Simulating the Mitigating Effects of Social Distancing and Vaccination during a Pandemic Grant Yang¹, Rostacia Lewis², Michael Loewenberg² ¹Scarsdale High School,²Yale University

Introduction

In the unprecedented wake of the COVID-19 (SARS-CoV-2) pandemic, techniques to understand and test preventative measures—like vaccination and social distancing—have become increasingly necessary. A compartmental computer model[1-4] was used to simulate the spread of COVID-19 in a population including the mitigating effects of vaccination and social distancing. The aim of our study was to assess strategies for minimizing the most harmful effects of the pandemic. Similar studies are underway by other groups[5,6].

Computer Model

Our computer model is a direct, stochastic simulation of pair interactions between individuals within a total population of N people, characterized in terms of their state of health with respect to COVID-19. As shown in Figure 1, separate compartments (sub-populations) are distinguished, including susceptible (S), infected (I), and recovered {R}[3,4]. The susceptible and infected groups are further subdivided according to vaccination status, indicated by the subscript u or v, referring to unvaccinated and vaccinated, respectively; a fraction (f) of the total population is vaccinated. Social distancing is incorporated in our model by limiting the proximity of pair interactions to ΔN_q =(1-q)N, where the q lies in the range 0 < q < 1.



Accordingly, q=0 describes the absence of social distancing and q=1 describes the limit where no interactions occur. The simulation begins with one infected person in the population. When a susceptible person interacts with an infected person, the former has a probability β (if unvaccinated) or α (if vaccinated) of becoming infected. People can only interact within their social distancing range (ΔN_{α}) . If infected, they then move to the infected group and have the same infectiousness regardless of their vaccination status. The simulation continues cycling over all people in the population, each person interacting with one randomly selected individual within their interaction range; a day is defined as one cycle. After an interval of Δt (days), an infected person becomes recovered and is immune. The simulation ends when there are no more infected people. Figure 2 shows one full run of our simulation. These results and those described in the next section were obtained using a Python code to implement the computer model described above.



N=1000, f=0.25, q=0.2, α =0.05, β =0.25, Δ t=15

Results

One of the first metrics explored was peak infection count, as it determines whether or not hospitals will be overwhelmed by a surge in cases. Here, we focus on the unvaccinated group of infected people since they are more likely to require hospitalization. Duration was also tested as a factor in the length of pandemic response, where longer durations are a result of "flattening the curve" of peak infections. Increasing degrees of social isolation and vaccination were tested and are shown in Figure 3:



Figure 3: Peak fraction of infected and unvaccinated group versus Social Distancing parameter and Vaccination fraction; parameters separately varied as indicated.

Vaccination has an approximately proportionate mitigating effect. By contrast, social distancing is only effective when the interaction range is strongly restricted, with ΔN_q equal to a small number. An inverse relation is seen with respect to the duration of the pandemic in Figure 4.



Figure 4: Duration of pandemic versus Social Distancing parameter and Vaccination fraction

Discussion/Conclusions

Reducing the reproduction number reduces the peak infected population but at the cost of prolonging the duration of the pandemic. Under the assumption of the dire consequences of overwhelming healthcare facilities, this approach seems prudent. The reproduction number, R_0 , is the average number of infections resulting from a single infected individual during the course of their illness at the initial stage of the pandemic[4]. In terms of the model parameters, $R_0 = min[(f\alpha + (1-f)\beta)\Delta t, \Delta N_a]$ This formula helps to explain our simulation results about how social distancing and vaccination mitigate the spread of COVID-19. Social distancing provides an upper bound on \mathbb{R}_0 but it is only effective if $\Delta N_a < \beta \Delta t$ corresponding to q≈1. By contrast, the vaccination fraction f directly reduces the probability of infection, given that $\alpha < \beta$. Increasing the vaccinated fraction of the population is a more effective mitigation strategy than social distancing.

References

Kermack, W. O., and A. G. McKendrick. "A Contribution to the Mathematical Theory of Epidemics." Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character, vol. 115, no. 772, 1927, pp. 700-721., doi:10.1098/rspa.1927.0118. ²Rvachev, L. A. "Modelling Experiment of a Large-Scale Epidemic by Means of a Computer." Dokl. Akad. Nauk SSSR, Volume 180, no. Number 2, 1968, pp. 294-296., Math-Net.Ru. ³Arino, J., Brauer, F., van den Driessche, P., Watmough, J., Wu, J. "A Model for Influenza with Vaccination and Antiviral Treatment." Journal of Theoretical Biology, vol. 253, no. 1, 2008, pp. 118-130. doi:10.1016/j.jtbi.2008.02.026. ⁴Coburn, Brian J., Wagner, B. G., Blower, S. "Modeling Influenza Epidemics and Pandemics: Insights into the Future of Swine Flu (h1n1)." BMC Medicine, vol. 7, no. 1, 2009, doi:10.1186/1741-7015-7-30. ⁵Pandey, K. R., Subedee, A., Khanal, B., Koirala, B., "COVID-19 Control Strategies and Intervention Effects in Resource Limited Settings: A Modeling Study." PLOS ONE, vol. 16, no. 6, 2021, doi:10.1371/journal.pone.0252570. ⁶Blavatska, V., and Yu. Holovatch. "Spreading Processes in Post-Epidemic Environments," Physica A: Statistical Mechanics and Its Applications, vol. 573, 2021, p. 125980., doi:10.1016/j.physa.2021.125980.