Mask and Vaccine Effectiveness

Effectiveness of Mask Use and Vaccination in The Prevention of COVID-19 Spread and Infection

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1 Introduction

1.1 Motivation

COVID-19 is an infectious respiratory disease that has greatly affected the world with potential long term impact. In the United States, spread of COVID-19 was met with lock downs and mask mandates throughout the Spring and Summer of 2020. These intervention methods came with mixed emotions of uncertainty across the nation, sparking debates over the importance of mask usage and the necessity of a future vaccine. It is important to note that 25-50% of people with COVID-19 have mild to no symptoms, meaning the presence of an infection is often unknown to carriers, who then spread the disease widely[7]. This study focuses on how to overcome COVID-19 in the United States in the quickest way possible. This study will look at mask usage and the role of masks in mitigating the spread of the virus. At the same time, it will look at vaccine effectiveness, the percentage of the population which will get vaccinated, and how these conditions will affect the total number of COVID-19 cases. All of this will help determine the best route possible for the US community to implement.

1.2 Overview

This research project focuses on the difference using a vaccine or enforcing a mask mandate has on the total number of COVID-19 cases the US is expected to experience.

To evaluate the primary questions, models based on SEIR are used. SEIR is a compartmental model of epidemiology in which people within the population move between the different classes **S**usceptible, **E**xposed, **I**nfectious, and **R**ecovered[9]. The SEIR model was used to model COVID-19 spread because it is assumed that mask use and vaccination will greatly affect the transition from the susceptible class to the exposed class. This is due in part to widespread mask mandates in the US which led to changes in hospitalization rates and in the spread of infection [10]. In the vaccination models, it is assumed that segments of the population will choose not to receive the vaccine. It is likewise assumed a vaccine available at some future date will likely not be 100% effective in the prevention of COVID-19.

The primary goal of the separate models is to consider the different mask and vaccine use scenarios and draw conclusions regarding the most effective way out of the pandemic. This paper intends to argue that vaccine use will provide a much quicker and efficient end to COVID-19, while examining the critical features that mask use provides in the period before and during vaccine administration.

2 Data

Data was collected from within the United States to keep consistent results. This is under the assumption that every country around the globe approached their responses to COVID-19 differently. To determine the proportion of the US population that wears masks, a survey of all 3,131 US counties was consulted. Participants responded to questions regarding their personal mask use with answers ranging from never, rarely, sometimes, frequently, and always [8]. The survey results are shown below:

Category	NEVER	RARELY	SOMETIMES	FREQUENTLY	ALWAYS
Percentage of Respondents	7.99%	8.29%	12.13%	20.77%	50.81%

Table 1: Proportions of Respondents in Each Category

Assuming that no person could always wear a mask when interacting with other people, particularly while at home with family or with close friends, a weighted average is factored into the responses from the New York Times survey. In order to arrive at a value for σ, the proportion of the US population wearing a mask, the results of the survey are weighed with an estimate of the percentage of time when a mask is worn. This is based on estimates and not intrinsic to the study itself. The weights used to obtain σ are displayed in the table below:

Category	NEVER	RARELY	SOMETIMES	FREQUENTLY	ALWAYS
Percentage of Time Wearing Mask	0%	10%	30%	70%	95%

Table 2: Percentage of Interactions With a Mask on for Each Category

With variations in the different weights, a rather stable average around 65-70% is found. Electing to maintain the initial estimates based on the weights above, it is estimated that $\sigma = 0.6728$.

3 Methodology

Under the SEIR model there are 4 main assumptions made:

1. There are no births and deaths in the population.
2. The population is closed, that is, no one from the outside enters the population, and no one leaves the population.
3. Those within the E class are exposed to the virus, but not infectious.
4. All recovered individuals have complete immunity and cannot be infected again.

3.1 Mask Use Model

Based on SEIR, a model is built to examine the effectiveness of mask use across the United States. This model takes into account that the nation primarily wears surgical masks and cloth/home-made masks [4]. This is due in part to the recommendation by the Centers for Disease Control (CDC) that health professionals should prioritize the use of N95 masks for their higher ratings of aerosol filtration. Important assumptions are made going forward with this model, those being: The surgical and cloth masks used by the public aren't 100% effective, only a proportion of the population reliably wears their masks, and lastly, each population of the classes within the model don't wear their masks 100% of the time, even when infectious.

$$\boxed{S} \xrightarrow{(1-\delta)\beta\sigma} \boxed{E} \xrightarrow{\gamma} \boxed{I} \xrightarrow{\alpha} \boxed{R}$$

Within the flowcharts, the susceptible class includes the number of people that can become infected by COVID-19. By epidemiological standards, not everyone will become infectious, some will always escape the disease. Once an individual is exposed to COVID-19, they move to the exposed class via the infection rate β. We have assumed that every individual that enters the exposed class will become infectious with COVID-19 and eventually move to the infectious class by the incubation rate γ. Once an individual is no longer infectious, they move to the removed class via the recovery rate α. The mask use flow chart gives rise to the following system of Ordinary Differential Equations:

$$
\begin{aligned}
\frac{dS}{dt} &= -\beta[(1-\delta)\sigma S + (1-\sigma)S] \cdot [(1-\delta)\sigma_1 I + (1-\sigma_1)I] \\
\frac{dE}{dt} &= \beta[(1-\delta)\sigma S + (1-\sigma)S] \cdot [(1-\delta)\sigma_1 I + (1-\sigma_1)I] - \gamma E \\
\frac{dI}{dt} &= \gamma E - \alpha I \\
\frac{dR}{dt} &= \alpha I \\
N &= S + E + I + R, \text{ where } N \text{ is the total population}
\end{aligned}
$$

In order to best answer the research questions, there was a wide variety of data analyzed. Primarily, there were five parameters evaluated in the mask use model:

σ - Proportion of susceptible class interactions with a mask

σ_1 - Proportion of infectious class interactions with a mask

δ - Mask efficiency or % of time that mask protects from COVID-19

β - Infection rate

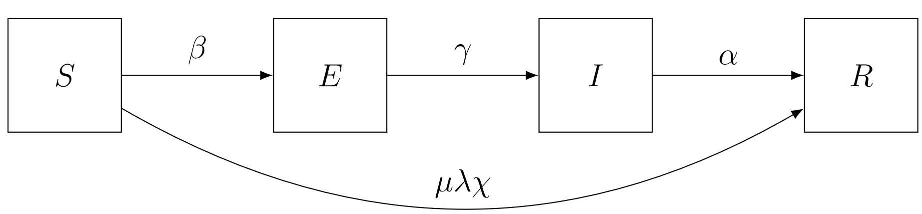
α - Recovery rate

γ - Incubation rate

These parameters, excluding σ, the proportion of people wearing masks, were obtained via research rather than data collection. The mask efficiency, δ, is obtained from viewing the trends that followed after large cities implemented mask mandates. Once mandates were in place, cities would see an average decrease in hospitalization rates and infection by 40%, therefore δ is estimated at 0.4 in the model [10]. The reproduction number for COVID-19 is obtained from the CDC and is estimated at 2.5 [5]. The infection rate, β, is then found by taking the reproduction number 2.5 times the recovery rate α divided by the total population of 330 million US citizens. This estimates β at $7.57e^{-10}$. The recovery rate α is based on the latest data and guidance from the CDC, which indicates that after roughly ten days COVID patients are no longer infectious [2]. The recovery rate α is estimated at 0.1, where time steps are measured in days; that is, recovery takes 10 days to complete. The incubation rate γ is outlined by the CDC, where the average time COVID-19 incubated is five days, therefore γ is estimated at 0.2 [6].

3.2 Vaccination Model

Based on SEIR, a model is built to examine the usefulness of a vaccine in eliminating or reducing the spread of COVID-19 in the US. This model assumes that immunity is permanent. What is important to note here in comparison to the mask use flowchart is the arrow that moves from the susceptible class to the removed class. This arrow is the vaccination process, which circumvents the possibility for an individual to ever become exposed or infected, because they are removed from the system via vaccination. This model assumes that a vaccine will likely not be 100% effective, the entire US population will not receive a vaccine, and lastly not everyone in the US will receive the vaccine immediately or at the same time.



The vaccination flow chart gives rise to the following system of Ordinary Differential Equations

$$
\begin{aligned}
\frac{dS}{dt} &= -\beta SI - \mu\lambda\chi S \\
\frac{dE}{dt} &= \beta SI - \gamma E \\
\frac{dI}{dt} &= \gamma E - \alpha I \\
\frac{dR}{dt} &= \alpha I + \mu\lambda\chi S \\
N &= S + E + I + R, \text{ where } N \text{ is the total population}
\end{aligned}
$$

There were a total of 5 parameters to estimate for the vaccine model:

β - Infection rate

γ - Incubation rate

α - Recovery rate

λ - Vaccine efficiency

μ - Proportion of population receiving vaccine

χ - Rate at which people receive vaccination

In the vaccination model, all parameters that are included within the mask-use model are the same. Otherwise the vaccine efficiency λ was estimated by researching about flu vaccine effectiveness. It is hypothesized that a future vaccine for COVID-19 will likely fall within the same efficacy of a usual flu vaccine. Therefore λ is estimated at 0.4 to 0.6 [3]. Lastly the proportion of the population that will receive the COVID-19 vaccine μ was estimated via a survey that asked the percentage of Americans that planned to get vaccinated. Therefore μ is estimated at 0.5 [1].

4 Analysis

There are multiple different angles of analysis that have been selected for further study regarding mask and vaccine usage. One angle is a hypothetical: what would have happened if the US implemented different mask policies before the COVID-19 outbreak began in force? From a different angle, the future is considered: what is likely to happen with a variety of scenarios now that the US outbreak has reached uncontrollable numbers? Both of these questions are considered in the Mask and Vaccination Models.

4.1 Mask Use Model

What if the US had implemented different policies from the beginning?

There are several interesting and potentially useful conclusions as a result of the mask model studied. There are 3 different codependent parameters which have been selected to evaluate the spread of COVID-19 in the United States (as detailed in the Methodology and Data sections). Here, attention is given to the effects that each salient parameter has on the spread of COVID-19. These parameters are as follows:

δ = Efficiency of masks when being worn
σ = Proportion of the susceptible population wearing masks
σ_1 = Proportion of the infectious population wearing masks

Each of these is analyzed below:

The efficiency of masks is a critical factor in the spread and prevention of COVID-19. This can be best demonstrated through the analysis of the outbreak when testing several different values.

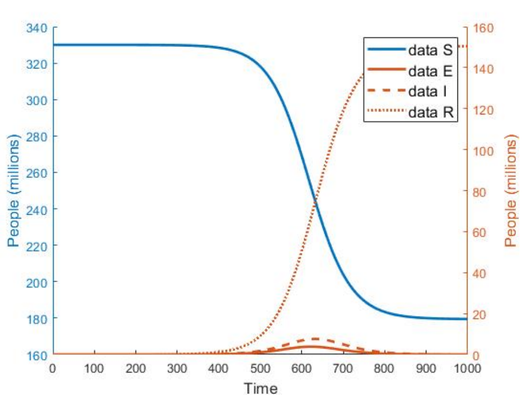


Figure 1: Scenario 1: $\sigma = 0.6728$, $\delta = 0.4$, $\sigma_1 = 0.6728$

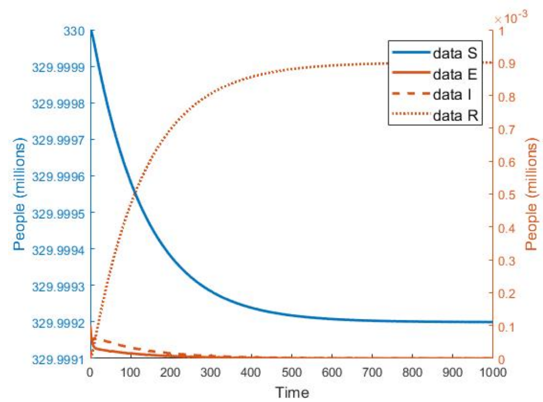


Figure 2: Scenario 2: $\sigma = 0.6728$, $\delta = 0.6$, $\sigma_1 = 0.6728$

Scenario 1 and 2 show the results when $\delta = 0.4$ or 0.6. The best estimate currently for mask efficiency is 0.4 [10]. In the graph for Scenario 1, the number of infectious people are measured in terms of millions. As the graph shows, masks do help initially slow the spread. However, as time goes on, the number of infections build dramatically and peak with around 8 million active U.S. cases around day 650 of the outbreak. As this scenario shows, with current mask observation rates and mask efficiency, a massive outbreak is still expected.

In Scenario 2, however, there are significant differences from Scenario 1. When the value of δ is .6 the outbreak barely gets off the ground, resulting in little to no spread of COVID-19. This is a surprising and important result. This seemingly minor increase in mask efficiency from 40%

to 60% led to a monumental decrease of total infections. This provides an interesting result for consideration and further inquiry.

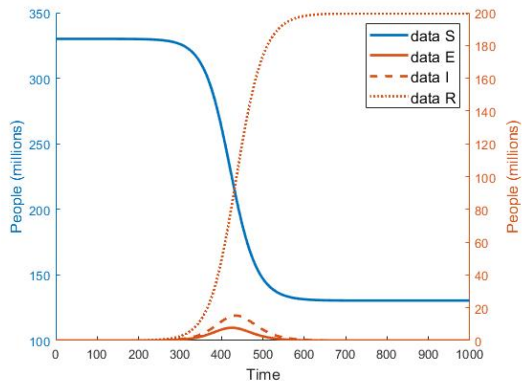


Figure 3: Scenario 3: $\sigma = 0.4$, $\delta = 0.4$, $\sigma_1 = 0.6728$

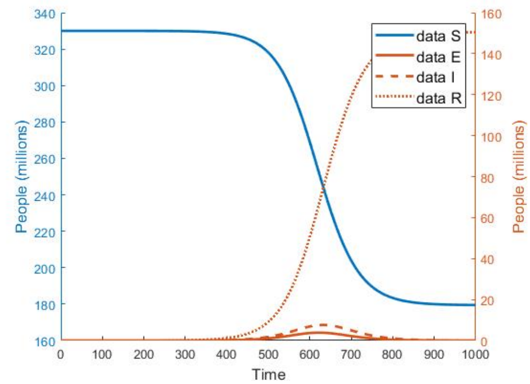


Figure 4: Scenario 4: $\sigma = 0.6728$, $\delta = 0.4$, $\sigma_1 = 0.6728$

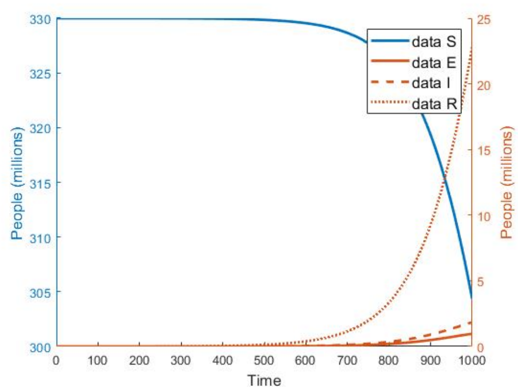


Figure 5: Scenario 5: $\sigma = 0.9$, $\delta = 0.4$, $\sigma_1 = 0.6728$

In Scenarios 3, 4, and 5, differing values of σ (proportions of people in the United States wearing masks) are compared. With values of 40%, 67.28%, and 90% respectively, huge differences can be observed in the number of total infections due to COVID-19. This finding lines up well with current guidance from health officials which state that wearing a mask does in fact significantly reduce the number of COVID-19 cases. With an increase from the current proportion of mask wearers to something more like 90%, the number of COVID-19 cases would drop to less than one-third of the cases expected under Scenario 4.

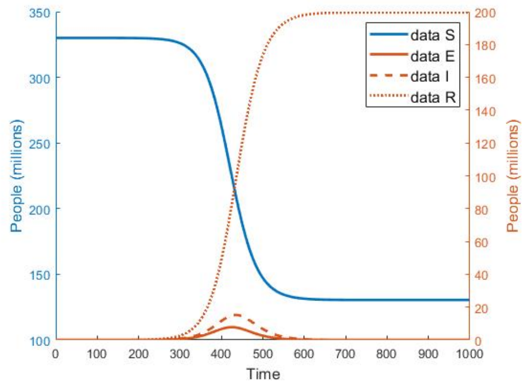


Figure 6: Scenario 6: $\sigma = 0.6728$, $\delta = 0.4$, $\sigma_1 = 0.4$

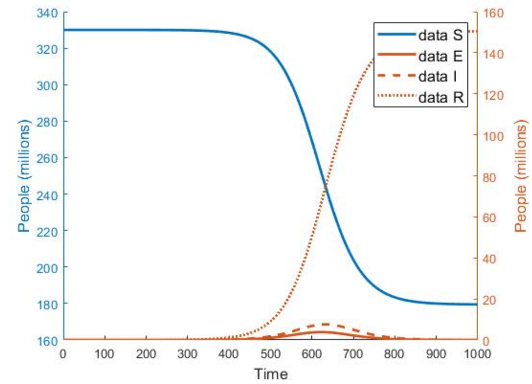


Figure 7: Scenario 7: $\sigma = 0.6728$, $\delta = 0.4$, $\sigma_1 = 0.6728$

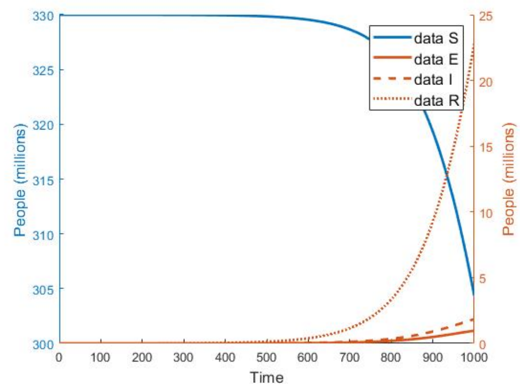


Figure 8: Scenario 8: $\sigma = 0.6728$, $\delta = 0.4$, $\sigma_1 = 0.9$

In Scenarios 6, 7, and 8, it is considered how changing the proportion of infectious people wearing a mask influences the total number of new infections. Unsurprisingly, it is most critical that the infectious class wear masks. The extent to which they do so largely determines the course of the outbreak. Potential values in Scenarios 6, 7 and 8 for σ_1 are considered to be 40%, 67.28% and 90% respectively. As has been thoroughly demonstrated at this point, higher mask wearing proportions decrease the number of COVID-19 cases drastically. Further assumptions could be made that the infectious class interacts with the susceptible class significantly less. This is an area for future inquiry.

What is likely to happen going forward?

While it is interesting to consider what could have been done differently in the early stages of COVID-19, "what-ifs" are useless in determining the best path forward for the country. That is what the remainder of the mask use scenarios are intended to show. The following scenarios differ in one key regard: instead of assessing in terms of a small number of initial cases, they assume the current state of the outbreak in mid-November 2020. Thus, the following scenarios assume approximately 1 million infections at $_0$, among other current conditions.

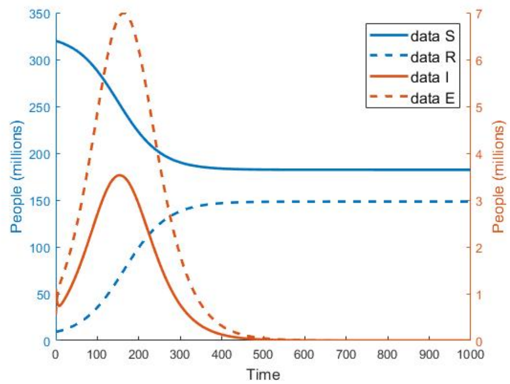


Figure 9: $\delta = 0.4$, $\sigma_1 = 0.6728$, $\sigma = 0.6728$

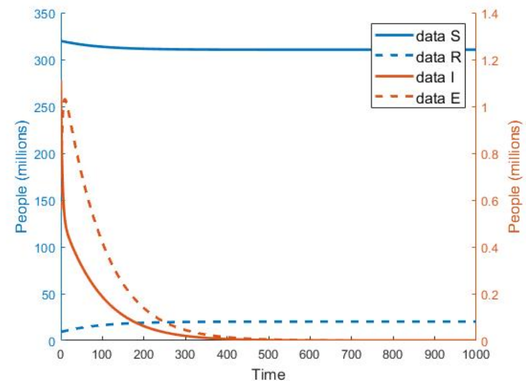


Figure 10: $\delta = 0.6$, $\sigma_1 = 0.6728$, $\sigma = 0.6728$

Figures 9 and 10 continue to highlight an important finding of this paper - more effective masks, even marginally so - prevent millions of cases. Figure 10 shows that a mere 20% increase from current mask effectiveness would be enough to wipe out the spread of COVID-19 within a year. As things currently stand, however, figure 9 displays the best prediction of the future, with cases continuing to mount and somewhere around 100 million Americans infected by the end of the pandemic. This is what is expected to occur if the status quo is maintained.

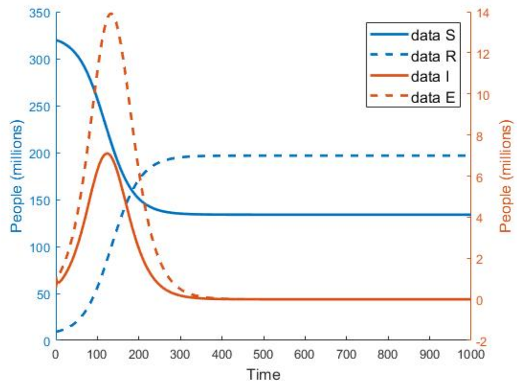


Figure 11: $\sigma = 0.4$, $\delta = 0.4$, $\sigma_1 = 0.6728$

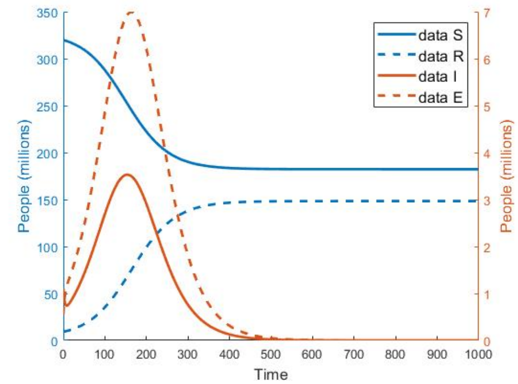


Figure 12: $\sigma = 0.6728$, $\delta = 0.4$, $\sigma_1 = 0.6728$

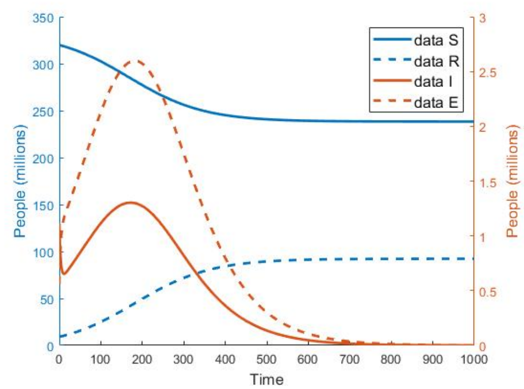


Figure 13: $\sigma = 0.9$, $\delta = 0.4$, $\sigma_1 = 0.6728$

Figures 11-13 demonstrate what can be expected in the US going forward, with varying rates of mask wearing. Figure 11 predicts the most cases as a result of only 40% of the population wearing masks. Figure 13, on the other hand, demonstrates the fewest cases on account of near 90% mask wearing. The difference in total cases between the two scenarios is a staggering 100 million. This continues to highlight the significance of mask wearing.

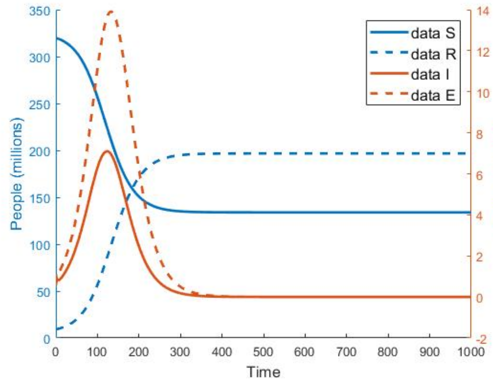


Figure 14: Scenario : $\sigma_1 = 0.4$, $\delta = 0.4$, $\sigma = 0.6728$

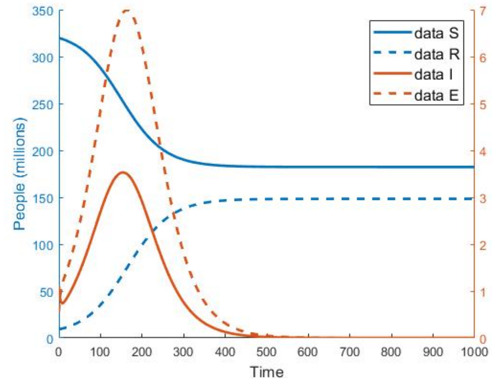


Figure 15: Scenario : $\sigma_1 = 0.6728$, $\delta = 0.4$, $\sigma = 0.6728$

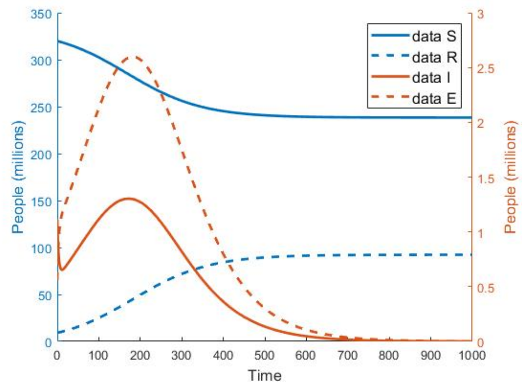


Figure 16: Scenario : $\sigma_1 = 0.9$, $\delta = 0.4$, $\sigma = 0.6728$

Figures 14-16 suggest another related result, which is the utmost importance of mask wearing among the infectious class. Figure 14 demonstrates that even with a majority of the US population wearing a mask, it is all for nought if the infected do not similarly wear masks. In order to see the best results, all infected people should wear masks. Due to the often subtle or nonexistent symptoms of COVID-19, it is best to impose mask wearing regulations on the population at large, in order to cover the subcategory of infected people.

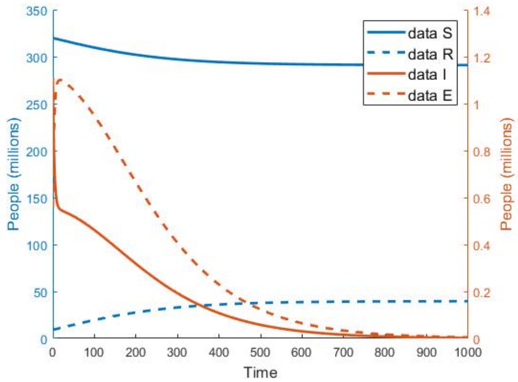


Figure 17: $\sigma_1 = 0.9$, $\delta = 0.4$, $\sigma = 0.9$

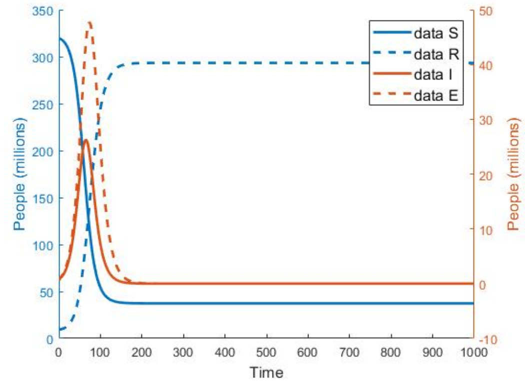


Figure 18: $\sigma_1 = 0$, $\delta = 0$, $\sigma = 0$

Additionally, it is considered, what would happen if the country were to consider a nationwide mask mandate (Figure 17). While it does drag out the length of the outbreak significantly, it can also be seen that the total number of infections reaches only 50 million at the final count, by far the lowest of any model yet observed. This, however, is offset by an outbreak length of approximately 2 more years. While the decrease in cases is certainly commendable, such length of a mandate may not be sustainable. Regardless, it offers a fruitful option for consideration.

Lastly, for perspective, what would happen if all mask wearing were to be abandoned (Figure 18). This scenario results in the shortest outbreak duration, but also an unacceptably high 300 million cases. It is apparent to the authors from these considerations that mask usage is imperative to mitigation of COVID spread.

4.2 Vaccination Model

There were 6 different simulations that were run for the vaccine model of this experiment. 4 of the simulations were used to test out the high end and low end of both vaccine efficiency compared to that of the range of flu vaccine effectiveness, as well as the high and low from polls that give the percentage of people that plan to get a COVID vaccine when one becomes readily available. The high end of the flu vaccine efficiency is 60% with a low of 40%, and the high end of people getting vaccinated is 70% with a low of 50%. The final 2 simulations were used to test to see what happens if a vaccine fails using a vaccine efficiency of 10% and to test what happens with an ultra-effective vaccine (one that is 90% effective or higher). All simulations were run with a starting population of 319,700,000, with an initial amount of infectious people at 1,112,000. The exposed class starts at 560,000 for all simulations and the initial recovered class is at 9,250,000. All simulations were also done with the time for everyone to get vaccinated at 120 days, or about 4 months.

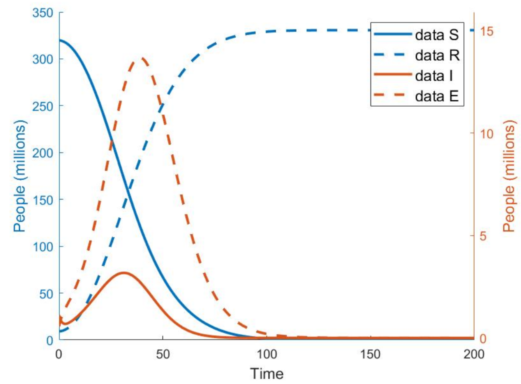


Figure 19: 60% effective vaccine with 50% of the population getting vaccinated

The first simulation was with a vaccine efficiency of 60% with 50% of the population getting the vaccination. When running this simulation, it took until the 31^{st} day for the number of infectious people to peak, with a total number of infectious at 3,174,000. It would take until about the 53^{rd} day until the total number of infectious people drops below 1,000,000 again. In total, it will take over 71 days for the amount of infectious individuals to fall under 100,000.

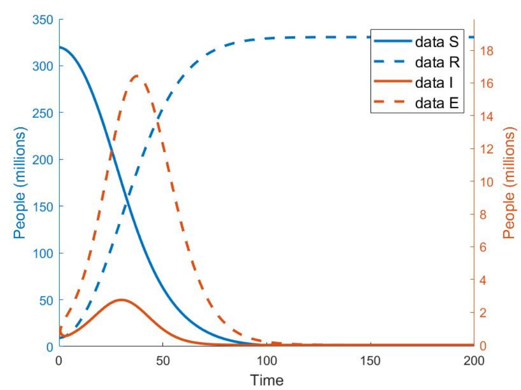


Figure 20: 60% effective vaccine with 70% of the population getting vaccinated

The second simulation was with a vaccine efficiency of 60% and 70% of the population getting vaccinated. On day 30 of this simulation the number of infectious people peaked at around 2,755,000. This number would not fall to under 1,000,000 until the 50^{th} day. Then it only took another 18 days for the infectious class to drop under 100,000.

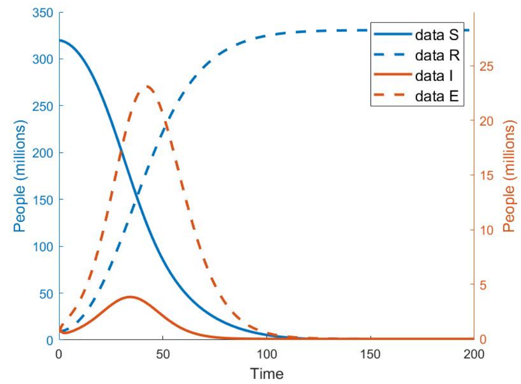


Figure 21: 40% effective vaccine with 70% of the population getting vaccinated

The third simulation had a vaccine efficiency of 40% with 70% of the population getting vaccinated. The total number of infectious individuals would peak on the 34^{th} day with approximately 3,840,000 people being infectious. It would take until about 2 months after the vaccine came out (day 59) for the infectious class to fall under 1,000,000 again. After day 78, the infectious class goes under 100,000.

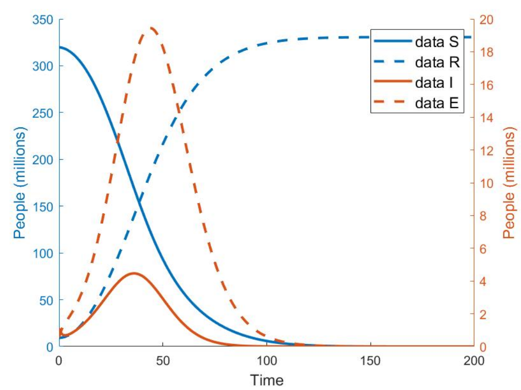


Figure 22: 40% effective vaccine with 50% of the population getting vaccinated

The next simulation used a vaccine efficiency of 40% with 50% of the population getting the vaccine. The infectious class peak occurs on the 36^{th} day, with a high of 4,465,000 infectious people. It would be another 27 days for the number of infected individuals to drop under 1,000,000 and another 19 days after that for the infectious population to fall under 100,000.

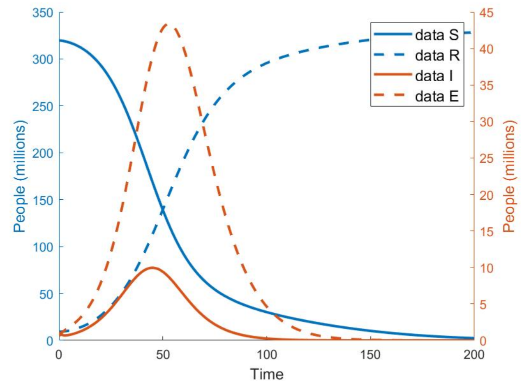


Figure 23: 10% effective vaccine with 50% of the population getting vaccinated

The fifth simulation looked at what would happen if the vaccine fails. This simulation used a vaccine efficiency of 10% with only 50% of the population getting vaccinated. The peak of this simulation would not occur until the 45^{th} day with a total of 9,950,000 people being infectious. The number of infectious people would not fall below 1,000,000 until day 84. It wouldn't be until day 110 for this number to fall under 100,000.

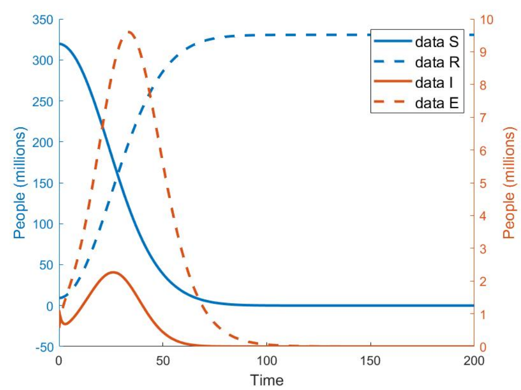


Figure 24: 90% effective vaccine with 50% of the population getting vaccinated

The final simulation examined what happens if a vaccine is 90% effective with 50% of the population getting vaccinated. This peak occurred on the 25^{th} day, with a total of 2,265,000 people being infectious. On the 43^{rd} day of this test, the number of infectious people dropped under 1,000,000 and 17 days later this number would drop to below 100,000 people.

5 Results

According to the different models shown, there are two very different outcomes when comparing mask use to a vaccination. According to the analysis, the more people wearing masks helps to decrease the speed of COVID-19 spread, but as time went on, the number of infected people would still increase until it reaches a peak. According to the mask-use graph, the infected curve was flattening with more people wearing the mask, and the infected peak also went down later. This flattening of the curve will help relieve some of the stress off of hospitals, as they will have more time to learn how to treat COVID-19 and will have fewer people in the hospital at once.

In the vaccination model, the number of infected people decreases a lot more compared to that of the mask-use model. It also takes much less time for the pandemic to end, so getting the vaccine can provide a more direct and durable solution to prevent the pandemic. Not only does the vaccination lessen the peak, but it also prevents any outbreak from occurring in the future as well. Based on the vaccination simulations and data, vaccination is a long-term solution that will bring the virus to the end within a short time.

The data and graphs from MatLab show that with the higher efficiency of mask use, the number of infected people will decrease, and the speed of infection also can decrease. In the vaccination model, it was shown that the vaccine efficiency has greater impact on the pandemic than the amount of people getting vaccinated does. In general, mask-use and vaccination both can prevent COVID-19 spread, though mask-use is a temporary solution to the pandemic while waiting for the vaccine to come out.

6 Discussion

This project has answered many questions, but at the same time created some new questions to be addressed. As the topic at hand was studied more intensively, it became readily apparent that to best answer the questions, inter-disciplinary expertise was required. In the process of completing the project, experts and studies from the fields of biology, virology, mathematics, statistics and more were consulted.

Going forward, it is important to consider further questions. One of the questions that is most important but was beyond the scope of this project is a combined model incorporating both mask usage and vaccination use. With this combination, transmission of COVID-19 could presumably be significantly less. This type of model could be plausibly more representative of what will actually occur going forward.

Another question that is beyond the scope of this paper but profoundly impacts the spread of COVID-19 and the timing that the country can return to normal is herd immunity. If herd immunity begins to take effect between 50% and 70% of the population being in the R class, it could take a drastically different amount of time to reach it as these two numbers account for significantly different lengths of the COVID-19 outbreak.

One final consideration for the future is the true number of R_0, the basic reproduction number. Although this paper makes usage of CDC estimates for R_0 at around 2.5, other studies have indicated that this estimate may be conservative, with R_0 more plausibly around 5-6 without mitigating interference via government policies and social challenges.

In sum, there is a wide variety of information to take into consideration in the assessment of these research questions, and more time and evaluation is required to draw firmer conclusions. Nonetheless, certain conclusions emerge as a result of the methods employed in this paper which offer valuable information for the containment of COVID-19 spread.

7 Appendix

PLACE FINISHED MATLAB CODES HERE

```
MASK USE MODEL:
function MaskModel_SEIR
clear all
close all
clc

%% Input parameters

% input the data in the table
% check that the sizes of the three vectors are the same
data_t = [];
data_S = [];
data_E = [];
data_I = [];
data_R = [];

%%
S0 = 319.7; % initial value of S
I0 = 1.112; % initial value of I (100 people)
T0 = 0; % initial time t = 0
T = 1000; % maximum time for the simulation
E0 = 0.560; %exposed at t = 0
R0 = 9.25;

% input the transmission rate and the recovery rate from your
   calculation
Reproduction_number = 2.5;
delta = 0.4;
sigma = 0.6728;
sigma1 = 0.6728;
gamma = .2;
alpha = .1;
beta = Reproduction_number*alpha/(S0+I0+E0+R0);
```

```
% The estimate of R0 can follow Glenn's talk
% R0 = beta*(S0+I0)/nu
% Reproduction_number = beta*(S0+I0)/alpha;

%% The code below this line can be kept unchanged.

    % define the SIR model
    % t: time
    % y: a vector for the dependent variables S(t) and I(t)
    % dy: the right hand side of the SIR model
    function dy = SEIR2(t,y,beta,alpha,sigma,sigma1,gamma,delta)
        dy = zeros(4,1); % store the derivatives
        dy(1) = -beta*( (1-delta)*sigma*y(1)+(1-sigma)*y(1) )*( (1-
           delta)*sigma1*y(3)+ ((1-sigma1)*y(3))); % S term
        dy(2) = beta*( (1-delta)*sigma*y(1)+(1-sigma)*y(1) )*( (1-
           delta)*sigma1*y(3)+ ((1-sigma1)*y(3)) - gamma*y(2); % I
           term
        dy(3) = gamma*y(2) - alpha*y(3);
        dy(4) = alpha*y(3);
    end

% use Matlab built-in function ode45 to calculate the solutions
% The first input term "@(t,y)(SIR(t,y,beta,alpha))" give the name
   of the
% function where the ODE stores.
% The second input term "[T0 T]" gives the initial time and end time
   .
% The third input term "[S0; I0]" give the initial values.
[sim_t, sim_y] = ode45(@(t,y)(SEIR2(t,y,beta,alpha,sigma,sigma1,
   gamma,delta)),[T0 T],[S0; I0; E0; R0]);
% The results stores the time points in "sim_t" and
% the values of S(t) and I(t) in the 1st and 2nd columns of "sim_y".
sim_S = sim_y(:,1);
sim_E = sim_y(:,2);
sim_I = sim_y(:,3);
sim_R = sim_y(:,4);
```

```
total_INFECTED_in_millions = S0 - sim_S(377,1)

% plot the data and the simulation results
figure; hold on;
% first plot data as a scatterplot
plot(data_t, data_S,'o');
plot(data_t, data_E, 'o')
plot(data_t, data_I,'o');
plot(data_t, data_R,'o')
% then plot the simulation results
yyaxis left
plot(sim_t, sim_S, 'linewidth',2);
plot(sim_t, sim_R, 'linewidth',2);
ylabel('People (millions)', 'FontSize',12)
xlabel('Time','FontSize',12);
yyaxis right
plot(sim_t, sim_E, 'linewidth',2);
plot(sim_t, sim_I, 'linewidth',2);
ylabel('People (millions)','FontSize',12);
legend({'data S','data R','data I','data E','simulation S(t)','
   simulation I(t)','simulationE(t)','simulationR(t)'},'FontSize'
   ,12)
end

VACCINE MODEL:
function Vaccine_SEIR
clear all
close all
clc

%% Input parameters

% input the data in the table
% check that the sizes of the three vectors are the same
data_t = [];
data_S = [];
```

```
data_E = [];
data_I = [];
data_R = [];

%%
S0 = 319.7; % initial value of S
I0 = 1.112; % initial value of I (100 people)
T0 = 0; % initial time t = 0
T = 200; % maximum time for the simulation
E0 = 0.560; %exposed at t = 0
R0 = 9.25;
x = 1/120; %Rate of vaccination
t = [0:1:1000]; %time variable

% input the transmission rate and the recovery rate from your
   calculation
Reproduction_number = 2.5;
m = .10% effectiveness of vaccine
lamda = .50%percentage vaccinated
gamma = .2;
alpha = .1;
beta = Reproduction_number*alpha/(S0+I0+E0+R0);

% The estimate of R0 can follow Glenn's talk
% R0 = beta*(S0+I0)/nu
% Reproduction_number = beta*(S0+I0)/alpha;

%% The code below this line can be kept unchanged.

    % define the SIR model
    % t: time
    % y: a vector for the dependent variables S(t) and I(t)
    % dy: the right hand side of the SIR model
    function dy = SEIR2(t,y,beta,alpha,m,lamda,gamma)
        dy = zeros(4,1); % store the derivatives
        dy(1) = -beta*y(1)*y(3)-lamda*m*y(1)*x;
        dy(2) = beta*y(1)*y(3) - gamma*y(2);
```

```
        dy(3) = gamma*y(2) - alpha*y(3);
        dy(4) = alpha*y(3) + lamda*m*y(1)*x;
    end

% use Matlab built-in function ode45 to calculate the solutions
% The first input term "@(t,y)(SIR(t,y,beta,alpha))" give the name
   of the
% function where the ODE stores.
% The second input term "[T0 T]" gives the initial time and end time
   .
% The third input term "[S0; I0]" give the initial values.
[sim_t, sim_y] = ode45(@(t,y)(SEIR2(t,y,beta,alpha,m,gamma,lamda)),[
   T0 T],[S0; I0; E0; R0]);
% The results stores the time points in "sim_t" and
% the values of S(t) and I(t) in the 1st and 2nd columns of "sim_y".
sim_S = sim_y(:,1);
sim_E = sim_y(:,2);
sim_I = sim_y(:,3);
sim_R = sim_y(:,4);

% plot the data and the simulation results
figure; hold on;
% first plot data as a scatterplot
plot(data_t, data_S,'o');
plot(data_t, data_E, 'o')
plot(data_t, data_I,'o');
plot(data_t, data_R,'o')
% then plot the simulation results
yyaxis left
plot(sim_t, sim_S, 'linewidth',2);
plot(sim_t, sim_R, 'linewidth',2);
%title('Highway Data')
%xlabel('States')
ylabel('People (millions)', 'FontSize',12)
xlabel('Time','FontSize',12);
yyaxis right
plot(sim_t, sim_E, 'linewidth',2);
```

```
plot(sim_t, sim_I, 'linewidth',2);
ylabel('People (millions)','FontSize',12);
legend({'data S','data R','data I','data E','simulation S(t)','
   simulation I(t)','simulationE(t)','simulationR(t)'},'FontSize'
   ,12)
end
```

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