Agent-Based Simulation Model of COVID-19

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## Problem Statement

### Background of the chosen case and Motivation

COVID-19, with its global scale and complex transmission dynamics, provides an ideal case for studying the spread of infectious diseases through agent-based modeling (ABM). Unlike other diseases, COVID-19 presents unique challenges, such as asymptomatic carriers, varying onset of symptoms, and the emergence of highly contagious variants. These characteristics make understanding its spread and the effectiveness of public health interventions crucial for future pandemic preparedness.

We chose COVID-19 because of its relevance and the availability of a large amount of data, which allowed us to validate the model effectively. The results of this study are intended to improve outbreak control strategies and provide insights for future pandemic preparedness. Historically, SIR models have been key to understanding infectious diseases. The foundational work of Kermack and McKendrick (1927) and more recent research by He et al. (2020) emphasize the importance of using mathematical models such as SIR to guide public health decision making.

### Suitability for Agent-Based Modelling

Agent-Based Modelling is well suited to simulate SIR models because it allows us to model the behaviour of individuals in a population. Unlike traditional models that assume uniform behaviour, ABM treats each individual as an agent with unique interactions. This flexibility is critical to understanding how COVID-19 is transmitted, especially given factors such as asymptomatic carriers and varying exposure rates.

Key parameters such as probability of infection, exposure time, and asymptomatic rate are critical for modelling real-world scenarios. For example, the probability of infection (set to 0.2) reflects the reproductive rate (R₀) of COVID-19, which is typically between 2 and 3 (SpringerLink, 2020). Adjusting these parameters helps create accurate simulations that capture the dynamics of disease transmission.

ABM also specializes in simulating how viruses spread in different environments, such as homes, workplaces, and public places. This makes it possible to test intervention strategies such as social distancing and isolation. The Squire model on GitHub allows users to modify parameters to fit the specifics of a population, making the ABM highly adaptable (GitHub, 2020).

Studies have shown ABM to be effective in pandemic simulations. The Annals of Operations Research and Epstein (2009) have shown that ABM can be used to predict outbreaks and inform public health decisions. These examples highlight the model's ability to reflect the complexity of real-world disease transmission

### Complexity of the Case for Simulation

The complexity of SIR modelling to simulate COVID-19 stems from several factors. First, individual differences (e.g., age, health status, and risk of infection) can lead to differences in transmission and recovery. Modelling these differences ensures more accurate predictions and gives a realistic picture of how COVID-19 affects different populations (Ferguson et al., 2020).

One of the most challenging aspects of modelling COVID-19 is asymptomatic transmission, where individuals unknowingly spread the virus. This adds uncertainty to the modelling, as tracking and controlling asymptomatic carriers is difficult. Therefore, the model must include methods that consider hidden transmission pathways.

Another important aspect is the behaviour of symptomatic individuals. If symptomatic individuals stop interacting with others (either voluntarily or due to government-imposed quarantine), this can significantly alter transmission dynamics. Such behaviours can significantly reduce infection rates, but also depend on the effectiveness of quarantine measures and adherence to public health guidelines. Incorporating these behaviours into the model adds another layer of complexity.

Additionally, the model must take into account government actions such as lockdowns, travel restrictions and social distance regulations. These interventions have a direct impact on how people move and interact in a variety of environments, such as homes, workplaces and public places, all of which affect transmission rates (Ferguson et al., 2020). Simulating these environments, as well as interventions such as mask-wearing and vaccination programmes, adds complexity to the model, but is essential to understanding real-world outcomes.

Finally, the model must adapt to the evolving nature of the outbreak, including policy changes, the emergence of new virus variants, and varying levels of immunity in the population. This dynamic aspect makes modelling both challenging and valuable for predicting future outbreaks and informing public health decision-making

## Simulation Results and Analysis

## Visualisation

This simulation model provides important insights into the spread of COVID-19 by tracking the changing states of agents over time, and visualisation plays a crucial role in understanding the dynamics of the pandemic. In this simulation, agents are classified into several health states: unexposed, asymptomatic and contagious, symptomatic and contagious, asymptomatic and non-contagious, post-COVID immune, naturally immune, and deceased. Over the course of 50 days, multiple visual representations of the state distributions reveal patterns in disease transmission and recovery.

The first visualisation illustrates the progression of the pandemic, starting with most of the population in the unexposed state. As the simulation proceeds, the number of unexposed agents rapidly decreases while the numbers of asymptomatic and symptomatic agents increase. The peak infection rate occurs around day 20, when the number of infected individuals reaches its maximum. This marks the point when the largest portion of the population is symptomatic and contagious, leading to widespread transmission. The graph also shows an increase in agents transitioning to the post-COVID immune state, indicating successful recovery after infection. However, a small but notable portion of the population transitions to the death state, representing COVID-19-related fatalities. As more factors are introduced, such as social networks and the reduction of social interactions among sick individuals, the spread of the pandemic slows, with a reduced growth rate of newly infected individuals and a rise in the number of unexposed people. However, when characteristics like super-spreaders and variants were added, the spread rate increased again, though not as rapidly as random transmission. In the final phase, the introduction of government interventions like lockdowns shows that while these measures slow the pandemic, they may lead to recurrent waves of infections, with fluctuations and minor peaks in the number of infected individuals.

In the early stages, the unexposed population dominates, but as the infection spreads, symptomatic cases and eventually recovered individuals become the dominant groups. Stacked bar charts clearly depict this trajectory, showing how post-COVID immune individuals ultimately dominate as the pandemic subsides.

The second key visualisation focuses on the SIR model, tracking the numbers of susceptible, infected, and recovered individuals throughout the simulation. It demonstrates the typical behavior of an epidemic curve, where the number of infected individuals rises rapidly at first, peaks, and then declines as individuals recover or die. The recovered population steadily increases, eventually making up the majority by the end of the simulation. The death curve also rises gradually, indicating an increase in fatalities, but remains lower compared to the number of recovered individuals, reflecting a balance between the virus and human immunity.

## Quantitative Analysis

In this COVID-19 outbreak simulation, the key quantitative measure is the number of infected individuals over time, including both asymptomatic and symptomatic cases. This value not only reflects the rate at which the virus spreads within the population but also reveals when the peak infection occurs and how the pandemic declines. By analyzing this data, we can clearly observe the progression of the pandemic: the number of infected individuals rises sharply, peaks, and then gradually declines until the outbreak is eventually controlled.

We used the SIR model to illustrate the changes in the number of susceptible, infected, and recovered individuals during the simulation. The curve of infected individuals plays a crucial role in depicting the evolution of the pandemic. Specifically, the changes in the number of infected individuals visually reveal the virus’s transmission speed and the timing of the peak. For example, in the simulation, we observe that the number of infected individuals peaks around day 20, after which it gradually declines and stabilizes around day 40. This quantitative analysis helps us identify the critical turning points of the pandemic and assess the effectiveness of public health interventions.

Another important metric is the death rate and recovery rate, representing the number of individuals who transitioned to the death state and those who acquired post-COVID immunity. These data allow us to assess the virus’s lethality and the healthcare system's effectiveness during the treatment process. By comparing the ratio of recovered individuals to the number of deaths, we can better understand the impact of medical interventions and vaccination campaigns in curbing the virus’s spread. The simulation shows that while the number of recoveries steadily increases, the growth in deaths during the pandemic remains a critical issue, especially among high-risk groups, highlighting the importance of allocating healthcare resources effectively.

## Parameter Impact

In the simulation, the infection probability and social interaction frequency are two key parameters that directly impact the infection curve. First, infection probability determines the likelihood of the virus being transmitted during each interaction. We adjust this parameter to simulate different pandemic scenarios. For example, when the infection probability increases, the number of infected individuals rises sharply and reaches a higher peak at an earlier time point. This mirrors real-life situations where the virus's transmission capacity increases or preventive measures weaken. Conversely, lowering the infection probability flattens the infection curve, delays the peak, and reduces the total number of infections. This demonstrates that when effective protective measures or widespread vaccinations are implemented, a reduction in infection probability can effectively slow the pandemic.

Social interaction frequency also plays a crucial role in virus transmission. In the simulation, when the number of daily interactions between individuals increases—such as when there are no lockdowns or restrictions—the virus spreads faster, causing a rapid increase in the number of infections and a peak in a shorter period. When the number of daily interactions decreases, such as during lockdowns or social distancing measures, the rate of infections slows significantly, and the peak is delayed. This mirrors the real-world effects of lockdowns or social distancing policies, showing the importance of reducing social contact to control virus transmission.

By adjusting these parameters, the simulation not only demonstrates how the pandemic evolves under different conditions but also provides valuable insights for policymakers on how to optimize their strategies. For example, by limiting daily interactions and reducing infection probability, the pandemic can be controlled over a longer period while avoiding the overwhelming of healthcare systems.

## Real-World Reflection

The simulation results provide valuable insights into the behaviour of pandemics, especially in the context of COVID-19. By simulating the spread of the virus within a structured population, the model effectively reflects how individual behaviours, government interventions, and biological factors influence the progression of a pandemic. One key reflection is the importance of social networks and behavioural responses in shaping transmission patterns. In the real world, individuals do not interact randomly; instead, they engage within tight-knit social circles. Some individuals, known as super-spreaders, have more contacts than others, highlighting the role of highly connected individuals in accelerating transmission. This reflects real-world observations where certain individuals or events, such as gatherings, have disproportionately large effects on the spread of COVID-19.

Introducing policy interventions like lockdowns in the simulation further strengthens real-world implications, as reducing daily interactions can slow the spread of the virus, flatten the infection curve, but also prolong the pandemic’s duration. This mirrors real-world challenges where interventions alleviate immediate healthcare system burdens but must be balanced with economic and social costs. Furthermore, the simulation shows that once restrictions are lifted, cases tend to resurge—a phenomenon seen in many countries grappling with successive waves of COVID-19 infections.

Finally, the simulation highlights the role of herd immunity—whether through natural infection or vaccination—in controlling virus transmission. When infection rates are high, the total number of infections decreases, consistent with real-world observations. The interaction between immunity levels, transmission rates, and behavioural factors in the simulation reflects the delicate balance required in managing pandemics. As such, this simulation provides valuable insights into how key factors interact to shape the course of pandemics, offering lessons for future public health strategies.

# Reference

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# Appendix