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DATA 512
Autumn 2022

COVID-19 Population Dynamics in King County, WA: A look into Vaccination and Mask Use Mitigation Strategies

Introduction

The COVID-19 pandemic has made an impact across the world. This project investigates the dynamics of COVID-19 in King County, WA with an initial focus on mask usage and an extension to vaccination efforts. By using a combination of epidemiological modeling and data science, we look at how different intervention strategies can help control the spread of COVID-19. This analysis can provide implications in policy prevention strategies for the community and insight for public health officials to make informed decisions in their response to COVID as well as influence the behaviors or decisions individuals make for the benefit of their health.

Background/Related Work

SIR compartment models have been fairly common in epidemiological research and studies. Similar models are done in various studies such as *Modeling Strategies for controlling SARS outbreaks.* Furthermore, a SEIR model for COVID-19 can be found in *Compartmental Models of the COVID-19 Pandemic for Physicians and Physician-Scientists*, without the application of a vaccination compartment or a proportion indicating mask usage. The findings from both papers determine the impact of COVID-19 in relation to their respective models and population dynamics. This approach is appropriate to fully determine which mitigation strategy will be the most effective as well as the most feasible. This type of modeling also has not been done specifically for King County, WA. These dynamics can help us determine what research questions and hypotheses we can analyze by looking at the predicted value of a specific compartment at a specified point in time.

With this model, we hope to answer the following questions:

1. How does the introduction of vaccines affect behaviors of COVID-19 disease dynamics in King County, WA during the COVID-19 epidemic from February 2020 to October 2021?
2. Does adding a masking proportion rate lower the rate at which individuals become infected?

We hypothesize that:

1. The introduction of a vaccine with vaccination of at least 30% of the population, initially, will decrease the disease death rate by at least 2%.

2. Adding a masking proportion of at least 40% of the population will slow the spread of the disease by about 10 days.

Methodology

The first analysis investigates how mask usage affected the pandemic in King County, WA in the months of February 2020 to the end of October 2021. In this analysis, we visualized and analyzed the change in COVID-19 over time. We consider different change points within the timeframe to see if there are differences in behavior in segments in time. In choosing this method, it will be helpful to pinpoint specific corresponding events in King County that could have led to a higher or lower rate of the spread of COVID-19. This method is easy to visualize and tells a human story related to the data shown.

We extend this more to further analyze the implication of "change" and "rate of changes" by looking at how the cases play a role in population dynamics. This analysis was chosen as it can definitely predict the movement of an individual through the several "stages" of COVID-19 and their chances of surviving the disease as well as provide a larger image of how the community dynamics look for public officials. Ethical concerns were taken into consideration when coming up with this model too. First off, the data mainly consists of a set of parameters where the computations to create them are fairly transparent. These parameters are used in a set of ordinary differential equations that can be easily solved with packages on Python or R and is accessible to everyone. Additionally, this model is very easy to interpret and highly flexible. Thus, it can adapt to other scenarios that others may want to analyze.

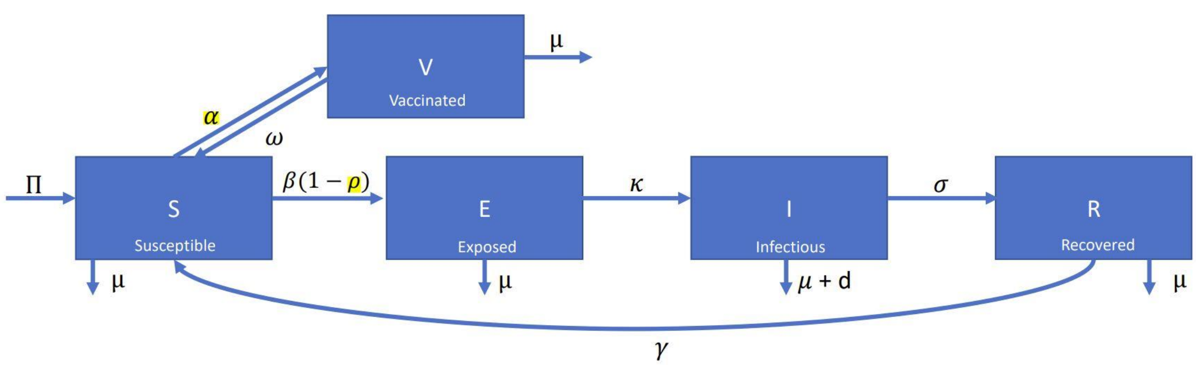

Figure 1: Susceptible, Vaccinated, Exposed, Infectious, Recovered (SVEIR) compartment model

$$\frac{dS}{dt} = \Pi + \omega V + \gamma R - (\mu + \alpha)S \; - \beta(1-\rho)SI$$

$$\frac{dV}{dt} = \alpha S \; - (\omega + \mu)V$$

$$\frac{dE}{dt} = \beta(1-\rho)SI \; - \kappa E \; - \mu E$$

$$\frac{dI}{dt} = \kappa E \; - (\sigma + d + \mu)I$$

$$\frac{dR}{dt} = \sigma I \; - (\gamma + \mu)R$$

Figure 2: Set of Differential Equations

Symbol	**Definition**	**Value**
Π	Birth rate	66
β	COVID-19 infectious rate	.0000005785
κ	Incubation rate	1/4
σ	Recovery rate	1/14
γ	Loss of immunity	1/90
d	Disease Induced death	0.0321
α	Vaccination rate	0.00236
ω	Wanning rate of vaccine	1/120
μ	Natural death rate	0.0000165
ρ	Mask usage proportion	0.724

Table 1: Parameter Values and Definitions (How to derive parameter values is shown in the Appendix)

Figure 1 shows the compartment model derived for this analysis. In this compartment model, we take into account two mitigation strategies: vaccination and masking. This rate and proportion are represented by α and ρ respectively. Figure 2 represents the set of differential equations corresponding to each of the compartments, which can be constructed by taking the net inflow and subtracting the net outflow. Utilizing compartment S as an example, one can interpret the model as follows. Individuals enter the compartment Susceptible (S) by the birth rate Π, the non lasting effect of the vaccine (ω from the Vaccinated compartment), and from being not immune to COVID-19 after receiving it (γ from the Recovered compartment). Individuals leave the compartment by becoming vaccinated at the rate of α, by being exposed to an infected individual β, or by natural death μ.

Findings

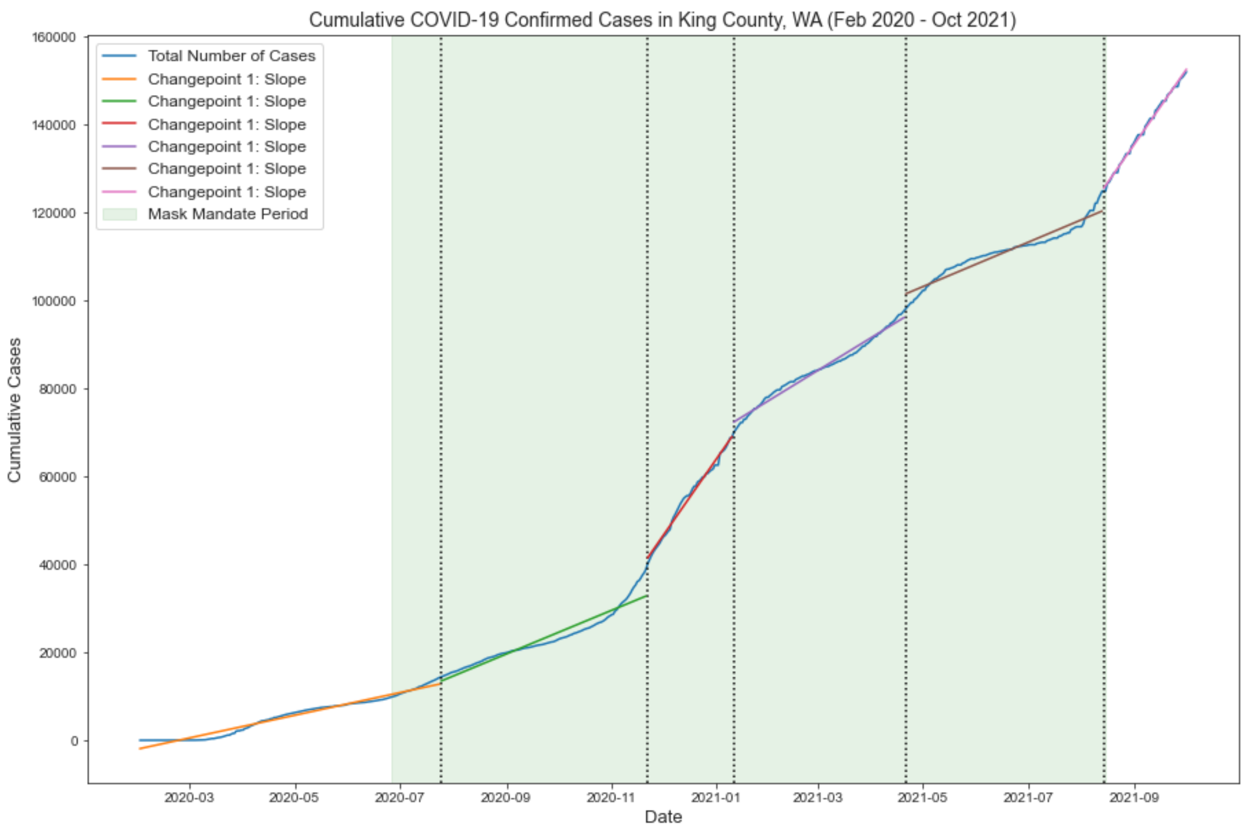

Figure 3: Cumulative COVID-19 Confirmed Cases in King County WA with changepoints and slopes within each changepoint

Figure 3 shows the number of changepoints with February 2020 and October 2021 and their respective slopes. The slopes can interpret the rate at which COVID-19 cases grew over a specific amount of time. Before the masking mandate, there was a slight increase in cases, however, this represents the start of COVID-19 in the area. In implementing masking mandates, we don't see results right from the start due to delays in testing. However, the masking mandate does seem to lower the rate of growth (a less steep slope) which is shown in the second, fourth, and fifth changepoint. There is a high increase in cases around the end of 2020 and the beginning of 2021. This can be due to a potential backlog of testing that was received before the holidays and tested all within the span of a week.

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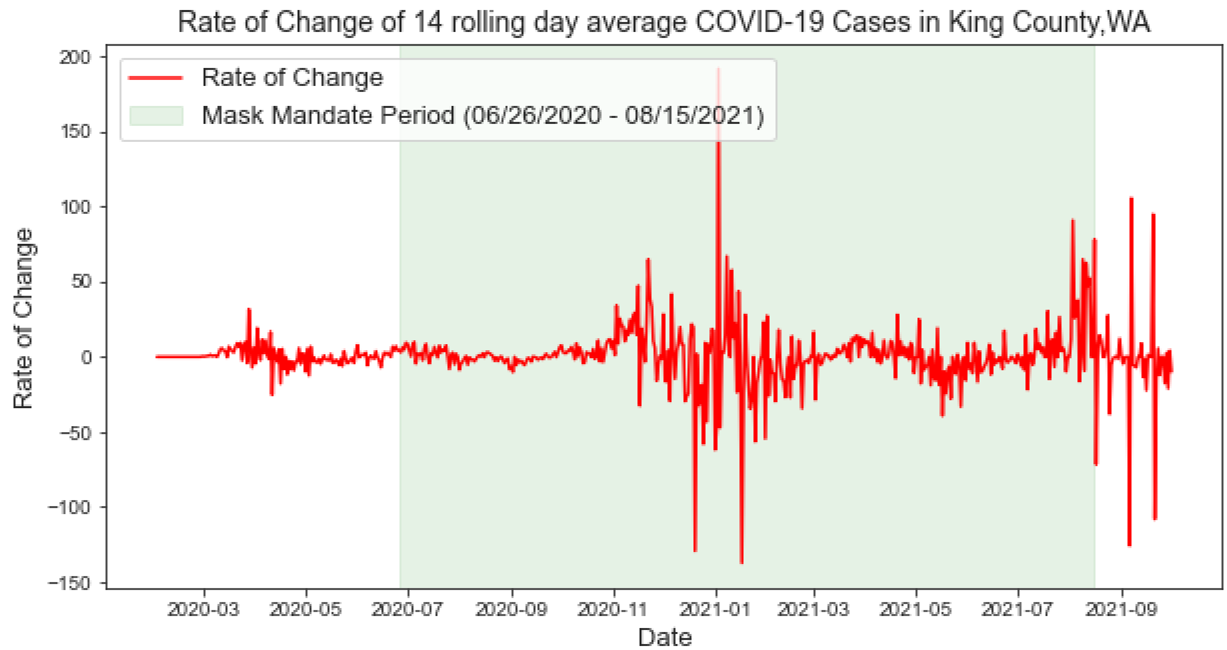

Figure 4: 14 Rolling Day Average of COVID-19 cases

In Figure 4, we see the largest jump that occurs at the beginning of 2021. However, before this giant spike, we see quite small rates of change, which can indicate consistent testing procedures or less variance in reported cases daily. After we see this jump, we have a small pattern in decreasing averages. However, in both graphs, it looks as if masking protocols alone did not help COVID-19 cases.

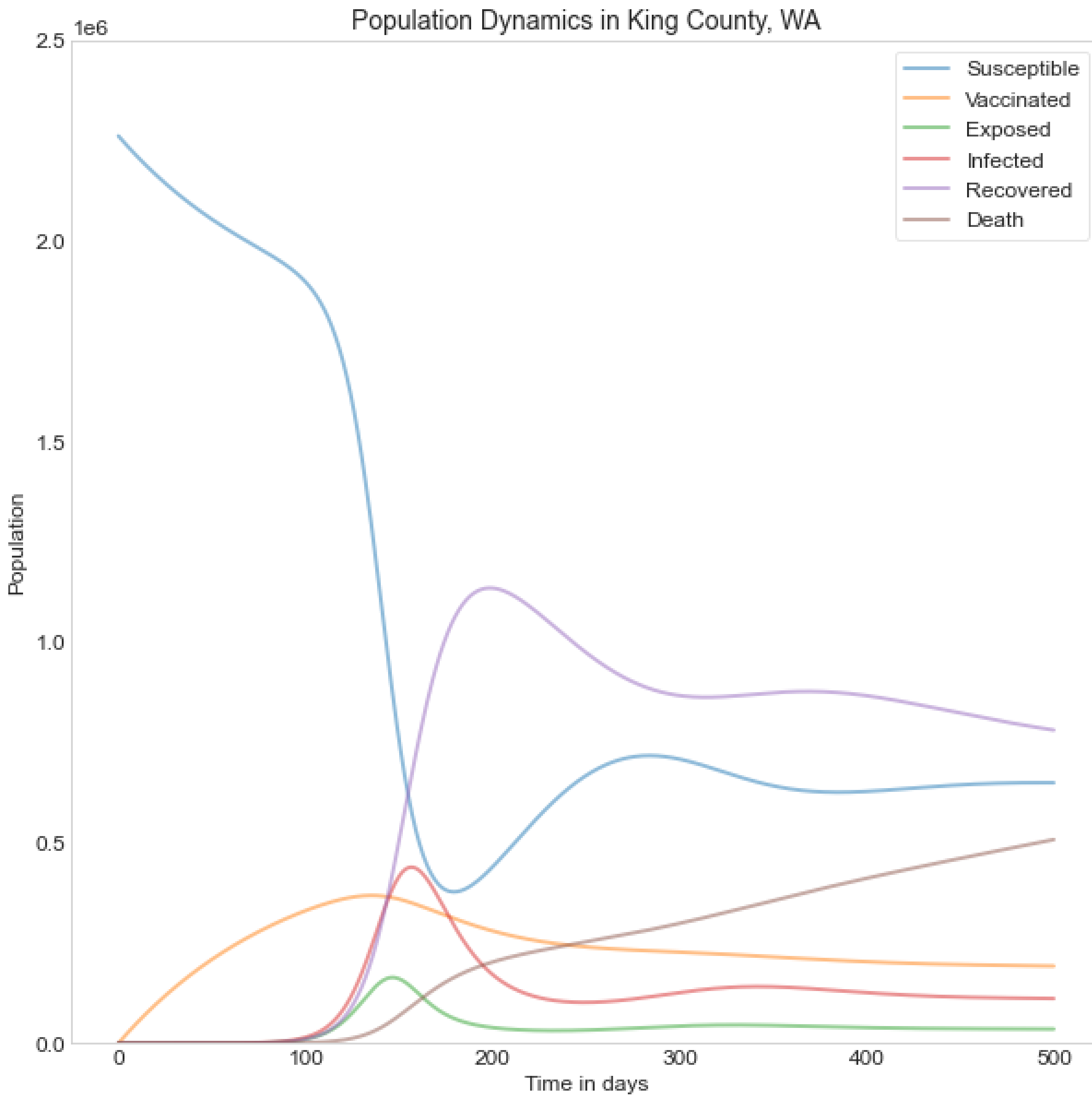

Figure 5: SVEIR Population Dynamics within 500 Days

Figure 5 represents the behavior of each compartment within the space of 500 days. It shows that as the susceptible population decreases, all other compartments increase. The vaccination compartment seems to reach some stability as at a specific point there are not too many more individuals that need to be vaccinated. This can be the same for the other compartments as well. Most of the changes in interactions seem to occur between day 100 and day 200.

In looking into our first research question, we plot the dynamics of the death compartment with different vaccination rates, the original derived from the daily vaccination data from King County, WA, and a theoretical rate in which we vaccinate 30% of the population initially.

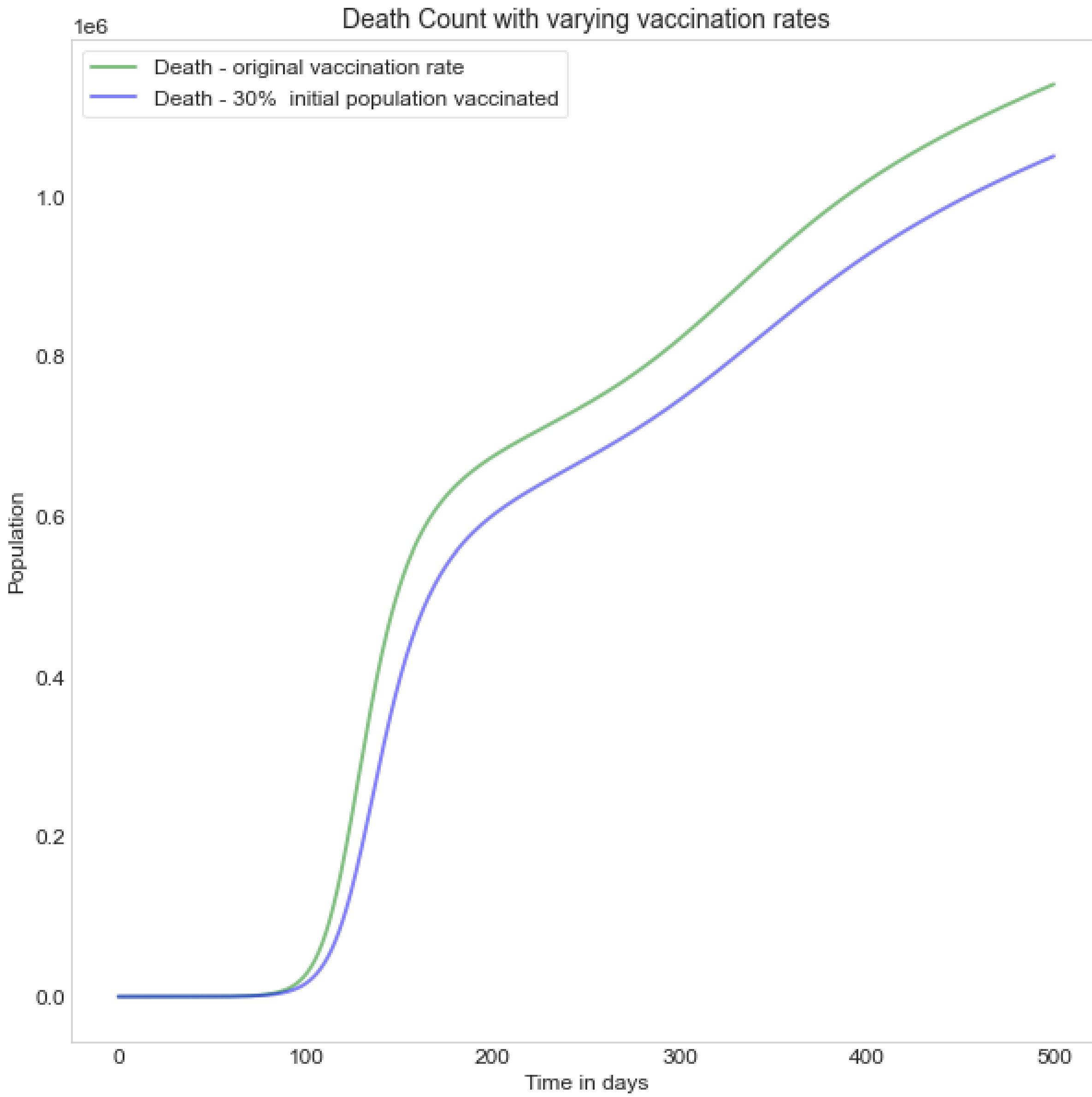

Figure 6: Death count with $\alpha = 0.00236$*, represented in green versus death count with* $\alpha = 0.00366$*, represented in blue*

From Figure 6, we can see that number of deaths slow down in time and the max value of deaths decreases between the different vaccination levels. The max number of deaths if the vaccination rate included an initial 30% of the population is at 1050205, whereas the max number of deaths with the original vaccination rate is at 1140060. The number of deaths definitely decreased by more than 2% and is closer to a 9%-10% decrease. Thus, we can see our first hypothesis being proven true.

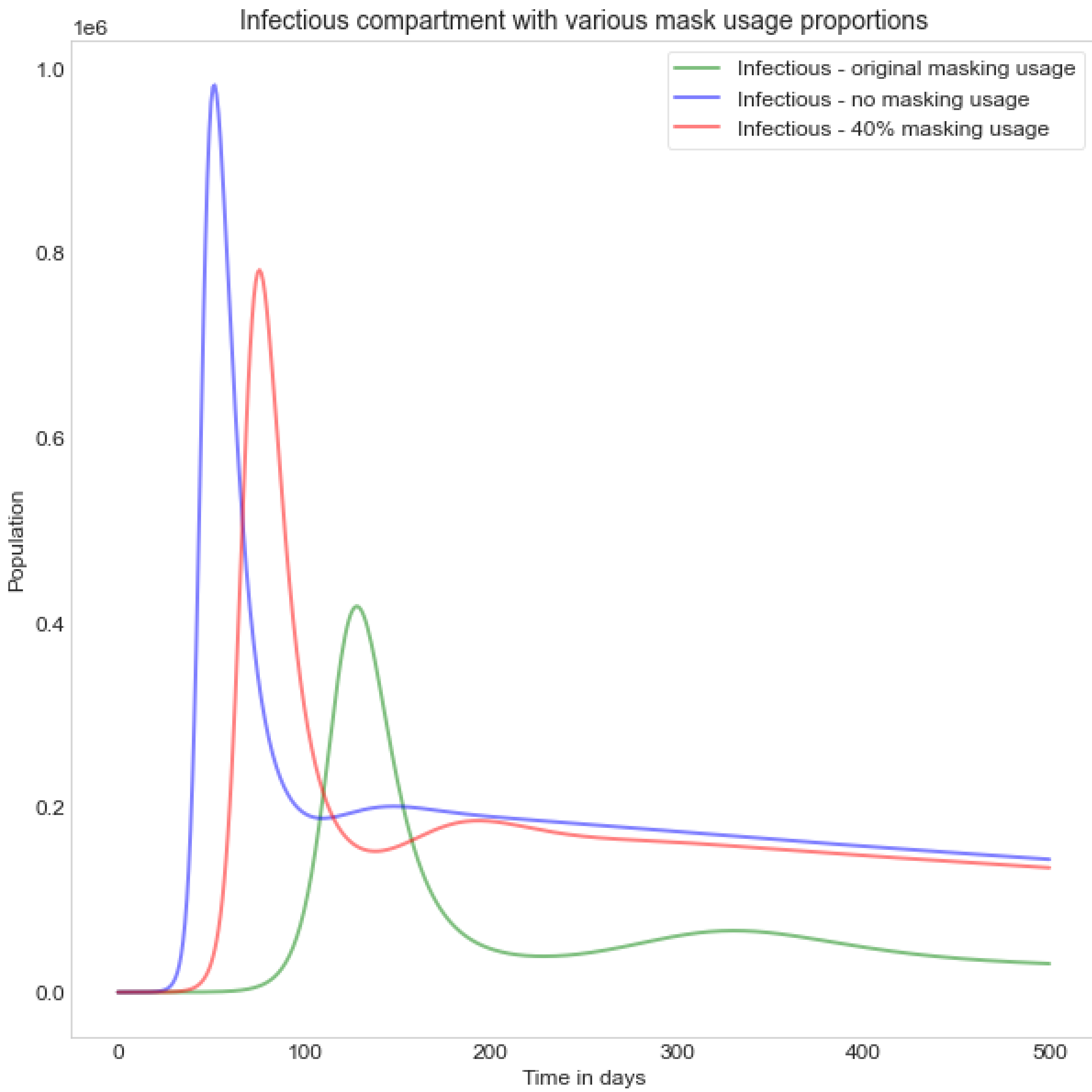

Figure 7: Infectious compartment with no mask usage (blue), 40% mask usage (red), and the NY Times given mask usage for King County, WA (green)

To answer our second research question, we analyze the infectious compartment with different mask usage. We see the differences between mask usage with 0% mask usage, 40% mask usage, and about 70%. In Figure 7, the difference in time between the max number of individuals in the infected compartment is apparent and the disease definitely slows down as the masking proportion increases. As the disease slows down for more than 10 days between 0% mask usage and 40% mask usage, we can prove our second hypothesis to be true as well.

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Discussion/Implications

Models like these or related to this can estimate the outcomes of COVID-19-like illnesses. Previous studies that analyzed how outbreaks of SARS played out could easily be interpreted into looking at how COVID-19 would behave due to the similarities of the disease behaviors. The results from this analysis show how vaccination and mask usage specifically, as well as, the various levels of vaccination and mask usage affect the transmission of COVID-19 within the local community. Compared to other mitigation strategies such as quarantine or isolation, vaccination and mask usage allow individuals to leave their homes and continue with their daily lives and activities. Future work can include an extension of the model to include quarantine and isolation to see how the dynamics play with a combination of all 4 mitigation strategies or to look at each component separately. Other work can be used to determine COVID-19's basic reproduction number, which is a value that can determine in which a disease will spread or die out, or to see what sort of herd immunity will be reached. Furthermore, game theory can be applied to determine what is the most optimal strategy relative to the cost of each mitigation strategy.

A human-centered approach was used throughout this project to ensure transparency and interpretability of the model. This approach combines epidemiological research as well as data science which can broaden the impact of the results. The outputs and plots are simple to understand and can help inform everyone within the community that is being affected of possible outcomes during the course of the disease. In the project itself, the set-up and computation of parameters were thoughtfully considered to ensure the most accurate representation of the transmission of the disease within King County, WA. It was important to consider human-centered design approaches for King County as one of its biggest metropolitan areas is Seattle, which is quite a densely populated area. The chances of obtaining COVID-19 are increased due to the nature of these areas.

Limitations

This analysis consists of multiple assumptions. First, we assume that the entire population is susceptible and equally susceptible. We know that this is not entirely true as COVID-19 behaves differently with different age groups and those with underlying health conditions. We also assume that this is a closed system and that no other factors play a role in these dynamics; we certainly know that restriction level and good hygiene practices played an important role in the prevention of COVID-19 at the individual level. This further explains why the number of individuals dying is fairly high, as nothing else is taken into consideration other than the compartments and factors specified. In this modeling scenario, we simply only look at the interactions of specific populations and not any other prevention strategy, such as quarantine or education level.

In Figures 6 and 7, we look at how the dynamics of specific compartments change with varying vaccination or mask usage rates. However, in each case, we still consider the other mitigation strategy to play a role. A more efficient analysis could consist of removing the other mitigation strategy entirely first, analyzing the effect of no masking, some masking, or mostly masking, and then incorporating vaccination to further see the implications of each mitigation strategy and their possible effect in the reduction of COVID-19.

Furthermore, when cleaning the data, the John Hopkins COVID-19 case data consisted of a few discrepancies. Some dates had to be linearly interpolated to get their case count. Another potential flaw may be that the John Hopkins data source for cases differs from what the King County government data source gives in which we obtain vaccination data and disease-included death data. Another thing to note is that King County also states that there may be chances of underreporting the testing data due to an issue with several hospitals' database systems.

Conclusion

In conclusion, analyzing the impact of vaccination and mask usage is fairly simple with the SVEIR compartment model. We constructed a compartment model and specified specific parameters that move an individual from one compartment to the other at a specific rate. These parameters were computed with real data relating to COVID-19 in King County, WA. With this analysis, we saw the dynamics of each compartment with respect to time.

The questions asked were related to the impact of an initial 30% of the population vaccination rate and a 40% mask usage proportion. findings suggest that with a higher mask usage proportion of the population, the disease slows down and the max number of infected individuals decreases as well. In vaccinating a higher proportion of individuals earlier in the epidemic, we see almost a 9%-10% decrease in the number of maximum deaths within a 500-day time frame.

Altogether, this analysis and study estimate the outcome of COVID-19 with these specific mitigation strategies. This study can provide valuable insights into the effectiveness of these measures to control the spread of the disease. This could help determine public health policy and decision-making on the best possible way to protect the population from COVID-19. By better understanding the dynamics of the virus and how it responds to different interventions, we can work at reducing the impact and protecting the health of our local community.

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2. A. B. Gumel, S. Ruan, T. Day, J. Watmough, F. Brauer, P. van den Driessche, D. Gabrielson, C. Bowman, M. E. Alexander, S. Ardal, J. Wu, and B. M. Sahai, “Modelling strategies for controlling SARS outbreaks,” *Proceedings of the Royal Society of London. Series B: Biological Sciences*, vol. 271, no. 1554, pp. 2223–2232, 2004.
3. F. Brauer, “Compartmental models in epidemiology,” *Mathematical Epidemiology*, pp. 19–79, 2008.

Data Sources

1. King County COVID-19 publicly available data, https://kingcounty.gov/depts/health/covid-19/data/aboutdata.aspx

2. Washington Department of Health, https://doh.wa.gov/data-and-statistical-reports/washington-trackingnetwork-wtn

3. Centers for Disease Control and Prevention, https://www.cdc.gov/coronavirus/2019-ncov/index.html

4. John Hopkins University COVID-19 data, https://www.kaggle.com/datasets/antgoldbloom/covid19-data-fromjohn-hopkins-university

5. New York Times mask compliance survey, https://github.com/nytimes/covid-19-data/tree/master/mask-us

Appendix

- infectious rate: We will compute this by computing the retransmission rate: the average sum of cases today divided by the average sum of cases yesterday.
- disease-induced death: We will compute this by getting the total number of COVID-19 deaths and dividing it by the total number of COVID-19 cases to proportion it to COVID-19.

- vaccination rate: We will get this by computing the average total number of people vaccinated daily divided by the population. We will only consider those who received their second dose of vaccinations to be fully vaccinated.
- mask usage proportion: Taken from NY Times Survey

Demographic Rates Computation

To get parameters for birth rate and natural death rate, we look at the values from the Washington Health Department online dashboards For Births and For Deaths. For these values, we take the value from 2019 as we assume that COVID-19 could have affected the proportion of birth and deaths.

- Birth Rate: In 2019, there was a total of 24,090 births. We will take this value and divide it by 365 to get the value daily. Thus, 24090/365 is approximately 66.
- Death Rate: In 2019, there were approximately 13,463 deaths. We will take this value and divide it by 365 to get the value per day, then divide by the total population in 2019 (2226300) to get the rate per day. Thus, 13463/365/2226300 is approximately 0.0000165.

Center for Disease Control and Prevention Computations

Other rates come from said CDC guidelines, such as:

- incubation rate: It takes about 3-5 days to develop symptoms after being exposed (if symptomatic), thus we will assume the rate will be 1/4.
- recovery rate: After having COVID-19, it takes about 2 weeks to fully recover from the virus, thus we will assume the rate will be 1/14.
- loss of immunity: After you have COVID-19, it is said that you are less likely to contract COVID-19 again within 3 months, thus we will assume the rate will be 1/90.
- Wanning rate of vaccine: It is recommended to get a booster shot after about 4 months of your second dose, thus the waning rate of the vaccine will be 1/120.