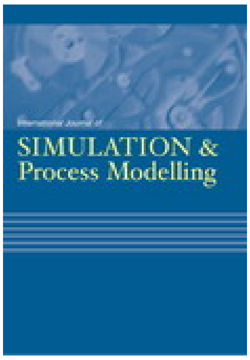

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Assessing the impact of non-pharmaceutical interventions on disease infection in the public health sector: a hybrid simulation approach

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Assessing the impact of non-pharmaceutical interventions on disease infection in the public health sector: a hybrid simulation approach

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Abstract: This study investigates the impact of non-pharmaceutical interventions (NPIs), including the use of cotton fabric masks and social distancing, on disease infections, such as COVID-19, and exposure rates within waiting areas of an emergency department. Employing a multi-agent simulation approach, the research models patient flow, with each agent representing a physical entity governed by predefined attributes and rules. The objective is to assess the performance of preventive measures quantitatively based on agent proximity and exposure time. Findings indicate that facemask usage reduces infections, and both facemask adherence and social distancing contribute to lower infection rates. The study highlights the similarity in effect between social distancing and a 20% facemask adherence rate. Additionally, it underscores that as more agents adopt facemasks, the time needed for exposure increases. Waiting areas emerge as potential hotspots for transmission.

Keywords: non-pharmaceutical interventions; NPIs; disease infection; COVID-19 exposure; hybrid simulation; waiting areas; public healthcare.

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Azmi M. Mahafzah is the Jordanian Minister of Education and Higher Education and Scientific Research. He was appointed as minister on 27 October 2022. Since 1984, Mahafzah has worked as a Lecturer and, since 2009, as a Professor at the University of Jordan. Additionally, he held several positions at Jordan University Hospital from 1989 until 2013. From 2010 until 2013, he served as Dean of the Faculty of Medicine. Since 27 October 2022, he has been Minister of Education and Higher Education and Scientific Research.

This paper is a revised and expanded version of a paper entitled 'Developing modern agent technologies in combating COVID-19 exposure: an application in a healthcare facility' presented at International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT), Sakheer, Bahrain, 20–21 November 2022.

1 Introduction

Researchers have focused on understanding the diverse dispersion patterns of COVID-19 across regions. For example, (Pereira et al., 2022) constructed a comprehensive risk model incorporating key variables such as probability, susceptibility, danger, vulnerability, and potential damage. Since the onset of the COVID-19 pandemic, researchers have conducted extensive studies in epidemiology to examine the behaviour and transmission dynamics of the virus. Their objective has been to identify effective preventive measures for reducing positive cases and mitigating the broader impacts of the pandemic, including economic repercussions resulting from interventions like lockdowns. A study by Mondal et al. (2022) revealed that the prevalence of respiratory viral diseases has significantly reduced following COVID-19, possibly due to the impact of non-pharmaceutical interventions (NPIs). Initial attention was directed towards open public spaces such as schools, universities, places of worship, shopping malls, and public transportation stations due to their high occupancy and potential for clustering, making them crucial in understanding infection curves. For example, a study by Hunter and Kelleher (2022) explored the impact of community mixing when schools reopen after the summer holidays. Another work done by Saleh and Adly (2023) concluded that the significance of lowering air pollution levels is underscored to alleviate the enduring health impacts of COVID-19. However, closed environments also play a significant role in virus transmission if appropriate preventive measures are not implemented (Shbool et al., 2022a).

Hospitals and healthcare facilities are of particular concern in closed spaces. Hospitals are susceptible to increased infection rates due to the influx of patients with varying health conditions, given the continuous operation regardless of epidemiological situations. Waiting areas within hospitals, where people gather before receiving medical attention, can contribute to congestion and facilitate higher transmission rates. Accurate prediction of infection rates is crucial for implementing effective measures and policies to mitigate the spread. In this study, we introduce an agent-based modelling (ABM) approach to assess the impact of NPIs, namely facemasks and social distancing, on the number of COVID-19 exposures among patients visiting an emergency department (ED).

Though computationally intensive, agent-based models provide essential insights into disease dynamics and interventions during pandemics, offering advantages such as capturing heterogeneity and generating possible outcomes (Hunter and Kelleher, 2022). By employing an agent-based model to simulate the flow and clustering of individuals within a hospital, decision-makers can gain insights into how COVID-19 infections may occur. This enables informed choices regarding the implementation of preventive measures within healthcare facilities. Additionally, the model facilitates predictions on how NPIs affect the infection curves of COVID-19. Our research supports healthcare decision-makers in confidently implementing preventive measures by identifying specific areas requiring increased attention and ensuring effective implementation of NPIs. Ultimately, the aim is to develop an agent-based system dynamics hybrid model to minimise the risk of infection within healthcare buildings and safeguard the well-being of individuals on these premises. The contributions of this work can be summarised as follows:

- Evaluating the influence of facemask mandates and social distancing measures on the extent of patient exposure within healthcare facilities.
- Examining the impact of NPIs on various factors, including total exposure time, average exposure time, duration until worker exposure, and the number of individuals exposed.

The rest of this paper is organised as follows: the second section reviews the related literature on COVID-19 exposure modelling and optimisation. The methodology section presents the utilisation of the agent-based approach. The results and discussion section provides a detailed analysis of the study results and computations. Finally, the paper concludes with a summary and outlines future work.

2 Literature review

Numerous studies have examined COVID-19 exposure in closed environments using simulation models. For example, Bandara et al. (2021) investigated the challenges of indoor COVID-19 transmission by modelling virus-laden aerosol trajectories in a study room using computational fluid dynamics. The impact of NPIs on COVID-19 exposure in closed spaces was evaluated by Al-Bazi et al. (2023) by introducing an innovative COVID-19 exposure prediction framework. This framework comprises three modules: an ABM approach, a clustering module (CM), and the application of the decision tree (DT) technique. Touchton et al. (2023) compiled a comprehensive dataset capturing national and subnational NPI implemented by governments in the Americas during the COVID-19 pandemic, allowing for dynamic and varied NPI comparisons within and across countries to understand their impact on health outcomes. Montcho et al. (2023) addressed the impact of NPIs on COVID-19 dynamics in Germany, which was assessed through a distributed lag linear model, considering challenges such as correlated interventions, time trends, and seasonal influences. The study revealed that the reduction in the number of intensive care patients is observed after a time lag of 10–15 days, with an overall decrease associated with increased intervention intensity after a time lag of 9 and 10 days, while acknowledging the complexity of drawing causal conclusions due to the absence of a suitable experimental study design. The impact of NPI on COVID-19 transmission by incorporating mobility data was also investigated using Bayesian modelling with Facebook mobility maps for the UAE by Hasan et al. (2022). The study assessed NPI efficacy, focusing on early epidemic stages to inform future pandemic response strategies. Ravkin et al. (2022) explored the impact of NPIs instituted during the SARS-CoV-2 pandemic on the atypical patterns of the 2020–2021 respiratory syncytial virus (RSV) season in children, where Google Trends data was used as a proxy. Mader and Rüttenauer (2022) investigated the NPIs effectiveness in reducing COVID-19-related fatalities beyond the initial wave, utilising a comprehensive approach across 169 countries from July 2020 to September 2021. The results showed the importance of NPIs in fatality reduction and underscored the significance of vaccinations in combating COVID-19-related deaths. This result is consistent with the conclusions of the study done in Europe from August 2020 to October 2021 by Ge et al. (2022), revealing that the combined effect of NPIs and vaccination resulted in a 53% reduction in the reproduction number. The reproduction number was estimated using a mathematical model in the study done by Saidan et al. (2020).

From the methodology perspective, Emroozi et al. (2022) conducted a study to assess COVID-19 dynamics using system dynamics modelling, exploring the impact of three proposed scenarios on disease management variables. Farkas and Chatzopoulos (2021) presented a mathematical model assessing the impact of self-quarantine on disease dynamics, revealing that actual peak case numbers may have been substantially higher than reported test cases and that solid adherence to self-quarantine rules had a more pronounced impact during the early phase of the outbreak, even when considering the reduction of the effective susceptible population size due to a national lockdown. Bahl et al. (2021) developed an agent-based model to predict the spread of COVID-19 in a college, highlighting the impact of interventions like facemasks and closures. (Patel et al., 2021) built a model for North Carolina to assess the combined effect of vaccines and NPIs on infection cases. Kaffai and Heiberger (2021) studied the effectiveness of NPIs in Germany, emphasising quarantine and working from home. Ying and O'Clery (2021) focused on COVID-19 spread in a virtual supermarket, emphasising the importance of limiting customer arrivals and mandating face masks. Alrashed et al. (2020) predicted COVID-19 spread in Saudi Arabia, demonstrating the impact of lockdowns. Cuevas (2020) introduced a model with behavioural rules to simulate infection transmission. Proverbio et al. (2021) extended the SEIR model to evaluate the effect of NPIs in different countries. A work by D'Orazio et al. (2021) assessed solutions for COVID-19 in university buildings, considering proximity, exposure time, and facemasks.

Hunter and Kelleher (2021) modified an epidemic model for measles to study COVID-19 transmission, addressing school closures and vaccinations. Kou et al. (2021) proposed a multi-scale agent-based model to study virus transmission between and within cities in China, highlighting the importance of vaccination and quarantine. Gathungu et al. (2020) presented a mathematical model to study the effects of NPIs. Hinch et al. (2021) developed an agent-based model to evaluate the performance of NPIs based on age stratification and social networks. Gharakhanlou and Hooshangi (2020) implemented an agent-based model to study the impact of preventive measures in Urmia, Iran. Panovska-Griffiths et al. (2021) modelled the effectiveness of face masks and tested trace isolate strategies in schools and communities. Álvarez and Rojas-Galeano (2020) explored the complex dynamics of COVID-19 mitigation through NPIs using agent-based models. It highlights the effectiveness of a 'zonal' strategy alongside individual NPIs in a conceptual city, offering insights for planning interventions in different epidemic stages.

Other studies focused on the disruptions faced by healthcare and supply chains due to COVID-19, emphasising the global spread of the virus and the critical role of vaccination. Narassima et al. (2021) used agent-based model and Grey Relational Analysis to rank regions based on key variables influencing virus transmission, aiding policymakers in rational vaccine distribution. The impact of other parameters, such as word-of-mouth, on the vaccination proportions has been investigated and found to have a positive effect. Sensitivity analysis explored the impact of positive/negative events, word of mouth, and session numbers, revealing significant increases in vaccination proportions with higher daily session rates. It is worth mentioning that the word-of-mouth factor is of great concern in supply chains, and it affects the spread of services and patient satisfaction, see Shboo et al. (2022b).

At the same time, many studies focused on the operational performance of healthcare facilities and hospitals. For example, Venkatesan et al. (2023) carried out in a multi-speciality ophthalmic outpatient clinic to analyse patient waiting time using data analysis and discrete event simulation (DES). Another work by Shbool et al. (2023) studied the patient's length of stay in the ED considering the effect of the COVID-19 pandemic. Another study by

However, a noticeable gap in the existing literature is the absence of studies focusing on assessing the exposure level of COVID-19 in waiting areas of healthcare facilities. This research aims to address this critical issue by introducing an innovative approach combining agent-based and system dynamics models. The integration of these models enables us to accurately estimate COVID-19 exposure in the waiting areas of a closed healthcare facility, specifically emphasising the ED. While prior literature has examined the dynamics of disease spread using agent-based models, our study uniquely directs attention to the often-overlooked waiting areas within healthcare facilities.

Our methodology distinguishes itself by evaluating the impact of facemasks and social distancing and quantitatively assessing the effectiveness of these preventive measures based on agent proximity and exposure time. This detailed analysis provides an in-depth understanding of how NPIs influence infection rates, particularly in high-risk environments such as hospital waiting rooms.

Our study significantly contributes to the existing literature by addressing the specific gap in understanding COVID-19 exposure dynamics within healthcare waiting areas. Integrating social distancing dynamics into an agent-based simulation and a quantitative assessment of NPI efficacy positions our research at the forefront of endeavours to enhance precision and suggest new healthcare facility risk mitigation strategies.

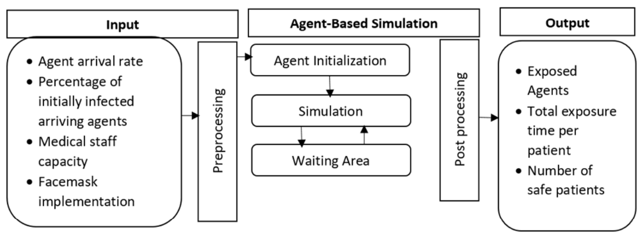
3 Methodology

This section presents the model components used in predicting the exposure rate of COVID-19 in waiting areas within closed environments. This work considers NPIs in waiting areas, including facemasks and social distancing. First, the model's inputs, processes, and outputs are identified and presented to understand the model requirements. The process core of the model consists of an agent-based model component and the SD model component.

3.1 Model framework

The primary goal of the model framework is to elucidate the interrelationship between model inputs, processes, and outputs, leading to a comprehensive prediction of the exposure rate for COVID-19. This understanding becomes pivotal in accurately forecasting potential risks. The visual representation of the COVID-19 exposure prediction model framework is depicted in Figure 1.

Figure 1 Model's inputs, process, outputs



For this investigation, we adopt an agent-based model to assess the impact of two NPIs within an ED: the utilisation of cotton fabric facemasks and the implementation of social distancing measures based on physical interactions. The model comprehensively incorporates a range of inputs, including patient arrival rate at the ED, the proportion of actual infected patients among the arrivals, patient compliance with wearing facemasks, adherence to social distancing norms in the waiting area, medication routes for individual patients, and the time taken at each medication stage. These inputs collectively form the basis for the first component of our model.

The process module consists of two components that are related to each other. The first component, the agent-based model, mimics the attributes (infected, susceptible, and facemasks) and patients' movements as represented by transitions between different departments inside the medical facility. The decision to employ an agent-based approach stems from its ability to effectively capture the behavioural dynamics of transient and permanent entities within the system.

The second component is the SD model, which is integrated with the agent-based model to monitor the movement of each agent inside the medical facility and capture their exposure to infected agents. It collects information about the total exposure time of each agent during their movement across the medical facility. It reports their medical status (susceptible, probably exposed, exposed) after visiting different waiting areas across the medical facility and experiencing various levels of exposure (distance, time, and mask). This component continuously checks the agent's status, and its calculations are triggered when the condition of an infected agent is satisfied, or the non-pharmaceutical intervention procedures are violated. This violation is represented when an infected agent exists within less than two metres of another agent. Ultimately, this component calculates the infection probability of each agent, which is used to decide which status the patient will be in upon leaving the ED. The infection probability is calculated when the effective exposure time is collectively reached.

Several key performance indicators represent the model outputs, including the number of safe and exposed agents, the average exposure time for exposed agents, and the total exposure time.

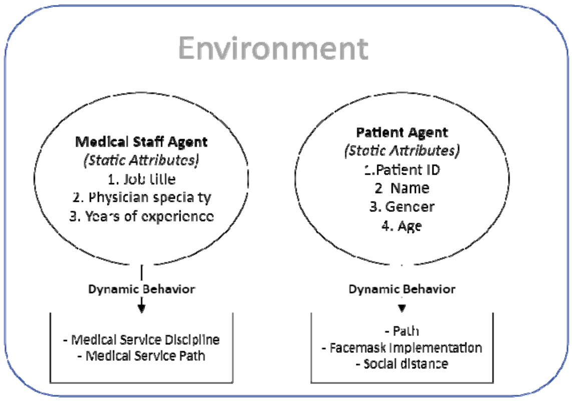
By adopting this sophisticated model framework, we strive to gain valuable insights into the dynamics of COVID-19 exposure and make informed decisions regarding implementing NPIs to mitigate risks effectively. The subsequent sections will discuss the methodology employed, presenting a coherent and detailed account of the modelling process. The following section explains the first agent-based module in detail.

3.1.1 Agent-based model

The agent-based component is designed to simulate the movement of patients within a medical facility accurately, encompassing waiting areas and seating arrangements. The model considers two types of agents: medical staff and patients, as depicted in Figure 2, along with their respective attributes.

Each agent possesses static attributes and follows specific behavioural rules that govern their interactions and movements. The attributes of the medical staff agents include job titles (such as a physician, imaging technician, nurse, pharmacist) and physician specialities (e.g., internal medicine, pediatric, orthopedic). Dynamic behavioural rules of the medical staff agent include medical service discipline and medical service path, dictate the actions of patient agents concerning their movement, waiting, and location. Patient agents are defined with static attributes like patient ID, name, and gender. Patients interact with the environment based on a set of dynamic behaviour rules, including path, facemask implementation, and social distancing.

Figure 2 Agents' attributes and behaviours (see online version for colours)



This model component effectively represents agents' behaviour from their arrival at the medical facility to receiving treatment and departing. Several inputs are required for the agent-based model to work, with the primary ones being the arrival rate of patients, the percentages of incoming infected and susceptible patients, and the service time for various medical procedures, including internal medicine, general surgery, pediatrics, and dentist orthopaedic treatments. The simulation environment used to develop the model encompasses the SD model and interior geometry of the building, incorporating walls, beds, and waiting areas.

Furthermore, the agent-based model replicates patient interaction to assess the potential exposure to infected agents. It takes into account factors like social distancing and facemask usage among patients. Additionally, the model accurately simulates the service process for each patient within different medical services departments, such as inspection, dental care, x-rays, and more. By identifying and tracking patient exposure to infected individuals throughout the medical facility, this data is passed on to the SD component for exposure prediction and level identification.

3.1.2 System dynamics

This model was designed to gather critical information, including exposure time, the number of infected agents within a two-metre range of a susceptible agent, and the facemask status of both infected and susceptible individuals as they evolve within the agent-based model. Integrating this model with the agent-based model allows real-time data collection during agents' movements within the medical facility. The SD model is activated upon an agent's departure from the facility to determine the final exposure level using the equations below. A snapshot of the SD model that captures all related statistics is shown in Figure 3.

Table 1 SD parameters

Factor	*Old*	*New*	*Description*
Infection prevention	pMj	IPFj	It indicates aggregated infection prevention for susceptible agent j from infected agents
Aggregated exposure time	Exposure Time	AETj	It indicates the total exposure time of infected agents
Mask aggregated	pMaskj (IM)	ICMj	Impact contribution of infected agents on the infection probability
Total number of infected agents	numInfected	NIAj	Total number of infected agents within 2 metres of the susceptible
Susceptible mask effect	maskEffect (SM)	SCMj	It indicates the infection prevention of the susceptible agent (0 if no mask, 0.88 if mask is applied).
Average exposure time	Normalised Exposure Time	NETj	= AETj/EET
Effective exposure time	T	EET	15 minutes
Infection probability	Infection probability	Pr (Infected)	Probability of infection

The SD model constantly assesses each agent, verifying compliance with predefined NPIs. It carefully records the duration of exposure for a susceptible agent within a distance of less than two metres from an infected agent. Furthermore, the model quantifies the collective impact of facemasks on the infected agents near the susceptible individual, denoted by the factor *pMaskj*. For a comprehensive understanding of the parameters utilised in the SD model and their respective explanations, refer to Table 1. These factors were identified by Al-Bazi et al. (2023).

The model sums the masking effect for the infected agents in variable *sumPMj*. The model gives the value of 0.88 (Rengasamy et al., 2017) for those wearing facemasks and zeroes for those who do not; these *sumPMj* variable values are stored in the *pMj* variable. Regarding the exposure time effect, the model calculates this time depending on how many infected agents are within the range of two metres, i.e., if there are two infected agents around the susceptible, the exposure time after one minute while both of them are there is two minutes as each agent is contributing to the exposure time. Table 2 shows the equation explanation.

Figure 3 System dynamics model (see online version for colours)

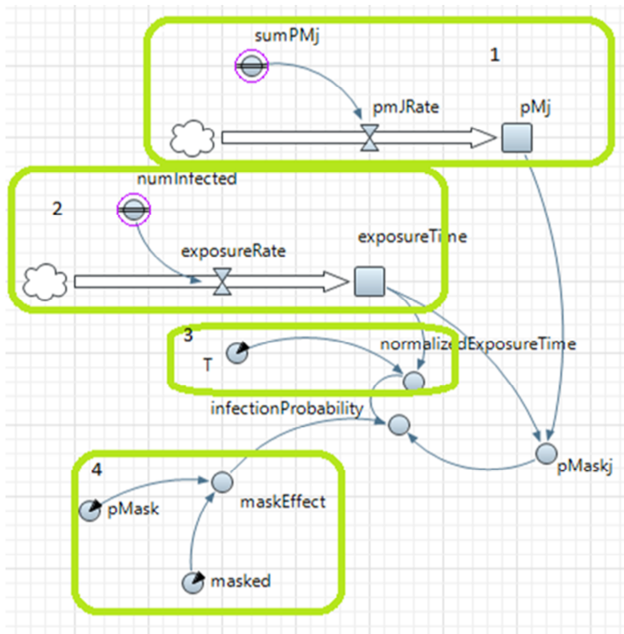


Table 2 SD equation sheet

Equation	*Equation*	*Explanation*
(1)	$pMj = \sum sumPMj$	Represents the green box number 1 in Figure 3
(2)	$T = Exposure\ Time = \sum num\ Infected * (1\ second)$	Represents the green box number 2 in Figure 3
(3)	$NET = NormalizedExposureTime = \frac{expsuretime}{T}$	Represents the green box number 3 in Figure 3
(4)	$pMaskj = \frac{pMj}{exposure\ Time}$	Represents the masking effect of the infected agents that are in the range of less than 2 metres
(5)	$maskEffect = \begin{cases} 0.88 & if\ susceptible\ agent\ is\ wearing\ a\ facemask \\ 0 & otherwise \end{cases}$	Represents the green box number 4 in Figure 3

Finally, all calculations feed into equation (6) (D'Orazio et al., 2021) to calculate the infection probability.

$$Infection\ Probability = \min(1, NET * (1 - SM) * (1 - IM)) \quad (6)$$

where

- Δt is the exposure time for the susceptible patient
- T equal to 15 minutes
- SM represents the reduction effect of facemasks on infection, assumed to be 0.88 (Rengasamy et al., 2017) considering the use of surgical facemasks in optimal conditions,
- IM represents the infection reduction effect based on the status of infectious agents nearby, with a value of 0.88 (Rengasamy et al., 2017), varying with the number of infectious agents and their facemask usage.

In our infection model, the exposure time (Δt) is pivotal in determining the infection probability for each susceptible agent. As per equation (6), the calculation of this probability assumes that initially infected agents possess a high transmission efficiency. Given the cumulative nature of exposure time, the infection probability for each susceptible agent is recalculated each time they come into proximity with an infectious agent. The probabilities are then summed until the susceptible agent leaves the department.

Each agent's probability is compared to a randomly generated number between zero and one upon departure. If the calculated probability surpasses the generated number, the agent is categorised as 'exposed'; otherwise, they are classified as 'safe.' The system dynamics library facilitates the systematic collection of information concerning exposure time and aids in continuously calculating infection probability. The cumulative exposure time is paramount in evaluating an agent's exposure status.

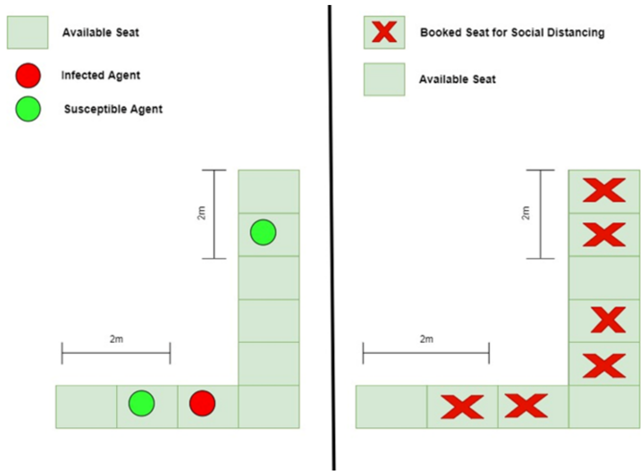
Furthermore, the model assesses the infection status of all infectious agents within the specified range, considering whether they wear facemasks. For a comprehensive understanding, Figure 4 offers an overview of the infection model's framework, illustrating the intricate interplay between exposure time, infection probability, and agent classifications.

3.1.3 *Waiting area settings and infection model*

This module implements a structured seating arrangement to ensure appropriate social distancing among patients awaiting medical services. The waiting area seats are treated as individual objects rather than dynamic agents, as illustrated in Figure 4, showcasing the applied waiting area configurations designed to maintain safe distances between patients.

Each seat within the waiting area is one metre long, ensuring that two seats effectively maintain the necessary safe social distance. The schematic on the right side of Figure 4 illustrates patients' responses to the waiting area settings identified by the second module. If a patient (whether infected or safe) selects an incorrectly designated seat, marked as 'red crossed,' it constitutes a breach of the prescribed safe social distancing measures set by the waiting area configuration. Consequently, this breach increases the risk of exposure, contingent upon other NPIs like facemask usage and the extent of exposure to an infected patient.

Figure 4 Social distancing in waiting area (see online version for colours)



In this module, we elucidate the virus transmission process and the specific conditions under which it occurs, see Figure 5.

Figure 5 Infection framework and rules (see online version for colours)

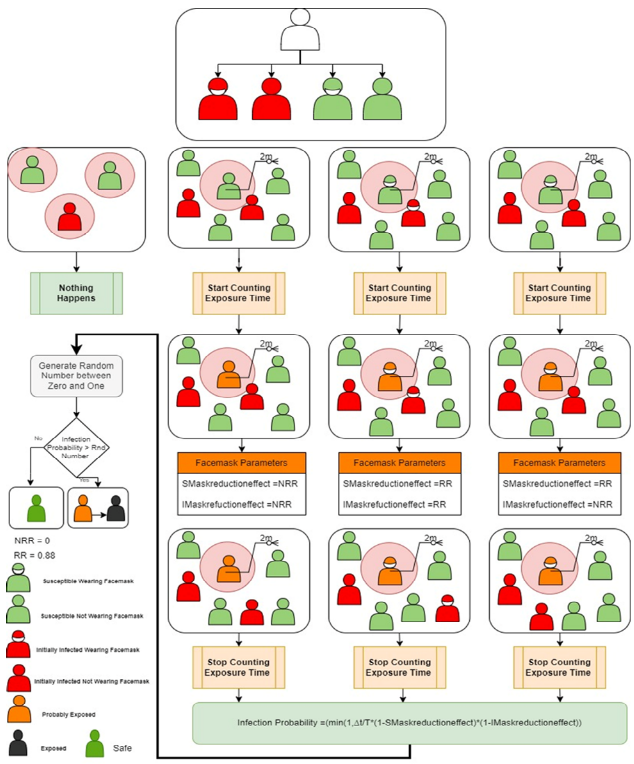
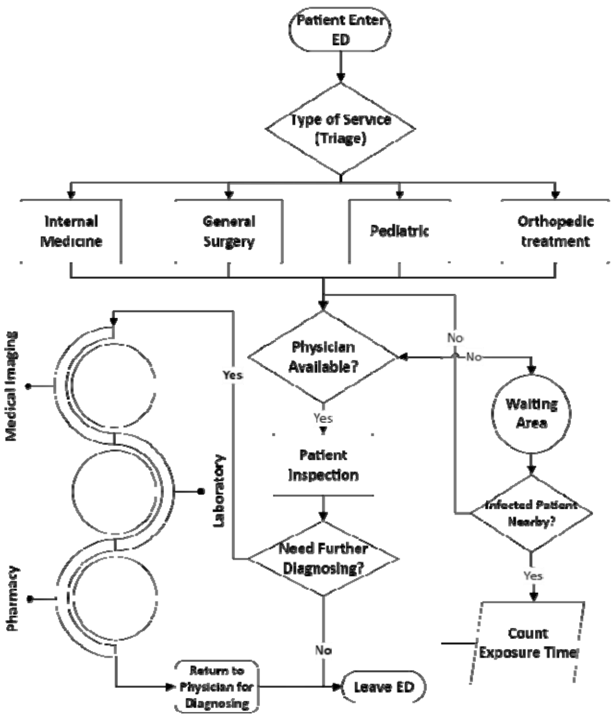


Figure 5 shows respiratory droplets as the sole mode of virus transmission between agents. As agents move within the medical treatment department, each susceptible agent is continuously monitored every second to determine whether a particular condition is met. The state is defined by infectious patients within a two-metre range of a susceptible agent. Once this condition is met, the susceptible agent is classified as ‘probably exposed, a time counter initiates, counting the time in seconds multiplied by the number of infectious agents, as long as the condition is not violated.

3.1.4 Agent dynamics

This section delineates the behaviour of agents, illustrated in Figure 6, as they progress from their arrival at the department, undergo medical procedures, and ultimately leave. The dynamics of the agents encompass factors such as arrival rates and waiting times specific to each section: internal medicine, general surgery, pediatrics, and orthopedic treatment. The development of this layer extensively utilised the AnyLogic pedestrian library, which was employed for constructing a significant portion of the model. The flow of patients is similar to traffic pedestrian transportation in a city, which is a problem for which agent-based simulation is utilised, see, for example (Dziecielski and Wozniak, 2022).

Figure 6 Agent dynamics flow chart



The Pedestrian Library played a crucial role in building the internal geometry of the facility, encompassing walls and beds and facilitating the representation of queues, service areas, and waiting zones. Notably, this library offers the advantage of enabling seamless movement of agents in a continuous space, ensuring avoidance of collisions with obstacles like walls, counters, and fellow agents, resulting in a more human-like behaviour. Within the ED, a small fraction of patients arrive solely for vital sign checks. The remaining patients have several possible paths to follow, leading them to sections such as internal medicine, general surgery, the pediatric hall, orthopaedics, or a visit to the dentist. However, agents only determine their destined section after undergoing diagnosis at the triage stage. Once an agent is assigned to a specific section, they proceed through three essential medical procedures, detailed as follows:

3.1.4.1 Medical imaging procedure

Agents may proceed to the imaging department to undergo X-ray, CT-Scan, or Ultrasound imaging procedures. Each imaging procedure entails its own set of waiting times, and notably, most orthopaedic visitors require X-ray imaging. Patients who visit the imaging area wait within its designated waiting zone. If the imaging technician is occupied, patients return to their previous bed, especially if the waiting area is at full capacity.

3.1.4.2 Specimen delivery

Patients might be required to provide urine or stool specimens in designated bathrooms, where separate facilities are available for men and women. The samples are delivered to the laboratory for analysis upon providing the required specimen. Subsequently, patients return to their beds, awaiting laboratory results. Physicians utilise these results to determine the necessity for further medical tests and required pharmaceuticals.

3.1.4.3 Blood sample collection

When a patient is required to provide blood samples, the nursing staff collects them while the patient remains in bed. After collection, the nurse transports the blood samples to the central laboratory. Patients await the availability of laboratory test results, which the physician then reviews to facilitate diagnosis.

After completing one or more of the procedures above, agents may go to the pharmacy to handle the medical prescriptions provided by the physician. Notably, a patient may undergo one or more of these procedures, and the sequence may vary, determined randomly. The dynamic component of the model heavily relies on the pedestrian library of the AnyLogic software. This library accurately defines the routes for patient medication, service routes for medical staff, medical procedures, waiting times, and designated areas within the facility. Furthermore, this component determines the rate at which agents arrive at the department and the rate of infection arrival.

Figure 7 Jordan University Hospital (JUH) emergency department layout

Figure 8 Simulation model – snapshot 1 (see online version for colours)

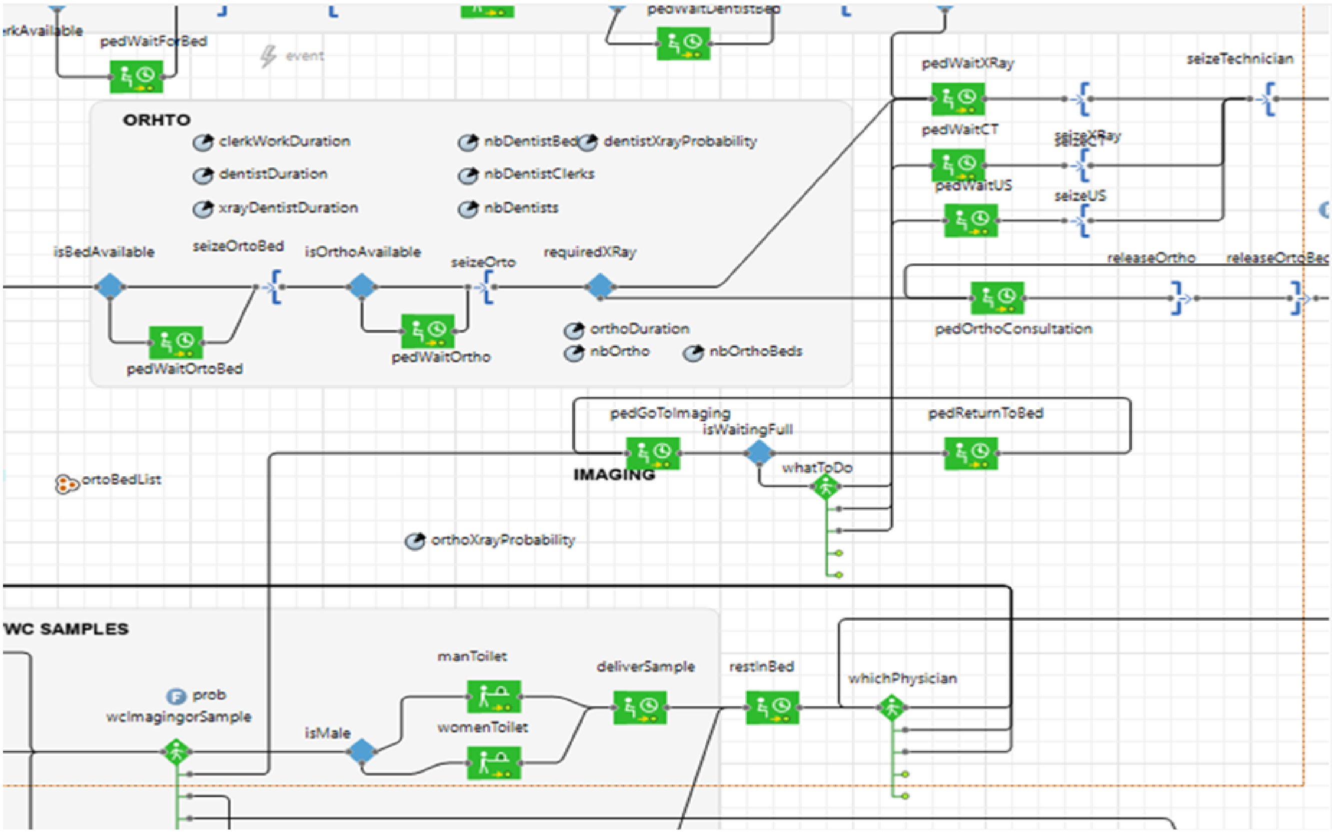


Figure 9 Simulation model – snapshot 2 (see online version for colours)

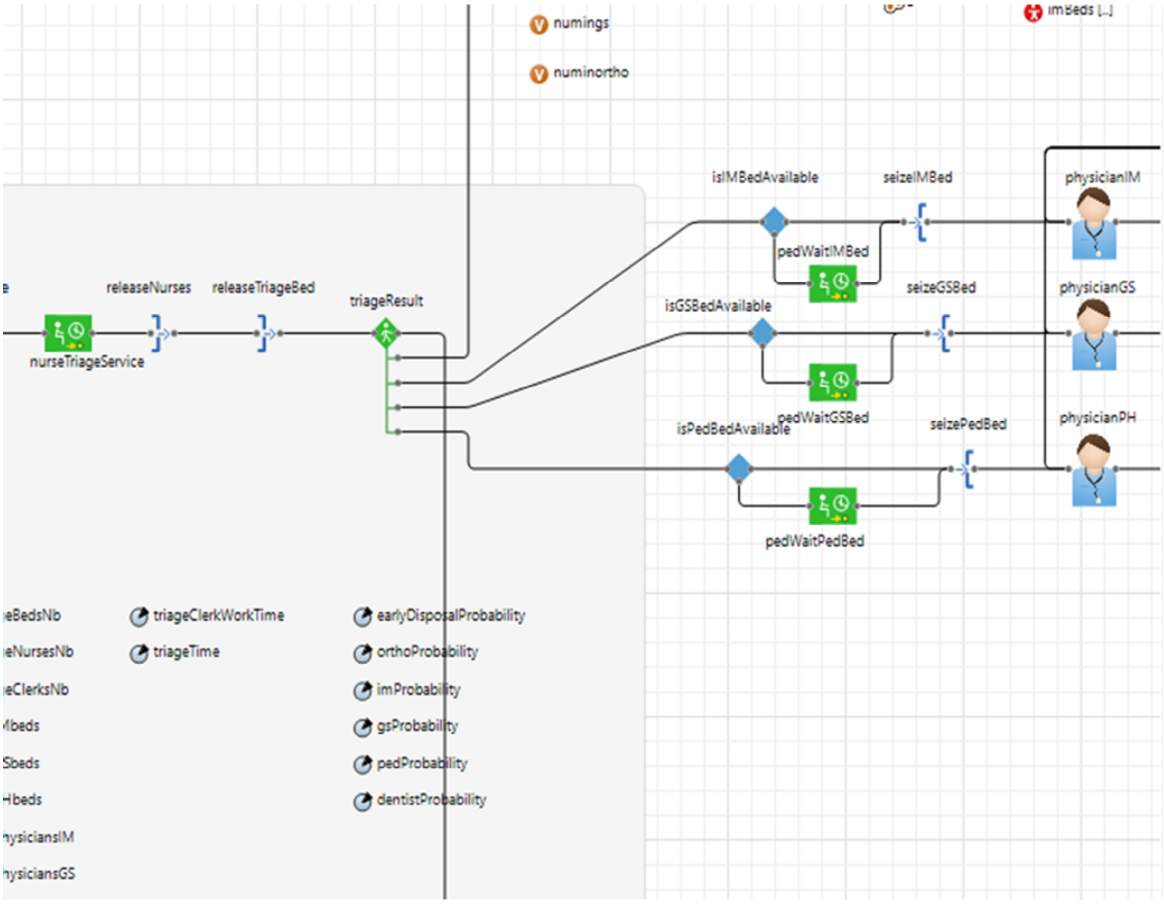


Table 5 Model input parameters

Parameter name	*Description*	*Value*	*Unit*
General			
Arrival rate	Patients arrival rate	12	patients/hour
Dentist			
Dentist probability	Probability of going to the dentist	0.125	
Number dentist beds	Number of dentist beds	2	
Clerk work duration	Time for clerk to complete work	T (1, 1.4, 2)	minutes
Number of dentists	Number of dentists	1	
Dentist X-ray probability	Probability of needing XRAY	0.5	
Dentist duration	Duration of consultation	T (15, 30, 40)	minutes
X-ray dentist duration	Duration of x-ray for dentist	T (2, 6, 10)	minutes
Triage			
Triage nurses number	Number of nurses in triage	2	
Triage beds number	Number of beds in triage	3	
Triage clerk worktime	Clerk time to process patient	T (1, 1.4, 2)	minutes
Triage time	Duration of triage	T (1, 1.5, 2)	minutes
Early disposal probability	1 minus the sum of these two is the probability of going to any medical hall	0.005	
Ortho probability		0.125	
IM probability	Some of these should be equal to 1	0.33	
GS probability		0.34	
Ped probability		0.33	

Table 5 Model input parameters (continued)

Parameter name	*Description*	*Value*	*Unit*
Number IM beds	Number of beds in IM	18	
Number GS beds	Number of beds in GS	14	
Number pediatric beds	Number of beds in pediatrics	5	
Ortho			
Number ortho beds	Number of beds in Ortho	2	
Number of ortho physicians	Number of Ortho physicians	1	
Ortho X-ray probability	Probability of needing XRAY	1	
Ortho duration	Duration of consultation	T(5, 30, 60)	minutes
WC samples			
toiletSeatsM_Nb	Number of male toilet seats	5	
toiletSeatsW_Nb	Number of female toilet seats	5	
timeOnWC_seat	Time spent on seat	T (1, 2, 3)	minutes
timeInLab	Time to give the sample in the lab	T (1, 1.5, 2)	minutes
wcRestTime	Time to rest after sample in bed	T (60, 60, 60)	minutes
tPhysWCsampReview	Duration of consultation	T (10, 15, 25)	minutes
Pharmacy			
nbPharmacists	Number of pharmacists	1	
pharmaTime	Time to buy medicine	T (1, 1.5, 2)	minutes
Imaging			
nbTechnician	Number of technicians	1	
ctProbability	Sum equals to 1	0.33	if random use 1/3
xrayProbability		0.33	if random use 1/3
ultrasoundProbability		0.33	if random use 1/3
ctTime	Time for CT	T (4, 5, 10)	minutes
xrayTime	Time for x-ray	T (2, 5, 10)	minutes
ultraSoundTime	Time for ultrasound	T (15, 20, 30)	minutes
tPhysImagingReview	Duration of consultation	T(5, 15, 25)	minutes
Nurse Samples			
nbSamplesNursesIM	Number of nurses to take samples IM	4	
nbSamplesNursesGS	Number of nurses to take samples GS	3	
nbSamplesNursesPed	Number of nurses to take samples Ped	1	
takeSampleTime	Time to take samples	T (2, 5, 7)	minutes
giveSampleTime	Time to give the sample in the lab	T (0.5, 1, 2)	minutes
sampleRestTime	Time to rest after sample in bed	T (60, 60, 60)	minutes
tPhysSampleReview	Duration of consultation	T (10, 15, 25)	minutes
Physicians			
nbPhysiciansIM	Number of physicians in IM	3	
nbPhysiciansGS	Number of physicians in GS	1	
nbPhysiciansPed	Number of physicians in Ped	1	

4 Case study

4.1 Background

A case study was chosen to implement and justify the developed agent-based system dynamics model. This case study occurred in one of the biggest hospitals in Jordan, Jordan University Hospital (JUH). Established in 1971, JUH is the first university teaching hospital in Jordan and one of the first in the Arab World. The JUH currently has a bed capacity of 600 and a team of 2,600 employees, 225 of whom are full-time consultants in various medical specialities, serving around 500,000 patients annually in outpatient clinics, (25,000) surgical cases, and (94,000) emergency cases. With this large number of emergency cases, the ED is considered one of the critical departments to manage and carefully watch as it might be a clustering point for highly potential disease transmission.

In the emergency room, various locations serve specific medical purposes, with the general surgery, internal medicine, dentist clinic, and pediatric room being the primary areas where patients receive assessments and medications. Refer to Figure 7 for a visual representation of the building layout, meticulously crafted using computer-aided design software. This layout was created from the ground up due to extensive modifications to the department building, necessitating precise on-site measurements and developing an entirely new drawing to accurately reflect the building's current state.

Given the study's primary focus on incoming patients, we focused solely on mapping out patient-related areas. Consequently, administrative spaces specifically catering to patient utilisation were omitted from this architectural layout.

4.2 Data collection

Table 3 presents bed and medical staff capacity data. The imaging department can accommodate one patient, including access to CT-Scan, Ultrasound, and X-ray facilities. Within the ED, patients receive medical care based on the availability of the medical staff, predominantly nursing staff responsible for blood sampling and laboratory delivery. At the same time, physicians conduct medical examinations and consultations.

Table 3 Capacity of resources

Section	*Number of beds*	*Physicians*	*Nurse*	*Technician*
General surgery halls	14	1	4	0
Internal medicine halls	18	3	3	0
Pediatric halls	5	1	1	0
Dentist clinic	2	1	1	0
Imaging department	3	0	0	1
Triage	3	0	3	0
Laboratory	0	0	0	2

The ED comprises four primary areas for patient examination and treatment: general surgery, internal medicine, dentist clinic, and pediatric room. The following table outlines the bed capacity for each section. The department's medical staff includes physicians, nurses, pharmacists, medical imaging technicians, and laboratory technicians. Specifically, one medical imaging technician, two laboratory technicians, and one pharmacist are on staff. The subsequent table summarises the medical staff, including physicians and nurses, allocated to each section within the department.

Agents in the emergency room are treated according to the availability of the medical staff, particularly the nurses tasked with collecting blood samples and delivering them to the laboratory. Inspection and consultation in medicine are the responsibility of doctors. Table 4 lists the infection-related parameters connected to the created model. These values were changed to investigate different scenarios.

Table 4 Model infection-related parameters

Parameter	*Description*	*Value*	*Unit*
T	Time used to normalise delta T	15	minutes
Pmask	Probability of infecting others and get infected if the mask is used	0.88	
pMasked	The probability of a patient wearing the mask	0	
pMaskedInfected	The probability of an infected patient wearing the mask	0	
fraction of infected patients	The probability of an incoming patient being infected	0.1	

4.3 Simulation model

The dynamic aspect of the model utilises the Pedestrian Library within the Anylogic software. Its primary function is defining the routes for patient medication, medical staff services, medical procedures, waiting times, and designated areas within the system. This component also plays a pivotal role in determining the agent arrival rate at the department, the influx of infected patients, their gender distribution, and the allocation of medical staff and beds. Given the modular nature of the code, it can be challenging to provide a comprehensive overview in a single description. Figure 8 and Figure 9 offer snapshots extracted from this model segment.

Figure 8 shows a part of the patients' flow within the ED. The top portion is for patients needing orthopaedics-related treatments where a logical check is first carried out (*isBedAvailable*) where the patient seizes a bed from the total available beds represented by the parameter (*nbOrthoBeds*) if the answer is yes and waits for a bed to be available otherwise. Next, the patient receives an initial check from one of the total available nursing staff represented by the parameter (*nbOrtho*) for an expected duration represented by the parameter (*orthoDuration*). If an X-ray is required, the patient must go through the X-ray logic like the above logic.

The snapshot in Figure 9 shows the logic of triage results where the patient is directed to the right specialised consultant, where the agent seizes the required resource if available, and if not available, waiting time is initiated until the physician becomes available.

In contrast, the infection component of the model is primarily comprised of a state chart, a system dynamics model, and an event that triggers every second. These elements within the infection module facilitate the simulation by defining various agent states and collecting data as agents move within the department.

The complete set of input parameters is detailed in Table 5. These values have been derived from the respective ED data, making them authentic and reflective of real-world conditions. These parameters have remained constant across various combinations of preventive interventions, and all simulations have been conducted using this standardised set of parameters.

5 Results analysis and discussion

This section provides a concise overview of the impact of NPIs and their combined use on the number of exposed individuals. As depicted in Figure 10, the chart illustrates a clear correlation between the percentage of exposed patients and the adoption of facemasks, particularly in scenarios where social distancing measures are absent. A full % adherence rate of 100% to facemask usage substantially reduces infection cases.

The rationale behind these results can be attributed to the well-documented effectiveness of facemasks in reducing the transmission of respiratory diseases. Without social distancing, facemasks act as a critical barrier to prevent the direct spread of respiratory droplets containing infectious agents. The noticeable decrease in the percentage of exposed patients as the facemask adherence rate increases underscores facemasks' pivotal role in mitigating the risk of infection.

Figure 10 Exposed patients vs. % of facemask commitment with no social distance implemented (see online version for colours)

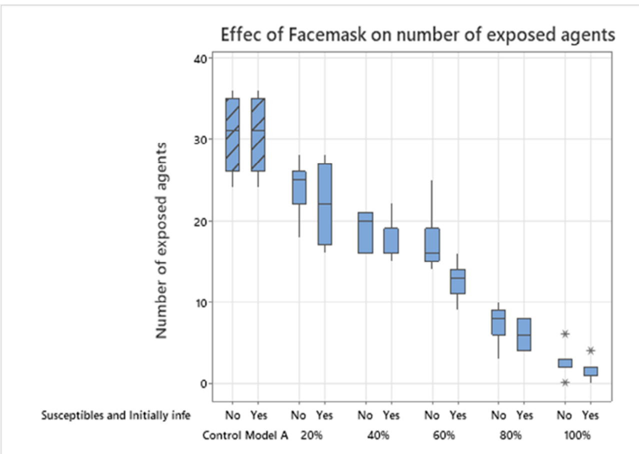


Figure 11 presents the effects of implementing two NPIs, facemasks and social distancing, in various scenarios. Control A represents no participation in preventive measures, Control B enforces social distancing alone, and the final scenario combines both NPIs and facemasks. Notably, both NPIs yield a significant decrease in the percentage of exposed patients, but using face masks is a particularly effective measure in preventing the spread of infection.

The rationale behind these findings lies in the complementary nature of facemasks and social distancing. Facemasks provide a physical barrier against respiratory droplets, reducing the chances of direct transmission. On the other hand, social distancing further decreases the likelihood of close contact and exposure to potentially infected individuals. When these NPIs are employed, combining physical and social distancing measures creates a formidable defence against the spread of infections, thereby substantially reducing the percentage of exposed patients.

Figure 11 Exposed patients vs. % of facemask commitment with social distance implemented (see online version for colours)

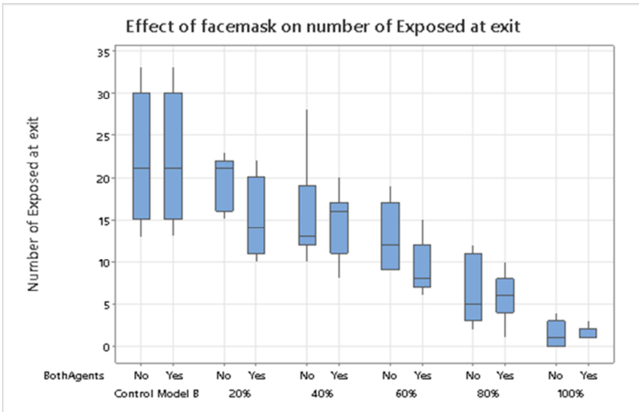
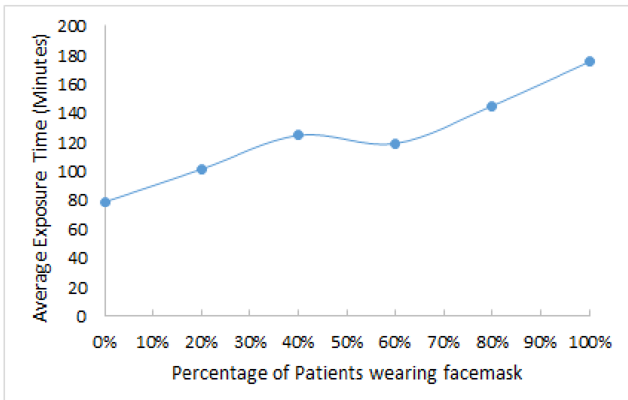


Figure 12 offers a comprehensive insight into the impact of facemask usage on the average time required for an individual to become exposed to COVID-19. Notably, the data reveals a direct correlation between the percentage of agents adhering to facemask mandates and the extended duration for an agent to become exposed.

Figure 12 Average exposure time for exposed patients vs. facemask % implementation (see online version for colours)

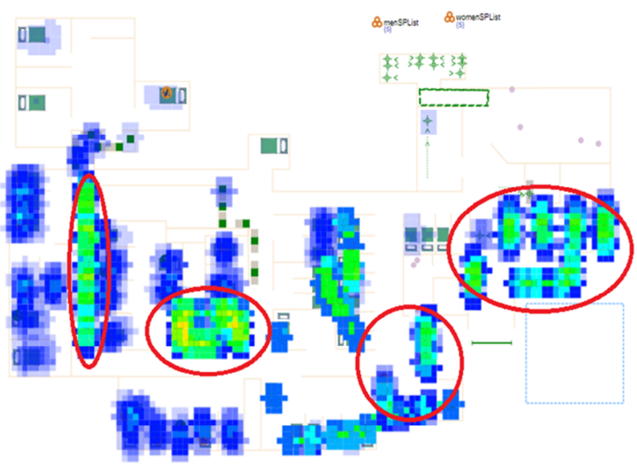


The rationale behind these findings lies in the fundamental concept of infection prevention. Facemasks are an effective barrier, reducing the likelihood of respiratory droplets containing infectious agents being transmitted from one individual to another. When a higher percentage of individuals within a population consistently wear facemasks, the overall risk of exposure decreases significantly.

This relationship between facemask adherence and increased time to exposure underscores the importance of broad facemask mandates in mitigating the spread of COVID-19. It reinforces the notion that collective commitment to this preventive measure protects individuals and has a wider societal impact by slowing the transmission of the virus. Consequently, it emphasises the vital role of facemasks in reducing the risk of COVID-19 transmission, ultimately contributing to the well-being of the community as a whole.

Figure 13 presents a density map illustrating the spatial distribution of patients within the facility. It is readily apparent that certain areas exhibit significantly longer waiting times for these individuals compared to others. The presence of red circles on the map highlights locations with higher patient densities and extended waiting times. These extended wait times elevate the risk of individuals being exposed to potentially infected agents over an extended period, increasing the likelihood of infection. To mitigate this risk, it is imperative for facility management to prioritise these areas and implement measures to alleviate such clustering.

Figure 13 Heat/density map of the ED (see online version for colours)

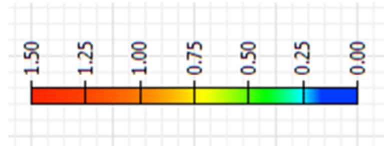


To provide a precise reference for the colour scheme used in the density map, please see Figure 14. In this context, blue represents areas with very low patient density, while red indicates the highest. The aqua colour is reserved for critical density areas, where the patient density reaches 1.5 individuals per square metre.

It is worth noting that the central spot in the density map, despite having a relatively high patient density, has not been highlighted. This omission is deliberate, as these patients are isolated, minimising the risk of infection.

As for the model accuracy and validation, the results were compared with the actual estimation from the hospital records. An error of 10.6% was found with the model results, which we believe is acceptable.

Figure 14 Colour index of the heat map (see online version for colours)



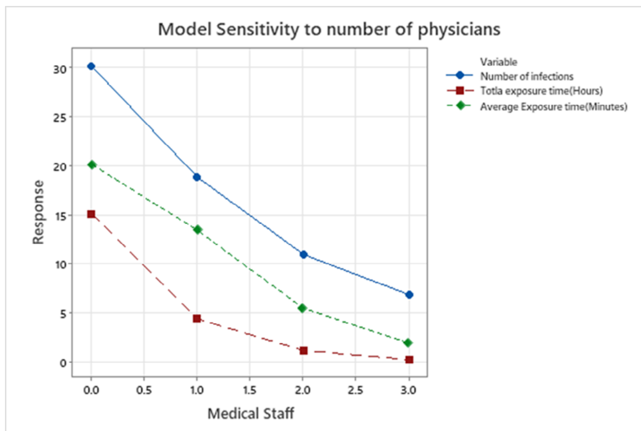
6 Sensitivity analysis

The objective of the sensitivity analysis study was to gain insights into the model's behaviour and its sensitivity to fluctuations in the number of medical staff. Descriptive statistical measures can be found in Table 6, while the graphical representation of this analysis is presented in Figure 15.

Table 6 Descriptive statistics of responses used in sensitivity

Facemask %	*Statistics*	*Number of agents who got infected*	*Number of agents who got exposed*	*Number of susceptible*
20%	Mean	15.0	114.4	61.7
	Std. dev.	4.6	20.7	15.3
40%	Mean	14.6	120.3	62.4
	Std. dev.	4.0	25.7	14.8
60%	Mean	9.3	120.7	62.0
	Std. dev.	3.1	17.7	15.8
80%	Mean	5.7	115.4	54.6
	Std. dev.	3.0	20.8	12.5
100%	Mean	1.6	135.7	56.4
	Std. dev.	0.8	12.9	15.5

Figure 15 Impact of the number of medical staff on the model response (see online version for colours)

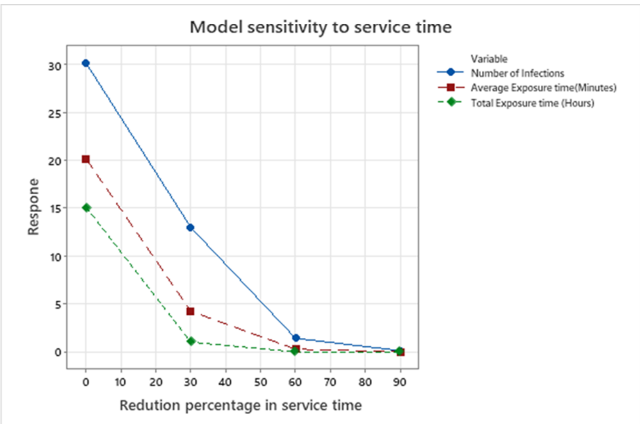


Sensitivity analysis is a valuable tool for gauging how the model reacts to changes in the number of physicians and the service time the medical staff provides. Figure 8 provides a visual depiction of the model's responses as the number of physicians varies. An incremental increase of one physician in each department was introduced in each model run, allowing for a comprehensive assessment of the model's behaviour.

In Figure 16, we delve into the model's reaction to alterations in service time. Here, we have deliberately reduced the service time by 30%, 60%, and 90%, comparing these scenarios against the baseline represented by control model A. This analysis sheds light on the model's sensitivity to variations in service time, which is a critical aspect of understanding its performance in different conditions.

By conducting this sensitivity analysis, we can better grasp how the model responds to medical staff numbers and service time changes, providing valuable insights for optimising and refining the system's performance in real-world healthcare settings.

Figure 16 Model's response to service time reduction (see online version for colours)



7 Conclusions and future work

The results obtained from various combinations of NPIs, such as facemask mandates and social distancing, have shed light on crucial parameters, including total exposure time, average exposure time, the time required for an agent to become exposed, and the number of exposed agents.

Facemask mandates have demonstrated a direct impact on the number of exposed agents. As more arriving individuals wear facemasks, there is a notable reduction in the number of exposed individuals. Furthermore, the data suggests that increased facemask usage corresponds to increased time needed for an agent to become exposed, underscoring the effectiveness of facemasks in minimising exposure risk.

On the other hand, implementing social distancing has significantly decreased the total exposure time and average exposure time for individuals close to infectious agents. Consequently, this has resulted in a reduced number of exposed agents. The figures corroborate these findings, highlighting the positive effect of social distancing on exposure reduction.

Analysis of heat density maps has revealed areas with high population densities within the department, notably the waiting areas, pediatric hall, general surgery waiting area, main waiting area, and imaging waiting area. A common factor among these areas is the insufficient medical staff, with limited physician and nursing staff presence, resulting in extended waiting times and increased exposure time. Increasing medical staff allocation in these sections is imperative to address this issue.

It is worth noting that bed areas with high agent densities were excluded from the analysis, as all patients in these areas are appropriately isolated with medical curtains, reducing the risk of virus transmission.

Challenges and limitations encompass model validation proved challenging due to inherent variability in patient behaviour within the dynamic ED environment. Data accuracy and availability significantly impact model reliability, necessitating improved data collection and validation methods. Considerations include temporal and spatial scale variations, socioeconomic and cultural influences, and the need for ethical data handling. Model calibration and generalisation must be ensured cautiously, given facility-specific nuances and regional variations. Addressing long-term dynamics and simplifying model complexity for broader accessibility are also noteworthy.

As future work, modifications to the model could incorporate viral load considerations for initially infected agents, enhancing the model's realism and predictive accuracy.

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