Simulation of Pandemic Impact on Patient Outcomes and Hospital Strain

ISYE 6644: Simulation and Modeling for Engineering and Science
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Abstract

Infectious diseases cause enormous amounts of strain on the healthcare system. As seen with the Covid-19 pandemic, hospitals can easily become overwhelmed if proper and timely interventions are implemented to mitigate disease spread. This simulation project models an example pandemic and focuses on how the effects of different mitigation strategies (masking, vaccinations, and lockdown) have on both the spread of infection and its effects on hospital resource usage. As such, patient outcomes were modeled based on the SEIRD model (susceptible, exposed, infectious, recovered, dead) in combination with a hospital queuing system.

Several major findings were discovered. With no interventions, transmission of disease is rampant and the population death rate is high. Meanwhile, lockdowns and masking reduce disease transmission and population death rates significantly. Though vaccinations do not appear to lower the transmission as significantly, the effect of vaccines on the death rate is the greatest due to the positive effect of vaccines on recovery rate.

1. Background

1.1 Introduction

Throughout COVID-19 pandemic, hundreds of thousands [1] of infected people were hospitalized due to COVID-19. Many hospitals found it difficult to deal with the incoming masses of COVID-19 patients, resulting in severe overcrowding in hospitals [2]. Some studies even showed how overcrowding due to COVID-19 may have significantly increased the death rate of patients [3], possibly endangering tens of thousands of lives.

Given the abrupt onset of the pandemic, it was understandably challenging for healthcare experts to anticipate how COVID-19 would affect hospitals. And while it may have been difficult for hospitals to accommodate every patient, efforts across the U.S. focused on reducing the spread of COVID-19 to minimize future hospitalizations. The introduction of public health interventions like mask mandates and temporary lockdown along with pharmaceutical breakthroughs in widespread vaccinations all contributed to slowing the spread of infection. As a result of these efforts and more, in 2024, hospitalization rates due to COVID-19 reached incredibly low levels, with 1.8 total hospitalizations per 100,000 people as of April 5th, 2025 [4].

While COVID-19 spread, hospitalizations, and death rates have declined in recent years, it is still important to analyze and simulate the impacts that future pandemics may have on both patient populations and hospital systems, which is the aim of this paper.

2. Analysis

2.1 Building the SIRD Model

We used a basic SIRD model which was modified for use in our discrete event simulation with the added hospital aspect. We started with the equations below that represent the change in each category (Susceptible, Infected, Recovered, and Dead) and made slight modifications for our use-case. Since recovered and dead entities are no longer susceptible to infection, entities that have already exited the system are not part of the calculation for N, the population. Also, the probability of infection is calculated per susceptible entity in a discrete event simulation (S=1), so S was not included in the calculations.

Figure 1

$$N = S(t) + I(t) + R(t).$$

$$\frac{dS}{dt} = -\frac{\beta IS}{N},$$
$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I - \mu I,$$
$$\frac{dR}{dt} = \gamma I,$$
$$\frac{dD}{dt} = \mu I,$$

[5]

Change in recovered and dead entities is slightly more complex as each is actually dependent on some parameters (priority/severity level, whether the entity chose to visit the ER, and whether the entity was admitted to the hospital).

Where k = 0, 1 (represents whether the hospital was visited or not), p = 1, 2, 3 (represents each priority level) and $\gamma_{p,k}$ represents the probability of recovery for each priority level and whether they visited the hospital. $I_{p,k}$ represents the number of entities that will complete the simulation through each respective path / with each respective priority level. We need one additional term (k=2) for E[R], the expected number of recovered patients, that represents the entities who decided to go to the ER, but were not admitted. This category only has a path to recovery, so this extra term is not needed in the equation for the expected value of dead (note: in the discrete event simulation, $\mu_{p,k} = 1 - \gamma_{p,k}$). :

Figure 2

$$E[R] = \sum_{k=0}^{1} \sum_{p=1}^{3} I_{p,k}\gamma_{p,k} + \sum_{p=1}^{3} I_{p,2}\gamma_{p,2}$$

$$E[D] = \sum_{k=0}^{1} \sum_{p=1}^{3} I_{p,k}(1 - \gamma_{p,k})$$

These are derived from the fact that there are three paths to recovery (At home recovery, Decide ER - not admitted recovery, and admitted to hospital recovery) and two paths to death (At home death or hospital-admitted death) in the simulation. Within each path, there are also different sets of probabilities for each of the three priority levels.

2.2 Model Structure and Invention Strategies

We created hospital systems for 4 different types of pandemic intervention models: no intervention, masking, vaccinations, and lockdown. Rates of infection and/or recovery along with hospitalizations were modified to model each type of strategy/intervention. The general model structure is shown below.

Figure 3

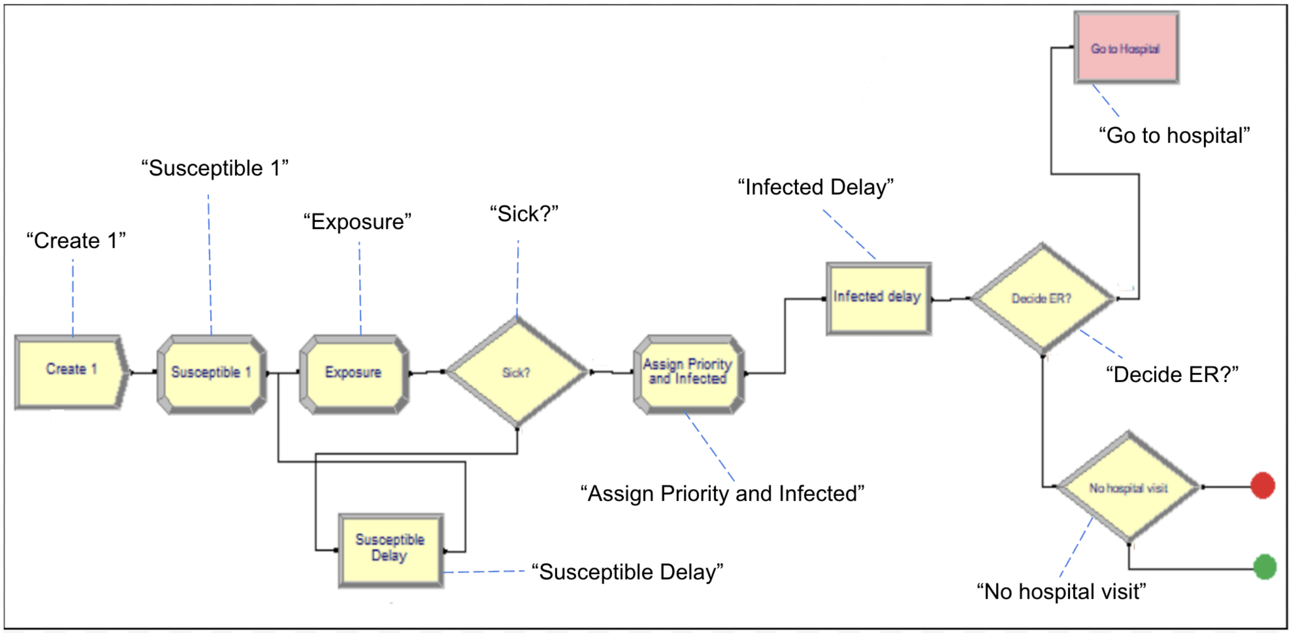


Figure 3 illustrates the flow of the S-I part of the SIRD model. As people enter the system, they are assigned a susceptible state and then become exposed to the virus. After exposure, if they get sick, people from the susceptible group are transferred to the infected group and assigned a severity level (priority level). If people don't get sick from the initial exposure to the virus, they loop back to the susceptible group before being exposed to the virus again. Infected individuals then decide if they want to go to the ER for further treatment.

Figure 4

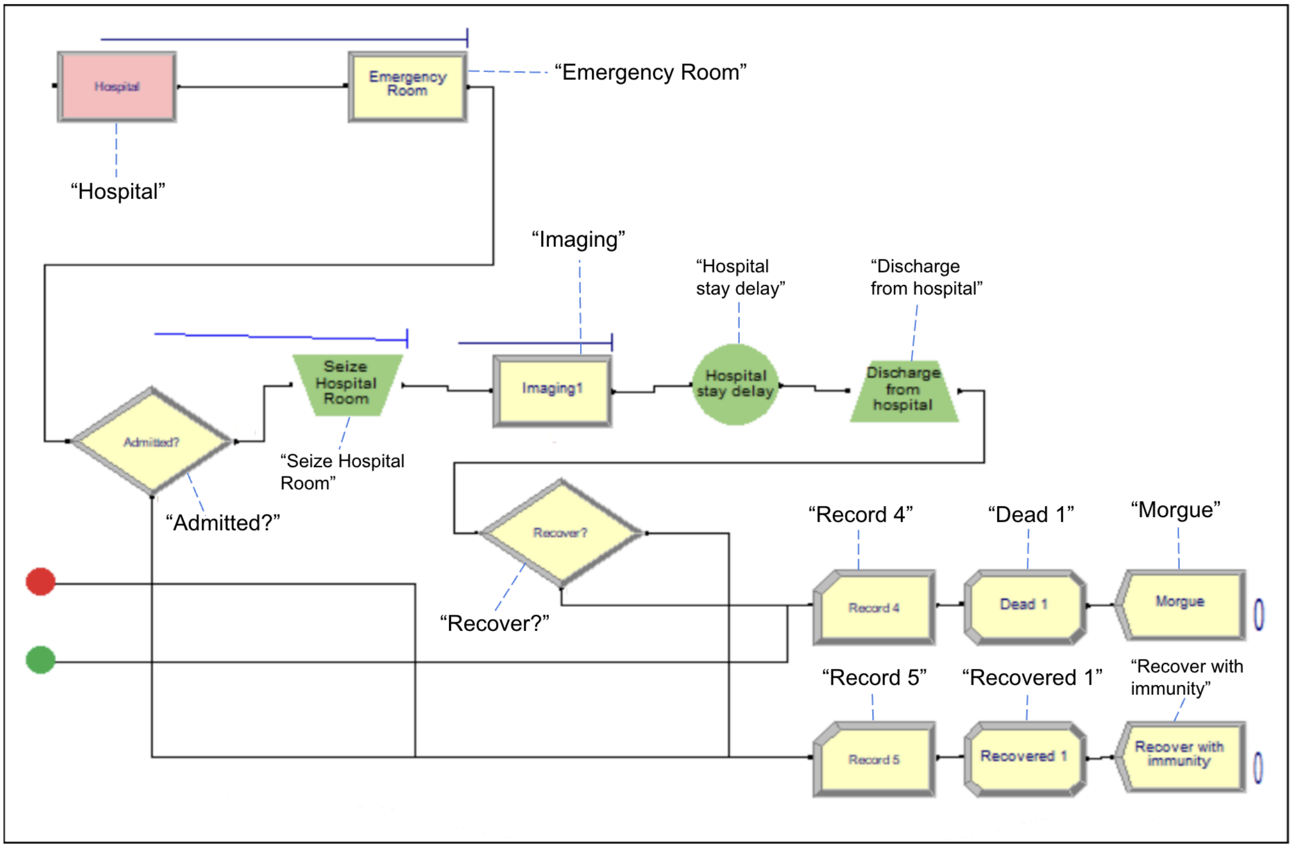


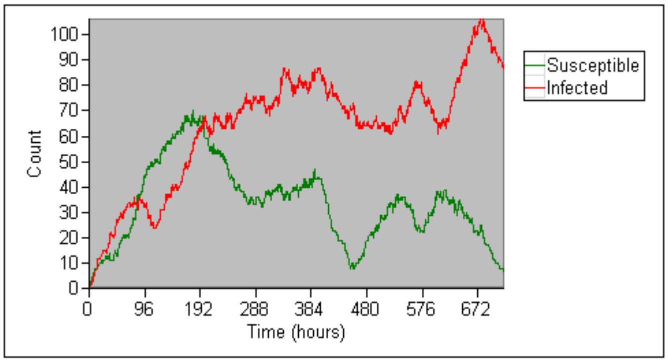
Figure 4 illustrates the flow of the R-D part of the model, along with the hospitalization process. If an infected person does not go to the hospital, they have both a chance to pass away from the virus or to recover with immunity. If the infected person opts to go to the hospital, they are then taken to the emergency room, which may have a queue.

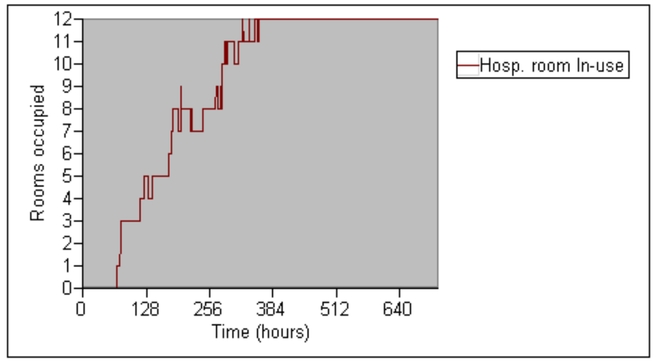
Patients in the emergency room are processed in order of their priority level, meaning that high priority patients leave first. If a patient leaves the emergency room and is not admitted into a hospital room, it means they were treated properly in the emergency room and recovered with immunity. If the patient is admitted, they are assigned a hospital room to stay at for 8 days of imaging and treatment, though sometimes hospital rooms get full and a queue starts to develop. After being discharged from the hospital, the patient either passes away (transferred from infected to dead) or recovers with immunity (transferred from infected to recovered).

2.3 Control/No Intervention Model

With no intervention and a baseline transmission rate (β) of 0.6, the number of infections spiked rapidly while the hospital quickly became overwhelmed, as illustrated below.

Figure 5, 6





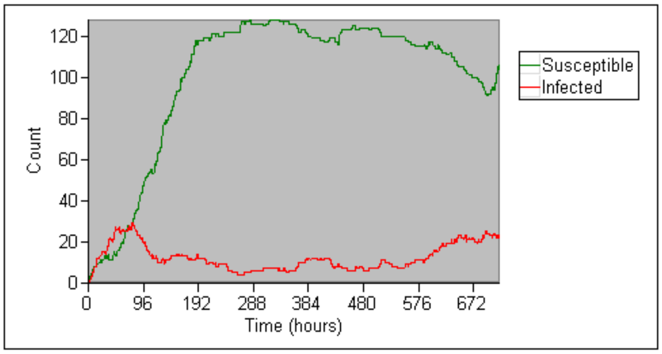
Utilization in the main hospital was roughly 0.89 ± 0.03 on average after five replications. The ER was also constantly accepting patients, with a utilization of 0.72 ± 0.07 indicating that both the main hospital and the ER form somewhat long queues. In this scenario, the population death rate was observed to be roughly 0.088.

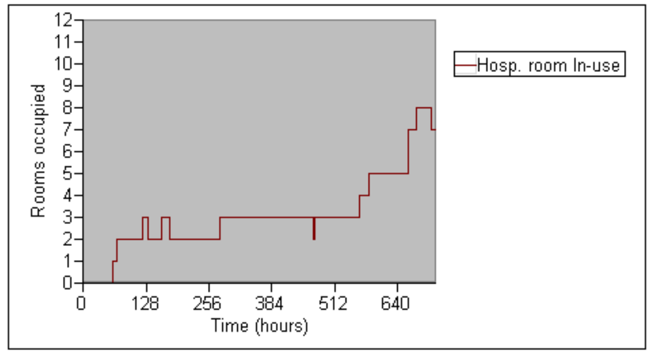
2.4 Masking Model

The first intervention strategy this paper examines was masking. Masking was shown to lower odds of infection by 62% (38% odds ratio) [6]. With roughly 70% of people wearing masks, the odds ratio would be increased to $1 - (1 - 0.7(0.38)) = 56.6\%$ which equates to roughly a 43.4% decrease in transmission of disease. This value (0.566), the adjusted odds ratio, was applied directly to the baseline β (transmission rate) to simulate the scenario where 70% of the population wears a mask.

An example graph showing the number of infected versus susceptible over time is shown below. Compared to the scenario with no interventions masking shows to be effective in lowering the transmission rate enough to prevent an early spike in infections.

Figure 7, 8

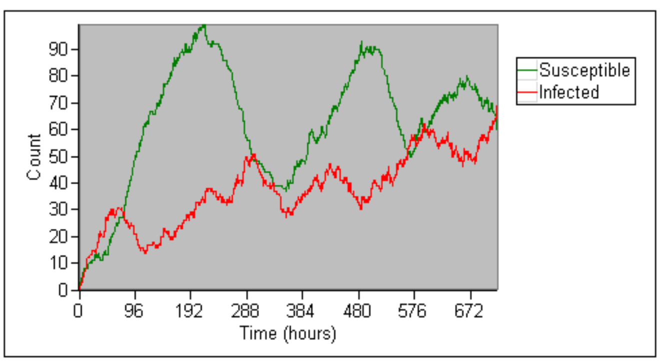


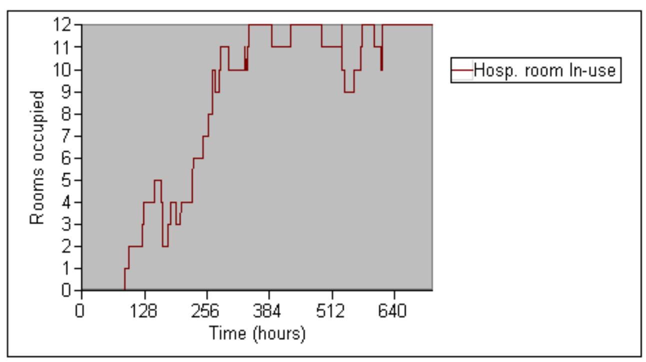


In addition to infection rates slowing significantly, hospital resource utilization was also drastically decreased. With the reduction in transmission rates as a result of 70% of the population masking, resource utilization in the emergency room and main hospital were cut to 0.36 ± 0.13 and 0.37 ± 0.14 respectively. With masking, the observed population death rate was calculated to be roughly 0.061.

2.5 Vaccination Model

For the vaccination model, two doses of vaccine were shown to decrease transmissibility by roughly 22% [8]. Similarly to the other interventions, this reduction in transmission was applied directly to the baseline β value of 0.6. Vaccines not only reduce transmissibility, but they also improve outcomes for those who had received them [9]. Vaccines seemingly slowed the early spike in infections and also provided better outcomes for sick people whether recovering at home or while in the hospital.



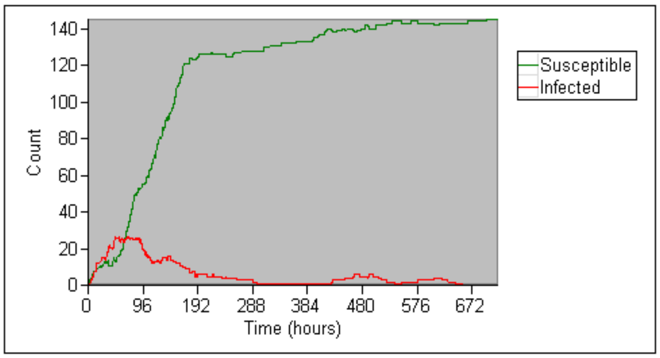


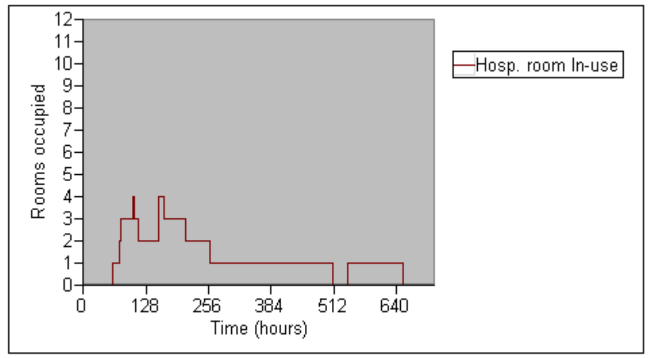
While hospital utilization remains high with 0.81 ± 0.11 and 0.67 ± 0.11 utilization in the emergency room and main hospital respectively, the observed population death rate was the lowest of the four models at 0.038.

2.6 Lockdown Model

The easiest/simplest way to model a lockdown is to, at some point, set transmission rate equal to 0. In a perfect world this may work but, some transmission of disease still takes place even with a lockdown in place. Lockdowns that occurred near the start of the COVID-19 pandemic were estimated to have resulted in a roughly 56% decrease in transmission of disease [7]. We applied this reduction as a coefficient (0.44) of our baseline β of 0.6. Graphs showing the number of infections and number of main hospital resources being used over the 30 days are shown below.

Figure 9, 10





Compared to the control model, the number of infected is much lower over the 30 day simulation. In the main hospital and emergency room utilization was, on average, 0.26 ± 0.18 and 0.21 ± 0.13 respectively. *Figure 9* shows that the hospital never reached full capacity at any point during the simulation. With early implementation of a lockdown, the observed population death rate was 0.049.

2.7 Statistical Analysis

Figure 11

No Intervention, Masks, Lockdown	Priority assignment probability	Decide ER? 2 way	Admitted?*	Outcome NO hospital admit (probability of recovery)	Outcome YES hospital admit (probability of recovery)
Priority1	65%	50%	10%	87%	92%
Priority2	27%		35%	70%	85%
Priority3	8%		90%	55%	75%
*not admitted go to recovery					

Figure 12

Vaccines	Priority assignment probability	Decide ER? 2 way	Admitted?*	Outcome NO hospital admit (probability of recovery)	Outcome YES hospital admit (probability of recovery)
Priority1	65%	50%	6%	95%	98%
Priority2	27%		2%	85%	93%
Priority3	8%		75%	70%	90%
*not admitted go to recovery					

Figure 11 shows the probabilities involved in each path to recovery for each priority level in the model for the no intervention, masking, and lockdown scenarios. *Figure 12*

shows the same for the vaccine scenario (vaccines improve recovery outcomes). As noted, probability of recovery <u>after deciding to visit the ER and not being admitted</u> will be equal to $1 - P(Admitted? \mid Priority\ level)$. In other words, all not admitted entities that decide to visit the ER will recover.

Figure 13

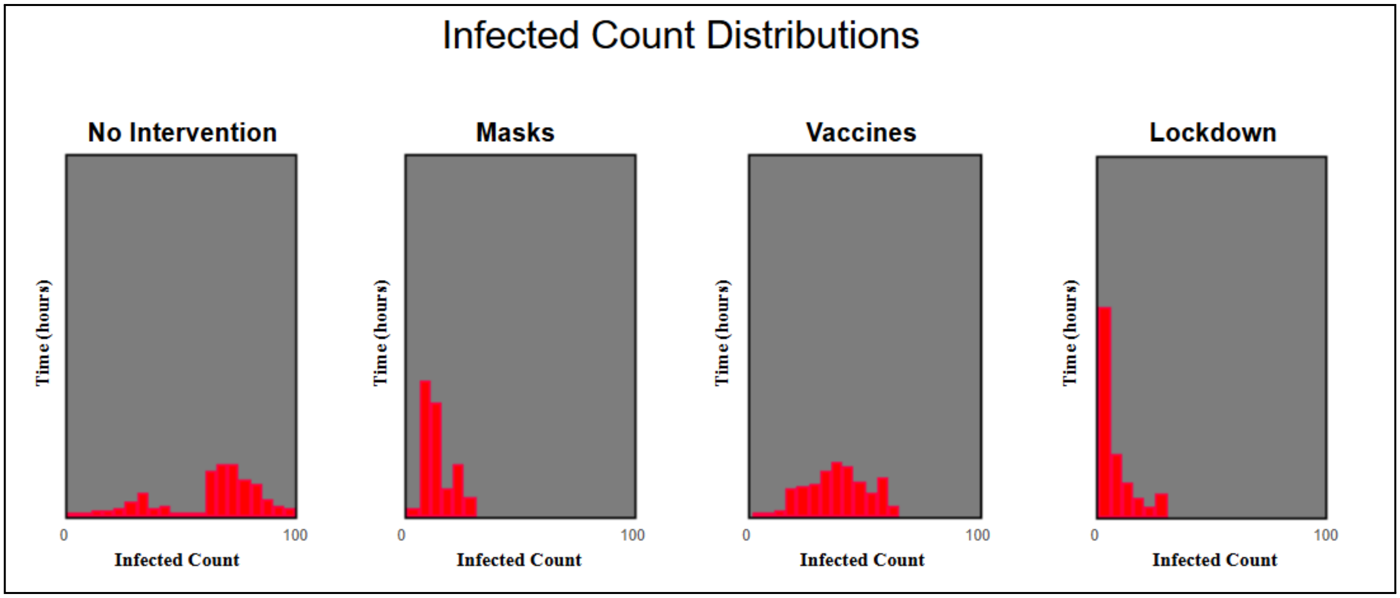


Figure 13 shows the distribution of infected counts under different intervention scenarios: No Intervention, Mask Mandate, Vaccination, and Lockdown. In the No Intervention case, the distribution is wide and left-skewed, indicating a consistently high number of infections across simulation runs. This reflects the rapid, unchecked spread of disease when no mitigation measures are in place. The Mask Mandate scenario shows a noticeable improvement, with the majority of infection counts concentrated at lower values, though variability still exists due to partial effectiveness. The Lockdown case demonstrates the most significant containment, with infection counts sharply concentrated at the lowest end of the spectrum, indicating high consistency in limiting spread. This outcome supports the effectiveness of reduced contact rates in flattening the curve.

In the Vaccines scenario, the distribution of infected counts is moderately concentrated toward the lower end, though slightly more spread out compared to the Mask Mandate and Lockdown cases. This reflects the effectiveness of early vaccination in reducing severe spread while allowing for some variability due to timing.

2.8 Hypothetical Scenario Analysis:

We explored several what-if scenarios to understand how small changes impact pandemic outcomes.

What if hospital capacity was reduced by 50%? This would likely increase hospital utilization, in both the ER and main hospital, due to reduced admission opportunities.

What if vaccines were introduced 20 days later? Delayed rollout would allow the infection to spread more widely early on, significantly increasing total infections and deaths.

What if the transmission rate increased by 10%? All intervention scenarios would show higher peak infections, but the No Intervention town would experience exponential growth and overwhelming healthcare demand.

What if masking compliance was only 50%? The mask mandate scenario would begin to resemble the No Intervention case, highlighting the importance of consistent public adherence.

3. Main Findings & Discussion

3.1 Results

Overall, the lockdown model resulted in the least amount of infected individuals (near zero at the end), which in-turn resulted in very low hospital utilization; also the lowest of all models. Masking had a similar effect, and may even be a better alternative due to the negative economic impact following lockdown protocol during COVID-19 [7]. Additionally, vaccinations proved to be most effective at lowering the death rate at 0.038 deaths per person in the simulation, but still resulted in an increasing number of infected individuals and a full hospital over the simulation time of 30 days.

Figure 14

Intervention Type	*No Intervention*	*Masking*	*Lockdown*	*Vaccines*
Population Death Rates	0.088	0.061	0.049	0.038

3.2 Challenges & Limitations

Even though this paper effectively simulates and analyzes the spread of a pandemic and its effects on a hospital system, there are a couple challenges and limitations to consider. One key limitation relates to the scale of the simulation model. The model only houses one emergency room and one imaging room for all patients, when in reality, hospitals tend to have multiple emergency rooms as well as multiple different rooms to send patients to depending on their immediate diagnosis. For the purposes of this paper, we chose to aggregate emergency and treatment rooms to better streamline the simulation and make it more understandable.

Another huge challenge was with the Arena software itself. Since we only had access to the unlicensed/free version, the 150 entity limit was a hindrance. To avoid errors presented when hitting the system's 150 entity limit, we implemented a workaround by tracking the total number of entities in the system. When the count approached the limit, we lowered the rate of new entity creation to prevent overload.

3.3 Policy Recommendations

A few policy recommendations can be derived from this study. Firstly, it is essential for the government to timely inform the public about a potential new pandemic along with necessary precautions. If the government is slow to acknowledge a new pandemic (like they were in 2020), infection could spread rapidly without the broad adoption of precautionary measures like masking. Spreading accurate information over television, newspapers, social media platforms, and other forms of media would incentivize people to take action and start practicing preventative measures like masking and social distancing to reduce the spread and hospitalization rate.

Moreover, during times of crisis, it is pertinent to allocate additional resources and spaces to hospitals to ensure they can accommodate for an influx of patients. As seen in the no intervention model, queues and waiting times for hospital treatment rapidly increase while consistently staying above 0. Therefore, during the early stages of a new pandemic, it is the government's responsibility to maximize hospital utility. As such, government support in providing temporary facilities for additional patient treatment would expand hospitals' capacity for care. Also, government assistance in providing additional funding and supplies to hospitals would greatly expedite patient treatment.

4. Conclusion

This paper simulated a pandemic in combination with different mitigation strategies to examine the effects on virus spread and hospital strain. As such, various strategies like masking, vaccinations, and lockdown protocol were considered and analyzed for their effectiveness. That being said, in addition to discrete event simulation, other analytical methods could be applied to build upon the results produced by this paper. For example, time series forecasting could be applied on existing COVID-19 data to analyze nuanced trends and changes in COVID-19 infection rates, hospitalization rates, etc. How these trends fluctuate following the implementation of different policies and mitigation strategies could be examined as well. Additionally, random forest generation could be employed to predict how a pandemic may evolve by determining the main drivers of virus transmission and hospitalization. These predictors could then be used to predict spread and hospital treatment demand. Overall, implementing both forecasting and random forests on top of the discrete event simulation shown in this paper will help to model past trends and bolster future predictions.

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