Public Health Strategies for Disease Mitigation in the SIR Model

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INTRODUCTION

As of January 2nd, 2023, the SARS-CoV-2 acute respiratory syndrome coronavirus, more commonly known as COVID-19, has infected over 100 million Americans, and killed nearly 2 million (Johns Hopkins Medicine, 2022). Currently, vaccines are readily available, and effective in reducing hospitalizations, as pharmaceutical vaccines have greatly reduced percentages of COVID-19 non-ICU and ICU hospitalizations by 63.5% (Moghadas et al., 2020). However, even with the availability of pharmaceutical interventions, the coronavirus is still a public health concern and has a possibility of resurgence through major public outbreaks and infectious contact. In addition, during the pandemic, the virus has demonstrated the ability to immensely strain healthcare capacities in hospitals, even in high-income nations such as the United States, European countries, and China. Stress on hospital capacity is often caused by pandemic waves, or curves in a disease model that indicate rapidly increasing infections from a virus (Cacciapaglia et al., 2021). If left uncontrolled, pandemic waves can induce mass hospitalizations and overwhelm capacities, leaving a portion of infected people or people with other vital healthcare needs without care. While it is unlikely that a pandemic can be completely eradicated through the implementation of mitigation strategies, for the purpose of reducing public outbreaks and flattening the curve of the wave, many countries used mitigation measures, including social distancing, quarantining, and masking to control outbreaks before pharmaceutical interventions became available. The specific strategy of mitigation measures has varied among countries. China, in particular, has resorted to implementing harsh mitigation strategies before gradually lifting them after infections have subsided (Ning, Ren, 2020). However, this strategy can often lead to the resurgence of infections, which can overwhelm healthcare capacities, and it is now clear that recurring periods with such a harsh mitigation strategy are needed. Therefore, it is of extreme value to study mitigation strategies that tackle several objectives: to impose the least burden to the population, minimize the overall number of infections during the duration of a pandemic, and stay under available hospital capacity. I investigated the creation of such optimal mitigation strategies in a popular model of infectious diseases – the SIR model. The results from this study will give options to public health officials who recommend strategies to deal with infectious diseases to government officials.

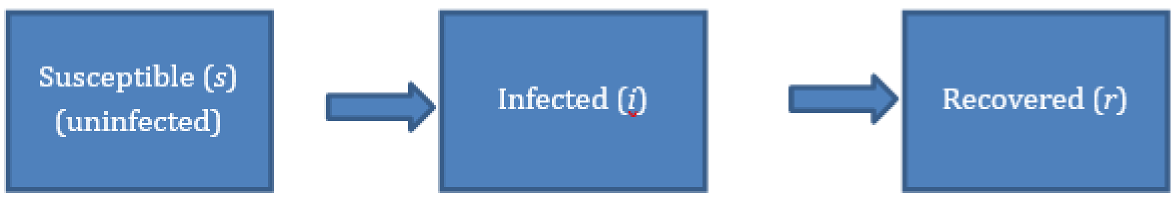
LITERATURE REVIEW

I. Infectious Disease Reduction: COVID-19 Cases

The SARS-CoV-2 pandemic provided an impetus for researchers to study disease modeling to evaluate the effect of various mitigation strategies on the spread of the virus through a population. While the research is now established on the effectiveness of social distancing and masking in managing the spread of infections, less work has been done on modeling the optimal duration and severity of mitigation strategies that do not overburden hospital care capacities. While a full isolation of the population stops the spread of an infectious disease, such a strategy comes at an immense cost to the population and, further, does not provide a long-term solution. Notably, China attempted to isolate its population to eradicate the virus to avoid overwhelming hospitals, but after several unsuccessful attempts, the country abandoned its strict isolation strategy (Ding, Zhang, 2022). On the other hand, Sweden undertook a voluntary social distancing strategy to allow the disease to course through the population in order to build natural herd immunity without straining hospital resources (Pashakhanlou, 2022). Many western nations, including the United States, took an intermediate strategy to bring infections below the hospital capacity while racing to develop pharmaceutical solutions (Mukherjee et al., 2021). In a study conducted by the Proceedings of the National Academy of Sciences (PNAS), 2,120 U.S. residents in participated in a self-reporting survey during the COVID-19 pandemic in the United States based on their activities during the pandemic and their adherence to social distancing. Participants were surveyed four months later whether they had contracted the coronavirus virus. The study actively supported the conclusion that increased adherence to social distancing negatively correlated with COVID-19 cases among the participants in the survey (Fazio et al., 2021). However, the study did not provide any insight into future public policy.

II. Hospital Capacity in Disease Modeling

Disease modeling " …[can] predict the impacts of the disease, plan and assess surveillance, or control strategies, and provide insights about disease causation by comparing model outputs with real life data" (Kirkeby et al., 2021). Disease modeling is a fundamental pillar of determining appropriate policy measures to enact in response to a disease outbreak and the intensity of mitigation strategies needed to sustain it. Disease models for a projected outbreak will not be absolutely accurate, as data projected in the model may not reflect changing circumstances in the public health environment (Kretzschmar, 2020). Despite this, COVID-19 disease modeling has helped to shape and guide public policy globally. Pre-existing research exemplifies the use of the popular SIR model and its variants. An SIR model of disease transmission models the mutual interaction between individuals and pathogens in a contained environment. These interactions are modeled through 3 different conditions or compartments: people susceptible to an infection (denoted by *s*), people who have been infected (denoted by *i*), and people who have recovered from an infection (denoted by *r*).



The model assumes there are no births and that a "recovered" person can no longer become reinfected either through immunity or death. A prominent example of the use of the SIR model to understand mitigation measures is a study conducted by researchers with the Institute of Disease Modeling in King County, Washington. In the study, researchers tested the effectiveness of public social distancing measures implemented by the Governor of Washington, also known as the "Stay Home, Stay Healthy" policy, using COVID-19 data from the State of Washington. This study proved the effectiveness of public social distancing measures, and showed how implementing these mitigation strategies was the most effective in reducing the transmission rate of COVID-19 (Thakkar et al., 2020). However, while the models generated by these researchers are effective at proving the effectiveness of social distancing models through measuring case correlation, they do not study the policy of "Stay Home, Stay Healthy" and the number of infection cases in relation to the hospital capacity in King County. Nevertheless, the effectiveness of disease modeling is also demonstrated through guiding the public by examining capacities and mitigation intensities, which is best illustrated by a study done by the Imperial College COVID-19 Response Team. Researchers from the Imperial College of London implemented models of COVID-19 transmission among a general population of 100,000 people in the United Kingdom and simulated the reductions in disease transmission, denoted as *R0*. The intensity of the mitigation strategies ranged from case isolation in homes to school and university closures, with the goal of reducing hospital utilization. According to the study, the baseline *R0* for the study was gradually reduced by implementing different mitigation strategies. The study concluded by noting that, "...a combination of case isolation, social distancing of the entire population and either household quarantine or school and university closures are required…" (Ferguson et al., 2020). However, while the researchers were able to address the intensity of mitigation necessary to remain under hospital utilization to inform public policy in the United Kingdom, their research did not consider the burden on the population through their strategy or the creation of a minimal mitigation strategy while keeping cases under hospital capacity. Other researchers have attempted to bridge this gap, notably Kissler et al. and Kennedy et al. In the research study of Kissler et al., researchers studied minimizing overall infections while staying below hospital capacity, but only with "on-off" strategies – where mitigation is activated upon cases reaching a set threshold and deactivated after falling to another threshold – to minimize the impact of mitigation on the population. However, such "on-off" strategies are not practical as a health policy. Much of the public would quickly grow weary and confused at increasing and decreasing their movements, interactions and even the donning of masks with such binary strategies. In the research study of Kennedy et al., researchers looked at step-down strategies that allowed reset back to the initial value of mitigation. These strategies, therefore, allow for the mitigation to become more stringent after a certain time. As with the strategies of Kissler et al., strategies that allow for the increasing and decreasing of the severity of mitigation only lead to confusion and non-compliance. In fact, in both studies, there is no analysis of minimizing infections over the stringency of a changing mitigation strategy. This consideration is important and necessary to inform health officials of the different options, as each option has a particular tradeoff – that is, overall cost or stringency of the mitigation which affects the overall compliance against minimizing infections based on that strategy.

III. Research Gap

The difficulties with the use of strategies in Kissler et al. and Kennedy et al. led me to consider the more practical strategies of a simple, step-down *only* strategy. A simple step-down, where the mitigation strategy can only be loosened and never made more stringent, has not been studied in the existing research. Furthermore, the existing research does not look at any measure of the overall stringency of a changing mitigation strategy. I proposed to use the average reduction in the reproduction rate over a mitigation strategy as the cost of that mitigation strategy. This is simple and easy to calculate and adequately captures the overall stringency of a mitigation strategy. This study produces a more realistic set of options to inform public health policy to manage an infectious disease outbreak, such as the COVID-19 pandemic, in a population.

RESEARCH DESIGN & METHODOLOGY

I. Study Justifications

Public health policy is best informed when choices are presented to government officials to decide tradeoffs and "sell" to the public any sacrifices to be made. Sacrifices are inevitable as the cost of minimizing the impact of a serious health concern, such as an infectious disease outbreak which has the potential to become widespread in a population. Furthermore, any policy must recognize the existing limitations. These limitations could be due to behaviors, such as the noncompliance of mandated practices, or due to the inherent limitations of the healthcare industry, such as the time to research and test drug interventions, capacity of hospitals, fixed number of medical workers and equipment. This study took into consideration the problem of compliance fatigue of mitigation mandates by considering only step-down strategies, so that a mandate can only be loosed and never made more stringent. I also considered the overall stringency of a particular mitigation mandate, as measured by the reduction in the reproduction rate, by using the average of the reductions as the measure of the overall stringency. This single number produced for each mitigation strategy will allow a health official to put a “cost” to each recommended strategy option. Finally, this study considered the limitations of hospitals and healthcare workers by looking at strategies which keep the number of infected people who are predicted to be hospitalized below the number of overall available hospital beds. The study will be tested using several incubation periods for the infectious disease.

Incubation periods in this study are defined as the time period from when the infection has been introduced in the population to the start of mitigation. This study tests the different incubation periods from 0 to 5 weeks. Our research utilizes the basic SIR model. The use of the SIR model and its extensions to investigate the path of a disease in the population has been commonplace among scientists beginning with the model’s introduction by Kermack and McKendrick (1927). Modeling a mitigation strategy in the SIR model and its extensions takes the form of a specific reduction in the reproduction rate, commonly denoted by *R0*. The SIR model is widely noted for being effective at predicting future infections and surges. A study done by Ian Cooper et al. tested the durability of the SIR framework by creating several SIR models of the COVID-19 pandemic from January 2020, and using datasets from several countries to determine their alignment with the initial predictions of case count for the SIR model over periods of time. In their conclusion, Cooper et al. praised the effectiveness of the SIR model: “The model can give insights into the time evolution of the spread of the virus that the data alone does not. In this context, it can be applied to communities, given reliable data are available. Its power also lies in the fact that, as new data are added to the model, it is easy to adjust its parameters and provide best-fit curves between the data and the predictions from the model” (2020).

II. The SIR Model

The SIR model is used to measure the evolution of a disease within a given population over a set time period, given that the population remains constant and that individuals who are infected are able to recover and gain immunity from the disease. The primary conditions for the SIR model include a fixed population, with no additions or subtractions from the population. The SIR model, in addition, is a compartmental model, so that every person in the population is put into exactly one compartment. The SIR model involves three differential equations: one equation that models $s(t)$, the fraction of the population who have not been infected, another equation that models $i(t)$, the fraction of the population who are infected, capable of spreading the disease and have not yet recovered, and a final equation that models $r(t)$, the fraction of the population who have recovered from an infection and can no longer spread the disease. Kermack and McKendrick model infectious disease flows through a population according to the following system of differential equations:

$$\frac{ds}{dt} = -\beta s(t)i(t)$$

$$\frac{di}{dt} = \beta s(t)i(t) - \sigma i(t)$$

$$\frac{dr}{dt} = \sigma i(t)$$

The constant *β* is the rate of disease transmission, while σ is the rate at which the infected population recovers. At the onset of an infectious disease, the number of uninfected people is the entire population less the small number of people who are beginning to spread the disease into the population. Dividing *β* by σ will result in the quantity *R0*,

$$\frac{\beta}{\sigma} = R_0 > 1$$

The basic reproduction rate of the infection, or *R0,* is defined as "…an estimate of the speed at which a particular infectious disease can currently spread through a given population…" (News Medical, 2021). The reproduction rate is typically larger than 1, resulting in the infectious disease to rapidly spread in the population rather than die out as an examination of the differential equations shows. As with previous researchers, such as Kissler et al., a percentage reduction in *R0* models the effects of a mitigation strategy, whether through closing schools, restricting public transportation, masking, or other mandates. Reductions to the reproduction rate that results in *R0* being less than 1 causes the infectious disease to die out in the SIR model. To further simplify the modeling, this study considered several reductions (0%, 10%, 20%, 30%, 40%, and 50%).

III. Runge-Kutta Fourth Order Method

To solve the differential equations of the SIR model, the Runge-Kutta Fourth Order method was employed to approximate the daily number of infections. Using Runge-Kutta, the differential equation for infections turns into the following difference equation over each day:

$$i(t+1) = i(t) + \beta(t)s(t)i(t) - \sigma i(t)$$

The other two differential equations of the SIR model are similarly reduced to difference equations.

IV. Process & Implementation

Following Kissler, the parameter *R0* was set as 2.2, the parameter σ as 0.2, and i(0) as 0.00001. To compare whether a particular mitigation strategy allowed infections to exceed the hospital capacity, 4.4% of infections who require hospitalizations were compared from Kissler et. al to the hospital capacity level of 23.765 beds per 10,000 people (American Health Association, 2022). In modeling the infectious disease, this study considered that mitigation would start either immediately or at the end of several weeks to allow the disease to rapidly spread in the population. These are the incubation periods used in this study which allow the infection to take hold in the population before health authorities are able to respond with a mitigation strategy. While mitigation is only active over a period of 12 months in our study, we solved the model over 24 months to test for the possibility of exceeding hospital capacity over the last 12 months. In our step-down only mitigations, the reductions to *R0* were allowed to start only from 10% to 50%, and the reductions would decrease from there by 10%. For example, after an incubation of 1 week, a possible strategy might be to begin at 40% reduction for 3 months, followed by a reduction of 30% for 6 months, and followed by 20% reduction for the remainder of the 12 months. The website NumberGenerator.org was used to produce all step-down possibilities, producing 6188 mitigation strategies.

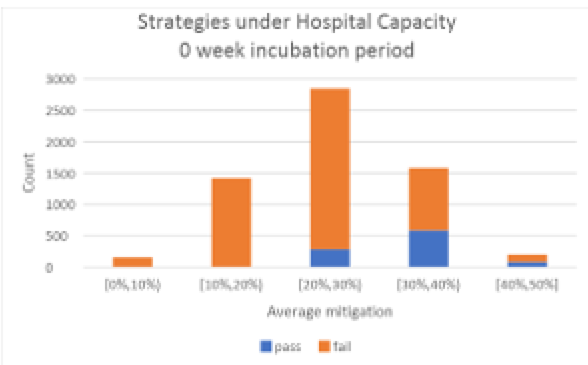
Using Runge-Kutta, the SIR model was solved in Microsoft Excel and the numerical results are graphed. In solving using Runge-Kutta inside Excel, the strategies where the infections exceeded the hospital capacity number at any time over the 24 months were flagged. Histograms were produced to report how many strategies failed to stay under the hospital capacity for each incubation scenario. Scatterplots were produced to report the final uninfected population against the average reduction of the mitigation strategy over the first 12 months for each incubation scenario. From the scatterplots, line graphs were produced of optimal curves demonstrated by the scatterplots.

RESULTS

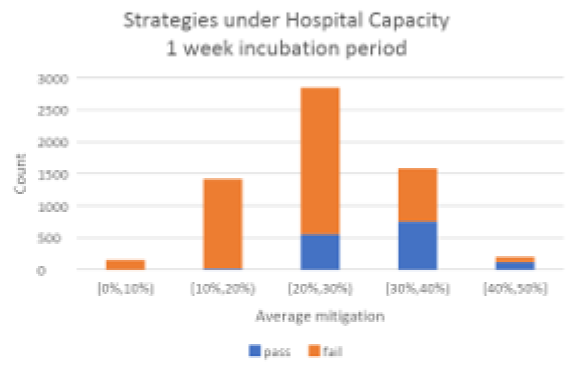
I. Hospital Capacity Test

The 6188 simulations (strategies) for each incubation period were run in Excel. For each incubation period, a histogram was created that reported the number of simulations that passed or failed the test of whether infections, at any time over the 24-month period, remained under the hospital capacity grouped by the average reduction imposed.

Figure 1: *Histograms for Results of Hospital Capacity Test Grouped by Average Mitigation*



(a)



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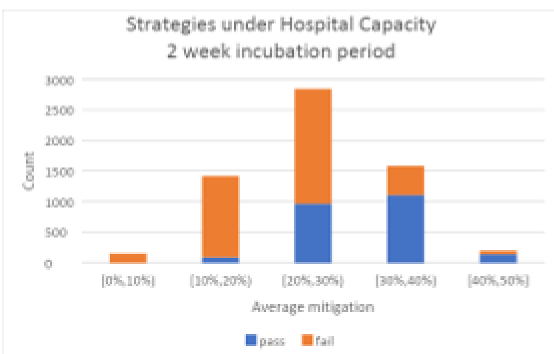

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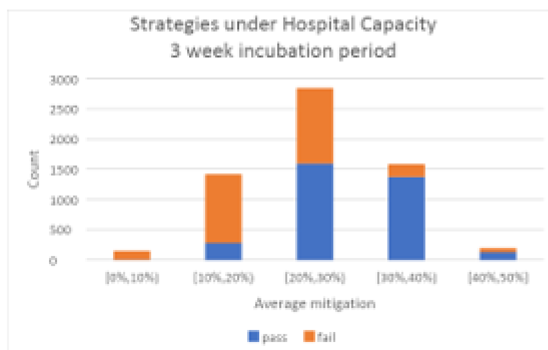

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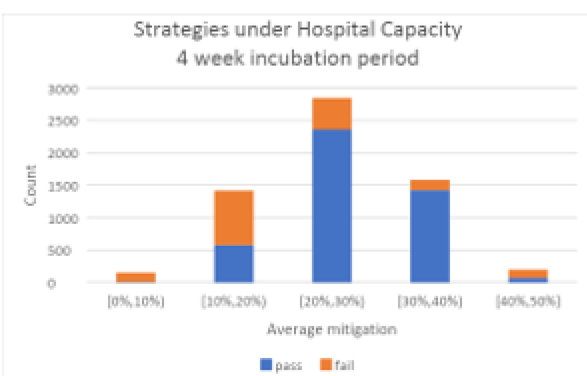

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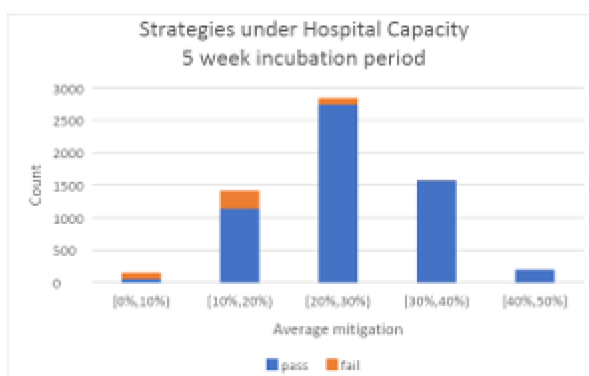


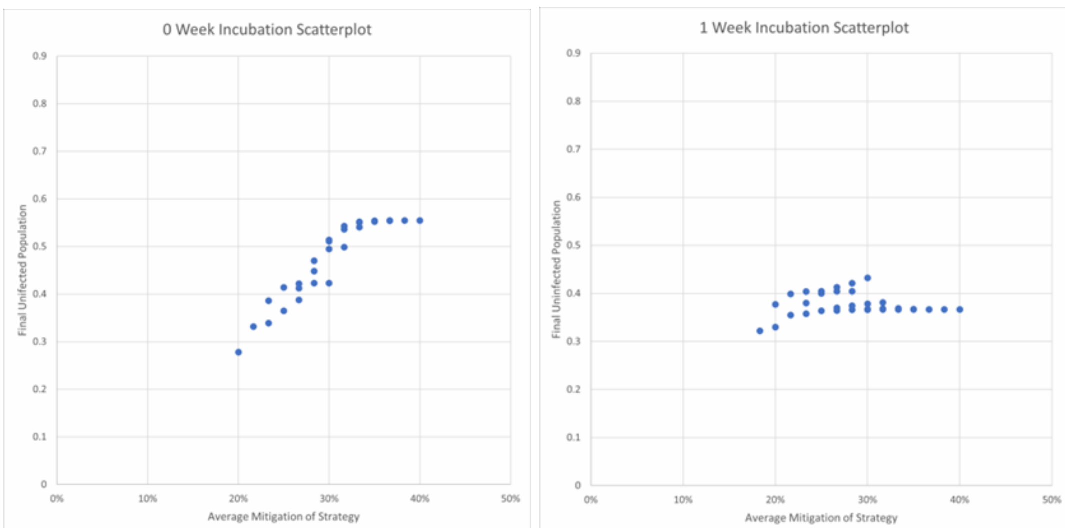
(f)

Initial intuition suggests that as the incubation period increases, there are fewer and fewer strategies that pass the hospital capacity test. However, the opposite effect occurs in the simulations. In Figure 1, for strategies having an average mitigation between 20% and 30%, the proportion of passing strategies increases from 36% (Figure 1a) to 82% (Figure 1d). A similar result holds for mitigation strategies between 10% and 20%: the proportion of passing strategies increases from 0% in the smallest incubation period to 37% in the largest incubation period. This counter-intuitive result comes from the fact that as the incubation period lengthens and more infections are present before the start of mitigation strategies and the pool of uninfected people is reduced, less *overall* stringent mitigation can successfully keep infection cases under the hospital capacity level in our step-down only setting. Conversely, fewer infections at the start of mitigation requires a more overall stringent mitigation as infections rise and mitigation needs to be maintained over a longer time period to keep peak infection cases under the hospital level. Therefore, in the SIR model and with step-down only mitigation strategies, a health policy to mitigate disease spread need not be implemented immediately upon the detection of an infectious disease – a waiting period of a few weeks may, in fact, be useful when looking solely at the cost of a stringent mitigation policy. The results of Figure 1 do not consider the total population infected over the 24-month time period. Thus, this additional variable was examined next.

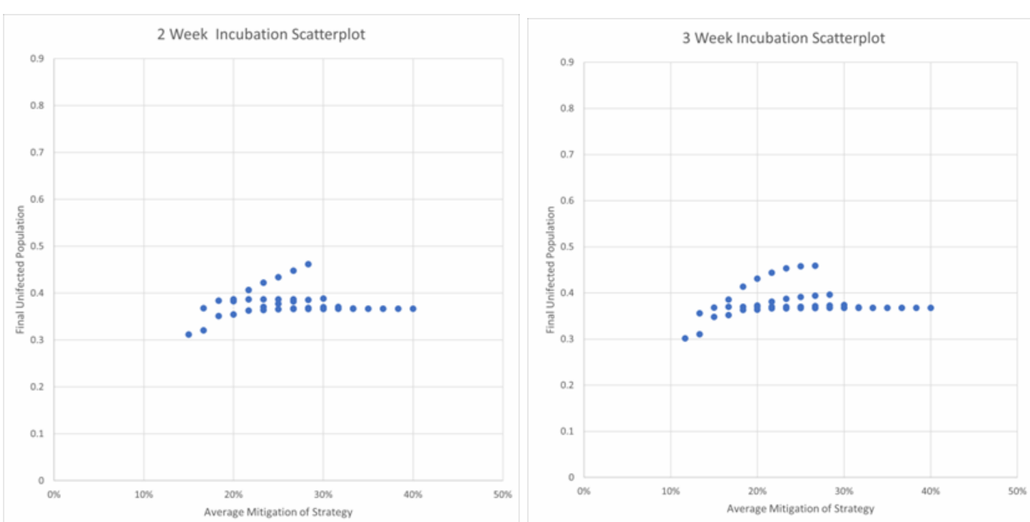
II. Optimal Curve to Balance Cost and Benefit

By recording the final number of uninfected population (or equivalently, the final infection cases), this study was able to record the benefit of each mitigation strategy. Scatterplots displaying the final uninfected population against the average mitigation values for each incubation period show the tradeoff between the cost of the mitigation versus the benefit of the mitigation. The optimal curve is defined as the curve that attains the highest uninfected cases at each average mitigation level. A straight-line interpolation is done in between different average mitigation numbers. Public health officials can use the optimal curve to provide options to government officials on the timing and severity of mitigation strategy to control overall infectious cases while remaining under the hospital capacity.

Figure 2: *Scatterplots of Final Uninfected Population (Benefit) versus Average Mitigation over the Period (Cost) for Strategies that Remain under Hospital Capacity.*



(a) (b)

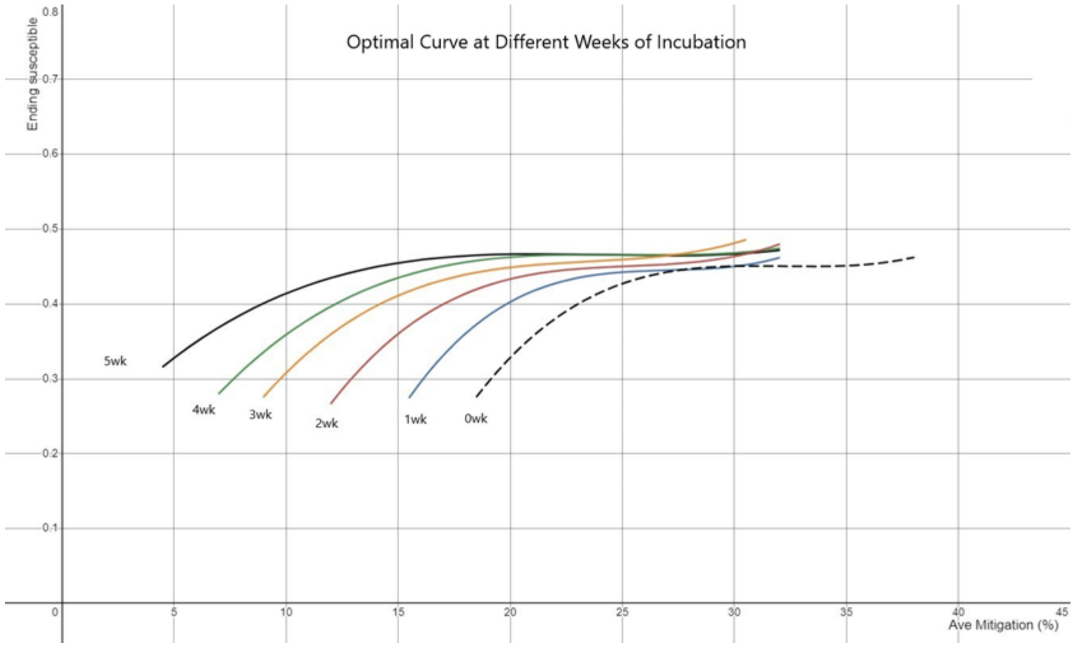


(c) (d)

Our intuition from the pre-existing research suggested that, as the incubation period increases, the final uninfected population should decrease for each average mitigation strategy. Astoundingly, below the level of an average mitigation strategy of about 30%, longer incubation periods lead to higher final uninfected cases – that is, there are fewer total infections. At an average mitigation strategy of 20%, beginning our step-down mitigation strategies immediately leads to a final uninfected population of 28% (Figure 2a), whereas waiting to start mitigation until the end of the third week leads to a final uninfected population of 43% (Figure 2d). About 15% of the population were spared infection when the model waited 3 weeks to begin a step-down mitigation at the 20% average level.

This inverse relationship breakdown is above about 30% average mitigation. In that region, according to Figure 1a, it is possible to achieve a final uninfected population above 50% by beginning our mitigation strategies immediately upon detection of the disease. This result comes from the fact that while more stringent mitigation is effective at controlling the spread of the infection after a period of incubation, there is no further benefit after an average mitigation of 30%. Thus, during the incubation period, the infected population increases which then decreases the final uninfected population.

Figure 3: *Optimal Curves for the Incubation Periods*



Keeping only the strategy for the highest final uninfected population and plotting that against the average mitigation produces the optimal curves in Figure 3. Here, the crossing point is about 30%; above this value, it is better to begin step-down mitigation immediately, and below this value, it is better to wait for the disease to incubate over a period before beginning step-down mitigation.

DISCUSSION

This study was designed to investigate the creation of an optimal strategy to mitigate an infectious disease in the SIR model to inform public health policy. This study restricted strategies to step- down only mitigation and considered the hospital capacity level. Any health policy involves tradeoffs, and our results quantify the tradeoff between stringency of mitigation and timing of mitigation versus maximizing the number of people uninfected by an infectious disease.

I. Findings

This study shows that more stringent mitigation does not necessarily lead to better health outcomes in all cases. In our selection of step-down mitigation strategies and requiring a potential strategy to keep infections below the availability of hospital beds, the study found that as the incubation period increased from 0 to 5 weeks, the number of possible strategies increased (Figure 1). In addition, to maximize health outcomes (fewer people being infected), it is not necessary to begin mitigation immediately upon discovery of an infectious disease nor to impose the strictest form of mitigation. These results were derived from simulations in the SIR model.

II. Implications

The results of this study have multiple implications for public policy. Primarily, public health advisors who are presenting policy options for government officials to control future disease outbreaks, or in a potential resurgence of the ongoing COVID-19 pandemic, and who were not previously aware of the results of this study, will be able to quantify the tradeoff between the timing and intensity of mitigation while keeping cases below the hospital capacity. Public health advisors will also be able to recommend the optimal mitigation strategy for any selected stringency of mitigation measures. The step-down strategies in this study are more favorable for public compliance as it avoids confusion and frequent changes in behavior for the population.

III. Pre-Existing Research Gap Resolution

This study has fulfilled several gaps posed by the pre-existing research. Primarily, the pure step-down strategies were not studied by pre-existing research. The existing research examined the ability to solely minimize infection cases through mitigation strategies that could be made stricter rather than solely loosened, such as the “on-off” strategies of Kissler et al. or the step-down/step-up strategies of Kennedy et al.

IV. Limitations

This study was developed in a simple SIR model. However, many researchers have used extensions of the SIR model to study mitigation strategies. Therefore, it would be important to verify if the results of this study extend to various extensions of the basic SIR model. It is likely, however, that our results will still hold because the essence of the result should not change with the incremental extensions used by other authors. By allowing finer increments of step-downs,it is prevalent that the results should be amplified rather than contradicted.

Finally, our study, like the existing research, does not analyze how to quantify various methods to mitigate the spread of an infectious disease. For example, it is uncertain how mitigation strategies, such as school closures, social distancing, and quarantining will correlate with reductions of mitigation. This area of study will likely be the most difficult to examine given the lack of accurate and available data. However, it is an imperative question to answer to allow similar studies to have the maximum impact as a guide to public health policy.

V. Future Research

Future research lies in some of the limitations of this study. *R0* can be examined further to determine the variations between seasons, such as the difference between winter and spring, as well as the correlation between reductions in *R0* and certain mitigation strategies. Aside from the limitations, one could also investigate the public verdict for certain patterns of reduction in

R0, as the potential defiance over the implementation of certain reductions impacts compliance with the reductions and the effect of the measures on the general economy.

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