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An Investigation of Mitigation Measures on the Spread of COVID-19 in a College Classroom Using Agent-Based Modeling

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Abstract
In this manuscript, we describe the process of using agent-based modeling in NetLogo to create a simulation of COVID-19 spread in a traditional college classroom. The model allows for an evaluation of different preventative measures implemented by the University of Pittsburgh, including the cohort classroom attendance model, mask and vaccine mandates, contact tracing, and classroom sanitation. Through the use of the model’s interactive interface, the impact of adjusting specific measures by the institution could be visualized, providing a valuable tool for combating diseases that spread through droplet transmission.

Keywords: agent-based modeling, COVID-19, college classroom, interactive simulation, preventative measures

1 Introduction
The Coronavirus SARS-CoV-2 pandemic, more commonly referred to as the COVID-19 pandemic, has grasped society over the past three years, bringing forth obstacles that will hinder progression for years to come. Communities and individuals alike have faced various degrees of opposition originating from the virus. Not only did society have to deal with combating the virus from a healthcare standpoint, but leaders also needed to address the social and economic abnormalities that the pandemic forced upon the masses such as the introduction of social distancing, high rates of business closures, and a transition to virtual learning and work. As such, researchers and healthcare professionals turned to a variety of different methods for mapping COVID-19 infections and viral spread in order to mitigate the public health risk [17].

An effective technique of tracking viral spread is agent-based modeling, an approach that utilizes mathematical and computational concepts. Agent-based modeling allows researchers to code and observe simultaneous interactions between multiple variables. These micro-scale representations can easily be altered to be used with different parameters such as location, number of individuals and interactions, and probability of event occurrence [10]. Traditional mathematical models, such as those utilizing partial differential equations, require a more advanced mathematical background and analysis can be challenging. Other researchers created various different agent-based models with the intention of mapping the spread of COVID-19. Wang et al. utilized agent-based modeling as a means of tracking the spread of COVID-19 on a community level, focusing on a simple societal model simulating spread in individuals’ workplaces, residences, and hospitals [17]. Bahl et al. focused on using agent-based modeling to track spread in a small, residential college, mapping COVID-19 infections across interactions on campus, in classrooms, and in common places [11]. Our model sought to incorporate certain elements of these simulations but focused specifically on classroom interactions to map COVID-19 spread in order to assess the dangers of in-person learning as well as evaluate the University of Pittsburgh’s specific mitigation measures.

This project utilizes agent-based modeling in the NetLogo program, a free multi-agent programmable modeling environment for simulating natural phenomena that can simulate interactions between thousands of individually operating agents over time [18]. We decided to use NetLogo due its intuitive nature for model-building, including an interactive interface, and overall accessibility. Utilizing the capabilities of agent-based modeling in NetLogo, the goal of this project was to create an accurate simulation of COVID-19 spread in a traditional college classroom [13]. The desire was to investigate the complications associated with in-person learning, in our home institution of the University of Pittsburgh, at the height of the pandemic as well as explore the impact that various preventative measures had on viral transmission over the course of time. Different institutions were implementing a variety of preventative measure combinations in an effort to best mitigate public health risks as conditions changed and new information became available. This model allowed
for an appropriate evaluation of the University of Pittsburgh’s mitigation techniques such as the utilization of the cohort classroom attendance model, mask mandates, contact tracing, and classroom sanitation between class meetings [13]. Due to the ease by which various variables can be altered, the project could also be used as a tool to combat many diseases that spread through droplet transmission (COVID-19, Influenza, Common Cold, etc.) or the methodology could be altered easily in order to map infection spread in a multitude of different environments, not limited to an academic setting.  

2 Methods

In this section, we will describe the makeup of the agent-based model, detailing all the components that allowed for the running of simulations.

2.1 Schedule

The model assumes 40 class meetings in a semester, each spaced 48 hours apart. Each class meeting lasted one hour, represented in the model by a time period of 500 ticks. Time spent outside of the classroom after the end of a class period and before the start of the next class session represented the 47 hours in between class meetings. To retain simplicity, we excluded weekends and holidays.

2.2 Classroom

The classroom was modeled after a standard college lecture hall, with 100 desks arranged into 10 even rows (Figure 1). Each desk was assumed to be one meter apart from others in the same row and one meter apart from others in the same column. In compliance with fire safety regulations, the classroom had two accessible entrances/exits on both sides of the front of the classroom [7]. A lectern for the professor was located in between the entrances on the ground floor of the lecture hall, 2 meters from the first row of student desks.

2.3 Agent movement

Each student was randomly assigned a specific seat in the setup procedure. Students remained assigned to their specific desk throughout the semester. Students entered randomly from either of the two entrances at the start of the class meeting and moved to their specific seat, first moving to the correct intersection between column and row and then moving down the row to their assigned seat. Movement speed and entrance time were randomized for each student every class meeting in order to mimic the varied behaviors of students and better represent the phenomenon. We assumed that no students arrived late or left early from the class meeting to retain simplicity. Each student would sit in their seat upon arriving and stay until the end of the class meeting (at 350 ticks). At this point, students would be dismissed and would start moving towards the exit closest to them. Again, movement speed and time of departure were varied. Upon reaching the exit, students would leave the classroom until the start of the next class meeting. The professor would follow this same movement path but would enter randomly from the entrance and move towards the lectern, staying there until the end of the class meeting.

2.4 Means of exposure

Students could become exposed through three interactions, characterized as student-to-student, environmental, and outside of the classroom. When within two meters of a contagious individual, students were given a rate of exposure of \( R_S \) [1]. Additionally, desks were given a specific probability of retaining viral load from possibly infectious students who had sat in the desks prior to this class period. Students had a rate of exposure from environmental interactions \( (R_E) \). Initially, as the perceived threat of environmental exposure was seen as a major factor in the spread of COVID-19, this rate of exposure was relatively high and played a large factor in infection probability. However, with more information about viral transmission dynamics over time, this exposure rate was made substantially lower during the development of the model in order to reflect the minimal impact of environmental exposure highlighted in CDC guidelines [3]. Lastly, based on Allegheny County’s rate of transmission and CDC classifications regarding the spread, students

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Figure 1: Model interface with classroom pictured on the left and variable sliders and graphs on the right.

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1The interested reader can find the NetLogo simulation and code referred to in this paper on the QUBES database doi:10.25334/KMTW-5605.
were given a specific rate of exposure outside of the classroom \( (R_O) \) \[1\]. These rates were based on overall rates and classifications outlined by the CDC. Classifications included high, substantial, moderate, and low \[4\]. This rate can be altered by the user on the model interface using the Rate-of-Transmission slider. To retain simplicity, the professor was excluded from exposure and progression of infection as it was assumed that, if infected, a substitute lecturer would take over teaching the class.

2.5 Progression of infection

Each student is assigned a vaccination status prior to the start of the simulation. The probability of vaccination can be altered by the user using the Percent-Vaccinated slider. Students can become exposed through the three interactions listed above: student-to-student, environmental, and outside of the classroom. Upon exposure, students will either return to susceptibility \( (E_H) \), as their viral load never crosses the threshold necessary to test positive for the virus, or progress to the asymptomatic classification \( (E_A) \) due to the sufficient build-up of viral load \[1\]. From there, these infected individuals will either proceed to the symptomatic classification or remain asymptomatic based on a asymptomatic rate \( (A_S) \). It is assumed that, throughout the model, symptomatic students do not engage in classroom activities once they develop symptoms and stay in their respective residences until their quarantine period had subsided. 100 percent compliance with recommended guidelines and quarantine timetables is also assumed in order to maintain simplicity. After the infection has subsided, the students return to susceptibility from either their asymptomatic classification \( (A_H) \) or their symptomatic classification \( (S_H) \). These flow rates are determined by the random number of days that the individual remains infectious. Students can then become re-exposed, at a lower rate equal to that of a vaccinated individual, due to the same interactions and will either progress through the entire viral cycle or return to susceptibility if viral load never exceeds the infected threshold \[12\]. An illustration was created to visualize the infection progression diagram for each student (Figure 2).

2.6 Preventative measures

With more information becoming available throughout the process of creating the model and the changing landscape of our understanding of transmission dynamics, a variety of preventative measures were implemented in order to vary rates of exposure/viral progression and mirror the methodologies utilized by educational institutions globally. During the early stages of the model, there were radical difference between university policies of dealing with the pandemic, with some institutions choosing to operate in a relatively normal fashion while others choosing to shut down all together. As we wanted to explore the dangers of in-person learning at our home institution, we decided to focus on evaluating the University of Pittsburgh’s preventative measures including the implementation of the cohort model, mask mandates, regular sanitation, random testing, contacting tracing, and eventually a vaccination mandate.

To reflect social distancing, three different classroom capacities were introduced: full capacity, half capacity, and cohort. Full capacity allows for all 100 students to participate in a traditional, in-person class meeting for all 40 class meetings in the semester \[5\]. All seats in the classroom are filled when this capacity is utilized. Half capacity allows for only 50 students to be enrolled in the class and enter the classroom to simulate for social distancing of two meters between individuals. The cohort model, on the other hand, allows all 100 students to be enrolled in the class. However, only 50 of these students, a cohort, will enter and participate in the classroom for each class day. Cohort A attends odd numbered class meetings while Cohort B attends even numbered class meetings. Each student was spaced two meters apart in this form of classroom capacity.

To further alter exposure rates, three different face mask mandates were implemented into the model: all individuals, unvaccinated individuals only, and none. Upon entering the classroom, face mask use reduces student-to-student exposure rates \( (R_S) \) by a factor of 0.5 \[1\]. Figure 2 gives the illustration of a masked student.

Furthermore, sanitation effectiveness was another measure introduced to vary the environmental exposure rate. Sanitation effectiveness is applied to the condition of the classroom before the simulated class entered, as we assumed that this classroom was used for prior class meetings before the simulated class meeting began. Users are able to change the sanitation effectiveness using the Sanitation-Effectiveness chooser on the interface and could alter the probability of viral load remaining on the
desk from the previous class meeting. High sanitation effectiveness reduces \( R_E \) by a factor of 0.1 while low effectiveness has a lesser effect, reducing by a factor of 0.5 \[9\].

Testing was another measure encoded into the model. The model allows for two types of testing: random and weekly testing for only unvaccinated individuals, both policies that were implemented by the University of Pittsburgh during different stages of the pandemic. Random testing randomly selects 1/3 of the class to be tested after every three class meetings. Weekly testing for the unvaccinated occurs after every three class meetings as well. If students test positive through the testing procedure, they are placed in a mandatory quarantine, with its length based on the Quarantine-Period slider in the interface, regardless of their symptoms. Additionally, the model allows for an option to introduce contact tracing. If selected, all students in the class will be subject to testing after a single positive test from one of their classmates and all positive individuals will be placed in quarantine \[8\]. To retain simplicity, it was assumed that testing was 100 percent accurate in determining infection status of students.

Finally, vaccination was another preventative measure that was implemented. Figure 3 gives the illustration of a vaccinated student. Vaccination decreases rates of progression for exposed individuals and increases the likelihood of developing minor symptoms that could be classified as asymptomatic \[5\]. Both vaccination and prior COVID-19 infection reduced rates of individuals progressing from the exposed classification to the asymptomatic classification \( (E_A) \). In return, vaccination and prior immunity from previous infection increased the rate of exposed individuals returning to the susceptible or recovered classification \( (E_H) \) \[15\]. Vaccination efficacy could be altered by the user on the interface in order to incorporate different estimates of efficacy based on the type of vaccine (Moderna, Pfizer, etc.) against a specific variant of COVID-19 (Delta, Omicron, etc.).

In order to evaluate the University of Pittsburgh’s policies regarding preventative measures over time, we selected three different Scenarios representing three different time periods throughout the course of the pandemic. The model simulated the university’s approach to combating the pandemic during these time points.

3 Parameters

In this section, we discuss the parameter values used throughout the model and the adjustments made to each variable based on the preventative measures implemented.

![Figure 3: Agent design when masked and vaccinated, respectively.](image-url)
3.3 Infection progression rates

Infection Progression Rates were identified directly from CDC data in Allegheny County and implemented into the model. The rates were based on data and cases studies of virus progression rates, number of symptomatic cases reported, and positivity rates identified by the CDC [4].

3.4 Infection progression rate preventative measures multipliers

Vaccination effectiveness was adjusted and averaged to incorporate the two most utilized vaccines at during the course of model creation (Pfizer-BioNTech and Moderna). These rates were directly applied to infection progression rates to reduce the likelihood of students progressing from the exposed classification to the infected classification [11]. This decision was based on the nature of the classifications used in the model as there was a distinct difference between exposure and infection. Vaccination did not alter the process of exposure as students were still exposed to the same viral load but did impact infection progression rates [5]. In order to retain the simplicity of the model, it was assumed that vaccination was as effective as prior infection in preventing infections [5].

4 Results

In an effort to analyze and evaluate the University of Pittsburgh’s methodology concerning reducing viral spread, we selected three different time-points and adjusted the parameters of the model to best reflect the University of Pittsburgh’s virus combating strategy at these points in time.

Results were collected from 100 simulations with preventative measures implemented, averaged and then compared to the control results from 100 simulations with no preventative measures.

4.1 Scenario One: September 2020

Scenario One reflected the University of Pittsburgh’s approach to combating COVID-19 spread in September of 2020. This time point involved students returning to the Oakland campus for the start of fall semester.

At this point, there was no COVID-19 vaccination, and this was the first instance in which students were allowed back to campus following the complete lockdown in the previous academic year. This point of time reflected the initial approach by the University of Pittsburgh in preventing viral spread and provided baseline efficacy estimates for each of the preventative measures implemented.

Sanitation was a major emphasis of the University of Pittsburgh’s preventative strategy as classrooms were

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Transmission Rate</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_S$</td>
<td>0.00048</td>
<td>Student-to-Student</td>
<td>19</td>
</tr>
<tr>
<td>$R_E$</td>
<td>0.000001</td>
<td>Environmental</td>
<td>2</td>
</tr>
<tr>
<td>$R_{OH}$</td>
<td>0.322</td>
<td>High OOC</td>
<td>4</td>
</tr>
<tr>
<td>$R_{OS}$</td>
<td>0.084</td>
<td>Substantial OOC</td>
<td>4</td>
</tr>
<tr>
<td>$R_O$</td>
<td>0.06</td>
<td>Moderate OOC</td>
<td>4</td>
</tr>
<tr>
<td>$R_{OL}$</td>
<td>0.04</td>
<td>Low OOC</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 1: This table gives the individual values of each of the exposure rate parameters used in the model with their respective labels and sources. OOC represented the outside of the classroom exposure rates.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>0.5</td>
<td>Mask Multiplier</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 2: This table gives the individual value of the mask multiplier used in the model with its respective label and source.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Transition Rate</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_{EH}$</td>
<td>0.885</td>
<td>Exposed to Susc.</td>
<td>4</td>
</tr>
<tr>
<td>$E_A$</td>
<td>0.115</td>
<td>Exposed to Asym.</td>
<td>4</td>
</tr>
<tr>
<td>$A_S$</td>
<td>0.845</td>
<td>Asym. to Sym.</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 3: This table gives the individual values of the infection progression rates used in the model with their respective labels and sources. Susc. represents the susceptible classification, Asym. represents the asymptomatic classification, and Sym. represents the symptomatic classification.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Multiplier</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.58</td>
<td>Vaccination or P.I.</td>
<td>11</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.72</td>
<td>Vaccination and P.I.</td>
<td>11</td>
</tr>
</tbody>
</table>

Table 4: This table gives the individual values of the infection progression rate multipliers, upon the implementation of preventative measures, used in the model with their respective labels and sources. P.I. represents prior infection.
cleaned before and after every lecture. A mask mandate was enforced as well as a mandatory 14-day quarantine period for positive individuals. Additionally, the university introduced the cohort attendance model, in which half the class would alternate attending in-person lecture every class day [8].

Rate of transmission was selected based on the peak 7-day average test positivity rate of Allegheny County during the month of September 2020. 4 percent test positivity was reported on September 1, 2020, translating to a “Low” CDC community transmission level [3].

The Preventative Measures simulations were run with the parameter values in Table 5 implemented. The No Preventative Measures simulations were run with no vaccination, no sanitation, no mask mandate, no quarantine period, and the same rate of transmission.

Figure 4 shows minimal difference between the average number of infected individuals over the simulated semester with and without the implementation of preventative measures with a slightly higher value for the simulations run with the implementation of preventative measures. Figure 5 shows slightly higher peak infections/symptomatic individuals for the preventative measures simulations.

4.2 Scenario Two: April 2021

Scenario Two reproduced the University of Pittsburgh’s preventative approach against COVID-19 in April of 2021. This time point represented the emergence and prominence of the Delta variant in a time when students were still on campus. In comparison to the original variant that was abundant in the beginning of this academic year, the Delta variant was considered to be more contagious and shortly after, in June 2021, became the dominant strain of COVID-19 in the United States. In terms of vaccination, April 2021 was the beginning of the Phase 1B stage, in which education workers were eligible for vaccination. At this point, 30 percent of U.S. adults had received at least one dose of the vaccine and this value was used to represent the overall student population in the model [3].

There was still a large emphasis on sanitation as classrooms continued to be sanitized between class meetings at the University of Pittsburgh. The mandatory mask mandate was still in place but, in accordance with CDC guidelines, the quarantine period for positive individuals was reduced to 10 days. The cohort attendance model was still in place and widely used [8].

Rate of transmission was selected based on the peak 7-day average test positivity rate of Allegheny County during the month of April 2021. 8.4 percent test positivity was reported on April 11, 2021, translating to a “Substantial” CDC community transmission level [3].

Table 5: Model parameter values used for the simulation of Scenario One: September 2020.

<table>
<thead>
<tr>
<th>Preventative Measure</th>
<th>Value</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Vaccinated</td>
<td>0</td>
<td>[8]</td>
</tr>
<tr>
<td>Sanitation</td>
<td>High</td>
<td>[8]</td>
</tr>
<tr>
<td>Mask Mandate</td>
<td>Everyone</td>
<td>[13]</td>
</tr>
<tr>
<td>Quarantine Period</td>
<td>14 days</td>
<td>[13]</td>
</tr>
<tr>
<td>Rate of Transmission</td>
<td>Low</td>
<td>[6]</td>
</tr>
</tbody>
</table>

Figure 4: Average number of infected individuals over the simulated semester across 100 simulations with and without the implementation of the University of Pittsburgh’s preventative measures in September 2020. Number of infected individuals was calculated by every student that had entered the asymptomatic classification due to the nature of the infection progression model.

Figure 5: Peak number of infected and symptomatic individuals over the simulated semester across 100 simulations with and without the implementation of the University of Pittsburgh’s preventative measures in September 2020.
The Preventative Measures simulations were ran with the parameter values in Table 6 implemented. The No Preventative Measures simulations were ran with 30 percent vaccination per CDC data, no sanitation, no mask mandate, no quarantine period, and the same rate of transmission [3].

Figure 6 shows a larger average infection value over time for simulations in which there were no preventative measures implemented compared to those in which they were implemented. Figure 7 shows higher peak infections/symptomatic individuals for the preventive measures simulations.

4.3 Scenario Three: January 2022

Scenario Three simulated the University of Pittsburgh’s preventative approach in January of 2022. This time point involved student returning to campus following winter break for the spring semester. Additionally, January of 2022 marked the emergence of the Omicron variant and the prevalence of the virus across campus. Again, in comparison to the original strain and the Delta variant, the Omicron variant was considered to be more contagious and had become the dominant variant in the United States the month prior. In terms of vaccination, the university implemented a vaccine mandate that resulted in over 95 percent students compared to the 67.6 percent of the eligible U.S. population being vaccinated at this point [8]. For this scenario, we were able to use data from the University of Pittsburgh on vaccinations as opposed to Scenario Two where we had to use national averages. Additionally, vaccine efficacy was heightened with the emergence of booster vaccines [3].

The university’s emphasis on sanitation had been reduced and classrooms were cleaned daily rather than between every lecture. With heightened rates of infection, a mask mandate for every individual was still in place but the quarantine period had been reduced to 5 days per CDC guidelines [3]. The university had returned to a full capacity attendance model [8].

Rate of transmission was selected based on the peak 7-day average test positivity rate of Allegheny County during the month of January 2022. 32.2 percent test positivity was reported on January 4, 2022, translating to a “High” CDC community transmission level [3].

The Preventative Measures simulations were ran with the parameter values in Table 7 implemented. The No Preventative Measures simulations were ran with 67.6 percent vaccination per CDC data, no sanitation, no mask mandate, no quarantine period, and the same rate of transmission [3].

Figure 8 shows a larger average infection value over time for simulations in which there were no preventative measures implemented compared to those in which

![Image of Table 6](https://www.sporajournal.org)

<table>
<thead>
<tr>
<th>Preventative Measure</th>
<th>Value</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Vaccinated</td>
<td>30</td>
<td>[4]</td>
</tr>
<tr>
<td>Sanitation</td>
<td>High</td>
<td>[8]</td>
</tr>
<tr>
<td>Mask Mandate</td>
<td>Everyone</td>
<td>[13]</td>
</tr>
<tr>
<td>Quarantine Period</td>
<td>10 days</td>
<td>[13]</td>
</tr>
<tr>
<td>Rate of Transmission</td>
<td>Substantial</td>
<td>[6]</td>
</tr>
</tbody>
</table>

![Image of Table 7](https://www.sporajournal.org)

<table>
<thead>
<tr>
<th>Preventative Measure</th>
<th>Value</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Vaccinated</td>
<td>95</td>
<td>[8]</td>
</tr>
<tr>
<td>Sanitation</td>
<td>Low</td>
<td>[8]</td>
</tr>
<tr>
<td>Mask Mandate</td>
<td>Everyone</td>
<td>[13]</td>
</tr>
<tr>
<td>Quarantine Period</td>
<td>5 days</td>
<td>[13]</td>
</tr>
<tr>
<td>Rate of Transmission</td>
<td>High</td>
<td>[6]</td>
</tr>
</tbody>
</table>
they were implemented. This difference is greater than that in Scenario Two. Figure 9 shows higher peak infections/symptomatic individuals for the preventive measures simulations, with the difference again being slightly greater than that in Scenario Two.

5 Discussion

The University of Pittsburgh implemented several exposure-based preventative measures, such as mask mandates, sanitation practices, and classroom attendance models, to mitigate the spread of infections within the campus community [8]. However, due to the limited time spent in the classroom by individuals, the majority of infections in the simulation occurred outside of the classroom, where individuals were exposed to the prevailing infection rates in Allegheny County. This discrepancy in time was adjusted for in the model through the use of relatively high outside-of-the-classroom exposure rates when compared to the in-classroom Student-to-Student Transmission Rate.

Although the exposure-based measures had a limited impact on reducing infections in the simulation, they did contribute to a slight decrease in total exposures across all three scenarios considered. This reduction in exposures subsequently led to a decrease in average infections over time in Scenario Two (see Figure 6) and Scenario Three (see Figure 8). Additionally, this reduction of exposures also contributed to a decrease in peak infections and peak symptomatic individuals during the course of the simulation when the university implemented preventative measures in Scenario Two (see Figure 7) and Scenario Three (see Figure 9).

Interestingly, despite the implementation of preventative measures in Scenario One, there was a slight increase in average infections over time compared to the control scenario (see Figure 8). This suggests that the traditional, preliminary measures employed (social distancing, mask mandates, etc.) were not as effective in this particular scenario and for this particular sample size.

However, the introduction of a vaccine mandate by the University of Pittsburgh had a notable impact on reducing average infections over time, particularly in Scenario Three (see Figure 5). Comparing the outcomes of simulations with the vaccination mandate to those based on the United States vaccination rate in January 2022, it is evident that the mandate was a crucial factor in reducing infection rates as most other preventative measures remained in use from the previous two scenarios.

The data from the model strongly supports the notion that the vaccination mandate was the most impactful preventative measure employed by the University of Pittsburgh. By ensuring that all students, staff, and faculty were required to be vaccinated, the university significantly reduced the overall number of infections and prevented a surge in peak infections.

In conclusion, the University of Pittsburgh implemented various preventative measures to mitigate the spread of infections on campus. While some of these measures had limited impact, they contributed to a slight decrease in total exposures and a reduction in average infections and peak symptomatic individuals in certain simulated scenarios. The introduction of a vaccination mandate in the model proved to be the most effective measure, significantly reducing overall infections and preventing a surge in peak infections. The data strongly supports the effectiveness of the vaccination mandate in combating the spread of infections within the campus community.

Author Contributions

Saharsh Talwar conducted the literature review, designed the model, ran simulations, created graphical visualizations, and wrote the manuscript. Anne E. Yust provided feedback and supervision throughout the course of the project.
References


