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Patient flow modeling and simulation to study HAI incidence in an Emergency Department

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Abstract

Healthcare-associated infections (HAIs), or nosocomial infections, refer to patients getting new infections while getting treatment for an existing condition in a healthcare facility. HAI poses a significant challenge in healthcare delivery that results in higher rates of mortality and morbidity as well as a longer duration of hospital stay. While the real cause of HAI in a hospital varies widely and in most cases untraceable, it is popularly believed that patient flow in a hospital—which hospital units patients visit and where they spend the most time since their admission into the hospital—can trace back to HAI incidence in the hospital. Based on this observation, we, in this paper, model and simulate patient flow in an emergency department of a hospital and then utilize the developed model to study HAI incidence therein. We obtain (a) a flowchart of patient movement (admission to discharge) and (b) anonymous patient data from University Health Medical Center for a duration of 11 months (Aug 2022–June 2023). Based on these data, we develop and validate the patient flow model. Our model captures patient movement in different areas of a typical emergency department, such as triage, waiting room, and minor procedure rooms. We employ the discrete-event simulation (DES) technique to model patient flow and associated HAI infections using the simulation software, Anylogic. Our simulation results show that the rates of HAI incidence are proportional to both the specific areas patients occupy and the duration of their stay. By utilizing our model, hospital administrators and infection control teams can implement targeted strategies to reduce the incidence of HAI and enhance patient safety, ultimately leading to improved healthcare outcomes and more efficient resource allocation.

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CRediT authorship contribution statement

Sarawat Murtaza Sara: Conceptualization, Methodology, Software, Validation, Visualization, Writing – original draft, Formal analysis. **Ravi Chandra Thota:** Writing – review & editing, Visualization, Writing – original draft. **Md Yusuf Sarwar Uddin:** Supervision, Conceptualization, Formal analysis, Project administration, Writing – review & editing, Methodology, Visualization, Writing – original draft. **Majid Bani-Yaghoub:** Formal analysis, Funding acquisition, Investigation, Project administration, Supervision, Conceptualization, Writing – review & editing. **Gary Sutkin:** Formal analysis, Investigation, Supervision, Project administration, Resources, Writing – review & editing. **Mohamed Nezar Abourraja:** Software, Validation, Resources.

Keywords

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1. Introduction

Healthcare-Associated Infections (HAIs) are infections that individuals acquire while receiving medical care in a healthcare facility. As per the US Centers for Disease Control and Prevention (CDC, 2018), in the United States, on any given day, approximately 1 out of every 31 patients admitted to a hospital is affected by at least one healthcare-associated infection (HAI). Nearly 1.7 million patients in the US acquire healthcare-associated infections annually, resulting in over 98,000 deaths. The consequences of HAIs extend beyond the individual, significantly impacting the healthcare system. These infections can lead to heightened illness, increased mortality rates, prolonged hospital stays, and additional strains on healthcare resources. The financial burden and challenges in treatment further amplify the impact, emphasizing the need for effective prevention strategies and a comprehensive understanding of the factors contributing to these infections.

The Emergency Department (ED) of a hospital is a critical location in healthcare where people seek urgent care. Just like other units in a hospital, the emergency department is subject to the hazards of HAI incidence. The fast-paced and dynamic nature of emergency treatment, combined with the rush of patients, provides a situation where HAI occurrences are more likely. The complexity of infection threats in the ED is further complicated by factors such as fast patient turnover, variable medical states, and the urgency of interventions. Understanding the factors affecting HAI incidences in an ED is very important, which this paper attempts to address. To properly address this issue, we need a detailed understanding as well as strategies. Exploring *how patients move* through the healthcare system is an important aspect. Healthcare practitioners obtain significant insights into the pathways via which infections may spread by describing and researching HAIs through the analysis and modeling of detailed patient flow. Understanding a patient's journey—from admittance to various healthcare units as she encounters medical staff or devices, and then finally gets discharged—provides a comprehensive picture. Healthcare practitioners can use *computer simulation* approaches to replicate and examine various scenarios, allowing them to discover possible infection hotspots, review existing protocols, and adopt focused interventions.

Key principles and concepts in patient flow modeling concentrate on tracing a patient's whole journey across a healthcare system, particularly in an emergency department area. This includes understanding the flow of patients from admission through various stages of care, such as triage, waiting areas, and various medical procedures, and the eventual discharge at the end. The process should also consider the cases of patients leaving halfway without being seen or taking any therapeutic response. Furthermore, the model should consider elements such as the duration of time spent at every stage, transitions between areas, and contacts with healthcare personnel. Examining these factors provides healthcare workers with an understanding of the system's efficiency, potential bottlenecks, and areas where modifications may be made to improve patient care as well as to contain and limit HAI incidence.

In our modeling approach, we utilize the technique of *discrete-event simulation* to model patient flow and HAI incidence in an Emergency Department (ED) in a hospital. This method creates a dynamic, time-dependent model that simulates patients' real-time movement through the ED areas and service points. Using this model, we can observe and study the occurrence of HAIs by simulating the intricate interactions between patients and numerous departments. This method depicts the healthcare environment in great detail and reality, providing helpful information about potential infection areas and the impact of patient flow on HAI incidence.

Toward this end, we develop a *data-driven simulation model* to explore the dynamics of patient movement in an Emergency Department (ED) of a hospital and the associated influence of various factors on HAI incidence among patients in the ED. Our proposed model considers different aspects within ED: the reasons for patient visits, different regions/ service areas patients visit (e.g., triage, testing, and assessment), and the duration of their stay in those areas. We obtained a detailed flowchart of patient movement in different areas of an ED from the University Health Medical Center in Kansas City (the hospital is the official partner of this research project). We also obtained, from the same hospital, *eleven months of data* (Aug 2022 to Jun 2023) on patient admissions, discharges, patients leaving without being seen, the amount of time they spent in waiting areas, and the *suspected* HAI cases among admitted patients in ED. These are real patient data who were admitted and serviced in the ED in University Health Medican Center during the mentioned period, with patients' personal and identifiable information withheld (this data is obtained following proper IRB (Institution Review Board) approval at the respective institutions). We used this data extensively to build our model as well as to validate the model.

The goal of our patient flow modeling is to provide a comprehensive understanding of how different factors interplay and affect the overall impact of healthcare-associated infections in the Emergency Department. The data obtained from the hospital is used to validate the simulation model, this is, to estimate the values of unknown parameters of the simulation model. To further study the impact of infection in ED, the simulation model is tested on three different "synthetic" scenarios: (a) doubling the patient arrival rate, (b) fewer beds available in the ED, and (c) higher severity of illnesses in incoming patients. Based on the simulation outputs, we subsequently demonstrate that patients in the ED are at a higher risk of infection in those scenarios compared to the baseline operations. Even though our modeling is based on the flowchart and patient data obtained from University Health Medical Center, our observation should hold for other tertiary hospitals.

Our paper makes the following contributions:

- Develop a detailed simulation model of patient flow in an emergency department in a hospital.

- Analyze real healthcare and HAI-related data obtained from University Health Medical Center, which we use for both building the model and validating the model (estimating its free parameters).
- Build the patient flow and HAI/infection model using state-of-the-art simulation software, `AnyLogic`.
- Analyze simulation output against the real-world data to validate the simulated model.
- Generate synthetic simulated scenarios ("alternate realities") to analyze the effects of certain changes (e.g., changes in the number of beds) on HAI incidence in the simulation environment in an ED.

The rest of the paper is as follows: Section 2 shows the impact of HAIs and the preventative tactics used in the industry through a literature review, Section 3 discusses the procedure and model creation, Section 4 analyzes data provided by University Health Medical Center and obtains the simulation model results for three different case scenarios, finally, Section 5 concludes this paper with a remark on future research directions in this area.

2. Literature review

In a study published by Casey and Chasens (2009), they addressed the challenges of detecting potential infections or colonization of patients by microorganisms, particularly those significant for public health, within the Emergency Department. They emphasized the complexity of accurately and promptly identifying these instances, attributing it to the dynamic and fast-paced nature of the emergency care environment. Hospital-acquired infections, or HAIs, represent a significant public health issue. An estimated 1.7 million infections and 99,000 fatalities annually in the US are attributed to HAIs. Harmful pathogens causing Healthcare-Associated Infections (HAIs) come from various sources. Key types include Central Line-Associated Bloodstream Infections (CLABSI), Catheter-Associated Urinary Tract Infections (CAUTI), Surgical Site Infections (SSI), and Ventilator-Associated Pneumonia (VAP). Other HAIs encompass non-ventilator-associated hospital-acquired pneumonia (NV-HAP), and gastrointestinal and urinary tract infections. HAIs are also categorized by affected systems according to Sikora and Zahra (2020), such as respiratory, skin, cardiovascular, bone, joint, central nervous system, and reproductive tract infections. Per the findings of Surapaneni (2015), MRSA was the most common isolated bacterial species at 10 of the 11 EDs. In a study by Alrashid et al. (2022), the occurrence of urinary tract infections (UTIs) in patients admitted through the Emergency Department (ED) was found to be 10.5 percent. This implies that approximately 10.5 out of every 100 patients admitted through the ED were diagnosed with a urinary tract infection.

In their study, Dadi, Radochová, Vargová, and Bujdáková (2021) investigated the impact of healthcare-associated infections (HAI), particularly focusing on device-associated infections such as central line-associated bloodstream infections, catheter infections, catheter-associated urinary tract infections, ventilator-associated pneumonia, and surgical site infections. The paper underscores the significance of detailed infection recording, adherence to hygiene measures, and preventive strategies to enhance care quality and reduce hospital costs. Another study aimed by Stewart et al. (2021) to report the Length of Stay (LOS) for patients with and without Healthcare-Associated Infections (HAI) and identify the specific types of HAI that contribute most significantly to the excess LOS by using a multi-state model.

Through a multidisciplinary approach and rigorous data analysis, another paper by Halperin et al. (2016) has achieved a 53 percent reduction in total Healthcare-Associated Infections (HAIs) over 18 months. This improvement was driven by a decrease in urinary catheter use and reduced patient transport from the Intensive Care Unit (ICU) for imaging procedures. Another author named Almeida (2015) was able to establish a risk for HAIs in emergency rooms (EDs) in crowded waiting spaces. Recent advancements in infection prevention (IP) technologies Pryor and Bearman (2022) tried to encompass electronic hand hygiene monitoring systems, antimicrobial textiles, ultraviolet C (UV-C) devices, and the integration of decision-support tools and predictive analytics using machine learning into electronic medical records (EMRs). These innovations aim to prevent healthcare-associated infections (HAIs). Furthermore, the importance of environmental factors is being highlighted by Gajendran, Kabir, Vadivelu, Ng, and Thota (2023) by incorporating Machine Learning (ML) techniques into the evaluation of Indoor Environmental Quality (IEQ). Leveraging IEQ techniques has the potential to improve environmental quality in congested areas such as emergency departments, as well as to improve strategies for preventing HAI transmission.

To enhancing the efficiency of the Hospital's Emergency Department (ED) (Abourraja et al., 2022) explored data-driven simulation of workflow and layout designs, with a focus on optimizing resource utilization and reducing waiting times by introducing a dedicated ward for patients with complex diagnoses (capacity of fewer than 20 beds) as a key strategy for achieving lower waiting times

These authors (Terning, Brun, & El-Thalji, 2022) offered a comprehensive and transparent description of constructing a multimethod simulation model that replicates realistic patient flow within an emergency department during the COVID-19 pandemic using a hybrid agent-based simulation model to explore how an elevated patient infection rate affects emergency department patient flow. The findings by Terning, El-Thalji, and Brun (2023) reveal that higher infection rates correlate with worsened metrics, specifically longer average length of stay and increased crowding, particularly with the introduction of waiting functions.

While these studies prioritize optimizing resource utilization, reducing waiting times, and simulating realistic patient flow with consideration for infection rates, they fall short in specifying the particular locations within the hospital setting where infections can occur. Additionally, none of the studies include modeling for hospital-acquired infections (HAIs), leaving a gap in understanding the localized dynamics of infection spread and its impact on patient care.

3. Procedure and modeling

In selecting the hospital Emergency Department (ED) as our modeling focus, the intricate dynamics of patient flow within a healthcare setting take center stage. A well-defined patient flow model is crucial for understanding and optimizing healthcare operations. This section will meticulously outline the procedures adopted and the models employed, shedding light on how our approach contributes to advancing both the theoretical and practical aspects of healthcare management.

3.1. Healthcare facility details

This paper provides a retrospective analysis of emergency department (ED) data spanning from 2018 to 2023 at University Health Medical Center, focusing on a facility with almost 4000 employees. Over this period, the ED accommodated about 60 thousand patient visits, resulting in almost 16,000 hospitalizations. The dataset includes information on the day of the week patients present to the ED, daily patient volumes, admission rates, total ED duration, average wait times, instances of patients going Away Without Therapeutic Response (AWTR), and cases of patients leaving without being seen by a physician (LWBS). The analysis sheds light on patterns in ED utilization, offering insights into patient flow and outcomes. Even though the data spans 2018–2023, we used the latest 11 months of data from Aug 2022 to Jun 2023 for model validation and other purposes.

3.2. Patient flow model

We have developed a comprehensive patient flow model, depicted in Fig. 1, to provide a visual representation of the dynamics within our University Health Medical Center's emergency department. This illustration offers a detailed insight into the intricate process of how patients navigate through various stages within the emergency department. In our model, patients arrive at the emergency department in two ways: by walking in or by ambulance (EMS). All admitted patients go through the triage area to do an initial assessment. From there, depending on the severity of the illness, a patient either gets a bed immediately in the ED or goes to the other assessment areas.

Consider patients who arrive by EMS and have a higher severity of illness. They get a bed immediately depending on the bed availability and continue their ED treatment processes as shown in Fig. 1. On the other hand, patients who arrive by walking in or have a lower illness severity level do not warrant any immediate bed but go directly to the assessment areas after the triage. Based on the triage assessment, patients may undergo additional assessments depending on their needs, which include diagnostic tests such as blood work, imaging, and consultations with specialists. Throughout the ED process, patients are also monitored for potential safety risks, such as falls, medication interactions, or allergic reactions. Patients with higher triage levels are seen by a healthcare provider sooner.

The patient who needs a bed gets one if a bed is available. Else they go to a waiting room to wait until a bed is free by another patient. While waiting, some patients choose to *leave*, which could be due to various reasons, such as long wait times, deciding against treatment, and seeking care elsewhere. These cases are popularly labeled as LWBS (Left Without Being Seen). Other patients will eventually get a bed and will go through the rest of the process.

After having lab tests, diagnostics tests, and multiple assessments done with a patient, the hospital staff decides if the patient needs further observation and treatment by observing their test and assessment reports. If their condition is deemed mild and appears manageable at home, they are discharged with a follow-up order written and prepared for them. Otherwise, they are admitted to the "inpatient care" and transferred to another department of the hospital based on their health issues. In between different stages and waiting, some patients may prefer to leave the hospital, which is referred to as AWTR (Away With Therapeutic Response) cases.

3.3. *Modeling patient-flow using* `AnyLogic`

In this study, we use the `AnyLogic` simulation tool and employ the Discrete Event Modeling (DEM) technique to model how patients move through healthcare systems (as narrated above). DEM is like a detailed clock that captures specific events in time, making it great for simulating timed "events". Patient flow, which involves managing queues and waiting times, is a crucial aspect of any healthcare system. Using DEM in `AnyLogic` allows us to realistically model these queues and waiting times, helping us find potential issues and areas where we can make healthcare processes better. So, by using `AnyLogic` and DEM, we aim to get a comprehensive understanding of patient flow dynamics and find ways to improve how healthcare is delivered.

Fig. 2 represents the *simulation model* of the earlier described patient flowchart, as appears in Fig. 1. This simulation model is constructed utilizing `AnyLogic`. Each component within Fig. 2 is assigned specific values, enabling a comprehensive and dynamic depiction of the patient flow in our University Health Medical Center's Emergency Department (ED). In ED, the space is usually divided into three distinct activity areas. The first area, denoted as Area 1 and marked in blue, serves as the Waiting Area. Here, patients await their turn for a bed. The second zone, Area 2, distinguished by its green color, functions as the Service Area. In this space, patients undergo various treatments and assessments. The final zone, Area 3, represents the concluding stage of the ED journey. Here, patients receive decisions regarding discharge or admission to inpatient care.

3.3.1. Simulation entities—We utilize the "Process Modeling Library" of `AnyLogic` to build our patient flow simulation model. The simulation entities are placed and connected to mimic the dynamic processes of patients going through steps in an ED. The model incorporates a "source" block, initiating the simulation by generating agents representing patients. These agents are drawn from a database designed to introduce variability in patient attributes, and their generation is controlled by a "schedule" block, allowing for day-specific agent generation rates."Decision" blocks are strategically placed throughout the model to determine agent flow based on predefined conditions, while "delay" blocks replicate real-world time intervals for activities such as waiting, diagnostics and treatments. We have used some datasets and functions from the "statistics" palette for storing the data to visualize the results later. The seamless integration of these simulation entities facilitates a comprehensive representation of the complexities within a healthcare environment, capturing patient movements, decision-making processes, and resource utilization dynamics.

3.3.2. Modeling delay blocks—The foundation of delay blocks in our simulation lies in the distribution of delays. Drawing from both literature reviews and real data, we determined the delay block values used in our model diagram (see Fig. 2). In most cases, delays follow a Uniform distribution, except for waiting room time and service room time, which follow Gamma distributions (fitted based on the hospital data).

One of the key items of interest in an emergency department's operation is the "length of stay" (LOS), the amount of time spent by a patient from entry to exit in the ED (either being discharged, left without treatments, or admitted inpatient care). Average LOS serves as a pivotal parameter in the model, reflecting the typical duration a patient spends in the department. In our hospital data, the average LOS in ED is 5.5 h. We set the delay distributions in various delay blocks in the model so that the total time, on average, sums to 5.5 h. Comprising delay blocks aligned with real-world observations, each corresponding to specific ED stages, the model ensures a realistic portrayal of patient interactions.

Consequently, two critical modeling constraints are imposed: first, the conservation of time, ensuring that all time durations sum up to the average LOS; and second, total duration alignment, requiring the sum of individual delay block durations to be consistent with the calculated average Length Of Stay. These constraints enhance the model's fidelity, capturing both the statistical average and temporal dynamics of patient flow within the emergency department, thereby contributing to a comprehensive evaluation of the ED's performance and efficiency.

Table 1 gives the names of the delay blocks, their delay distributions, and their average times.

3.3.3. Model parameters—Parameters play a critical role in shaping our modeling approach, serving as pivotal factors that influence decision-making within our simulation. These parameters essentially act as guiding rules, exerting a significant impact on the entire simulation process. Table 2 outlines six key parameters that are central to our model. It is noteworthy that altering any one of these parameters has the potential to substantially alter the overall outcome of the simulation.

For instance, let us consider the parameter "bed availability". This particular parameter holds considerable importance due to its direct influence on the computational dynamics of the simulation. The value assigned to "bed availability" is a key determinant in the simulation's results. Changing the number of available beds directly affects critical aspects, such as the number of patients who may leave without being seen.

To ensure the validity of our simulation, we prioritize realistic and meaningful parameters. To achieve this, we have conducted parameter optimization, refining values based on our dataset. This process enhances the accuracy of our simulation, aligning it closely with real-world dynamics for more reliable insights.

The simulation experiment incorporated various parameters, including immediate bedding with a value of 0.2 fixed we got it from the data as it depends on the severity of patients, a fixed available bed count of 39 for 2–4 h. Additionally, there are values assigned to the decision factors such as the likelihood of deciding to stay1 (0.96), then deciding to stay2 (0.98), and opting for inpatient care (0.09). These values we got from using the parameter optimization method. The goal of the experiment was to assess the impact of these parameters on resource utilization, length of stay, number of patients staying in the hospital, and number of infections. The parameters were categorized as fixed, variable, and discrete, and the objective was to identify optimal parameter values that minimize the gap value which is shown in Table 2.

3.4. Modeling HAI risk in emergency department

In our model, we focus on three key sections within ED: namely (1) The waiting area (Area 1), (2) the service area (Area 2), and (3) the concluding stage (Area 3), as shown in Fig. 2. These zones align with specific activities: patient entry, medical procedures, and discharge/admission decisions. Our approach aims to uncover how infections may relate to these distinct ED areas, offering insights into healthcare-associated infections (HAIs) shown in Fig. 4. This intentional segmentation enables us to assert that the occurrence of infections is intricately tied to both the specific locations patients traverse and the duration of their stay within these areas. By leveraging the infection rates depicted in Fig. 3 to model various regions, we acquire a nuanced insight into the distinct risk profiles associated with each section of the Emergency Department (ED). This enhances our ability to conduct a more thorough analysis of infection dynamics within the healthcare setting.

Within the spectrum of infections considered, our primary focus encompasses Urinary Tract Infections (UTIs), Methicillin-Resistant Staphylococcus Aureus (MRSA), and other types of Healthcare-Associated Infections (HAIs). In the Emergency Department (ED), the risk of Urinary Tract Infections (UTIs) and Methicillin-Resistant Staphylococcus Aureus (MRSA) are heightened due to prolonged patient stays, exposure to various medical devices, and the close proximity of individuals with different health conditions. The frequent use of catheters and other medical instruments in the ED increases susceptibility to UTIs, while the dynamic and crowded environment raises the likelihood of MRSA transmission among patients with compromised immune systems. These specific HAI categories have been strategically utilized in various areas within our modeling framework to quantify the spread of infections. This targeted approach allows us to discern distinct patterns and dynamics associated with UTI, MRSA, and other HAIs, contributing to a comprehensive understanding of infection transmission within different sections of the modeled environment.

3.4.1. Effects of waiting room dynamics on HAIs—In the Emergency Department (ED), the waiting room holds particular importance, especially for patients with lower illness severity or those awaiting bed availability. This area is marked by prolonged waiting times, and its significance lies in exposing individuals, often with compromised immunity due to various medical conditions, to a diverse range of illnesses. The waiting room serves as a convergence point for patients with different health concerns, potentially increasing the risk of susceptibility to Healthcare-Associated Infections (HAIs). In our meticulous modeling framework of the ED, where we delineate waiting, service, and comprehensive areas, the waiting room emerges as a key focus.

In particular, our focus within the waiting room area is on the occurrence of infections, with a special emphasis on MRSA and other potential infections. It is worth noting that, based on our historical data, we have derived that 1/3 of the total Healthcare-Associated Infections (HAIs), including MRSA, originate in the waiting room area. This specific focus underscores the importance of understanding and mitigating the risk of infections in this critical space, contributing to a comprehensive and targeted approach in our simulation model of the Emergency Department (ED).

3.4.2. Effects of service area dynamics on HAIs—Within our modeling framework, which meticulously delineates three integral sections within the emergency department (ED), the role of healthcare-associated infection (HAI) transmission is particularly accentuated in the service area. This sector, dedicated to essential medical procedures such as labs, diagnostic tests, and assessments, poses a unique risk environment. Here, patients are exposed to an array of medical devices and instruments, fostering an intricate interplay between patients, healthcare professionals, and equipment which is shown in Fig. 5. This close interaction establishes a potential pathway for the transmission of infections, as discussed in Puspasari, Ridhova, Hermawan, Amal, and Khan (2022).

The prolonged duration of patient stays in the service area, both during waiting periods and while receiving medical services, significantly increases the likelihood of infection transmission. Our modeling approach specifically identifies the service area as a zone with an elevated risk profile, with particular attention to the prevalence of urinary tract infections (UTIs) and Methicillin-Resistant Staphylococcus Aureus (MRSA) within this critical zone. Utilizing our data, we have incorporated the observation that 75% of UTI infections occur in the service area, as this is a location where patients may be more susceptible to infections due to contact with medical devices such as catheters.

3.4.3. Effects of other areas on HAIs—In addition to the previously highlighted focal points of the emergency department (ED), namely the waiting room and service area, our comprehensive modeling approach underscores the significance of other critical areas within the ED landscape. Notably, the admission room for inpatients and the discharge room, while representing relatively brief phases in patient interaction, emerge as pivotal stages given their position as the concluding steps in the ED journey.

Despite the relatively shorter duration of patient stays in these areas, their significance lies in serving as the concluding phases after extended periods within the ED. Here, the potential for infection transmission persists, exemplified by the heightened risk of pathogens such as MRSA. Beyond these terminal phases, our modeling discerns that infections, including but not limited to Enterocolitis due to Clostridium difficile and candidiasis of skin and nail, may manifest during the overall ED stay. Our modeling paradigm is inherently centered on the premise that infection spread is proportionate to the duration of patients' sojourn in the ED. This approach helps us explore the different ways infections can happen throughout the entire ED. It gives us a fuller picture of how germs might move around and affect patients during their time in the emergency department.

4. Results and analysis

Our analysis consists of two parts. First, we analyze the historical patient admission and discharge data from University Health Medical Center . We also use the data to validate our simulation model. Second, we analyze the simulation outputs for three scenarios to study the impact of various parameters affecting HAI incidence in ED.

4.1. Analysis of hospital data

We analyzed an extensive dataset encompassing ED visits and subsequent referrals during the period from 2022 to 2023. Key variables extracted from the local hospital's records included the registration fishnet, date, month, the count of LWBS (patients leaving without being seen), the count of AWTR (patients leaving without receiving full treatment), Length of Stay (LOS) in the Emergency Department (ED), waiting periods, the number of infections recorded, and the count of inpatients. This comprehensive dataset forms the foundation for a thorough investigation into the dynamics of ED operations, patient flow, and the potential impact on healthcare outcomes, providing valuable insights for further understanding and optimization of emergency care services.

Our examination involved scrutinizing daily patient arrival patterns and analyzing infection counts on different days. The objective was to establish connections and discern potential correlations between patient arrivals and infectious incidences. The key insights derived from our dataset analysis are presented in Table 3.

The number of patients visiting the emergency department (ED) each day varies, with the most common number of patients being between 140 and 180 as shown in Fig. 6. This information has been used to staff the ED appropriately and to identify potential bottlenecks in patient care.

The analysis of patient arrival rates, depicted through line graphs, reveals notable distinctions between weekdays and weekends, as shown in Fig. 6. We conducted a thorough analysis comparing patient arrivals on weekdays and weekends to investigate potential correlations with infection rates. This investigation aimed to discern any patterns or relationships between the timing of patient influx and the occurrence of infections within the studied context. Weekdays exhibit higher variability in patient arrival rates, with an overall higher average compared to weekends. Further scrutiny of the line graph indicates that Wednesdays stand out as having the highest patient arrival rates. Based on the investigation by Dubois et al. (2017) this observation is attributed to a surge in emergency cases, notably stemming from surgeries performed on Tuesdays. The influx of post-surgery emergencies contributes to heightened patient arrivals, creating increased congestion on Wednesdays.

In terms of Hospital-Associated Infections (HAIs), there has been a consistent number of patients flagged as "suspected" for possible HAI infections. The data reveals that, on average, the number of patients contracting infections on a single day is 3, with occasional peaks reaching up to 6 patients on certain days Fig. 7(a). Note that the numbers reported in our obtained data are "suspected" cases, a small of which are later confirmed by rigorous lab/wet tests as suggested by the CDC (the Centers for Disease Control and Prevention). The confirmed cases are not reported in the data.

The analysis of the boxplot in Fig. 7(b) reveals noteworthy variations in the number of infections across different days of the week. Notably, the median number of infections remains relatively consistent throughout the week. However, the highest count of infections is observed on Monday and Thursday, both weekdays when patient arrival rates are notably elevated. The correlation between higher infection counts on weekdays and increased patient arrival rates suggests that a crowded hospital environment may contribute to prolonged wait times for treatment. This extended waiting period exposes patients to a heightened risk of Healthcare-Associated Infections (HAIs). The data underscores a crucial connection between the duration of patient waiting and an increased susceptibility to infections, emphasizing the need for targeted interventions to mitigate these risks within the healthcare setting.

According to Peterson (2020) on weekends, the Length of Stay (LOS) in the ED tends to be higher, partly because of the processing dynamics of laboratories. Laboratories experience reduced staffing levels on weekends, leading to delays in test processing and reporting. This delay in test results contributes to longer patient stays in the Emergency Department, highlighting a key factor in the observed weekend effect on LOS.

4.2. Simulation experiments

Two distinct trails were utilized in the simulation experiments. The first experiment focused on developing a patient flow model, utilizing comprehensive information obtained from local hospital data. This model was subsequently validated. The second experiment centered around an infection model, incorporating parameters such as the specific areas patients traverse and the duration of their stays. This infection model provides insights into the dynamics of infection transmission based on patient movement within different sections of the healthcare environment. In the following, we describe these two sets of results.

4.2.1. Validating simulation model—Validation of the model development process refers to estimating unknown free parameters of the simulation model so that the simulation outputs match the observed data. According to Law, Kelton, and Kelton (2007), the validation process occurs in two pivotal phases, mirroring established practices in simulation methodology. Step 1 involves an expert review and Step 2 involves testing the model accuracy with either a numerical or discussion method. Similarly, experts reviewed the proposed conceptual model to make sure it was correct and aligned with existing knowledge before moving on to the implementation stage. Post-implementation, the validation process focused on the accuracy of the simulation model, adopting a distinctive approach. Instead of traditional numerical methods, the validation process involves partitioning the entire dataset into two partitions: one is called the *training* dataset, which is used to *estimate* the parameters of the model, and the other one is called the *testing* dataset, which is used match with the simulation output against once the estimated parameters are used (similar to machine learning practices).

In particular, three parameters in the patient flow model were estimated from the training dataset: “Decide to stay1”, “Decide to stay2”, and “inpatient care”. To compare and obtain values for optimization, “LWBS” (Left Without Being Seen), “AWTR” (Away without therapeutic response), and the number of “inpatient” cases were utilized. More specifically, the values of the three parameters are determined in a fashion so that the three outputs obtained from the simulation become close to the corresponding data obtained from our study hospital. The degree to which the simulation outputs differ from the real data is measured in Mean Squared Error (MSE), and the goal of parameter estimation is to minimize this error. Let $\boldsymbol{\Theta} = \{\theta_1, \theta_2, \ldots\}$ be the list of parameters of the simulation, $\mathbf{sim}(t; \boldsymbol{\Theta})$ and $\mathbf{obs}(t)$ be the simulated and observed output vectors, which consist of counts of LWBS, AWTR, and “inpatient”, for tth time instance (here, a day, in our case), the parameter estimation boils down to finding $\boldsymbol{\Theta}$ so as to—

$$\min_{\boldsymbol{\Theta}} \frac{1}{T} \sum_{t=1}^{T} (\mathbf{sim}(t; \boldsymbol{\Theta}) - \mathbf{obs}(t))^2 \tag{1}$$

Fortunately, `AnyLogic` provides a tool, called “experimentation”, by which the optimal parameters can be determined once the stated objective function (here, the MSE, as shown in Eq. (1)) and the possible ranges of parameter values (cf. Table 2) are specified. Consequently, the optimized parameter values we obtained from this process were 0.96, 0.98, and 0.90, respectively, as shown in Table 4.

A similar optimization approach was applied to the infection model. Recall from Fig. 2 that the ED facility is divided into three areas: Area 1, Area 2, and Area 3, each corresponding to an infection parameter (“infection 1”, “infection 2”, and “infection 3”), and their respective values were estimated from the actual data set provided by the hospital and compared with the simulation outputs. The resulting optimized values for these parameters are 0.005, 0.01, and 0.005, respectively (shown in Table 4).

The optimization process is conducted using the possible value ranges from Table 4 and using the hospital data from August and September (*training* dataset). The resulting parameters are then applied to simulate the cases in October and November (*testing* dataset). The results of the validation tests appear in Figs. 8 and 9, for both the Patient Flow Model and the Infection Model. These visualizations encompass data from both training and testing datasets. The close correspondence between simulated and observed values during this period serves as a validation of the model’s accuracy. The mean squared error (MSE) of the simulation for each of these validation tests can be seen in Table 5.

4.2.2. HAI incidences in ED areas—The presented plot in Fig. 10 shows the incidence of infections across three key areas within the Emergency Department (ED): the waiting room (Area 1), the service room (Area 2), and the overall ED (Area 3). Notably, the highest number of infections is observed in the service room (Area 1), followed by the overall ED (Area 3), and then the waiting room (Area 2). This pattern implies that the service room stands out as the most infectious area in the ED. Given that patients spend extended periods in this space for both waiting and receiving treatments, the elevated infection count underscores the significance of prolonged patient exposure. It is noteworthy that the service room, being the primary site for medical procedures, is inherently associated with increased contact with medical devices and equipment, potentially contributing to the heightened risk of Healthcare-Associated Infections (HAIs). This finding underscores how the amount of time patients spend in certain risky areas, such as the service room, is closely linked to a higher chance of getting infections. It highlights the urgent need for specific plans to reduce these risks in healthcare settings.

4.2.3. Simulation under different scenarios—
Once the patient-flow and infection model is validated from data, the simulation is conducted under three scenarios to further study the various aspects of hospital operations on HAI incidences. These three scenarios are:

- Scenario I: Higher patient arrival rates
- Scenario II: Fewer beds available in ED
- Scenario III: Higher severity of illness in patients

In Scenario I, the patient arrival rate is doubled to evaluate its impact on the density of patient influx and subsequently its effects on infection rates. Fig. 11 illustrates the outcomes, showing that an increase in patient rates significantly affects infection rates across all three areas. Compared to the baseline scenario, higher infection rates in all areas are observed. This increase can be attributed to the higher number of patients in the same area, leading to increased delay times and, consequently, heightened susceptibility to infections.

Scenario II decreases the number of available beds from 39 to 25 to explore its impact on infection rates. Fig. 12 illustrates that this change significantly influences Area 1, where people experience longer wait times in the waiting room due to reduced bed availability. As individuals wait, their susceptibility to infections increases, particularly affecting Area 1 compared to the baseline scenario.

Finally, Scenario III elevates the severity level of patients, transitioning from 25% to 40%. The objective was to assess the impacts of this severity level change, and the results, depicted in Fig. 13, indicated a notable increase in infections within Area 1 compared to the baseline scenario. This outcome is attributed to the heightened demand for beds when patients have higher severity levels. Consequently, the existing bed occupancy may limit the availability of new patients, prompting them to wait in the designated waiting room area. Unfortunately, this waiting period exposes patients to a higher susceptibility to infections. The scenario alteration sheds light on the intricate interplay between patient severity, bed availability, and the subsequent infection dynamics within the healthcare system.

5. Conclusion and future works

Our exploration into the dynamics of patient movement within the Emergency Department (ED) has revealed compelling insights. In our experimental model, we observed a distinct pattern—patients predominantly allocate more time to the Treatment area, followed by the overall ED, and then the waiting room as they await bed availability. Notably, the Treatment area exhibited a higher infection rate compared to other sections, prompting a closer examination of the relationship between patient location, duration of stay, and infection incidence.

This investigation provides compelling evidence supporting the hypothesis that infection rates are directly proportional to both the specific areas patients occupy and the duration of their stay. The longer patients spend in targeted ED zones, particularly within treatment or service areas, corresponds with an elevated risk of infection. These findings underscore the nuanced interplay between spatial and temporal factors in influencing infection dynamics within healthcare environments.

In essence, our study emphasizes the importance of considering both the physical trajectory and time spent within ED areas to formulate effective strategies for infection prevention. These insights contribute significantly to the broader conversation surrounding patient safety in emergency care settings, paving the way for more targeted interventions and improved healthcare outcomes.

Future works.

In the subsequent phase of our research, an ongoing collaboration with the University Health Medical Center has unfolded promising avenues for novel initiatives. This collaborative effort involves the real-time tracking of patient's movements using the installed Real-Time Location Systems (RTLS) with a particular focus on high-risk areas within the healthcare facility. The incorporation of real-time analytics capabilities represents a groundbreaking approach that facilitates swift, data-driven decisionmaking. By harnessing this innovative strategy, we aim to actively address and mitigate the spread of Hospital-Acquired Infections (HAIs) in the forthcoming stages of our research. This collaborative approach holds the potential to significantly enhance patient safety by modeling the transmission dynamics of HAIs. The insights gained from this real-time data will enable targeted interventions, offering a proactive means of limiting the transmission of infections within the hospital setting.

Discussion.

The construction of the flowchart in Fig. 1 must align with the specific flow of the emergency department. However, the techniques employed can be adapted to accommodate the unique flow of other departments. This flexibility allows for the application of the same methodology to study different departmental workflows. Moreover, the proposed model is applicable to other patient-related departments, including inpatient wards, intensive care units (ICUs), and coronary care units (CCUs), for identifying Healthcare-Associated Infections (HAI). Furthermore, it can be effectively utilized in various nursing units across healthcare facilities. The versatility of the model allows for its implementation in diverse clinical settings, thereby enhancing the identification and management of HAIs across different patient care environments.

Acknowledgments

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Md Yusuf Sarwar Uddin reports financial support was provided by Centers for Disease Control and Prevention. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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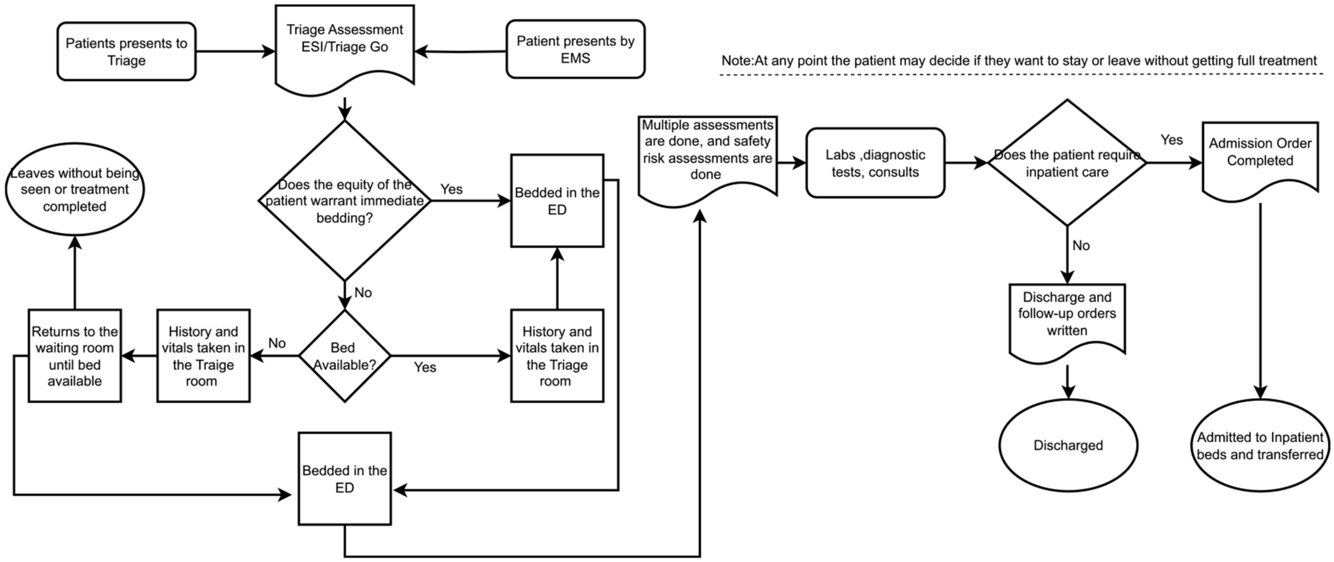


Fig. 1.

An in-depth look at the procedural steps within the Emergency Department in University Health Medical Center, presented in a comprehensive flowchart diagram.

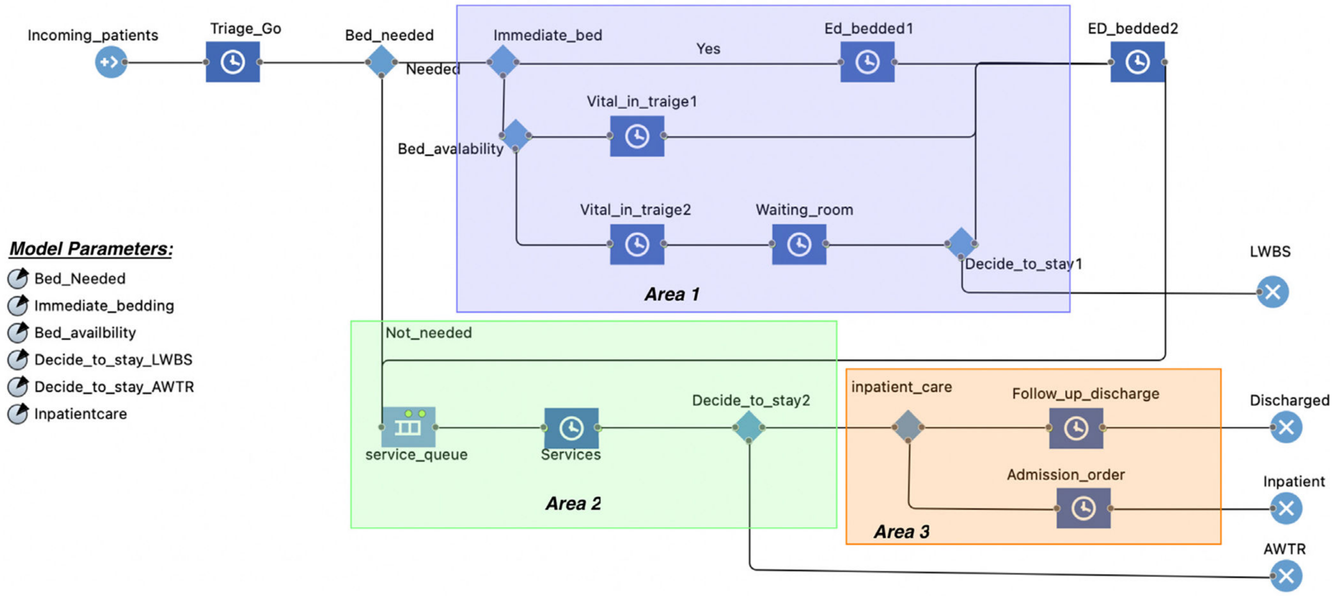
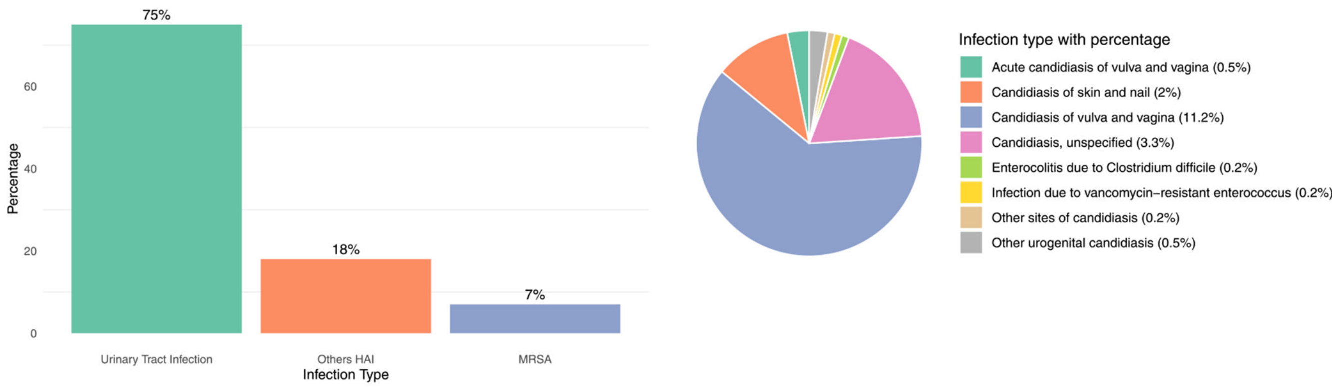


Fig. 2.
Simulation of patient flow in an emergency department (modeled in `AnyLogic`). The diagram features rectangular boxes with clocks, representing "delay blocks" for patient services, and diamonds indicating binary decision points, where patients take one route or the other (with some random probabilities). Queues signify patient waiting areas, while bubbles with an X mark the endpoint and small bubbles on the left denote parameters used in the model.



(a)

(b)

Fig. 3.

(a) Bar chart of popular HAI cases in the emergency department. In our data obtained from our Hospital, 75% are (suspected) UTI cases, 7% are (suspected) MRSA, and 18% are other HAI(suspected) cases. (b) In Figure a, where “Other HAI” cases are indicated, this segment provides a breakdown of specific infection names falling under the category of “Other HAI” and their respective percentages.

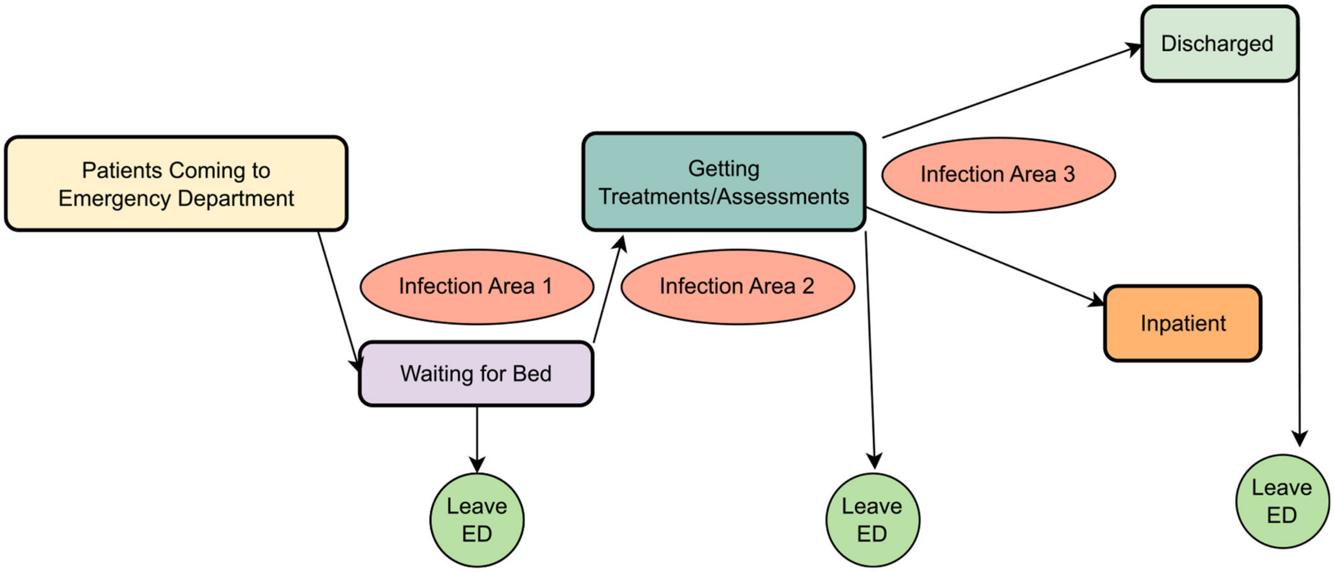


Fig. 4.

Schematic diagram of patient flow in the Emergency Department (ED) with highlighted infection areas.

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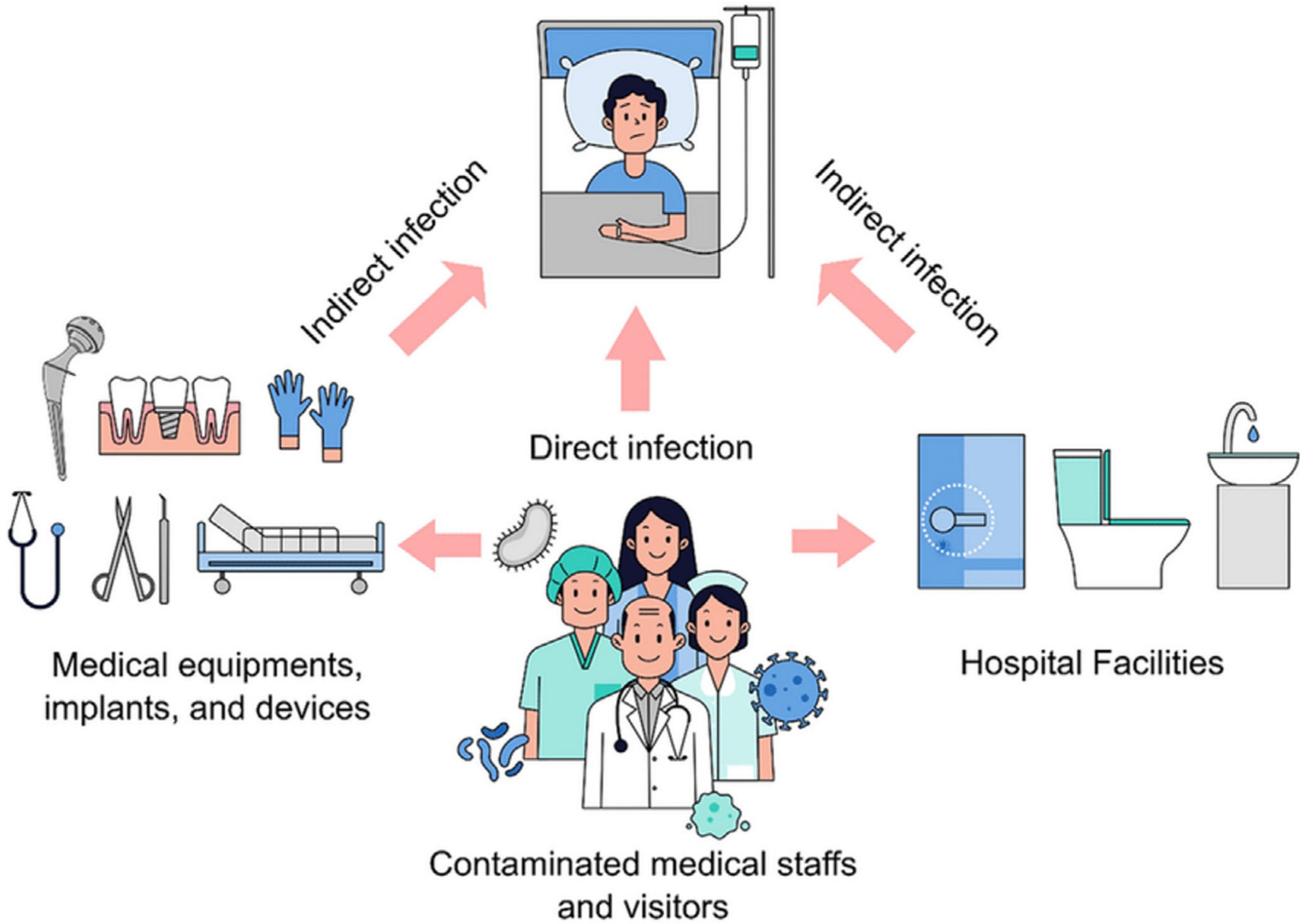


Fig. 5.
Schematic illustration of transmission routes of hospital-acquired infections (the figure is cited from Puspasari et al. (2022)).

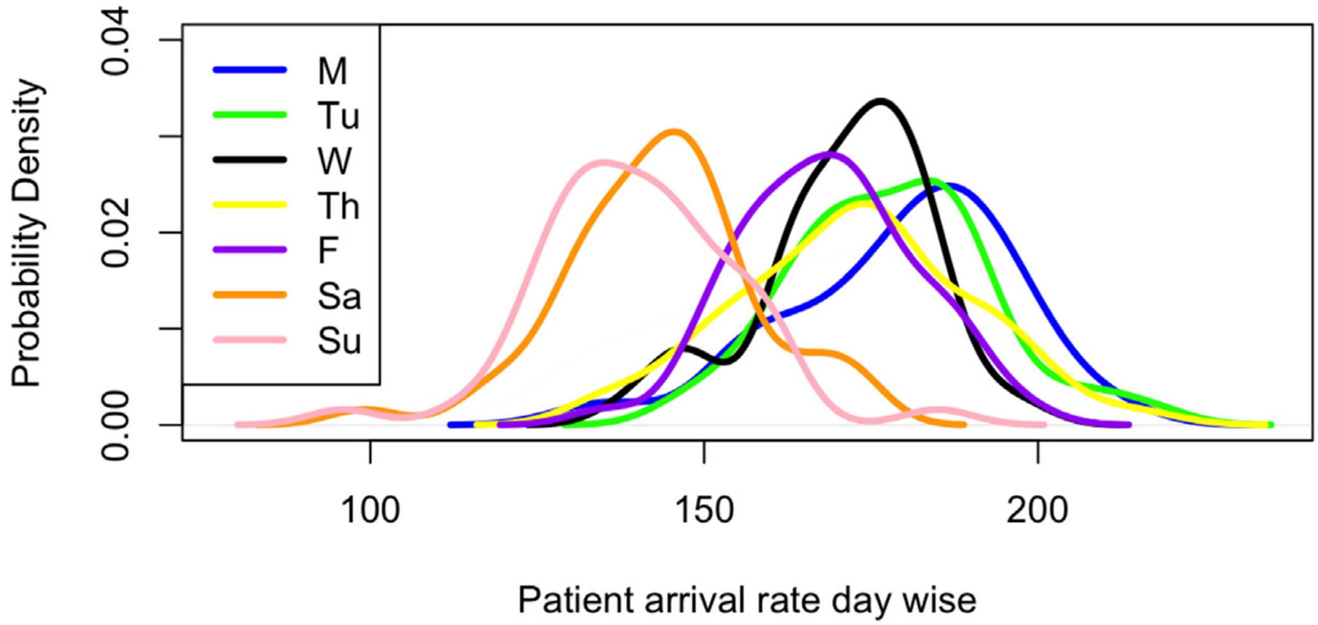
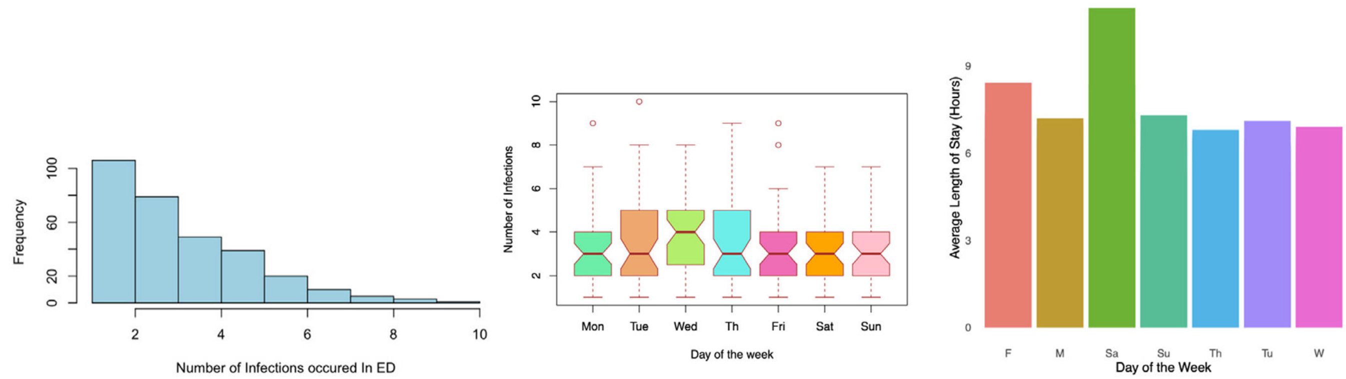


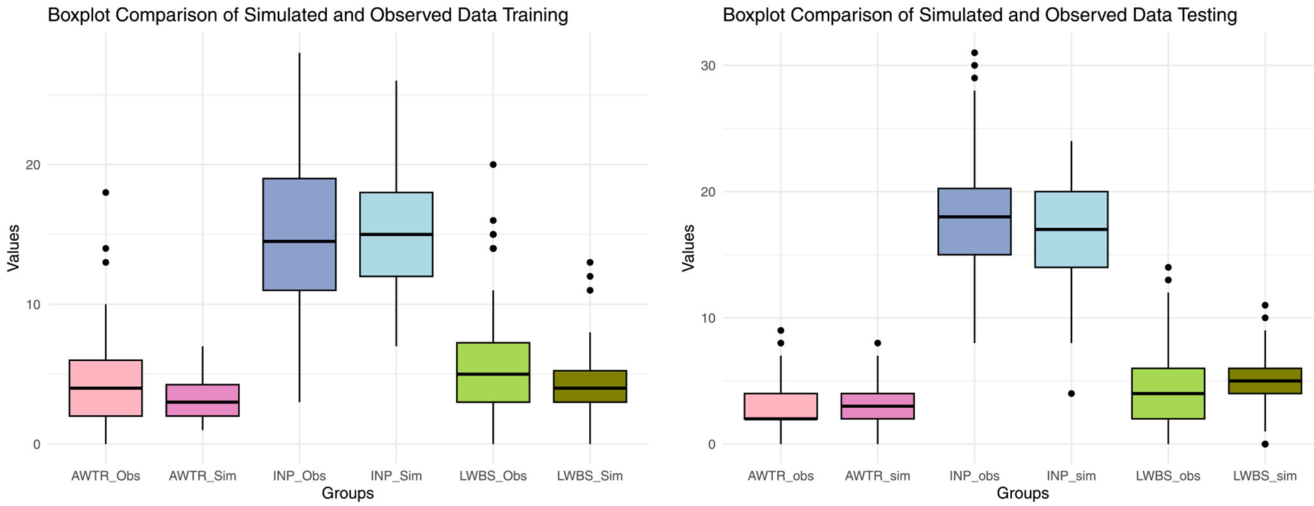
Fig. 6.
Exploring the daily patient arrival rate at the Hospital's emergency department and contrasting the density between weekdays and weekends. Weekdays (Monday through Friday) have a higher number of admissions than weekends (Saturday and Sunday).



(a) (b) (c)

Fig. 7.

(a) A closer look at the infection density rate within the Emergency Department of the local hospital, (b) A day-wise analysis of infection cases in the Emergency Department, including counts and identifying the peak day of the week, (c) Analyzing the Length of Stay in the Emergency Department on a daily basis to pinpoint the peak day of the week.

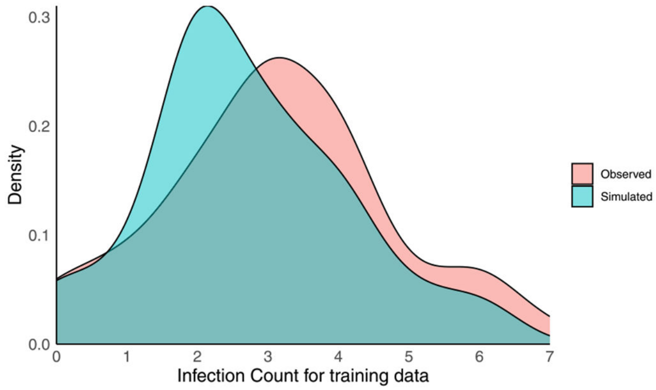


(a) Training Data Simulation

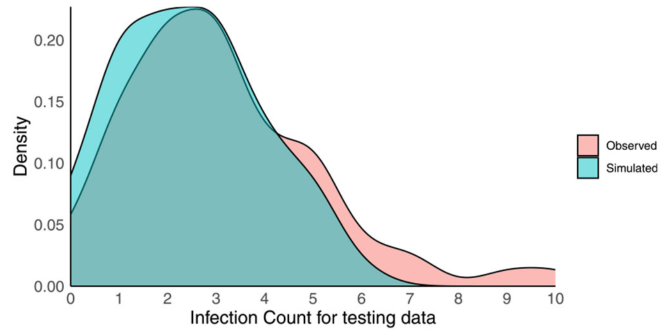
(b) Testing Data Simulation

Fig. 8.

Boxplots for validation outcomes of patient flow model, illustrating variations in testing data simulation versus training data simulation.



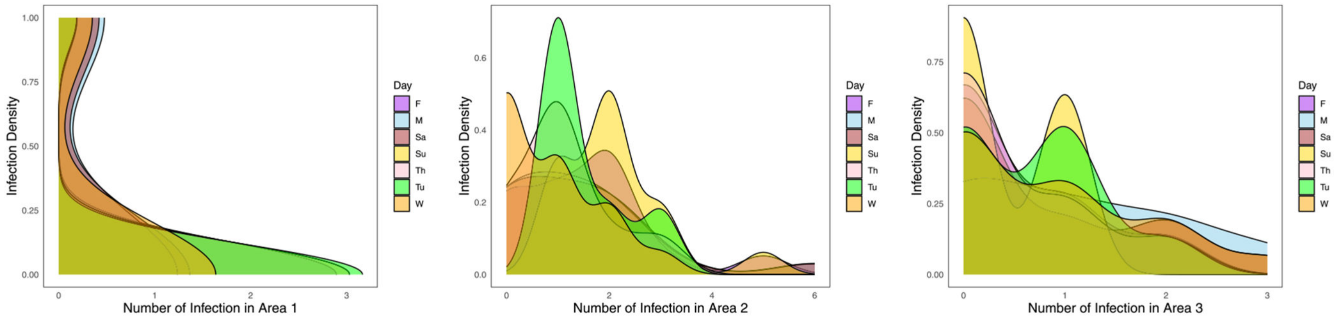
(a) Training Data of Infection



(b) Testing Data of Infection

Fig. 9.

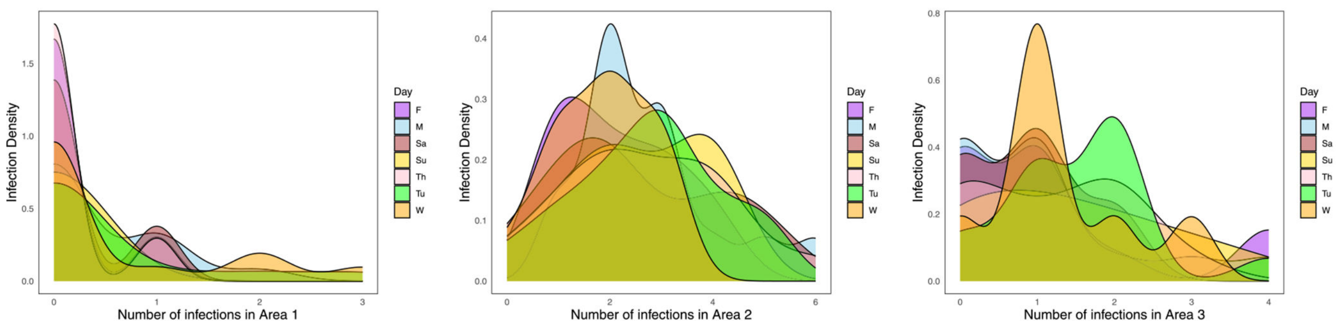
Density plots for validation outcomes of infection model, illustrating variations in testing data simulation versus training data simulation for infection counts in ED.



(a) (b) (c)

Fig. 10.

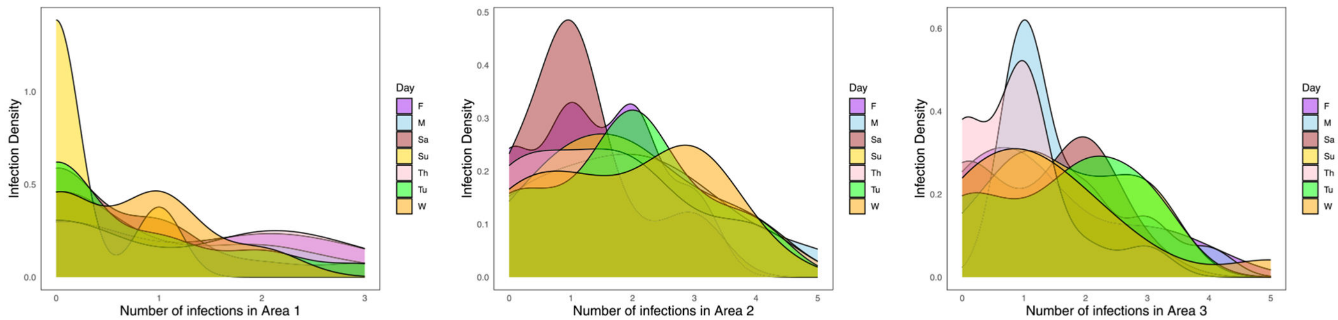
Exploring infection patterns in the ED from a simulation model, highlighting differences in occurrence across three distinct areas.



(a) (b) (c)

Fig. 11.

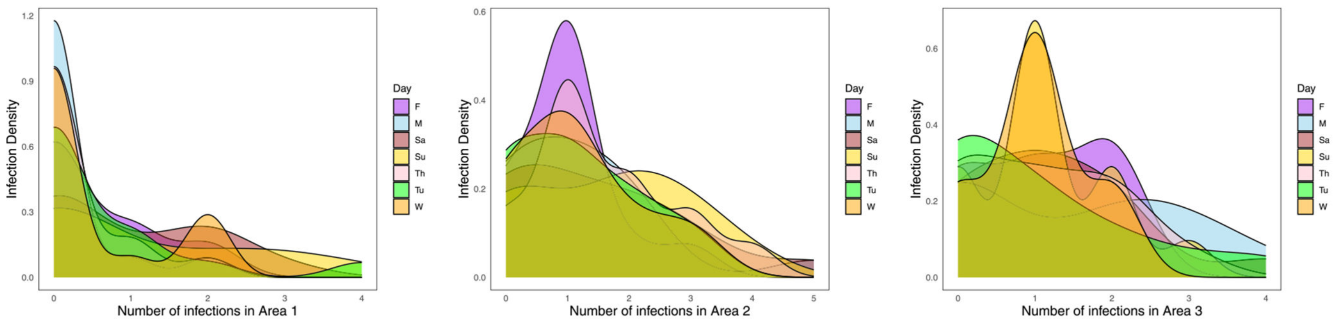
Exploring infection patterns in the ED, highlighting differences in occurrence across three distinct areas when the patient rate is double.



(a) (b) (c)

Fig. 12.

Exploring infection patterns in the ED, highlighting differences in occurrence across three distinct areas when the number of available bed is less.



(a) (b) (c)

Fig. 13.

Exploring infection patterns in the ED, highlighting differences in occurrence across three distinct areas when the severity level is higher.

Table 1

Distribution of different delay blocks used in the simulation.

Block name	Distribution	Average time (min)
Triage	Uniform(5,15)	10
Vital in traige1	Uniform(5,10)	7.5
Vital in traige2	Uniform(5,10)	7.5
Bedded In the ED1	Uniform(5,15)	10
Bedded in the ED2	Uniform(60,120)	90
Waiting Room	Gamma(α, β)	35
Service+Waiting Room	Gamma(α, β)	150
Discharge area	Uniform(10,20)	15
Admission Area	Uniform(10,20)	15

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Table 2

Parameter ranges assigned for Experimentation in `AnyLogic`.

Parameter	Type	Value	Step
Immediate bedding	Fixed	0.20	–
Patients per day	Variable	164 ± 50	–
Bed capacity	Fixed	39	–
Deciding to stay1	Range	0.5–1.0	0.01
Deciding to stay2	Range	0.5–1.0	0.01
Inpatientcare	Range	0.0–0.5	0.01

Table 3

Summary statistics of 11 months data.

	Aug 2022 to Jun 2023										
	Aug	**Sep**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**
Total Admitted Patients (monthly)	5070	4887	5074	4912	4874	4943	4530	5267	5100	5277	5123
Median Admitted Patients (per day)	163	171	164	166	161	163	159	172	168	173	170
Avg. Length of Stay (hours)	5.87	5.78	5.41	5.79	5.92	5.32	5.42	5.96	5.19	5.15	5.38
Median Infection Count (per day)	3	3	3	3	3	4	2	2	3	3	3
Median Inpatient Number (INP) (per day)	14	16	18	20	14	13	15	17	17	17	16
Median LWBS (per day)	5	3	4	3	6	4	4	6	2	4	5
Median AWTR (per day)	4	3	3	2	2	2	4	5	4	5	4

Table 4

Parameter values obtained by AnyLogic's optimization method.

Parameter	**Value**
Decide to stay1	0.960
Decide to stay2	0.980
Inpatientcare	0.090
Infection 1	0.005
Infection 2	0.010
Infection 3	0.005

Table 5

Mean Squared Error (MSE) for parameter estimation.

Model	MSE value
Patient Flow model	91.05
Infection Model	2.47