Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

ENHANCING PANDEMIC PREPAREDNESS USING MEAN FIELD AND SIMULATION MODELING

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ABSTRACT

The COVID-19 pandemic has emphasized the importance of preparedness and response plans for healthcare providers and rational responses from society to effectively manage infectious disease outbreaks. Strategic guidelines should be created to ensure the availability of required resources while considering the rational response of individuals under different policy scenarios. This study uses a simulation-optimization-game theory approach to first determine the daily number of infected people in response to social distancing policies in a game theoretical setup. Second, this daily number of infected people is used in a simulation to determine an optimal replenishment policy for restocking personal protective equipment (PPE) items. The model incorporates a combination of mean field games modeling and a simulation model in Simio to perform optimization tasks. This approach aims to guarantee the availability of required resources by taking into account the rational response of individuals under different policy scenarios.

1 INTRODUCTION

Many healthcare providers in the USA experienced a shortage of personal protective equipment (PPE) during the COVID-19 pandemic due to the lack of preparedness and response plans (Dai et al. 2020). This shortage of PPE can jeopardize the safety of frontline medical staff and impact the quality of care provided. The level of preparedness to combat unprecedented outbreaks depends on proactive planning, strategic thinking, and demand forecasts (Petrović 2020). Effective preparedness plans provide operational and strategic insights and ensure critical resources such as staffing needs, beds, and equipment are available when needed. Simulation is an essential tool during outbreaks to study infectious diseases, understand outbreak dynamics, and analyze the impact of interventions (Eriksson et al. 2009).

This study demonstrates the capabilities of simulation modeling to support healthcare providers in making informed decisions and improving hospital preparedness. To account for the rational decision-making process of individuals during an outbreak, the simulation is combined with mean field game modeling, introducing a game-theoretical point of view. In other words, individuals control their contact rate (i.e., socialization levels) to minimize their own individual costs (such as costs from not following the policies set by the government closely or the cost of being infected) while taking into account other individuals' decisions. Accordingly, the daily number of infected people will be endogenously determined instead of exogenously inputted by finding a Nash equilibrium in the population. It is known that finding a Nash equilibrium becomes a more complex task when the number of players are increased because of the increasing number of interactions. Therefore, in order to find a tractable equilibrium in games with a large number of players, the mean field games methodology is adopted (Lasry and Lions 2006a; Lasry and Lions 2006b; Huang et al. 2006). In mean field games, the players are assumed to be identical and have symmetric interactions. In this way, the methodology focuses on a *representative* player and her interactions with the distribution of the population. In this way, the equilibrium can be characterized by forward and backward (partial or stochastic) differential equations. Because of the tractability for finding the Nash equilibrium, mean field games approach was implemented in different applications, such as modeling of energy markets in (Alasseur et al. 2020; Aid et al. 2021; Carmona et al. 2022) and modeling of financial systemic risk in (Carmona et al. 2015; Élie et al. 2020). Later extensions to introduce heterogeneities among players are introduced through multipopulation mean field games, see e.g. (Bensoussan et al. 2018) and graphon games, see e.g. (Parise and Ozdaglar 2019; Aurell et al. 2022).

This paper aims to highlight the importance of accurate modeling for disease outbreak preparedness. Having an accurate model to predict infected cases, as well as an accurate model to simulate hospital operations, is crucial to have a well-suited decision-making tool for healthcare managers. Therefore, this paper's main contributions are:

- Introducing a game theoretical model that can predict the number of infected patients during a pandemic and integrating them with a simulation model that can properly model hospital operations.
- Implementing this hybrid model to demonstrate its practicality.
- Analyzing healthcare resource requirements in different pandemic situations.

The approach proposed in this paper comprises of two interconnected modules. The first module employs a *mean field model* to compute infectious disease spread and generate expected daily patient numbers by building a game theoretical model in order to take into account the rational decision making of individuals. The second module simulates hospital operations by estimating resource utilization and PPE consumption rates under different circumstances. To achieve this, the study employs the mean field games methodology and uses Simio, a well-known and powerful simulation software with optimization capabilities. The generated number of daily patients by using our mean field model in Module 1 is used as the input of the simulation model in Module 2.

The paper is organized as follows: Section 2 presents a summary of related works, followed by a description of the mean field games model in Section 3, which is used to simulate daily number of infected people to be inputted in the Simio model. This section also provides simulation modeling details and healthcare center operations. Experimental analyses are conducted in Section 4 to demonstrate the applicability of simulation modeling for outbreak preparedness. Finally, the paper concludes in Section 5, followed by some future extension insights.

2 LITERATURE REVIEW

Simulation has proven to be a useful tool for hospital preparedness plans during outbreaks such as poliovirus, influenza, and Ebola. It has been used for decision-making problems related to pandemic preparedness, including resource allocations, disease spread modeling, and vaccination plans. Simulation is also useful for analyzing the supply chain of healthcare systems during epidemics. Studies have used simulation and optimization software to predict supply chain performance, address sustainability concerns, and mitigate drug shortage risks. Currie et al. (2020), Ivanov (2020), Goodarzian et al. (2021), Tirkolaee et al. (2022) offer further insights into the topic. This section provides an overview of existing works that address healthcare preparedness for combating pandemics from two perspectives: (i) applied discrete event simulation models and (ii) Mean Field models.

2.1 Healthcare Preparedness using Discrete Event Simulation

Several studies have addressed the importance of adequate staffing in healthcare preparedness during pandemics. Beeler et al. (2016) used discrete-event simulation (DES) to determine staffing levels at mass immunization clinics (MICs). Beeler et al. (2011) developed a DES model to estimate the expected number of infections in healthcare facilities. Lu et al. (2020) used Arena to evaluate bed utilization and supply needs during a pandemic in individual hospitals. The Winter Simulation Conference in the past two years saw many researchers contribute to simulation modeling to address COVID-19 related problems. Currie et al. (2020) developed an optimization-based, data-driven hospital load balancing model, while Schultz et al. (2021) simulated an airport environment to evaluate the impact of COVID-19 restrictions. Neuner et al. (2021) used simulation to analyze patient treatment in an Italian hospital's ED, while Maghoulan et al. (2022) developed a simulation-optimization approach to determine an optimal replenishment policy for PPE and proactive demand planning for critical resources.

2.2 Pandemic Preparedness using Mean Field Models

Recently, mean field models have been commonly used to find approximate equilibrium and social optimum in the applications with large number of interacting agents. In order to find the equilibrium behavior of the agents, Cho (2020), Charpentier et al. (2020) uses mean field games, Tembine (2020) uses mean field type games and Lee et al. (2020) uses mean field control. In order to find the optimal incentives to mitigate the epidemics Aurell et al. (2022) analyzes Stackelberg mean field game equilibrium between a regulator (i.e., principal) who sets social distancing policies and a population of agents responding with their Nash equilibrium socialization levels. Hubert et al. (2020) focuses on a Stackelberg equilibrium between a principal that controls the testing accuracy and a cooperative population of agents. Related to epidemiology applications, efficiency of vaccination has been studied by Doncel et al. (2022), Gaujal et al. (2021), Laguzet and Turinici (2015). In order to model the heterogeneity among the agents (either through asymmetricity in the interactions and/or through heterogeneity in agents model parameters), graphon games have been used to model the epidemics by Aurell et al. (2022).

2.3 Paper Novelty

This study aims to leverage simulation modeling to assist with disease outbreak preparedness and response by incorporating the game theoretical decision-making process in the simulation of daily infected numbers of people. The applied simulation model will serve as a decision support tool to estimate the capacities and quantities required for care delivery to the infected population.

3 METHODOLOGY

Simulation is an excellent tool for testing various scenarios and drawing insights based on different outbreak circumstances. Simio, a powerful data-driven simulation tool, allows users to apply user-defined parameters and input data tables (Dehghanimohammadabadi and Kabadayi 2020). The aim of this study is to model demand uncertainty and assess the capacity of critical hospital resources to cope with unprecedented conditions using a hybrid simulation-optimization approach. The model consists of two interconnected modules. The first module uses mean field models to generate expected daily patient numbers and applies a game theoretical approach to capture the rational decision-making process of individuals who try to attain their best outcomes. The second module simulates hospital operations, estimating resource utilization and PPE consumption rates under different circumstances. This integrated approach enables the study to make more informed decisions regarding hospital preparedness for future outbreaks (Figure 1).

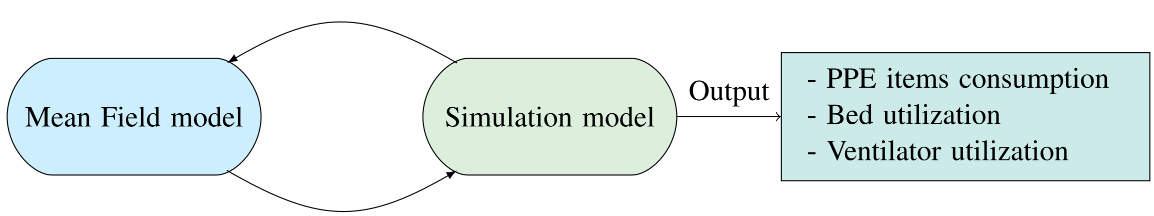


Figure 1: Hybrid integration of Module 1: Mean Field model and Module 2: DES simulation model.

3.1 Module 1: Mean Field Models for Disease Spread.

In order to add the game theoretical decision making process of the agents in the simulation process, the generation of daily patient numbers will be made through a graphon game model. In general, a graphon is defined as a symmetric measurable function such that $w : [0,1] \times [0,1] \mapsto [0,1]$ where $w(x,y)$ denotes the strength between agent x and agent y. In order to incorporate heterogeneities of the individuals (such as different age groups), we move beyond the naive mean field game setup and use a graphon model where the graphon is chosen to be a piecewise constant graphon similar to the setup given in (Aurell et al. 2022). Choosing a piecewise constant graphon to model the interactions creates a similar structure to multi-population mean field games. We want to stress that each individual has their own objectives and they give their best responses by taking into account other individuals behavior and different policies (such as *no social distancing restrictions*, *quarantining infected people* or *full lockdown*). Individuals are assumed to be rational players which means that they do *not have to* follow the policies perfectly, instead individuals decide on their behavior by giving their best responses to other's behavior and the policies and an equilibrium in the population is found. In this way, we calculate daily number of infected people when individuals react to different types of policies. This is different than just simulating SIS dynamics or finding the *optimal* behavior of only one individual under different policies, since it incorporates the decision making of individuals who *interact* with each other to find the Nash *equilibrium* in the population.

We divide the population to 9 age groups (0-9, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80+) where m_i for $i \in \{1,\dots,9\}$ denotes the weight of the group i in the population such that $\sum_{i=1}^{9} m_i = 1$. As usual in the graphon games setup, we focus on agent x where $x \in [0,1]$ denotes the index of the agent and agent x will be placed in group $k = 1$ if $x \in [0, m_1)$, etc. We will assume that the individuals in the same group are indistinguishable; however, individuals in different age groups can have different hospitalization rates and contagion rates (β). They also have differences between group and within group connection rates: The connection between agent x in group i and agent y in group k will be given by $w(x,y) = w_{ik}$. The individuals control their contact rate (i.e., socialization level) over the time interval $t \in [0,T]$ that is denoted by $(\alpha_t)_{t\in[0,T]}$ where $\alpha_t \in [0,1]$. When α_t is lower it means they decrease their contact rates. The individual's state is denoted with $e \in E$ and they are either in susceptible (S) or infected (I) state, i.e., $E = \{S, I\}$. They jump from state S to I after an exponentially distributed time with a rate that depends on the exogenous contagion rate β that depends on the disease specifications, the individuals own contact rate (i.e., socialization level) and the aggregate interactions with the other agents Z_t^x. The aggregate interactions of agent x in group i with the other agents are given as

$$Z_t^x = \sum_{k=1}^{9} w_{ik} \bar{\alpha}_t^k(I) p_t^k(I) m_k$$

where $p_t^k(I)$ denotes the proportion of infected people in group k at time t, w_{ik} gives the connection strength between group i and group k and $\bar{\alpha}_t^k(I)$ denotes the average contact rate of the infected people in group k at time t. Intuitively, this gives a the weighted (according to the connection strength) average of the contact rates of the infected individuals in the population. In Figure 2, we can see the jump rates of agent x between states S and I where $\beta^x > 0$ and $\kappa^x > 0$ are contagion and recovery rates respectively that are exogenous. In our simulations, we take $\beta^k = [0.3, 0.35, 0.35, 0.3, 0.3, 0.3, 0.2, 0.2, 0.2]$, $\forall k \in \{1,\dots,9\}$ to have differences among different age groups where $\beta^x = \beta^k$ when agent x is in group k. Furthermore, we take $\kappa^x = 0$, $\forall x \in [0,1]$ since we want to simulate the hospitalization and recovery processes in Module 2. We can see that the jump rate of agent x from state S to I at time t is given as $\beta^x \alpha_t^x Z_t^x$.

Each individual aims to minimize the following cost function over the time interval $T > 0$ where in the simulations T is taken to be 100:

$$\mathbb{E}\left[\int_0^T \mathbb{1}_{\{e_t=S\}} \left(\frac{c_S}{2}(\lambda_t^S - \alpha_t)^2\right) + \mathbb{1}_{\{e_t=I\}} \left(\frac{1}{2}(\lambda_t^I - \alpha_t)^2 + c_I\right) dt\right].$$

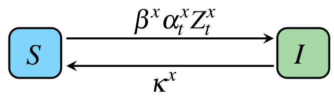


Figure 2: Diagram of SIS model for individual x

Here, λ_t^S and λ_t^I are the social distancing policies set by the regulator (i.e., government) at time t for susceptible and infected people, respectively. The policies can be set differently for different age groups; however, in our simulation, we assume that government sets population level policies. Therefore λ_t^S and λ_t^I do not depend on agent group k. From the cost function, it can be seen that both susceptible and infected people want to be close to the social distancing levels prescribed by the regulator and the infected people incur an extra cost $c_I > 0$. The parameter $c_S > 0$ is exogenous and should be chosen to show the importance given to the social contact by the susceptible people depending on the properties of the population modeled. In our experiments we took $c_S = 5$ and $c_I = 1$ for all age groups. However, they could be chosen differently for each age group, too.

In order to be able to write the forward backward differential equations, we introduce the value function:

$$u_t^x(e) = \min_{\alpha_{s|s\in[t,T]}} \mathbb{E}\left[\int_t^T \mathbb{1}_{\{e_s=S\}}\left(\frac{c_S}{2}(\lambda_s^S - \alpha_s)^2\right) + \mathbb{1}_{\{e_s=I\}}\left(\frac{1}{2}(\lambda_s^I - \alpha_s)^2 + c_I\right) ds \Big| e_t = e\right].$$

Intuitively the value function is the minimum cost incurred between time t and T when the agent x starts from state e at time t. By following the ideas in Aurell et al. (2022), we find the optimal contact rate of agent x in states S and I by minimizing the Hamiltonians:

$$\begin{aligned} H^x(t,S,\alpha,Z,u) &= \frac{c_S}{2}(\lambda_t^S - \alpha)^2 + \beta^x \alpha Z\big(u(I) - u(S)\big), \\ H^x(t,I,\alpha,Z,u) &= \frac{1}{2}(\lambda_t^I - \alpha_t)^2 + c_I + \kappa\big(u(S) - u(I)\big). \end{aligned}$$

Therefore, the optimal contact rate of agent x at states S and I are given as:

$$\hat{\alpha}_t^x(S) = \frac{\beta^x Z_t^x(u_t^x(S) - u_t^x(I)) + c_S \lambda_t^S}{c_S}, \qquad \hat{\alpha}_t^x(I) = \lambda_t^I.$$

Since we assume the underlying graphon is piecewise constant, all agents in group k will have the same optimal contact rates which can be denoted by $\hat{\alpha}_t^k(S)$ and $\hat{\alpha}_t^k(I)$. Therefore, we also have $\bar{\alpha}_t^k(I) = \hat{\alpha}_t^k(I)$. Then, the Nash equilibrium in the population can be characterized by the following forward backward ordinary differential equation system (FBODE):

$$\begin{aligned} \dot{p}_t^k(S) &= -p_t^k(S)\beta^k Z_t^k \hat{\alpha}_t^k(S) + p_t^k(I)\kappa^k \\ \dot{p}_t^k(I) &= p_t^k(S)\beta^k Z_t^k \hat{\alpha}_t^k(S) - p_t^k(I)\kappa^k \\ \dot{u}_t^k(S) &= -\Big(\frac{c_S}{2}(\lambda_t^S - \hat{\alpha}_t^k(S))^2 + \beta^k \hat{\alpha}_t^k(S) Z_t^k \big(u_t^k(I) - u_t^k(S)\big)\Big) \\ \dot{u}_t^k(I) &= -\Big(c_I + \kappa^k\big(u_t^k(S) - u_t^k(I)\big)\Big) \\ u_T^k(e) &= 0, \quad p_0^k(e) = p_0^k(e), \quad e \in \{S, I\}, \\ Z_t^k &= \sum_{i=1}^{9} w_{ki} \hat{\alpha}_t^i(I) p_t^i(I) m_i, \quad t \in [0,T],\ k \in \{1,\dots,9\}, \end{aligned}$$

where $p_t^k(e)$ denotes the proportion of individuals with state e in group k at time t and $u_t^k(e)$ denotes the value function of an individual with state e in group k at time t. For the detailed derivation of this system, please refer to Aurell et al. (2022). Realize that the forward and backward equations in the FBODE are coupled. In order to solve them, we time discretize the FBODE and simulate the forward and backward components iteratively until convergence. In the simulation, the initial proportion of the infected individuals ($p_0^k(I)$) is taken as 3% for age groups between 0 and 19, 2% for the age groups between 20-59, and 1% for the age groups above 60+. Since $\kappa^k = 0$, $\forall k \in \{1,\dots,9\}$ in our simulations $p_t^k(I)$ will give the cumulative infections in group k until time t. After finding the cumulative infected proportion at time t in each group k, ($p_t^k(I)$), we find the daily infected proportions by calculating $p_t^k(I) - p_{t-\Delta t}^k(I)$. Finally, we find the daily number of infected in each age group k by multiplying this proportion with the number of people in each group and input this number in our Simio simulations. We focus on 3 different scenarios in our daily infected number of people simulations: i) No social distancing restrictions (i.e., $\lambda_t^S = 1, \lambda_t^I = 1$ for all $t \in [0,T]$), ii) Quarantining infected people (i.e., $\lambda_t^S = 1, \lambda_t^I = 0.5$ for all $t \in [0,T]$), iii) Lockdown for everyone (i.e., $\lambda_t^S = 0.5, \lambda_t^I = 0.5$ for all $t \in [0,T]$).

3.2 Module 2: Hospital Operations and Resource Allocation

The model considers hospitalized cases as a *Patient Entity*, and they undergo the steps outlined in Figure 3. Firstly, patients arrive at the hospital and are assigned to an available bed if possible. Next, it is checked whether a ventilator is required, and the number of PPEs used by the patient is calculated. Finally, the patient is discharged based on the assigned length of stay. The patient arrival rate is directly determined by the mean field model explained in subsection 3.1.

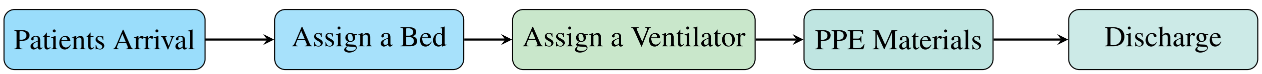


Figure 3: Hospital operations and resource allocation process.

3.2.1 Resource Allocation Process

Figure 4 illustrates the implementation details of this process. The process first determines if a hospitalized patient requires a ventilator based on their age. If a ventilator is necessary and available, the patient will occupy one unit through the *Seize* step. The Seize step in Simio refers to the process in which a patient, if a ventilator is necessary and available, will acquire and occupy a designated unit, specifically a ventilator unit. Otherwise, the *VentDeficientCount* variable will be incremented by 1 to account for ventilator unavailability. If a ventilator is not required, the patient will be delayed for the length of stay without using the ventilator. The variables defined in these processes provide measures for the number of times a critical resource was unavailable, including beds, ventilators, and PPE items. The ultimate goal is to ensure that all resources are available when needed to avoid deficits throughout the simulation run.

3.2.2 PPE Items Replenishment Process.

During pandemics, donning and doffing of personal protective equipment (PPE) is essential (Murray, Heather and Purdy, Eve 2020) both for staff and patients. The rampant nature of COVID-19 has caused a shortage of PPE in high-demand areas (Ahmed et al. 2020). Therefore, it is critical for a hospital to have a robust replenishment policy to ensure PPE items are available for both its patients and staff.

To model the demand/supply trade-off of the PPE items in the simulation environment, a process is defined based on a (s,S) inventory policy. As depicted in Figure 5, in this policy, an order is placed when the inventory level drops to the reorder point (s) or lower. This way the inventory can be replenished to level S (order up to level or upper stock) (Helal et al. 2021). The order will be delivered based on the defined lead time for each item. Table 1 lists the *order lead time* and *consumption rate* of each of the PPE items in this study. To implement this inventory policy in Simio, the *PPE re-order* process (Figure 5) is triggered to *Produce* the required PPE item after some delay based on its lead time distribution defined

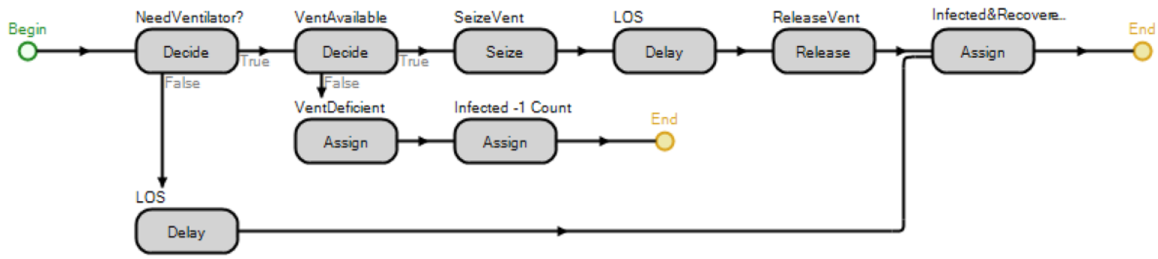


Figure 4: Hospital operation process in Simio. In this process, the *Decide* step checks whether the patient requires a ventilator. If the patient needs a ventilator, the subsequent *Decide* step verifies its availability. If a ventilator is available, the patient seizes the unit using the *Seize* step. The patient then utilizes the ventilator resource until the Length of Stay (LOS) specified by the *Delay* step is completed, after which it is released using the *Release* step. If the patient does not require a ventilator, they experience a delay based on their LOS. All patients are discharged and counted as Recovered patients.

in Table 1. The Discrete distribution is specified using the syntax Discrete (α_1, X_1, α_2, X_2, ...), where X represents discrete values and α is corresponding cumulative probabilities.

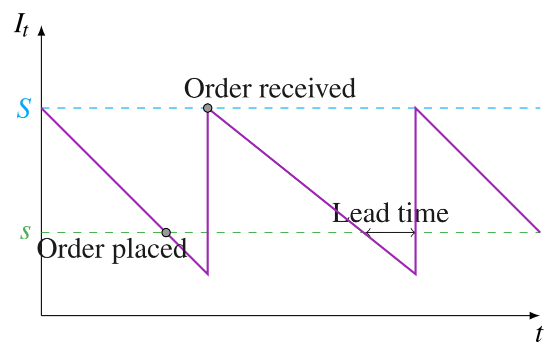


Figure 5: Inventory level over time for PPE items with (s,S) replenishment policy model. Here, t represents Time and I_t represents Inventory level. When the inventory level falls below the reorder point s, an order is placed to replenish the inventory up to the maximum level S.

Table 1: PPE supplies.

Items	Order Lead time	Patient use per day
Masks	Triangular(1,1,4)	Discrete (0.50, 1, 1.0, 2)
Gloves	Uniform(2,4)	Discrete (0.75, 2, 1.0, 4)
Gowns	Uniform(4,7)	1

3.3 Simulation Model Parameters and Data-table Inputs

The simulation model utilized in this research is a data-driven model, constructed based on multiple data-table inputs. These tables contain information related to patients' age groups, hospitalization rates, population mix, and the probability of requiring a ventilator for different age groups. To construct these tables, various data sources are utilized, based on a regional hospital in the Boston, MA area. Simio's data-table function capabilities are used to import this data, which is listed below:

- Hospitalization Rates by Age Groups: Obtained from the Massachusetts Department of Public Health (Figure 6-a).

- Ventilator Needs by Age Groups: Obtained from a study conducted by (Nicholson et al. 2021) (Figure 6-b).
- Population Mix by Age Groups in the City of Boston: Obtained from available demographic data (Figure 7).

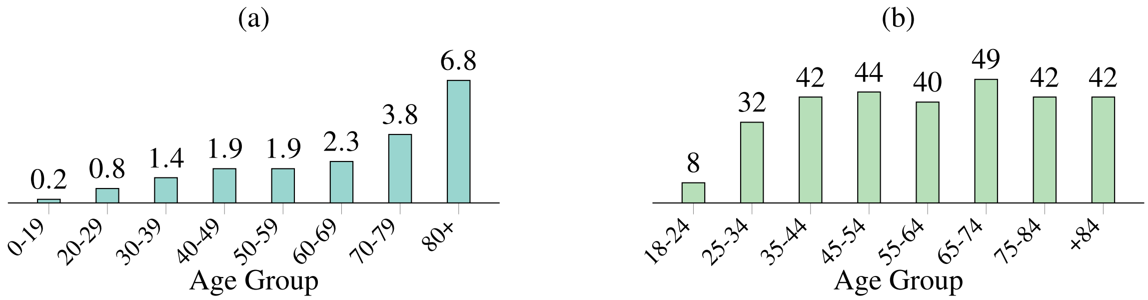


Figure 6: Hospitalization needs, (a) hospitalization rate - August 2020 (in percentages) (Mass.gov 2021), (b) age group-wise percentage of ventilator need (Nicholson et al. 2021).

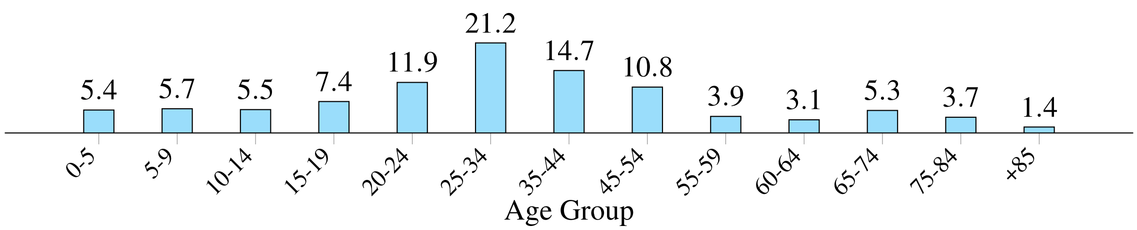


Figure 7: Percentage distribution of the population in the city of Boston (worldpopulationreview 2021).

The important simulation model parameters are listed in Table 2. The length of stay for hospitalized patients in the hospital is determined by a triangular distribution with a minimum of 1 day, a maximum of approximately 3 weeks (20 days), and a mode of 2 weeks (14 days). Congestion duration refers to the time it takes for an infection to be diagnosed after the initial infection. This duration follows a uniform distribution ranging from 1 day to 2 weeks (14 days).

It needs to be noted that these values are subject to change depending on the hospital's capacity and the disease's characteristics. In the next section, an experimental analysis is provided to study how changing the Contagion Factor and Social Distancing Factor can impact the supply needs of the PPE items. The other factors are remained the same throughout the study, however, interested readers can extend the scope of the experiment and analyze the effect of other parameterization combinations.

Table 2: Simulation model parameters.

Model Settings	Values	Fixed Parameters	Values
Ventilator Capacity	50	Hospital Stay Length	Triangular(1,7,20)
Beds Capacity	100	Service Area Population	25,000
Reported Cases	50	Contagion Duration	Uniform(1,14)

4 EXPERIMENTAL RESULTS, COMPARISON, AND ANALYSIS

To demonstrate the applicability of the proposed hybrid model, three scenarios are considered as follows:

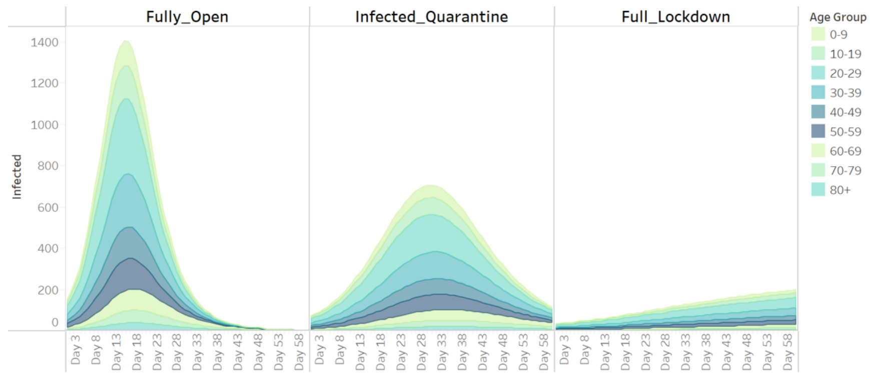


Figure 8: Area chart showing the number of infections based on three scenarios: 1) fully open, 2) infected quarantine, and 3) full lockdown segregated by age group.

- **Fully Open:** In this scenario, there are no restrictions on movement, and individuals are free to move around without any limitations.
- **Quarantine:** In this scenario, individuals who are infected or have come into contact with infected individuals are required to stay in quarantine, while others are free to move around without any restrictions.
- **Full Lockdown:** In this scenario, all individuals are required to stay in their homes, and movement is strictly restricted.

The policy parameters in the mean field model for each scenario are also presented in Table 3. The experimental analysis is conducted to understand how different pandemic situations and policies will impact healthcare resource utilization and optimal replenishment policy for PPE items.

Table 3: Experiment settings with three scenarios.

Scenarios	Mean Field Model Parameters	
	λ_t^S	λ_t^I
Fully Open	1	1
Quarantine	1	0.5
Fully Lockdown	0.5	0.5

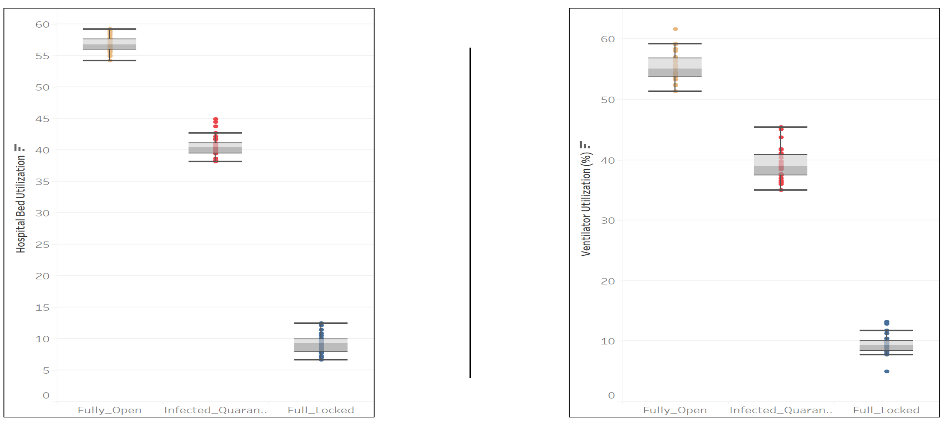
The mean field model generated infected patients for each of the above-mentioned scenarios distributed into different age groups. As shown in Figure 8, more people are infected in Scenario 1, where the community is fully open and there are no restrictions such as social distancing or wearing masks. The provided graphs give an overview of how different infected patients will emerge within a 60-day period. Furthermore, when we compute the value function of the agents under different scenarios, we can see that at time 0, for susceptible people it gets lower as the restrictions are getting stricter. The reason for this is that when there are less restrictions it is a higher possibility a susceptible person becomes infected which is costlier with the extra cost c_I; therefore, their expected cost is higher.

Each of these scenarios is simulated in Simio and followed by an optimization process to find the optimal replenishment policy for parameters such as reorder point s and reorder quantity S for each PPE item. The experimental results are presented in Table 4, which provides guidance on how hospitals should set their replenishment policy in different stages. It is evident that there is a higher burden in a fully open situation, and therefore hospitals need to set higher values for the reorder point and reorder quantity for masks, gloves, and gowns. Implementing quarantine measures can provide some relief for hospitals and enable them to fulfill their PPE item requirements at a lower rate and frequency. Finally, in the lockdown situation, the consumption of PPE items becomes minimal.

Table 4: Optimal reorder points and order quantities for each PPE item are determined under different pandemic situations.

	Fully Open		Quarantine		Fully Lockdown	
Items	s	S	s	S	s	S
Masks	5,050	17,200	4,940	10,450	2,800	5,300
Gowns	5,000	21,500	4,350	12,200	2,850	4,500
Gloves	5,300	19,975	4,940	14,300	4,250	8,500

The impact of each scenario on resource utilization is illustrated in Figure 9, where boxplots represent the average utilization of resources obtained from multiple simulation replications. It is evident that ventilators play a critical role during the fully open phase, while during the lockdown phase, there are available resources for both ventilators and hospital beds. It should be noted that while every patient requires a bed for hospitalization, the number of ventilators needed for each patient is determined by the process described in Figure 4.



(a) (b)

Figure 9: Resource utilization for (a) ventilators, (b) hospital beds.

5 CONCLUSION

In summary, this study proposed a novel approach that combined simulation-optimization and game theory to assess the impact of various pandemic scenarios on healthcare resource utilization and optimize the replenishment policy for PPE items. By considering three different scenarios, fully open, quarantine, and fully locked, this study provided insights into the resource utilization and demonstrated the importance of having effective PPE replenishment policies in place. The simulation results revealed the significance of the community's engagement and the level of restriction in managing a pandemic. The optimization model provided hospitals with guidance on setting up an effective replenishment policy for PPE items under different scenarios. The proposed approach could significantly contribute to decision-makers' efforts to develop well-prepared supply chain strategies for pandemics, ultimately improving the healthcare system's overall response to public health emergencies.

This study is one of the early examples that integrates a discrete event simulation and mean field model, providing potential opportunities for improvement and extensions. Some future works that could be considered include:

- Investigating the impact of different vaccination rates and distribution strategies on the proposed hybrid model's results.
- Considering the impact of other pandemic-related variables, such as infection rate and mortality rate, on the healthcare resource utilization and PPE replenishment policy.
- Extending the model to include other healthcare resources, such as medication and medical equipment, and optimizing their replenishment policies during pandemics.

These future works can further enhance the proposed approach's applicability and contribute to developing effective and efficient supply chain strategies for healthcare systems during pandemics.

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