Modeling and Preventing Virus Spread Using Agent-Based Modeling and Computer Simulations

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1. ABSTRACT

This agent-based model simulates the spread of a virus through a community, as well as the effects that preventative measures, specifically masks and vaccines, have on the spread rate and death toll. This model can be utilized to simulate any virus, but this paper focuses on simulating the spread of the COVID-19 virus. Agent based modeling was used for this topic because interactions between individual people are difficult to represent without an ABM. This virus spreading model is unique because it uses spatial data and models the agents as they move around the map. Other COVID-19 models consider hundreds of factors, but they do not include a geospatial or visual element that shows the agents/people as they are moving and interacting with each other. Through various experiments, I have concluded that using both masks and vaccines as preventative measures is more effective in reducing deaths, while implementing just masks as a preventative measure works best in reducing virus spread.

2. INTRODUCTION

The spread of viruses is a complex system. It is fully dependent on the movements of people, which are unique, random, and difficult to model. It is important to examine this system, however, because understanding which preventative measures work best through models is important information that can be quickly applied to real life and reduce deaths/infections. This paper summarizes the agent-based model titled 'Preventing Virus Spread', developed to explore and understand this phenomenon. The specific research question or objective that guided this project is: How can preventative measures such as masks and vaccines affect virus spread and deaths caused by the virus?

3. BACKGROUND

3.1 The Topic

This model visualizes the spreading of a virus in a community. It also explores how using preventative measures can change the death rate and spread rate of the virus. The COVID-19 pandemic caused many deaths, and it spread rapidly. However, many people were reluctant to implement preventative measures - for whatever reason - and as a result, the deaths and spread rate were higher than they should have been. This model shows how implementing preventative measures earlier could have made the impact of COVID-19 much less significant.

3.2 Related Research

The COVASIM model by Cliff et al. is an agent-based model that models COVID-19 spread. It accounts for many detailed factors, such as social layers. Social layers are layers that connect agents that would normally randomly interact or not interact at all. Examples of social layers that Cliff et al. used in their model are school, household, and workplace networks. However, one downside of this model is that it does not have a visual/spatial element. It does not actively show agents contracting COVID-19 and interacting with other agents.

Another related model is the Fire Spreading/Segregation model by Cuevas. This model was highly mathematical. However, it also had the same problem as the COVASIM model. It did not spatially or visually represent interactions between the agents, only using scatterplots as the visual output.

3.3 Why Utilize Agent-Based Modeling?

Agent-based modeling shows us just exactly how individuals interact and how a virus is spread. We can use agent-based models and apply them to real world scenarios. Additionally, the premise of an agent-based model is that each agent is an individual person who makes individual "choices" (Bonabeau, 2002). In this model, each agent must make their own decision not only about where to move, but which preventative measures to use. This would have been difficult without an agent-based model!

4. DATA

The only data used in this model was geospatial data from Open Data DC's Roads Database (Open Data DC). This database was used to create the roads that the agents would traverse upon. QGIS was used to clip the roads to the area of Washington, D.C. That shapefile was then moved to Netlogo and used to draw the roads.

I also used The New York Times' 'A Detailed Map of Who Is Wearing Masks in. the U.S.' (Katz et al) to assign the original mask-wearing percentages when setting up the agents. To set up the percentage of people initially infected or vaccinated, I used the CDC's COVID Data Tracker. Finally, I used the 'COVID-19 deaths reported in the U.S.' page by Statista to create the death method.

5. MODEL DESIGN

The key components of this model are a move function, mask and vaccine functions, and death functions.

The move function randomly determines the amount that the agent will move, given that they stay on the road. If they move off road, they correct themselves by rotating.

The mask and vaccine functions change the mask and vaccine status depending on how many people around the agent have their mask on/off or are vaccinated. It is important to note that vaccines can only be administered, they cannot be removed. So once an agent is vaccinated, they cannot be unvaccinated. This is not true for masks, however, as they can be put on or taken off depending on the mask status of the current neighbors.

Appendix A includes a detailed description of the model following the Overview, Design concepts, and Details (ODD) protocol (Grimm et al., 2006). The ODD enables transparency of the model components and to both reproducibility and reuse of the model (Grimm et al, 2020).

5.1 Model Development

To develop the agent-based model, the modeling framework of Netlogo (Wilensky, 1999), version 6.2.1, was used. In addition to its robust coding language to support agent-based model development, Netlogo provides users with a graphical user interface to view the model and conduct experiments in real time during each model iteration. For this model, the GIS extension for Netlogo was used to enable display and utilization of spatial datasets to inform agent and environment attributes as well as model parameterization.

A screenshot of the geographical area was also added underneath the roads, which was taken from OpenStreetMap. To allow the agents to move on the roads, patches underneath the roads were set to a specific color. This is because the agents cannot recognize the GIS data, they can only recognize patches and follow the color of the patches as they move. This helps the agents stay on the roads.

5.2 Model Components

5.2.1 Model Initialization and Parameters

This agent-based model enables the user to adjust parameters to setup initial conditions and to experiment with different model scenarios. The user-controlled parameters and interactions are noted in Table 1. By adjusting the preventative measures used, the user can note the effects of each parameter separately or all together.

Table 1: User input parameters and controls

Parameters	Range	Meaning
use-masks	true/false	A switch that allows the user to setup the environment with masks as a preventative measure
use-vaccine	true/false	A switch that allows the user to setup the environment with vaccines as a preventative measure

5.2.2 Agents

This model only has one overall type of agent - people. And for simplicity, I am only defining one group of agents and their attributes and decision-making processes in Table 2. However, the people are split into two main categories: people without the virus and people with the virus. Let's discuss the differences between agents with the virus and healthy agents.

The main difference between these two categories is that the people with the virus have a chance to die, while healthy people cannot die. Additionally, people with the virus are able to transmit the virus if they themselves are unmasked and the person near them is unmasked and unvaccinated.

Other common traits that both of these types of agents share are the ability to be masked and vaccinated. Once a person is vaccinated, however, they cannot be infected with the virus. So, the subgroup of healthy people also includes the group of people with their vaccine.

For both of these groups of agents, a key decision making process is deciding whether or not to wear their mask and get their vaccine. In this model, masks can be taken on and off depending on the masking status of the majority of the agent's neighbors. If half or more of the neighbors are wearing masks, the agent will also wear their mask and vice versa. Vaccines are determined similarly. Once the vaccine is administered, it cannot be reversed.

Table 2: Agents and key attributes and behaviors used in the model

Agents	Select attributes	Key Decisions
People	mask, vaccine, virus	wearing a mask, getting vaccinated, transmitting the virus

5.2.3 Environment

The model incorporates a spatially-explicit environment for the geographic area of Washington DC. The area represented in the model is shown in Figure 1. Spatial data for the roads are loaded into the model during setup. The spatial extent represented in the model is an area of about 68 sq miles.

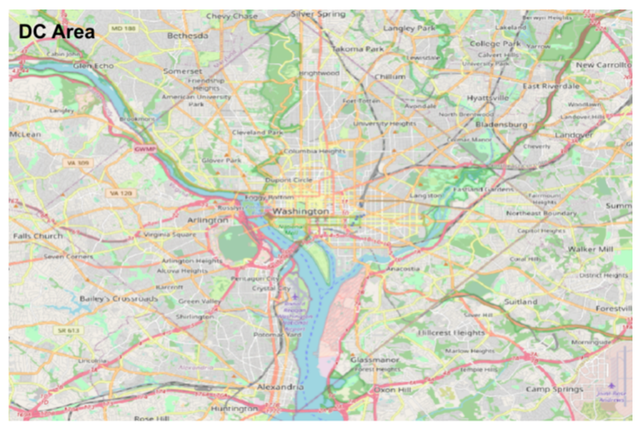

Figure 1: Geographic area of the model is Washington, D.C.

5.2.4 Sub-models

The key sub-models incorporated in this agent-based model are the agent-agent interactions and the decision-making processes for masks and vaccines. These are briefly summarized.

Healthy-Infected: The infectious agent can transmit the virus to a nearby healthy agent if both are unmasked and the healthy agent is unvaccinated. The agent remains infected for 240 ticks. Once the 240 ticks are over, they are healthy again.

Mask: If 4 or more of the agent's neighbors are wearing a mask, the agent wears a mask. Alternatively, if 4 or more of the agent's neighbors are not wearing masks, the agent does not wear their mask.

Vaccine: If 4 or more of the agent's neighbors are vaccinated, the agent gets vaccinated. The agent cannot become "unvaccinated" after the vaccine has been administered.

5.3 Model Logic and Flow

The processes that take place during each model iteration are summarized as a flow diagram in Figure 2.

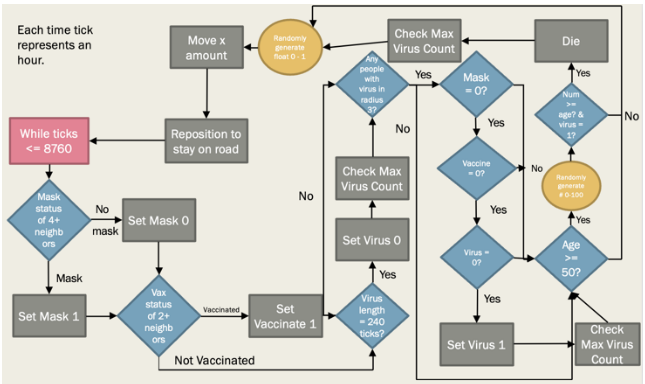

Figure 2: Model flow diagram.

5.4 Model Interface

A screenshot of the model interface and results during a sample run are shown in Figure 3.

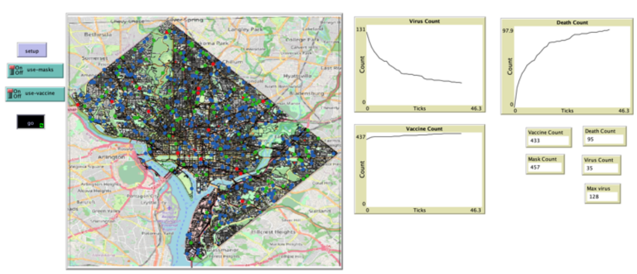

Figure 3: Graphical user interface of the Preventing Virus Spread model.

6. EXPERIMENTS AND RESULTS

The model was tested by running a baseline and three experiments, each testing a different configuration of the preventative measures. Each test was run three times.

In the baseline, 617 people died on average. Additionally, no more than 336 people were carrying the virus at one time. The trends in deaths and virus transmission are shown in Figures 4 - 6. In all the graphs, there is a large spike in virus count at the beginning of the month, which eventually decreases.

The first experiment used only masks as a preventative measure. With a death count of 219, the death rate decreased from the baseline by 64.51%. The maximum number of people with the virus at any given time also decreased by 56.55%, from 336 to 146 on average. This shows exactly how effective masks are, and how having many people wear masks reduces the risk of death and catching the virus. The graphs for these experiments are shown in Figures 7-9. Interestingly, the virus count seemed to increase a bit towards the end, but it quickly died down before it was able to make a large impact. The graphs also showed a large spike in the beginning of the month, but the spikes were not nearly as large as the control experiment.

The second experiment with just the vaccine as a preventative measure, was predicted to have similar results. However, this was not the case in terms of the virus' spread. The deaths were similar to the masking experiment, with 201 deaths (a decrease of 67.42% from the control). The maximum number of people with the virus at any given time was higher, however, at 162 people on average (51.79% decrease from the control). These results do not present a compelling argument for vaccines, as the spread seems to be greater. However, with this experiment, the figures tell a much more interesting story. The figures for this experiment are Figures 10-12. In all the other figures, there is visible fluctuation in the virus counts graphs, as well as a sharp increase at the beginning of the experiments. With this experiment, on the other hand, the virus counts sharply decrease, with little fluctuation. Additionally, the virus counts reached 0 earlier than any of the other experiments so far. This proves that vaccines work to eradicate the virus much faster than just masking.

The final experiment combined both masks and vaccines. There were 128 deaths, on average (a 79.25% reduction from the baseline), and at most 124 people who had the virus at any given time, on average. That is a 63.09% reduction from the baseline value. Looking at Figures 13-15, the same pattern of sudden decrease that was observed in the vaccine experiments is visible here as well. The virus was also eradicated early on with both masks and vaccines implemented.

In conclusion, the experiment with both masks and vaccines implemented had the most success in decreasing the amount of people who died from the virus, as well as reducing the virus spread.

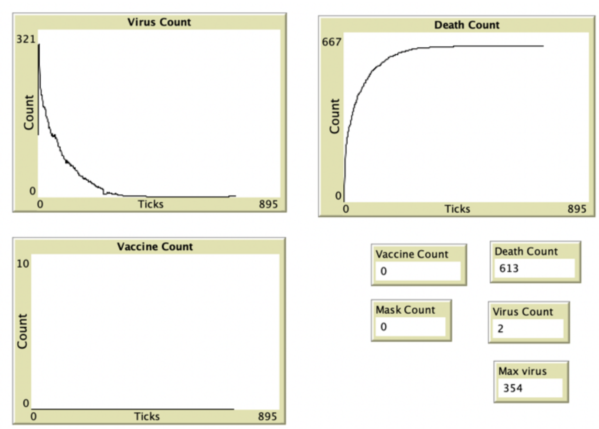

Figure 4. Trial 1 of Control Experiment

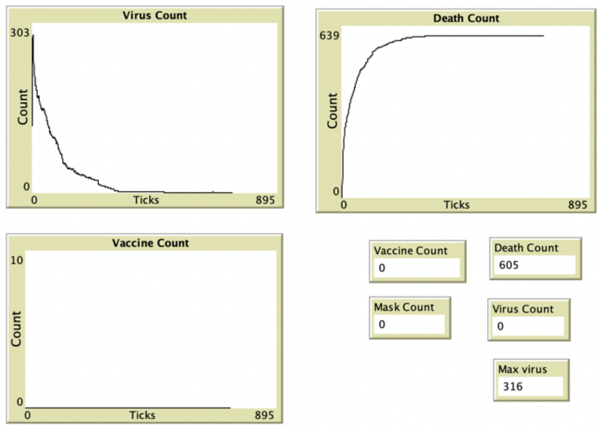

Figure 5. Trial 2 of Control Experiment

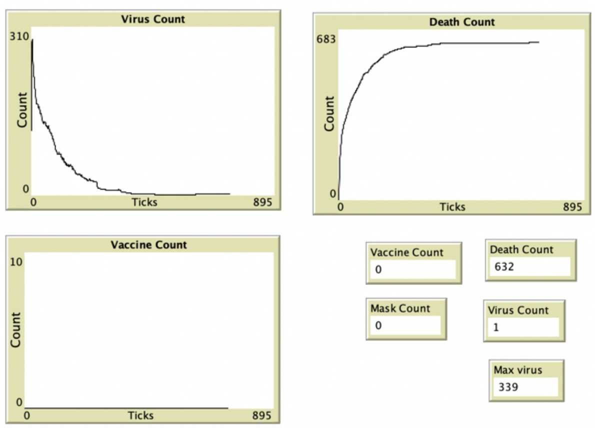

Figure 6. Trial 3 of Control Experiment

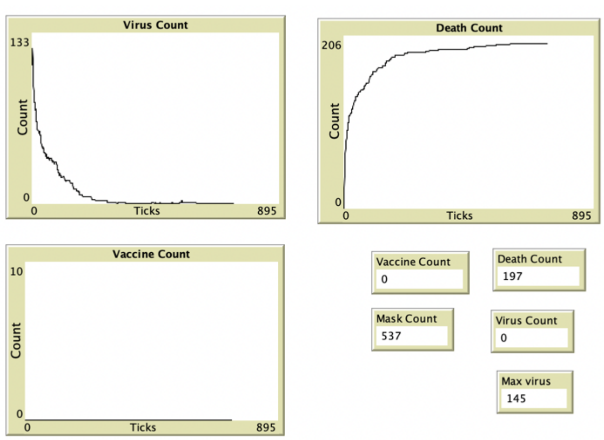

Figure 7. Trial 1 of Masks Experiment

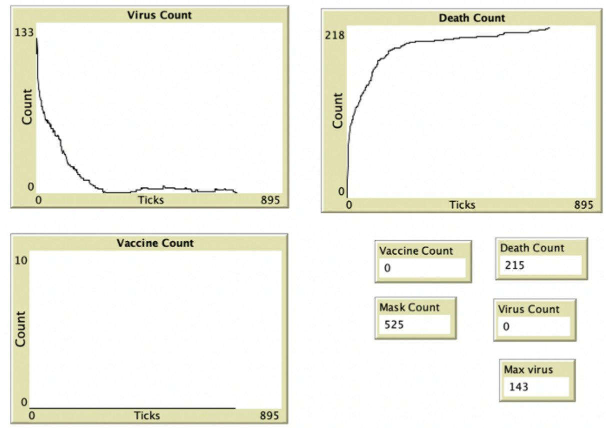

Figure 8. Trial 2 of Masks Experiment

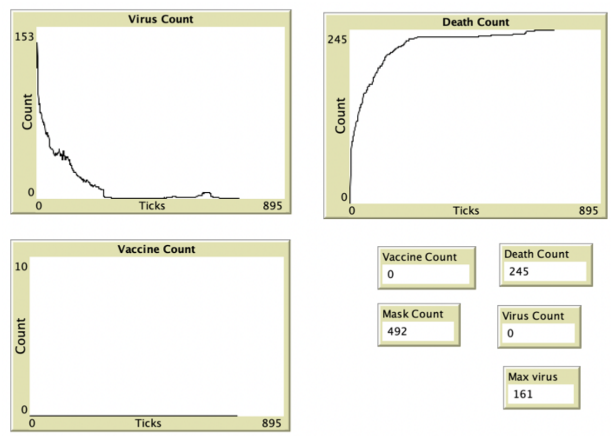

Figure 9. Trial 3 of Masks Experiment

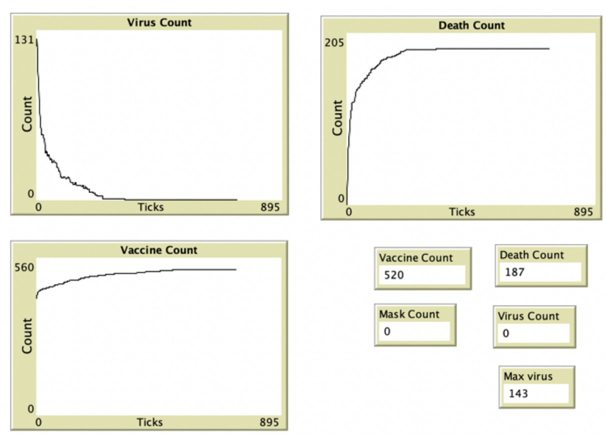

Figure 10. Trial 1 of Vaccine Experiment

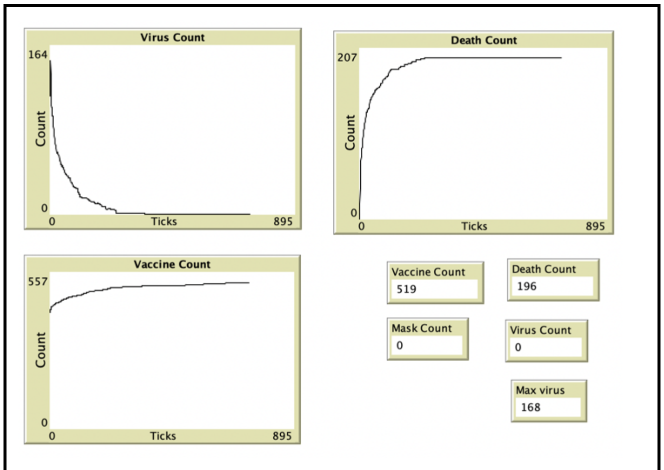

Figure 11. Trial 2 of Vaccine Experiment

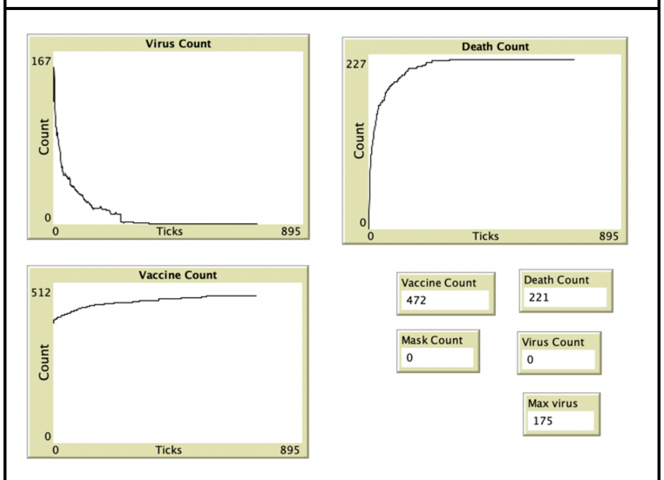

Figure 12. Trial 3 of Vaccine Experiment

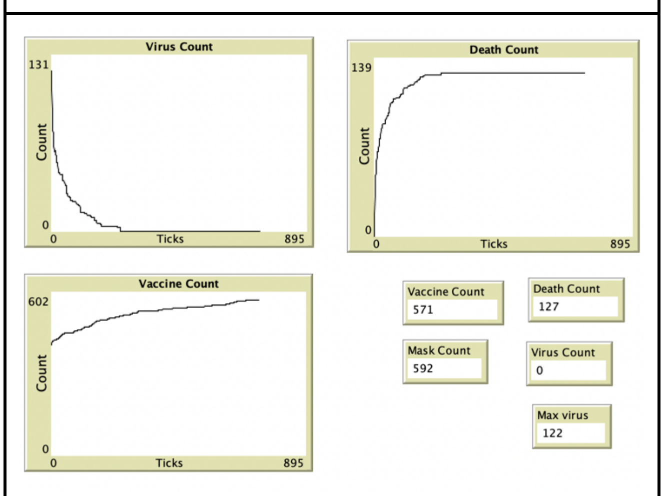

Figure 13. Trial 1 of Masks + Vaccine Experiment

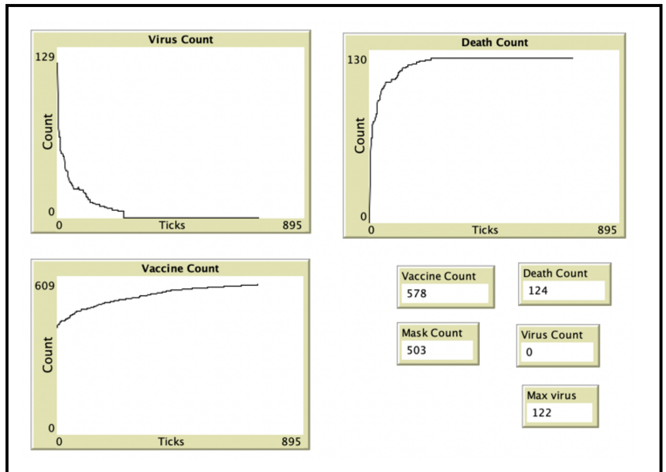

Figure 14. Trial 2 of Masks + Vaccine Experiment

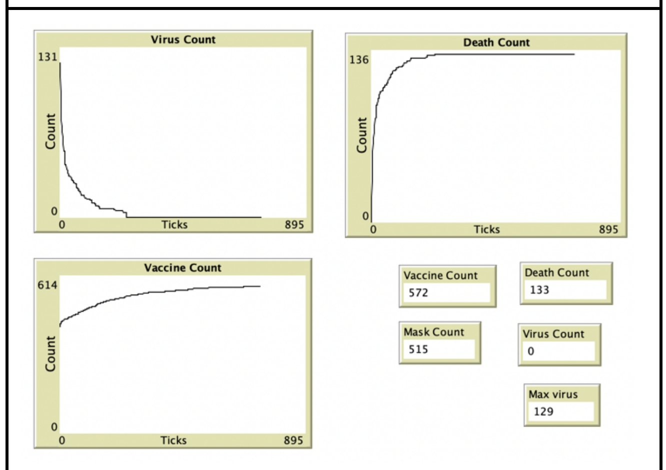

Figure 15. Trial 3 of Masks + Vaccine Experiment

7. CONCLUSION AND AREAS OF FURTHER WORK

This model displays the importance of implementing preventative measures to combat a virus. Even utilizing the bare minimum (just masks or just vaccines) had an impact on the virus spread rate. This model is useful not only for modelling the COVID-19 virus, but any other virus provided that some small elements of the model are changed to fit that specific virus. Two areas for improvement on this model include adding additional networks and expanding the region mapped out in order to make the model more accurate. Additional networks refer to social networks such as schools, workplaces, and homes. Currently, the agents in this model move randomly, but having them meet a specific group of people regularly might change how the virus spreads and how preventative measures work.

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APPENDIX A – ODD: PREVENTING VIRUS SPREAD

This document provides the detailed overview, design concepts, and details (ODD) of the agent-based model on preventing virus spread.

1. OVERVIEW

1.1 Purpose and Patterns

The overall *purpose* of this model is to test how a virus spreads through a community and if we can implement preventative features. Specifically, we are addressing the following question: How does implementing fear of the virus affect the rate at which the virus spreads throughout the community and number of deaths? Additionally, how does implementing preventative measures such as vaccination status and masks change this rate as well? To consider our model realistic enough for its purpose, we use *patterns* in vaccination rates and COVID-19 case rates.

1.2 Entities, State Variables, and Scales

The model includes the following *entities*: people and square grid cells, which have the *scale* of 0.01 x 0.01 mile^2. The *state variables* characterizing these entities are listed below in Table 1. People can have and spread the virus, but they can avoid catching it by having a mask or vaccination. Also, people with the virus are more likely to die as they get older. This reflects the death rates of the COVID-19 virus. The virus is spread through movement, as most of the agents will be moving along the roads.

For the *spatial* and *temporal* resolution and extent: A tick in the model represents 1 hour and the model is run for 1 month - or 730 ticks. The model was run on a 260 x 240 cell structure in NetLogo. The structure represents the area of Washington, D.C.

Table 1. Entities and state variables of the virus model

Entity	Variable	Description	Possible Values	Units
Person	virus?	If the person has the virus or not	True/False	--
	mask?	If the person wears a mask or not	True/False	--
	vaccine?	If the person has a vaccine or not	True/False	--
	age	Age of a person	0-99	Years
	virus-start	The tick count when the agent first got the virus	1-8760	Ticks
	amt-moved	The amount the agent moved	1+	Units
	status	Living status of the agent	dead/alive	--
Road	road-here	If a road crosses over that patch	0/1	--

1.3 Process Overview and Scheduling

The most important *processes* of the model, which are repeated every *time step,* are the movement of the people and the viral status of the people. A person can transfer their viral status to another by being neighbors with them (passing them on the street) and if they are both unmasked and unvaccinated. A person has the virus for 240 ticks - this represents the 10 days a person is infectious with COVID-19. Within those 240 ticks, they may die, with a greater chance of death as they age. The *scheduling* of my model is as follows:

The environment sets up the roads, the agents, and their properties using the 'setup' function. It then executes its 'go' function, which contains references to other functions - 'move', 'death', 'mask-on', 'virus-transmit', 'virus-length', and 'vaccination'.

Movement is determined based on a combination of variables. The people move along the roads by using the road-here variable. The amount of movement is determined by random number generation.

Death is determined based on the age and viral status of the person. Death is possible for all people who have the virus, but the probability increases as the age increases - this mirrors the COVID-19 trends of death (Statista).

The mask variable can change depending on the neighbors' mask variables. I will use the 'herd mentality' theory to set the mask variable. Therefore, if more than 4 of a person's neighbors do not wear masks, then they won't wear one either. I will set vaccination status similarly. However, once it is set, it cannot change.

The virus is transmitted as stated above. Before transmitting, however, we check to see how long the agent has had the virus for. If they have had the virus for 240 ticks, they can become healthy again.

The display and output are updated.

2. DESIGN CONCEPTS

2.1 Basic Principles

The *basic principle* of this virus model is to demonstrate how a virus spreads among a population, and predict if preventative measures can reduce the spread of the virus and deaths. Does implementing only masks change the number of deaths? What about just vaccinations? Does combining the two methods save more lives? Demonstrating the effectiveness of these preventative measures in a model can show people the importance of utilizing these preventative measures in their daily lives.

2.2 Emergence

The key *emergent* behaviors are the amount of people with the virus and the amount of deaths. By tracking the patterns of these behaviors, we can see which combination of preventative measures works the best in reducing virus transmission.

2.3 Adaptation

The *adaptive* behavior that agents adopt in this model is determining how much to move based on the viral status of neighbors and also whether to wear a mask or not based on the mask status of their neighbors.

2.4 Objectives

The *objective* of this model is to track the number of cases and deaths caused by the virus in different scenarios. I would consider my model a success if there is a correlation between the trends of virus cases and the preventative measures.

2.5 Learning

This model does not implement *learning*.

2.6 Prediction

This model does not implement *prediction.*

2.7 Sensing

The agents in this model use *sensing* to sense the viral status, mask status, and vaccination status of their neighbors. For simplicity's sake, we are assuming that the agents know these statuses with 100% accuracy throughout the entire model.

2.8 Interaction

Additionally, the agents in this model use *direct interactions* with each other to transmit the virus, as well as mask and vaccination statuses. These interactions occur randomly, just based on the agents that are "in the neighborhood" of the current agent.

2.9 Stochasticity

Stochasticity is a very important factor in this model. The locations of the agents are determined randomly, as are the initial viral status, mask status, and vaccination status. The length of the "steps" that each agent takes are also determined randomly. Stochasticity is important in this model because it represents the randomness of people, and it makes the model more realistic.

2.10 Collectives

This model does not implement *collectives*.

2.11 Observation

The key *observations* that are made in this model are the number of cases and deaths. These will both be shown graphically. By tracking these graphically, we can see the trend of cases and deaths over time.

3. Details

3.1 Implementation

Netlogo 6.2.0 is used in this model.

3.1 Initialization

For the user to set up the model, they just need to click the 'setup' button. The roads will be taken from the Open Data DC Roads database (Open Data DC). Approximately 700 agents will be randomly placed on the map, with 119 agents with the virus. I chose 119 agents because the current percent positivity rate in Washington DC is 17% (Coronavirus DC). About 69% will be vaccinated (Our World In Data), and 63% will be masked (Katz). This is the approximate masking rate in Washington DC.

The rates of vaccination, viral status, and masking status will remain the same across multiple runs of the model. The roads will also remain the same. This is a generic model. However, the locations of the agents will differ, as they are chosen randomly.

3.2 Input data

This model only uses spatial data from the Open Data DC Roads database (Open Data DC) to create the roads. It does not take any other *input data*.

3.3 Submodels

There are two main *submodels* in this model, however, there are additional subcategories to these submodels. The first main submodel is healthy agents.

Healthy agents are free to move as much as they want. They cannot transmit the virus, they can get it if they are not either masked or vaccinated. If at least one of the agents' neighbors has the virus, the agent will get the virus.

Agents with viruses have free movement as well. Agents with viruses can also have masks, but they cannot be vaccinated. They can transmit it to any agent without a vaccination and mask. As soon as their 240 ticks are over, they are healthy agents. Each agent has a chance of dying with the virus, but as the age of the agent increases, their chance of dying increases as well. The risk of death was determined by actual COVID-19 death data. Death will be decided with random numbers. These are the two main submodels, but there are also submodels within each submodel - masks and vaccination status.

Masking status is determined by the agents' neighbors as well. If 4 or more of the neighbors wear masks, the agent will also wear a mask.

Vaccination status is determined similarly. If 4 or more of the neighbors are vaccinated, the agent will also get vaccinated. However, it cannot be reversed.

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