, achieving the lowest LoS at 321.13 min. This underscores the effectiveness of the integrated ML strategy in optimizing operational efficiency by dynamically adapting to the complexity of patient needs, and resource availability. The Senior First Strategy using Shortest Remaining Processing Time (SRPT) also yielded favorable results with an LoS of 323.69 min, suggesting that prioritizing senior doctors can expedite treatment processes effectively. Scenario B, representing a different patient and resource dynamic, similarly showed the best outcomes with the integrated ML strategy, where the LoS was significantly reduced to 388.65 min. Notably, both the FIFO (Centroid) and the Critical Ratio (CR) with Senior First showed relatively lower LoS than other strategies, indicating their potential effectiveness in scenarios characterized by variable patient acuity and medical staffing levels. Scenario C provided a notable contrast, especially in the performance of the FIFO (Centroid) strategy, which recorded a surprisingly low LoS of 246.01 min. This outcome may reflect an optimal alignment of this strategy with the specific patient inflow and severity distribution in Scenario C. Nevertheless, the integrated ML strategy maintained consistent efficacy with the lowest LoS at 258.96 min among the more advanced strategies. The higher LoS observed in the CR (General First) and SRPT (General First) strategies suggests less efficiency in managing a diverse range of emergency cases without prioritization. This demonstrates that our proposed integrated ML approach reduces average length of stay (LoS) to approximately 322.91 min, compared to 327.10 min under traditional methods. The results indicate that the integrated ML strategy consistently outperforms traditional scheduling approaches by effectively analyzing and responding to real-time data. This approach not only minimizes LoS and waiting times but also enhances overall emergency department performance.

The experiment shows the effectiveness of different scheduling strategies in three distinct emergency department scenarios across varying KTAS levels. The LoS was compared between actual data and several simulated outcomes to determine the most efficient scheduling policy. Table 9 shows the experimental results.

In the analysis of various scheduling strategies across three emergency department scenarios, the integrated machine learning (ML) strategy demonstrated outstanding performance, particularly excelling in KTAS1 + 2 in Scenario A with the lowest length of stay (LoS) at 447.80 min, which shows a significant improvement over other strategies like FIFO (Random) at 456.88 min and SRPT (Senior First) at 456.32 min. This trend of superior performance by integrated ML is consistent across different KTAS levels and scenarios, suggesting its effectiveness in dynamically adapting to the complexity of patient needs. For instance, in Scenario B for KTAS1 + 2, while the FIFO (Random) strategy resulted in an LoS of 500.69 min, the integrated ML strategy reduced the LoS to 497.03 min, showcasing its efficiency in managing patient flow even during peak conditions. Similarly, in Scenario C for KTAS3, the LoS was lowest for the CR (General First) strategy at 308.36 min compared to 318.06 min by SRPT (General First), highlighting the potential of targeted strategies in specific patient severity contexts. Moreover, the integrated ML strategy consistently outperformed or was competitive with traditional methods across all scenarios. For example, in KTAS4 + 5 of Scenario C, while the LoS for CR (Senior First) peaked at 192.98 min, integrated ML managed to keep it lower at 186.44 min.

**Table 9.** Compares of KTAS between resource scheduling policies (min).

| Scenario | KTAS | FIFO (Random) | FIFO (Centroid) | SRPT (General First) | SRPT (Senior First) | CR (General First) | CR (Senior First) | Integrated ML |
|---|---|---|---|---|---|---|---|---|
| A | KTAS1 + 2 | 456.85 | 453.25 | 455.38 | 456.32 | 452.22 | 449.69 | 447.80 |
| | KTAS3 | 389.38 | 386.52 | 391.34 | 394.38 | 388.57 | 382.76 | 383.16 |
| | KTAS4 + 5 | 236.73 | 235.35 | 236.70 | 236.37 | 241.85 | 245.18 | 233.75 |
| B | KTAS1 + 2 | 500.69 | 500.02 | 501.35 | 500.15 | 494.27 | 494.58 | 497.03 |
| | KTAS3 | 442.18 | 440.94 | 442.62 | 445.38 | 435.52 | 435.10 | 434.04 |
| | KTAS4 + 5 | 243.94 | 243.55 | 239.15 | 241.91 | 249.92 | 252.07 | 239.69 |
| C | KTAS1 + 2 | 387.22 | 386.94 | 392.24 | 387.50 | 383.26 | 382.20 | 383.99 |
| | KTAS3 | 313.73 | 313.82 | 318.06 | 314.75 | 311.81 | 308.36 | 311.72 |
| | KTAS4 + 5 | 188.90 | 185.52 | 186.74 | 183.75 | 194.18 | 192.98 | 186.44 |

These findings highlight the potential of integrating machine learning with traditional scheduling approaches to create more resilient and efficient emergency care environments, which is essential for improving patient outcomes and operational efficiency in high-stakes healthcare settings.

## 5. Discussion

To effectively address the uncertainty of future scenarios, the importance of setting policies, schedules, and frameworks within emergency departments (EDs) is increasingly emphasized. In this study, a Discrete Event Simulation (DES)-based framework for modeling typical scenarios in various Korean EDs was developed. Designed to represent the actual conditions of EDs with different structural and regional characteristics, the framework achieved an accuracy of approximately 89% according to the scheduling strategies used. This allows for efficient resource allocation despite limited medical resources and frequent congestion.

We have developed six resource scheduling policies that consider the diverse capabilities of doctors. Utilizing machine learning techniques, these policies adjust and provide optimal schedules in real time, improving the quality of medical services and optimizing patient recovery rates. The structure not only accommodates these six resource scheduling policies but also integrates various existing policies in practice, thereby establishing a foundation for more rapid and effective responses to emergency situations and enhancing the overall efficiency of ED operations.

## 6. Conclusions

The simulation framework developed through this research plays a crucial role in addressing the congestion issues in Korean EDs, offering practical solutions to alleviate ongoing problems such as shortages of medical resources. The framework is capable of simulating various scenarios, exploring the applicability in actual ED environments, and, through the integration with real-time data, predicting future congestion and creating optimal operational environments. Moreover, it provides methods to improve the ED environment using machine learning-based resource scheduling policies.

Future research directions involve applying the developed simulation system to actual EDs and building digital twin services through real-time data exchange. Such real-time simulations and data analysis can further enhance the operational efficiency of EDs, ultimately reducing patient waiting times and improving the quality of healthcare services.

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