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Evaluating the Impact of COVID-19 on Emergency Department Operations: A Combined Agent-Based and Discrete Event Simulation Model with Anomaly Detection

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Abstract: The COVID-19 pandemic has significantly impacted healthcare systems, particularly altering the operations of emergency departments (EDs). This study evaluates ED operational efficiency during and after the pandemic using a hybrid approach that combines Agent-Based Simulation (ABS) and Discrete Event Simulation (DES), integrated with an anomaly detection system. The simulations provide a comprehensive analysis of patient flow, resource utilization, and treatment processes, while the anomaly detection system identifies unusual operational patterns and potential crises in real-time. Key performance metrics, including average dwelling time, wait times, treatment times, and staff utilization, were analyzed. Results show substantial differences between the pandemic and post-pandemic periods: during the pandemic, the ABS model recorded an average dwelling time of 44.3 minutes with 60% staff utilization, while the DES model showed 122.2 minutes with 110.1% utilization. Post-pandemic, the ABS model improved to a dwelling time of 24.5 minutes and 70% staff utilization, and the DES showed reductions to 69.2 minutes and 49.5% utilization. Moreover, integrating anomaly detection further enhanced the ED's ability to manage operational disruptions proactively, reducing response times and improving overall efficiency. This study underscores the importance of combining simulation and anomaly detection to enhance ED preparedness and resilience for future healthcare crises.

Keywords: Agent-based simulation, Anomaly detection, COVID-19, Discrete event simulation, Healthcare, Simulation modelling.

1. Introduction

The outbreak of COVID-19 posed unprecedented challenges to healthcare systems worldwide [1], particularly within emergency departments (EDs), which were at the frontline of managing the crisis. The sudden influx of patients, coupled with the need for stringent infection control measures, severely disrupted standard ED operations. This disruption led to increased patient waiting times [2], prolonged treatment durations [3], and heightened stress on healthcare resources [4], exacerbating existing operational inefficiencies. As the pandemic's immediate threat subsides, it is critical to analyze these impacts and understand how ED operations have adapted and might further optimize for future crises. Current studies have primarily focused on short-term responses and descriptive analyses of operational changes during the pandemic [5-7], but there is a significant gap in research that quantitatively evaluates the impact of these changes using advanced simulation techniques integrated with real-time data analytics.

Recent literature underscores the value of simulation modeling as a robust method for exploring complex systems like healthcare operations [8, 9]. Among these, Agent-Based Simulation (ABS) [10, 11] and Discrete Event Simulation (DES) [12, 13] are two prominent methodologies. ABS focuses on individual behaviors and interactions within the system, providing granular insights into patient flow and staff-patient dynamics [14, 15]. Conversely, DES models the ED as a series of discrete events, offering a process-oriented perspective that helps identify systemic bottlenecks and inefficiencies [16, 17]. However, existing studies [18, 19] using these methods often lack an integrated approach that combines the strengths of both simulations to provide a more comprehensive understanding of ED operations under crisis conditions. Additionally, they do not incorporate real-time data analytics, such as anomaly detection, to enhance the responsiveness and adaptability of ED operations.

While some studies have explored the use of ABS and DES individually to simulate ED operations during the pandemic [20-23], there remains a critical gap in integrating these simulations with advanced data-driven techniques, such as anomaly detection. For instance, [24] used ABS to model patient flow but did not account for real-time data variances or system-level disruptions. Similarly, [25] employed DES to analyze resource allocation in EDs but did not integrate predictive analytics to foresee potential crises. The unique contribution of our study lies in bridging this gap by combining ABS and DES in a hybrid simulation model enhanced with an anomaly detection system. This approach allows for both micro-level behavioral insights and macro-level process optimizations, significantly improving the ED's operational resilience and efficiency during and after a healthcare crisis.

The integration of anomaly detection into the simulation framework represents a novel contribution to the field. Unlike previous studies that relied solely on retrospective analysis, this research incorporates real-time monitoring capabilities to detect unusual patterns in ED operations, such as sudden spikes in patient arrivals or unexpected delays in treatment times. This proactive feature enables healthcare administrators to implement timely interventions, potentially averting operational crises before they escalate [26]. Recent advances in machine learning, particularly in anomaly detection techniques like autoencoders and isolation forests, offer robust tools for real-time data analysis [27, 28], yet their application in healthcare simulations remains underexplored. Our study leverages these techniques to enhance the predictive power and adaptability of the simulation models, addressing the dynamic and often unpredictable nature of healthcare emergencies.

This study, therefore, makes several key contributions. First, it introduces a hybrid simulation approach that combines ABS and DES, providing a comprehensive framework for analyzing ED operations under pandemic and post-pandemic conditions. Second, it integrates anomaly detection to enhance the real-time responsiveness of the simulation models, a novel application that improves ED preparedness and operational management. Third, by quantifying key performance metrics such as dwelling time [29], wait times [30], treatment times [31], and staff utilization [32], this research provides actionable insights into optimizing resource allocation and improving patient care quality. These contributions not only advance the theoretical understanding of ED operations during crises but also offer practical solutions for enhancing resilience and efficiency in future healthcare emergencies [33, 34].

This paper is organized as follows: a comparison of business processes in the ED is explained in Section 2; the research methodology is provided in Section 3; the simulation setup and results are described in Section 4; we discuss the anomaly detection results and their impact on the ED in Section 5; and the conclusion is drawn in Section 6.

2. Business process comparisons

The comparison highlights the significant changes in business processes in the ED during the COVID-19 pandemic and the transition back to standard procedures post-pandemic. The business process is adopted from a private hospital in Surabaya, Indonesia.

During pandemic:

- **Pre-screening:** Patients were pre-screened for COVID-19 symptoms before entering the ED.
- **Segregation:** Separate areas for COVID-19 suspected cases and non-COVID-19 patients.
- **PPE:** Mandatory use of personal protective equipment (PPE) for all staff.
- **Enhanced Screening:** Temperature checks and symptom questionnaires at entry points.

After pandemic:

- **Standard Triage:** Return to regular triage processes with basic symptom screening.
- **Unified Areas:** Reversion to a single intake area for all patients.
- **PPE:** Continued use of PPE based on infection control protocols, but less stringent than during the pandemic.
- **Routine Screening:** Basic symptom checks without specific focus on COVID-19.

P2. Patient Flow Management

During pandemic:

- **Isolation Protocols:** Immediate isolation of suspected COVID-19 patients.

- **Reduced Capacity:** Limitation on the number of patients in waiting areas to maintain social distancing.
- **Streamlined Processes:** Fast-tracking of COVID-19 testing and results.

After pandemic:

- **Normal Flow:** Standard patient flow without the need for extensive isolation measures.
- **Full Capacity:** Waiting areas functioning at full capacity.
- **Routine Testing:** Regular diagnostic processes with no fast-tracking unless necessary.

P3. Staffing and Safety Protocols

During pandemic:

- **Shift Adjustments:** Modified shifts to reduce staff exposure and ensure availability.
- **Training:** Intensive training on handling infectious diseases and use of PPE.
- **Health Monitoring:** Regular health checks for staff, including temperature and symptom screening.

After pandemic:

- **Standard Shifts:** Return to regular staffing schedules.
- **Ongoing Training:** Continued training on infection control but less frequent.
- **Routine Monitoring:** Health checks as per normal occupational health protocols.

P4. Infection Control and Sanitation

During pandemic:

- **Intensive Cleaning:** Frequent and thorough cleaning of all surfaces and areas.
- **Sanitation Stations:** Increased availability of hand sanitizers and hygiene stations.
- **Air Filtration:** Use of enhanced air filtration systems to reduce airborne transmission.

After pandemic:

- **Regular Cleaning:** Routine cleaning and sanitation processes.
- **Sanitation Access:** Hand sanitizers available but not as widespread.
- **Standard Filtration:** Regular air filtration systems without pandemic-specific upgrades.

P5. Visitor and Patient Communication

During pandemic:

- **Restricted Visits:** Limited or no visitor access to reduce potential virus transmission.
- **Virtual Communication:** Use of telehealth and virtual communication for patient updates.
- **Clear Signage:** Extensive signage on COVID-19 protocols and safety measures.

After pandemic:

- **Open Visits:** Resumption of normal visitor policies with some restrictions based on current health advisories.
- **In-person Updates:** Return to in-person communication with patients and families.
- **Standard Signage:** Regular hospital signage without COVID-19 specific instructions.

P6. Resource Allocation

During pandemic:

- **Prioritization:** Resources prioritized for COVID-19 treatment and critical care.
- **Stockpiling:** Increased stock of PPE, ventilators, and other critical supplies.
- **Telehealth Expansion:** Rapid expansion of telehealth services to reduce in-person visits.

After pandemic:

- **Equitable Allocation:** Resources allocated based on normal medical priorities.
- **Standard Stock:** Maintaining necessary supplies without pandemic-specific stockpiling.
- **Telehealth Integration:** Continued use of telehealth integrated into regular care options.

P7. Regulatory and Reporting Requirements

During pandemic:

- **Frequent Reporting:** Daily or real-time reporting of COVID-19 cases and hospital capacity.
- **Regulatory Compliance:** Adherence to emergency regulations and guidelines from health authorities.

After pandemic:

- **Routine Reporting:** Regular reporting as per standard healthcare regulations.
- **Compliance:** Compliance with standard healthcare regulations without additional pandemic-specific requirements.

3. Research methodology

This research uses a hybrid simulation approach, combining ABS and DES with an anomaly detection system, to evaluate ED operational efficiency during and after the COVID-19 pandemic. This method leverages both simulation techniques and real-time data analytics to improve the adaptability of ED operations under different conditions.

3.1. Dataset

The datasets used in this research were generated in July 2022 for data during the pandemic and in July 2023 for data after the pandemic. In Indonesia, the pandemic officially ended in June 2023, as stated in Presidential Decree of the Republic of Indonesia Number 17 of 2023 on the Declaration of the End of the Corona Virus Disease 2019 (COVID-19) Pandemic Status in Indonesia [35].

The dataset during the pandemic can be seen in Table 1 and the dataset after the pandemic can be seen in Table 2. These datasets provide detailed information on patient flow and treatment times in the emergency department during different periods, allowing for a thorough analysis of the department's operational efficiency and resource utilization.

Pandemic simulation data includes several key metrics: Arrival Time, which records when each patient arrived at the emergency department; Severity, categorizing each patient's condition as 'mild', 'moderate', or 'severe'; and COVID Status, indicating whether the patient is COVID-19 positive (True) or not (False). It also tracks the Start Treatment Time, marking when treatment for each patient began, and End Treatment Time, noting when treatment ended (NaN if treatment is ongoing or not started). Meanwhile, post-pandemic simulation data similarly encompasses Arrival Time, Severity, Start Treatment Time, and End Treatment Time but no longer includes COVID-19 Status.

3.2. Development of hybrid simulation models

To execute the methodologies for both the ABS and the DES of the ED operations during and after the COVID-19 pandemic, we begin by defining clear objectives. The primary goals are to measure the impact of COVID-19 on ED operations and to compare average dwelling time, wait times, treatment times, and staff utilization during and after the pandemic. These objectives guide the entire simulation process, ensuring that the results are relevant and useful for understanding the changes brought by the pandemic.

Table. 1 Part of Pandemic Simulation Data

Arrival Time	Severity	COVID Status	Start Treatment Time	End Treatment Time
0	severe	false	8	70
8	severe	false	16	58
9	severe	true	15	85
16	severe	true	21	67
22	moderate	false	30	61
28	mild	true	39	92
37	severe	true	48	113
39	severe	false	48	124
44	severe	true	59	116
53	moderate	true	60	134

Table 2. Part of Post-Pandemic Simulation Data

Arrival Time	Severity	Start Treatment Time	End Treatment Time
0	severe	12	39
4	moderate	14	52
11	moderate	22	51
15	mild	24	61
21	moderate	29	63
26	severe	38	73
35	severe	40	80
39	moderate	48	74
40	severe	50	87
44	moderate	61	100

3.2.1. Agent-based simulation

The ABS method models ED operations under both pandemic and post-pandemic conditions to evaluate key performance metrics. This simulation captures the complexities and dynamics of ED operations by modeling the individual behaviors of patients and medical staff. The aim is to understand how varying factors—such as patient arrival rates, severity of conditions, and COVID-19 status—affect overall ED performance. The ABS provides insights into how the ED can manage resources more effectively and improve patient care under different operational conditions, as shown in Fig. 1.

The simulation begins with configuring initial parameters, including the number of staff, patient arrival rates, and setting the total duration at 1000 time units. Patient arrivals are then simulated using a probability distribution, with patients assigned to triage based on their arrival times and medical staff allocated according to availability. Treatment times vary between pandemic and post-pandemic scenarios to reflect changes in protocols, with durations defined by patient severity and COVID-19 status to ensure realistic care requirements. Throughout the simulation, key performance metrics such as dwelling time, wait time, treatment time, and staff utilization are monitored. The simulation runs for the specified duration, collecting data on all metrics. This data is then analyzed to calculate average metrics, and results are compared between the pandemic and

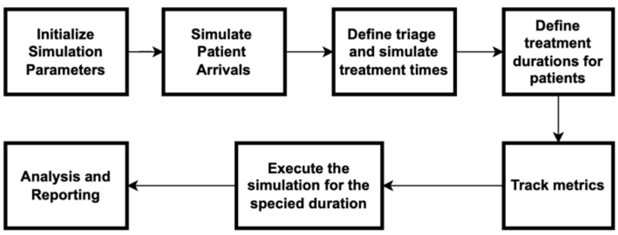

Figure. 1 Agent-based simulation method

post-pandemic periods to identify operational differences and gain insights.

3.2.2. Discrete event simulation

The DES approach models ED operations under both pandemic and post-pandemic conditions to assess their impact on key performance metrics. By simulating patient flow through discrete events representing various stages of ED operations, such as triage and treatment, the DES evaluates how resource constraints and patient influx rates affect ED efficiency. This process-oriented simulation helps identify bottlenecks and inefficiencies within the ED's workflow, enabling strategic planning and resource optimization for improved patient care and management during both crisis and recovery phases. The methodology for the DES is outlined in Fig. 2.

The simulation starts by setting initial parameters, including the number of staff, patient arrival rates, and a total duration of 1000 time units. The patient arrival process is modeled using a probability distribution to mimic the variability and unpredictability of real-world patient flow.

Next, the triage process is simulated to manage patient wait times and resource allocation, guiding patients to appropriate care pathways based on their condition and resource availability. The treatment process is simulated by assigning medical staff and treatment rooms, with varying treatment times for pandemic and post-pandemic scenarios to reflect protocol changes. Treatment durations are based on patient severity and COVID-19 status, ensuring realistic care scenarios. Key performance metrics such as dwelling time, wait time, treatment time, and staff utilization are monitored and recorded throughout the simulation. The simulation runs for the specified duration, processing events sequentially, and results are collected for analysis. In the final stage, data is analyzed to calculate average metrics, and results are compared between pandemic and post-pandemic periods to identify operational differences.

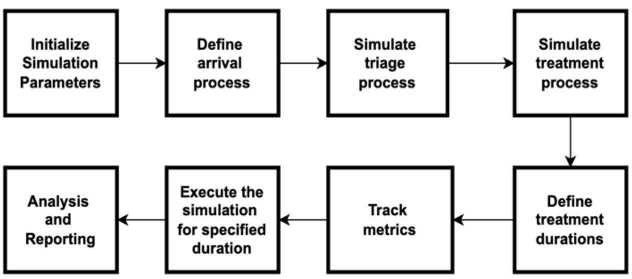

Figure. 2 Discrete event simulation method

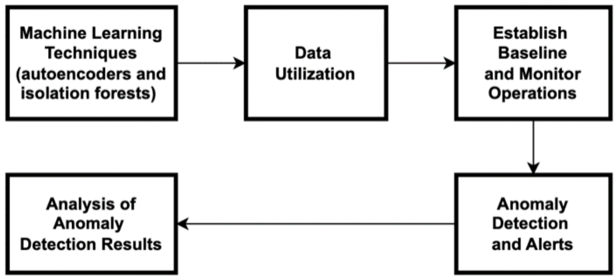

Figure. 3 Anomaly detection method

3.3. Integration of anomaly detection system

To enhance the capability of hybrid simulation models in handling real-time operational data, an anomaly detection system is integrated to provide early warning alerts for potential operational disruptions in the ED. The primary objective of this system is to continuously monitor ED operations for unusual patterns, such as unexpected surges in patient arrivals or prolonged treatment delays, that could indicate potential crises or inefficiencies. To achieve this, advanced machine learning models, including autoencoders [36] and isolation forests [37], are utilized. These models are trained on a combination of historical simulation data and real-time ED operational data to establish a baseline of normal operational metrics. By defining this standard baseline, the models can effectively detect deviations that may signify anomalies. The anomaly detection models are then integrated with the ABS and DES simulations to continuously analyze incoming data. When anomalies are identified, the system triggers alerts to ED administrators, prompting immediate investigation and necessary adjustments to mitigate issues and ensure the ED operates smoothly. This continuous monitoring and alert mechanism enhances the ED's ability to proactively manage operational disruptions, as illustrated in Fig. 3.

4. Simulation results

In this section, we present the experimental results of simulations for both ABS and DES. We implemented the simulations using the python programming language.

4.1. Agent-based simulation results

For the ABS in the python implementation, we define patient and medical staff classes, then create an ED class and define the simulation methods. Finally, we run the simulation for both scenarios.

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4.1.1. Agent-based simulation results

```
Class Patient:
  Function Initialize(arrival_time, severity, covid_status):
    Set self.arrival_time to arrival_time
    Set self.severity to severity
    Set self.covid_status to covid_status
    Set self.start_treatment_time to None
    Set self.end_treatment_time to None
Class MedicalStaff:
  Function Initialize():
    Set self.available to True
```

The code defines two fundamental classes, Patient and MedicalStaff, essential for simulating the operations of an emergency department. The Patient class models individuals arriving for treatment, encapsulating attributes such as arrival_time, severity, covid_status, and treatment times (start_treatment_time and end_treatment_time). These attributes allow the simulation to handle various aspects of patient care, from arrival and severity assessment to specific needs arising from their COVID-19 status. On the other hand, the MedicalStaff class represents the healthcare personnel within the department, primarily managing their availability with a boolean available attribute, which tracks whether staff members are free to attend to new patients or are currently engaged.

4.1.2. Create emergency department class and define simulation methods

The class EmergencyDepartment encapsulates the functionality needed to simulate the operations of an emergency department under both normal and pandemic conditions. It initializes with a boolean flag pandemic to adjust treatment protocols and durations accordingly.

It also includes a list patients to track incoming patients and a list staff filled with instances of MedicalStaff to represent the available medical personnel. The current_time attribute helps keep track of the simulation time.

The simulate method iterates through each time unit up to a specified duration, updating the current time, processing new patient arrivals with arrive_patients, and managing ongoing patient treatments with process_patients. At the end of the simulation, it returns performance metrics calculated by calculate_metrics.

```
Class EmergencyDepartment:
  Function Initialize(pandemic=True):
    Set self.pandemic to pandemic
    Set self.patients to an empty list
    Set self.staff to a list of 10 MedicalStaff instances
    Set self.current_time to 0
  Function Simulate(duration):
    For time in range from 0 to duration - 1:
      Set self.current_time to time
      Call self.arrive_patients(time)
      Call self.process_patients(time)
    Return self.calculate_metrics()
  Function ArrivePatients(time):
    If random number between 0 and 1 < 0.1:
      Set severity to a random choice of 'mild', 'moderate', or 'severe'
      Set covid_status to a random choice of True or False
      Create patient with (time, severity, covid_status)
      Append patient to self.patients
  Function ProcessPatients(time):
    For each patient in self.patients:
      If patient.start_treatment_time is None and self.assign_staff():
        Set patient.start_treatment_time to time
      If patient.start_treatment_time is not None and patient.end_treatment_time is None:
        If time - patient.start_treatment_time >= self.treatment_duration(patient):
          Set patient.end_treatment_time to time
          Call self.release_staff()
  Function TreatmentDuration(patient):
    If self.pandemic:
      If patient.covid_status:
        Return random integer between 50 and 70
      Else:
        Return random integer between 30 and 50
    Else:
      Return random integer between 20 and 40
  Function AssignStaff():
    For each staff in self.staff:
      If staff.available:
        Set staff.available to False
        Return True
    Return False
  Function ReleaseStaff():
    For each staff in self.staff:
      If not staff.available:
        Set staff.available to True
        Break
  Function CalculateMetrics():
    Set total_dwelling_time to 0
```

```
        Set treated_patients to 0
        Set total_wait_time to 0
        Set total_treatment_time to 0
        For each patient in self.patients:
            If patient.end_treatment_time is not None:
                Set dwelling_time to
patient.end_treatment_time - patient.arrival_time
                Set wait_time to
patient.start_treatment_time - patient.arrival_time
                Set treatment_time to
patient.end_treatment_time -
patient.start_treatment_time
                Add dwelling_time to
total_dwelling_time
                Add wait_time to total_wait_time
                Add treatment_time to
total_treatment_time
                Increment treated_patients by 1
        If treated_patients > 0:
            Set avg_dwelling_time to
total_dwelling_time / treated_patients
            Set avg_wait_time to total_wait_time /
treated_patients
            Set avg_treatment_time to
total_treatment_time / treated_patients
        Else:
            Set avg_dwelling_time to 0
            Set avg_wait_time to 0
            Set avg_treatment_time to 0
        Set staff_utilization to sum of non-available
staff / total staff
        Return dictionary with "Average Dwelling
Time", "Average Wait Time", "Average
Treatment Time", and "Staff Utilization"
```

The arrive_patients method randomly generates new patients with a 10% chance each time unit, assigning them a severity and COVID-19 status, which influences their treatment within the simulation. The process_patients method checks each patient’s treatment status: if a patient has not yet started treatment and a staff member is available (as determined by assign_staff), treatment begins. If the patient is already under treatment, the method checks if the treatment should conclude based on the duration provided by treatment_duration, which varies depending on the patient's COVID-19 status and whether the simulation is set to pandemic mode. The calculate_metrics method aggregates data such as total and average dwelling time, wait time, treatment time, and staff utilization rates to assess the efficiency and responsiveness of the emergency department under simulated conditions.

4.1.3. Run simulation for both scenarios

This code initiates two simulations of an emergency department's operations, one set during a pandemic and the other after the pandemic, using the EmergencyDepartment class. The simulations are configured by setting the pandemic attribute to True for the first simulation and False for the second, to reflect the different operational protocols and conditions specific to each scenario. Each simulation runs for a total of 1000 time units, simulating the flow of patients and resource management over this period. The results, which likely include metrics such as average dwelling time, wait time, treatment time, and staff utilization, are then calculated and stored in results _ pandemic and results _ post _ pandemic.

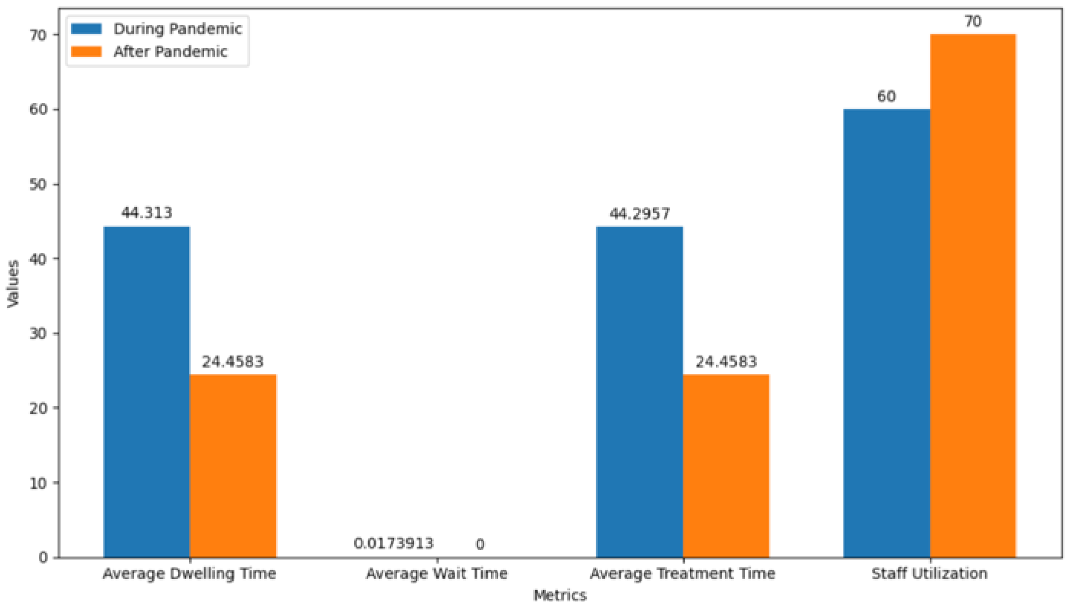

Figure. 4 Comparison results of agent-based simulation

Finally, these results are printed out to provide a comparative overview of the department's efficiency and effectiveness during and after the pandemic.

```
Initialize ed_pandemic as EmergencyDepartment
with pandemic set to True
Set results_pandemic to the result of calling
ed_pandemic.simulate with duration 1000

Initialize ed_post_pandemic as
EmergencyDepartment with pandemic set to
False
Set results_post_pandemic to the result of calling
ed_post_pandemic.simulate with duration 1000

Print "During Pandemic:" and results_pandemic
Print "After Pandemic:" and
results_post_pandemic
```

The result of ABS is presented in Fig. 4. The results reveal that ABS models exhibit quicker adaptation to changing conditions. During the pandemic, the average dwelling time is 44.313 minutes. The average wait time during the pandemic is virtually negligible at 0.0174 minutes, suggesting that patients are processed almost immediately upon arrival. The average treatment time is 44.296 minutes, reflecting focused and timely medical interventions. Staff utilization is at 60% during the pandemic, showing that resources were effectively managed without overburdening the staff.

Post-pandemic, the ABS results continue to show improvements. The average dwelling time further decreases to 24.458 minutes, indicating highly efficient patient throughput. The average wait time drops to zero, emphasizing the immediate treatment response modeled in the ABS. The average treatment time is 24.458 minutes, consistent with the efficient handling of patient care. Interestingly, staff utilization increases to 70% post-pandemic, suggesting a more optimal use of resources compared to the pandemic period, ensuring that staff are well-utilized but not overworked.

4.2. Discrete event simulation results

For the DES in the python implementation, we also define patient and medical staff classes similar to the ABS, and the implementation is similar to Section 4.1.1. Then, we define the emergency department class. Finally, we run the simulation for both scenarios.

4.2.1. Run simulation for both scenarios

```
Class EmergencyDepartmentDES:
    Function Initialize(env, pandemic=True):
        Set self.env to env
        Set self.pandemic to pandemic
        Set self.triage to simpy.Resource with env
and capacity 2
        Set self.treatment to simpy.Resource with
env and capacity 5
        Set self.total_dwelling_time to 0
        Set self.total_wait_time to 0
        Set self.total_treatment_time to 0
        Set self.total_patients to 0
        Set self.treatment_time_busy to 0
    Function PatientProcess(name):
        Set arrival_time to self.env.now
        With self.triage.request() as triage_request:
            Yield triage_request
            Set triage_time to random integer between
5 and 15
            Yield self.env.timeout(triage_time)
        Set start_treatment_time to self.env.now
        With self.treatment.request() as
treatment_request:
            Yield treatment_request
            Set treatment_time to
self.treatment_duration()
            Yield self.env.timeout(treatment_time)
        Set end_treatment_time to self.env.now
        Increment self.treatment_time_busy by
(end_treatment_time - start_treatment_time)
        Set dwelling_time to end_treatment_time -
arrival_time
        Increment self.total_dwelling_time by
dwelling_time
        Increment self.total_wait_time by
(start_treatment_time - arrival_time)
        Increment self.total_treatment_time by
treatment_time
        Increment self.total_patients by 1
    Function TreatmentDuration():
        If self.pandemic:
            If random.choice([True, False]):
                Return random integer between 50 and
70
            Else:
                Return random integer between 30 and
50
        Else:
            Return random integer between 20 and 40
    Function Run(duration):
        Call self.env.process with
self.simulate(duration)
        Call self.env.run()
```

```
    Function Simulate(duration):
        For i in range from 0 to 49:
            Call self.env.process with
self.patient_process('Patient' + i)
            Yield self.env.timeout(random integer
between 1 and 10)
        Yield self.env.timeout(duration -
self.env.now)
    Function CalculateMetrics():
        Set simulation_time to self.env.now
        Set staff_utilization to
(self.treatment_time_busy / (simulation_time *
self.treatment.capacity)) * 100
        Return {  "Average Dwelling Time":
self.total_dwelling_time / self.total_patients if
self.total_patients else 0,
            "Average Wait Time":
self.total_wait_time / self.total_patients if
self.total_patients else 0,
            "Average Treatment Time":
self.total_treatment_time / self.total_patients if
self.total_patients else 0,
            "Staff Utilization": staff_utilization   }
```

The class EmergencyDepartmentDES encapsulates the functionality for a discrete event simulation of an emergency department using the SimPy framework, specifically designed to assess operations during and potentially after a pandemic. Upon initialization, it sets up the environment with necessary resources such as triage and treatment facilities, each with defined capacities. Additionally, it initializes counters for total dwelling time, wait time, treatment time, and the number of patients processed, as well as a tracker for the total time treatment resources are actively used (treatment_time_busy). This setup reflects a dynamic environment where the availability of resources and the demands placed on them can vary significantly, particularly under pandemic conditions.

The patient_process method details the journey of a patient through the emergency department. It starts with the patient arriving and requesting triage, which involves a random duration for initial assessment. This is followed by a request for treatment, which also lasts for a randomly determined duration based on whether there's a pandemic. The method tracks the start and end times of treatment to compute the total time resources are engaged, updating global counters for various metrics such as dwelling time (total time spent by the patient from arrival to departure), wait time (time from arrival until treatment begins), and actual treatment time. This detailed tracking allows for a nuanced view of how each patient's experience contributes to overall resource utilization and system efficiency.

The simulation is driven by the run method, which orchestrates the overall simulation for a set duration. It repeatedly schedules the patient_process for a number of patients, with random inter-arrival times to mimic the unpredictability of emergency department admissions. After the simulation runs, the calculate_metrics method compiles the key performance indicators, including average dwelling, wait, and treatment times, along with a calculation of staff utilization as a percentage. This percentage is calculated by comparing the accumulated busy time of treatment resources against the total simulation time and the capacity of these resources. This provides insights into how effectively resources are being used throughout the simulation.

4.2.2. Run simulation for both scenarios

```
Initialize env_pandemic as a new
simpy.Environment
Initialize ed_pandemic as a new
EmergencyDepartmentDES with env_pandemic
and pandemic set to True
Call ed_pandemic.run with duration 1000
Set results_pandemic to the result of calling
ed_pandemic.calculate_metrics()

Initialize env_post_pandemic as a new
simpy.Environment
Initialize ed_post_pandemic as a new
EmergencyDepartmentDES with
env_post_pandemic and pandemic set to False
Call ed_post_pandemic.run with duration 1000
Set results_post_pandemic to the result of calling
ed_post_pandemic.calculate_metrics()

Print "During Pandemic:" and results_pandemic
Print "After Pandemic:" and
results_post_pandemic
```

The code sets up and executes two DES using the SimPy library, one simulating an emergency department's operations during a pandemic and the other in a post-pandemic scenario. Each simulation initializes a separate SimPy environment and an instance of the EmergencyDepartmentDES class, with the pandemic parameter set to True for the pandemic scenario and False for the post-pandemic scenario. The simulations are run for a duration of 1000 time units, after which performance metrics such as average dwelling time, wait time, treatment time, and staff utilization are calculated using the calculate_metrics method. Finally, the results from

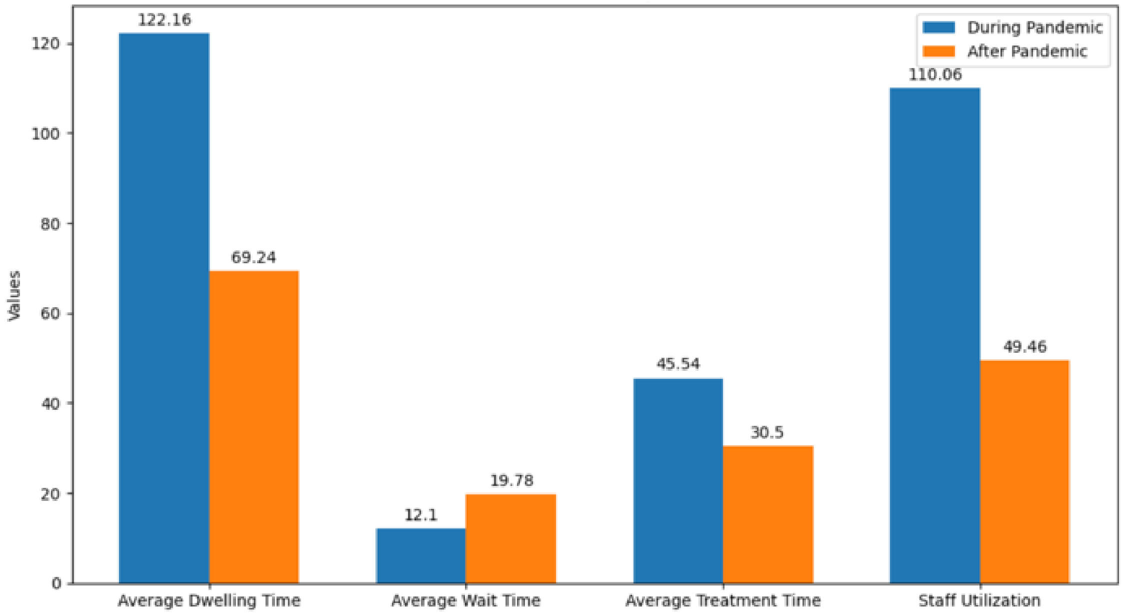

Figure. 5 Comparison results of discrete event simulation

each scenario are printed, allowing for a comparison of the impact of pandemic conditions on emergency department operations to those of a normal, post-pandemic period.

The graphs in Fig. 5 provides a comparison of ED operations during and after the pandemic using the DES. Key performance metrics show significant differences between the two periods. During the pandemic, the average dwelling time is notably high at 122.16 minutes, indicating that patients spent a considerable amount of time in the ED, likely due to the increased complexity of care and stringent safety protocols. The average wait time during the pandemic is 12.1 minutes, suggesting moderate delays in patient processing. The average treatment time is 45.54 minutes, reflecting the longer procedures required for treating pandemic-related conditions. Staff utilization during the pandemic is alarmingly high at 110.06%, which implies that healthcare workers were operating beyond their capacity, likely due to the overwhelming demand and extended treatment protocols.

After the pandemic, the DES results show improvements in operational efficiency. The average dwelling time decreases to 69.24 minutes, indicating more efficient patient flow as pandemic-specific protocols are relaxed. However, the average wait time increases to 19.78 minutes, which could be due to a temporary adjustment phase as the department transitions back to normal operations. The average treatment time drops to 30.5 minutes, highlighting quicker medical interventions post-pandemic.

Staff utilization also significantly decreases to 49.46%, reflecting a more balanced workload and sustainable operations for healthcare workers, aligning with the reduced demand and less intensive care requirements.

4.3. Results overview and analysis

The outcomes from both ABS and DES reveal distinct dynamics in the operations of emergency departments during and after a pandemic. This analysis seeks to explore the reasons behind these differences, elucidate their implications, and provide a comparative assessment grounded in the theoretical foundations of each simulation methodology.

Results from both ABS and DES during and after the pandemic are explained in Table 3. The DES results highlight the significant operational challenges faced by EDs during the pandemic, with high dwelling times, moderate wait times, extended treatment durations, and excessive staff utilization. Post-pandemic, while efficiencies improve, some adjustments in wait times are observed. In contrast, the ABS results demonstrate a more dynamic and efficient handling of ED operations, both during and after the pandemic, with significantly lower dwelling and treatment times, almost negligible wait times, and balanced staff utilization. These differences underscore the strengths of ABS in modeling real-time interactions and adaptability, while DES provides a more detailed view of systemic bottlenecks and resource constraints. Combining insights from both simulations can help optimize ED operations for future health crises and standard conditions.

5. Anomaly detection results

5.1. Results

Combining autoencoder and isolation forest for anomaly detection in ED operations offers a robust and complementary approach to identifying unusual patterns and potential inefficiencies. The results of the anomaly detection analysis, using both isolation forest and autoencoder methods on the pandemic and post-pandemic datasets, provide key insights into operational anomalies in the ED, as shown in Fig. 6.

For the pandemic data, the isolation forest model identified two anomalies, indicated by 'Anomaly_ISF' values of -1 for indices 5 and 9. These anomalies suggest the presence of outliers in patient flow, treatment times, or other operational characteristics that deviate significantly from normal patterns observed during the pandemic. The autoencoder model, which detects anomalies based on reconstruction error, flagged one data point as an anomaly (index 5) where the reconstruction error exceeded the defined threshold. This indicates a significant deviation from the expected operational pattern, potentially due to irregular treatment times or inefficiencies in patient management processes during the pandemic period.

In the post-pandemic data, the isolation forest model again detected two anomalies, specifically at indices 0 and 9. These anomalies might reflect unusual operational behaviors or shifts in patient flow that do not align with the expected patterns in a post-pandemic environment. Meanwhile, the autoencoder model identified one anomaly (index 9), based on a high reconstruction error. This suggests that this particular data point deviated significantly from the learned patterns of post-pandemic operations, potentially indicating an area where operational adjustments were not fully effective.

Combining both isolation forest and autoencoder methods offers a comprehensive approach to anomaly detection in ED operations. The isolation forest is effective in identifying a broader range of anomalies, including both subtle and pronounced outliers, which may reflect unexpected shifts in patient flow or operational practices. In contrast, the autoencoder is particularly adept at detecting complex deviations based on the reconstruction of learned patterns, which might signify deeper, underlying inefficiencies or operational disruptions. Together, these methods enhance the accuracy and robustness of anomaly detection, providing a reliable early warning system for potential operational disruptions or inefficiencies in ED management during and after the pandemic. This combined approach allows ED administrators to proactively address issues, optimize resource allocation, and maintain high standards of patient care.

Table 3. Results Overview

	During Pandemic	After Pandemic
ABS	• **Average Dwelling Time**: 44.313 minutes • **Average Wait Time**: 0.0174 minutes • **Average Treatment Time**: 44.296 minutes • **Staff Utilization**: 60%	• **Average Dwelling Time**: 24.458 minutes • **Average Wait Time**: 0.0 minutes • **Average Treatment Time**: 24.458 minutes • **Staff Utilization**: 70%
DES	• **Average Dwelling Time**: 122.16 minutes • **Average Wait Time**: 12.1 minutes • **Average Treatment Time**: 45.54 minutes • **Staff Utilization**: 110.06%	• **Average Dwelling Time**: 69.24 minutes • **Average Wait Time**: 19.78 minutes • **Average Treatment Time**: 30.5 minutes • **Staff Utilization**: 49.46%

5.2. Impact of anomalies on ED operations

Anomalies detected in patient arrival times, start treatment times, and end treatment times indicate disruptions in patient flow through the ED. For example, anomalies that occur at specific times may suggest a sudden surge in patient arrivals that the ED is not adequately prepared to handle, leading to overcrowding. This overcrowding can result in delays in initial assessments, increased wait times, and prolonged overall treatment durations, all of which are critical performance metrics in an ED setting. Additionally, anomalies detected in severity and COVID status combined with treatment timings could indicate mismatches in triage and resource allocation. For instance, if a severe patient with COVID experiences delayed treatment, as indicated by an anomaly, this could lead to critical care delays. Such disruptions undermine the ED's ability to manage resources effectively and maintain timely and appropriate care for all patients.

Anomalies also often reflect irregularities in staff utilization and resource allocation. If an anomaly corresponds to a period when treatment times are unexpectedly long or short, this could suggest inefficient use of medical staff or facilities, such as

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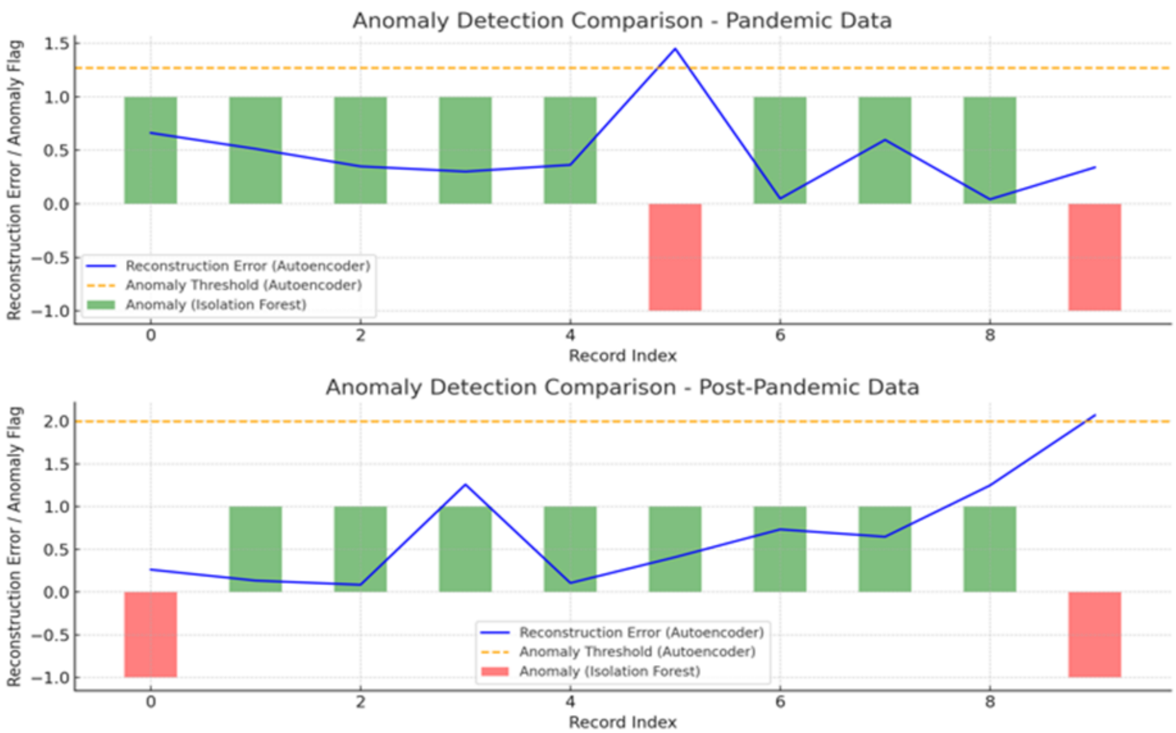

Figure. 6 Anomaly detection results

treatment rooms or medical equipment. Prolonged treatment times could imply that staff are overburdened or improperly allocated, which can lead to burnout and decreased quality of care. Conversely, unusually short treatment times might indicate rushed care or errors in patient handling, both of which could compromise patient outcomes. Anomalies in staff utilization directly impact the overall operational capacity of the ED, potentially leading to increased costs and reduced staff morale.

The quality of patient care and safety is directly impacted by anomalies that highlight prolonged waiting times or extended treatment durations. Extended waiting times can lead to patient dissatisfaction and worse health outcomes, particularly in cases where timely intervention is critical. For example, a severe COVID patient experiencing delayed treatment could see their condition worsen, leading to higher morbidity or mortality rates. On the other hand, anomalies indicating shortened care times could mean critical steps in treatment protocols were missed or rushed, potentially compromising patient safety. This risk is particularly acute during pandemic conditions, when the ED must balance high patient volumes with the need for thorough and comprehensive care.

During the pandemic, anomalies related to COVID status and treatment protocols might suggest that the ED was struggling to manage both COVID and non-COVID patients simultaneously, reflecting challenges in adapting to crisis conditions. These anomalies might indicate lapses in infection control measures or inadequate segregation of patients, which are critical during a pandemic. In the post-pandemic phase, anomalies might indicate a failure to return to normal operational efficiency or adjust to a new "normal." They could highlight continued inefficiencies or emerging problems as the ED transitions back from crisis-mode operations to standard procedures.

In conclusion, anomalies detected in ED operations provide valuable insights into areas of potential concern that require further investigation and intervention. These anomalies can negatively impact key performance metrics, such as average dwelling time, wait times, treatment times, and staff utilization, which are crucial for maintaining operational efficiency and high-quality patient care. By identifying and analyzing these anomalies, ED administrators can proactively address underlying issues, optimize resource allocation, and improve both patient outcomes and staff well-being. Integrating anomaly detection into the ED management framework enhances preparedness for future healthcare challenges and helps ensure a resilient and responsive healthcare environment.

6. Conclusion

The experimental results from the ABS, DES, and anomaly detection analysis provide valuable insights into the operational efficiency and resilience of ED operations during and after the COVID-19 pandemic. The ABS results highlight the importance of understanding individual-level interactions within the ED, such as patient flow, staff-patient dynamics, and resource allocation. During the pandemic, the ABS indicated an average dwelling time of 44.313 minutes, an average wait time of 0.0174 minutes, and an average treatment time of 44.296 minutes, with a staff utilization rate of 60%. After the pandemic, the simulation showed a significant improvement in operational efficiency, with a reduced average dwelling time of 24.458 minutes, no wait time, and a consistent treatment time of 24.458 minutes, while staff utilization increased to 70%. These findings suggest that proactive adjustments in patient management strategies, such as prioritizing severe cases and optimizing staff allocation, were critical in maintaining operational efficiency during crisis conditions and helped streamline operations in the post-pandemic phase.

The DES results provided a broader view of the ED's systemic processes, identifying key bottlenecks and inefficiencies in patient flow during both pandemic and post-pandemic scenarios. During the pandemic, the DES reported a significantly higher average dwelling time of 122.16 minutes, an average wait time of 12.1 minutes, and an average treatment time of 45.54 minutes, with a staff utilization rate exceeding 110%, indicating overburdened staff. Post-pandemic, the DES model showed improvements, with the average dwelling time decreasing to 69.24 minutes, the average wait time increasing slightly to 19.78 minutes, and the average treatment time reduced to 30.5 minutes. Staff utilization decreased to 49.46%, reflecting a more balanced workload. These results underscore the challenges faced during the pandemic and highlight the need for process changes, such as modifying triage protocols or redistributing resources, to improve efficiency and reduce bottlenecks.

The integration of anomaly detection using isolation forest and autoencoder methods enhanced the simulation models' ability to identify unusual operational patterns that could indicate potential crises or inefficiencies. The results showed that both methods effectively detected anomalies related to patient flow, treatment times, and resource utilization, which are critical for maintaining ED efficiency. The isolation forest method was particularly effective at identifying a broader range of anomalies, including subtle and pronounced outliers, while the autoencoder was adept at detecting complex deviations based on learned patterns. The combination of these techniques provided a robust early warning system that enabled ED administrators to proactively manage operational disruptions, optimize resource allocation, and improve both patient outcomes and staff utilization.

Combining ABS, DES, and anomaly detection methodologies provided a comprehensive framework for evaluating and enhancing ED operations under varying conditions. The experimental results demonstrate that during the pandemic, ED operations were heavily strained, as evidenced by longer dwelling and treatment times and overburdened staff utilization rates. However, in the post-pandemic phase, the ED showed considerable improvement in operational efficiency, with reduced dwelling and treatment times and better-managed staff resources. The integration of real-time anomaly detection further improves the ED's responsiveness and adaptability, ensuring that operational challenges are swiftly addressed to maintain high standards of patient care. These findings highlight the critical role of simulation models and data-driven decision-making tools in optimizing healthcare operations, especially during times of crisis. By providing actionable insights, this comprehensive approach helps healthcare administrators prepare for future challenges, ensuring a resilient and efficient healthcare environment. Future studies could use advanced deep learning models, such as LSTM and CNNs, to enhance anomaly detection in ED operations by learning complex temporal and spatial patterns in patient flow and resource utilization.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, All Authors; Methodology, Yutika Amelia Effendi; Software, Yutika Amelia Effendi; Validation, Yutika Amelia Effendi and Riyanarto Sarno; Formal analysis, Yutika Amelia Effendi and Stefania Widya Setyaningtyas; Writing—original draft preparation, Yutika Amelia Effendi; Writing—review and editing, Stefania Widya Setyaningtyas; Supervision, Riyanarto Sarno.

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