Covid-19: A Guide to Understanding its Prevention Measures

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Keywords: Agent-Based Modeling, COVID-19, Masking, Social Distancing, Netlogo.

1 Overview

Agent-Based Modeling is a useful tool in understanding disease transmission, seen in research of related community-impacted models, such as the 1918 Spanish flu and isolated variants of Ebola in Africa. Moreover, Agent-Based Models are also important in predicting COVID-19 trends and developing proper prevention measures, each country taking a different strategy given their respective cases, positivity rates, death rates, etc. In this paper and through our model, we extend our current understanding of transmission rates and prevention measures to simulate the spread of COVID-19 in a human population, specifically. In order to accurately model disease spread in an isolated country, we use policies and data provided by the CDC to enhance our country-specific knowledge of contact tracing and interpersonal communication. Our base model simulates COVID-19 interactions within a population, and, with each interaction, the chance of contracting the virus increases. We extend our model to incorporate prevention measures- a person wearing a face mask who simultaneously practices social distancing will not transmit the virus, nor will they contract the virus themselves. Furthermore, we indicate whether a person returns to a healthy or dead state following infection. The parameters in the model are well-documented and are modifiable in order to adapt to other countries' data.

1.1 Purpose and Patterns

The purpose of this model is to understand and identify virus spread when the population adheres to COVID-19 prevention measures, namely masking and social distancing. This model initially simulated the COVID-19 spread of the Hong Kong general population, with data collected from a COVID-19 data website called *OurWorldinData* that indicates daily cases. The finalized model did not incorporate country data, but the CDC statistics remained constant. Social distancing and masking are analyzed in this process, though we acknowledge that there are other aspects that can cause an increase or decrease in overall cases, death rates, transmission rates, etc., such as government lockdowns, ease of restrictions, religious gatherings, school breaks, and new variants.

The model does not attempt to provide reliable predictions of future cases of disease; it focuses on the daily case rate and moving average of cases in-country. Due to the aforementioned aspects that can drastically affect COVID's presence within a population, it is highly unlikely that one can predict an accurate number of cases in the future. There are certain kinds of patterns that can prescribe a change to this model. Those patterns are:

1. Wearing a mask and not practicing social distancing
2. Wearing a mask and social distancing
3. Not wearing a mask and not practicing social distancing
4. Not wearing a mask and social distancing

These patterns will determine the chances of each person contracting COVID. From CDC guidance, along with other online sources, we estimate the COVID-transmission rates using prevention measures as follows: a person who wears their mask but doesn't practice social distancing will have a 20% chance of contracting COVID, a person who wears a mask and practices social distancing will have a 5.7% chance of getting infected with the virus, a person who doesn't wear a mask and social distances will have a 20% chance of COVID transmission, and a person who decides not to wear a mask and not practice social distancing will have a 32% higher chance of contracting COVID compared to the others.

1.2 Entities, State Variables, and Scales

1.2.1 Agents

The model includes agents that will hold one of several variables, and each agent is identified by one of the following characteristics:

- *Mask* factor, which represents whether a person is wearing a mask or not. Each scenario has a different outcome.
- *Social Distancing* factor, which represents whether a person is practicing social distancing or is not practicing social distancing. Each one of those have different outcomes.
- *Health Status*, an ordinal factor that represents the status of an individual within a four compartment HASD model, where *H* represents the healthy people, *A* represents the people that are infected but doesn't know it, *S* represents the people that are sick and infectious and visible, and *D* represents the people who are dead.

Table 1: Protocols following that affect state variables

Wearing a mask, No Social Distancing	Wearing a mask, Social Distancing
Not Wearing a mask, No Social Distancing	Not Wearing a mask, Social Distancing

During its model run, each agent holds one of the following states:

Table 2: State variables describing the X agents

State Variable	Description	Data Type
Healthy	Social distancing/ masking effective	Green
Infected, doesn't know	Possible recovery, slight masking	Blue
Sick, infectious, visible	Possible recovery, slight masking, automatic result from previous stage	Red
Dead	No social distancing practice	Invisible

1.2.2 Spatiotemporal Scales

This model does not represent space, and agents interact within a broad population rather than spatial proximity. The time step represents one week. The user is able to control the number of ticks in the model. Each week will show us the total number of positive cases, deaths, people that have recovered, and asymptomatic cases.

1.2.3 Environment

The model initializes by having all the healthy agents present in the environment. The environment includes all of the agents presented in the state variable column of Table 1.

1.3 Process Overview and Scheduling

At each time step (a week), two things can happen:

1. Each agent who is either in the *A* or *S* stage will progress to the next state which will be the *H* or *D* within the span of a week. If the agent ends up in the *D* state, then it won't be able to play a part in the environment since it will be dead.
2. Every agent that is part of the *S* stage will infect the *H* stage right away, unless the *H* agent is practicing social distancing and/or is wearing a mask.
3. Almost every agent in the *A* state will end back up in the *H state.* Though in some cases, they might end up being a part of *S* state.

2 Design Concepts

2.1 Basic Principles

At its core, the model is designed to provide an understanding of COVID-19 preventative measures. After consulting various sources, our model uses prior knowledge of the effectiveness of masking and social distancing, sourced from the CDC; this prior knowledge, combined with our data, is used to affirm beliefs in masking policies and social distancing measures.

2.2 Emergence

The key outcome from this model comes from comparing the effectiveness of mask-wearing and social distancing practices.

2.3 Adaptation

This model implements adaptation in the case where agents will change their social interactions as the number of cases will increase to bring down the number of daily/ weekly cases in the future. Some prime examples of this can be school shutdowns, lockdowns, and stay at home orders.

2.4 Memory

This model does not implement memory.

2.5 Learning

This model does not implement learning.

2.6 Prediction

The agents do not engage in prediction.

2.7 Sensing

This model does not implement sensing.

2.8 Interactions

In this model, agents interact through the general population. If a healthy person interacts with an asymptomatic person or someone who has tested positive, they can contract the virus. This is how infections are transmitted.

2.9 Stochasticity

In this model, the disease progress is stochastic with probabilities that vary with the amount of time each agent has spent in a specific status. A prime example of this would be the progress of an agent who is in the S stage and will go to each H or D state over time. Same applies for A with a higher chance of going to the H stage. Transmission of disease is stochastic. It is used in initializing the amounts of each agent.

2.10 Collectives

This model does not implement collectives.

2.11 Observation

There are several outputs being observed by the model:

(1) The total number of people who contract COVID-19
(2) Percentage of overall population that contract COVID-19
(3) Percentage of non-mask-wearers who contract COVID-19, as compared to their mask-wearing counterparts

These statistics evolve as the model runs; hard values, such as total numbers, will show a monotonic increase of values, but our percentages may increase or decrease based on how long we run the simulation and how we toggle the user-input switches, i.e. increasing the amount of people who wear masks or social distance.

3 Details

3.1 Implementation

The model is implemented in Netlogo 6.2.0, using Python and SQL for data cleanup.

3.2 Initialization

Through user input, the model can be initialized with a varying infection-rate (1-10%), amount of people (0-1000), social-distancing toggles, and masking toggles.

3.3 Input Data

There is one external data source that is used as input for this model. The CDC presents probabilities of disease transmission when one uses prevention measures. These statistics are coded within our model, and these probabilities drive the simulation.

3.4 Submodels

3.4.1 Attributes

setup: This function is used to set up the model. User is prompted to click on this button to reset all the settings to default settings.
go: This function is used to run the model. Once the user clicks on this button, the user will be able to see the simulation based on the settings they chose.
next-week: This button will move the simulation forward by one week.
show-dead: user toggled to identify whether the portion of the population that dies is visible, defaulted invisible

3.4.2 Strategy

Not Wearing a mask, No Social Distancing: This strategy would be set as the default setting. Users can choose to either keep this setting or change to another strategy before running the model.
Wearing a mask, No Social Distancing: This strategy would be set as the secondary strategy and the user will have an option to choose this strategy over the other three.
Wearing a mask, Social Distancing: This strategy would be set as the secondary strategy and the user will have an option to choose this strategy over the other three.
Not Wearing a mask, Social Distancing: This strategy would be set as the secondary strategy and the user will have an option to choose this strategy over the other three.

4 Model Components

4.1 Model Logic and Flow

The process that takes place every time the model runs is summarized as a model flow diagram in Figure 1.

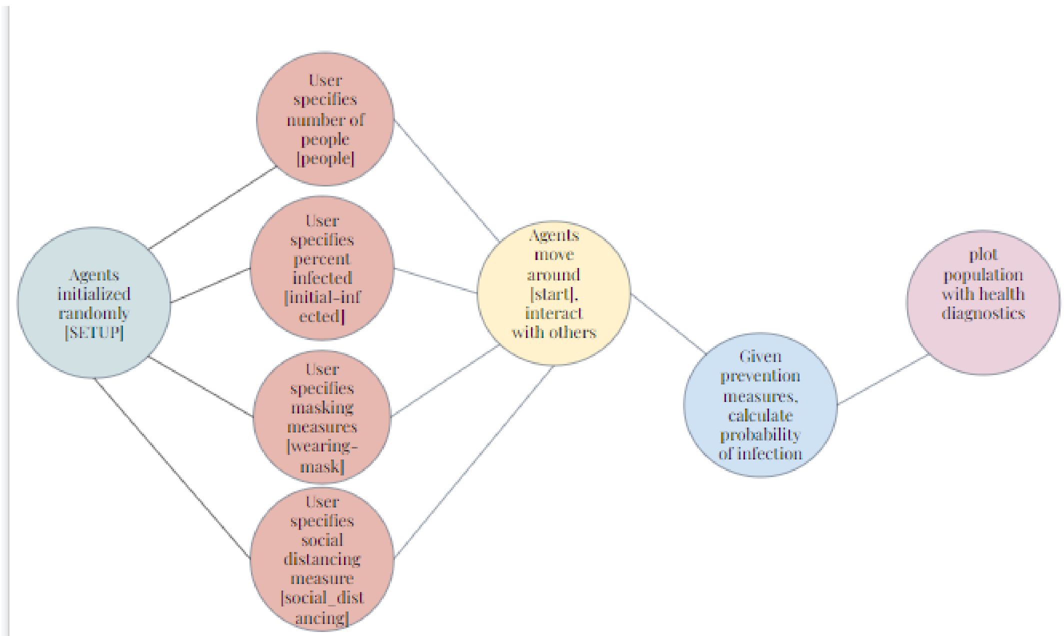


Figure 1: Model Flow Diagram.

4.2 Model Interface

A screenshot of the model interface and the results that are being shown at the time time the model is running are shown in Figure 2.

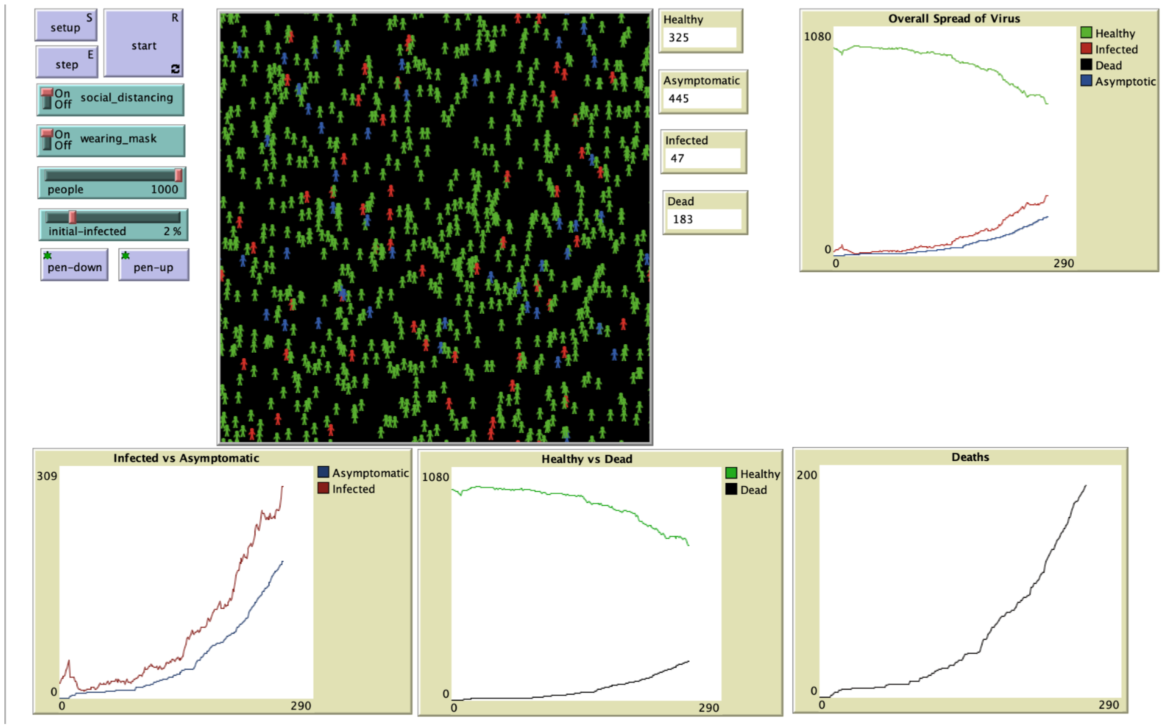


Figure 3: Visual representation of the model that shows rates of COVID infections when prevention measures are used.

5 Experiments, Results, and Findings

5.1 Experiments

In this experiment, we attempt to test the impact of two different Covid-19 prevention measures. As there are four separate outcomes, we will toggle each switch after each simulation to infer results about our model behavior. We make the change to the model prior to simulating its behavior; the switches will be toggled prior to starting the model. The test will be conducted across a period of 300 ticks and the values for healthy, asymptomatic, symptomatic, and dead persons will be recorded through monitor output, as well as a plot documenting the spread of the virus, for a total of two simulations per experiment. We choose to initialize our model with 500 people with an initial-infected rate of 5% for all simulations.

In the first experiment we will leave both toggles that represent social distancing and masking off. It is anticipated that the model will show an exponential increase in cases and deaths, and the healthy population will decrease at an equally decreasing rate. In the second experiment we will toggle-on masking and leave social distancing off. It is anticipated that the model will show a delayed response to the masking measures as compared to the first experiment, but the amount of deaths will similarly follow the infection rate, though delayed. In the third experiment we will toggle-on social distancing and leave masking off. It is anticipated that the model will show similar results to the second experiment, where the model will show a delayed response to the social distancing measures as compared to the first experiment, but the amount of deaths will similarly follow the infection rate, though delayed. In the fourth experiment we will toggle-on both social distancing and masking. It is anticipated that the model will show a virtually healthy population throughout the simulation. As a result, it might be inferred that these prevention measures are effective against COVID transmission.

5.2 Results and Findings

The first experiment sought to create a baseline scenario over a test period of 300 ticks. The results of the model experiment across three model runs are shown in the plots below. As expected, both the plot and the simulation indicate a high transmission rate and a high death rate.

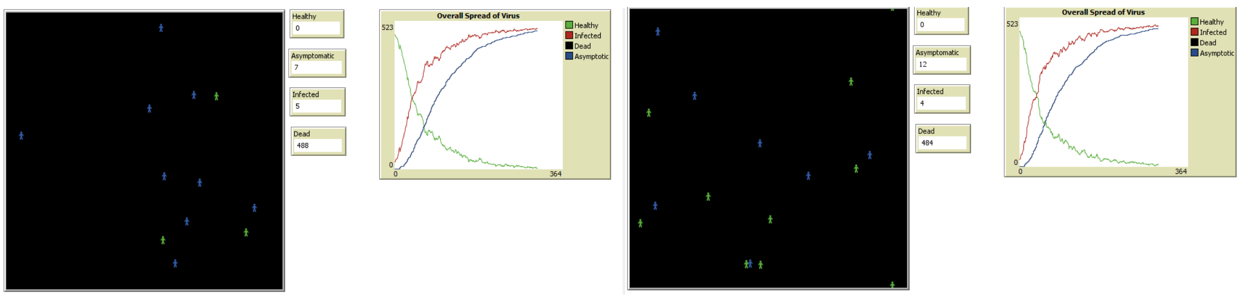


Figure 3: Experiment 1 Results

The second experiment sought to test the impact of masking measures relative to the baseline scenario over a test period of 300 ticks. The results of the model experiment across 100 model runs are shown in the plots below. The model shows a delayed response to the masking measures as compared to the first experiment.

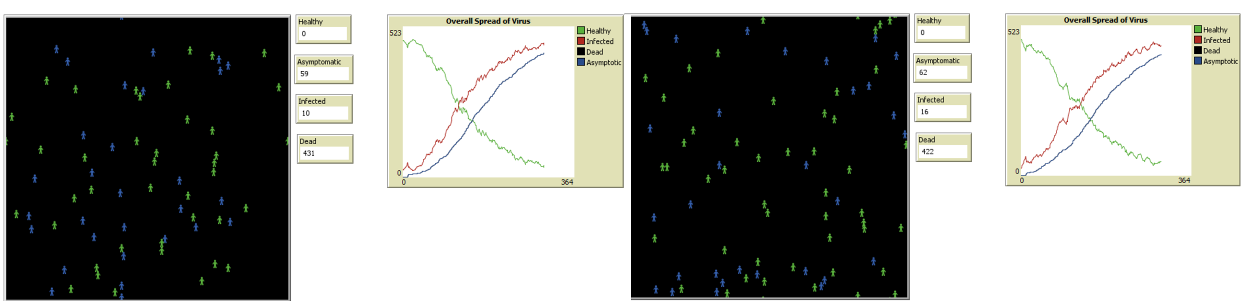


Figure 4: Experiment 2 Results

The third experiment sought to test the impact of social distancing relative to the baseline scenario over a test period of 300 ticks. The results of the model experiment across three model runs are shown in the plots below. The model shows a delayed response to the social distancing measures as compared to the first experiment.

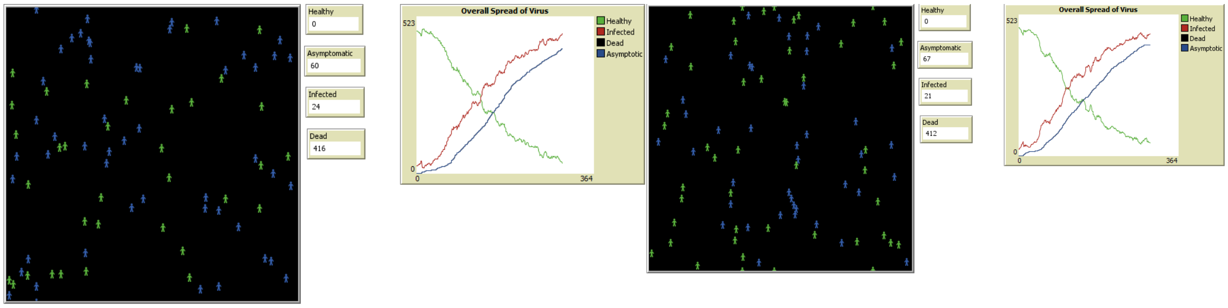
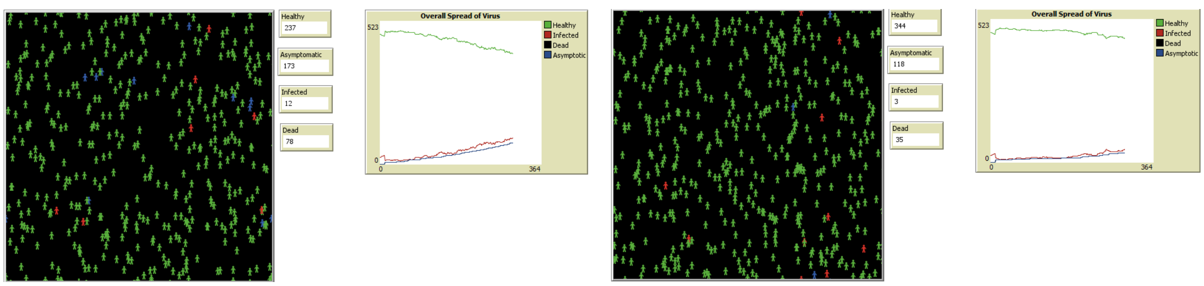


Figure 5: Experiment 3 Results

The fourth experiment sought to test the impact of both masking measures and social distancing measures relative to the baseline scenario over a test period of 300 ticks. The results of the model experiment across three model runs are shown in the plots below. The model shows a virtually healthy population throughout the simulation.



6 Conclusion

This model shows us the significance of implementing preventative measures to fight against such a viral virus. Even following one of the prevention methods had a huge change in the number of cases and number of deaths. This model is designed in a way that it can be changed to fit any other virus by changing the percentages and a couple of variables.

7 References

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Appendix A

ODD: A Guide to Understanding its Prevention Measures

This document provides the detailed overview, design concepts, and details (ODD) of the agent based model on COVID and its prevention methods.

Keywords: Agent-Based Modeling, COVID-19, Hong Kong, Social Distancing, Netlogo.

1 Overview

Agent-Based Modeling is a useful tool in understanding disease transmission, seen in research of related community-impacted models, such as the 1918 Spanish flu and isolated variants of Ebola in Africa. Moreover, Agent-Based Models are also important in predicting COVID-19 trends and developing proper prevention measures, each country taking a different strategy given their respective cases, positivity rates, death rates, etc. In this paper and through our model, we extend our current understanding of transmission rates and prevention measures to simulate the spread of COVID-19 in a human population, specifically Hong Kong. In order to accurately model disease spread in an isolated country, we use policies and data provided by the Hong Kong government to enhance our country-specific knowledge of contact tracing and interpersonal communication. Our base model simulates COVID-19 interactions within a population, and, with each interaction, the chance of contracting the virus increases. We extend our model to incorporate prevention measures- a person wearing a face mask who simultaneously practices social distancing will not transmit the virus, nor will they contract the virus themselves. Furthermore, we indicate whether a person returns to a healthy or dead state following infection. The parameters in the model are well-documented and are modifiable in order to adapt to other countries' data.

1.1 Purpose and Patterns

The purpose of this model is to understand and identify virus spread when the population adheres to COVID-19 prevention measures, namely masking and social distancing. This model initially simulated the COVID-19 spread of the Hong Kong general population, with data collected from a COVID-19 data website called *OurWorldinData* that indicates daily cases. The finalized model did not incorporate country data, but the CDC statistics remained constant. Social distancing and masking are analyzed in this process, though we acknowledge that there are other aspects that can cause an increase or decrease in overall cases, death rates, transmission rates, etc., such as government lockdowns, ease of restrictions, religious gatherings, school breaks, and new variants.

The model does not attempt to provide reliable predictions of future cases of disease; it focuses on the daily case rate and moving average of cases in-country. Due to the aforementioned aspects that can drastically affect COVID's presence within a population, it is highly unlikely that one can predict an accurate number of cases in the future. There are certain kinds of patterns that can prescribe a change to this model. Those patterns are:

1. Wearing a mask and not practicing social distancing
2. Wearing a mask and social distancing
3. Not wearing a mask and not practicing social distancing
4. Not wearing a mask and social distancing

These patterns will determine the chances of each person contracting COVID. From CDC guidance, along with other online sources, we estimate the COVID-transmission rates using prevention measures as follows: a person who wears their mask but doesn't practice social distancing will have a 20% chance of contracting COVID, a person who wears a mask and practices social distancing will have a 5.7% chance of getting infected with the virus, a person who doesn't wear a mask and social distances will have a 20% chance of COVID transmission, and a person who decides not to wear a mask and not practice social distancing will have a 32% higher chance of contracting COVID compared to the others.

1.2 Entities, State Variables, and Scales

1.2.1 Agents

The model includes agents that will hold one of several variables, and each agent is identified by one of the following characteristics:

- *Mask* factor, which represents whether a person is wearing a mask or not. Each scenario has a different outcome.
- *Social Distancing* factor, which represents whether a person is practicing social distancing or is not practicing social distancing. Each one of those have different outcomes.
- *Health Status*, an ordinal factor that represents the status of an individual within a four compartment HASD model, where *H* represents the healthy people, *A* represents the people that are infected but doesn't know it, *S* represents the people that are sick and infectious and visible, and *D* represents the people who are dead.

Table 1: Protocols following that affect state variables

Wearing a mask, No Social Distancing	Wearing a mask, Social Distancing
Not Wearing a mask, No Social Distancing	Not Wearing a mask, Social Distancing

During its model run, each agent holds one of the following states:

Table 2: State variables describing the X agents

State Variable	Description	Data Type
Healthy	Social distancing/ masking effective	Green
Infected, doesn't know	Possible recovery, slight masking	Blue
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Dead	No social distancing practice	Invisible

1.2.2 Spatiotemporal Scales

This model does not represent space, and agents interact within a broad population rather than spatial proximity. The time step represents one week. The user is able to control the number of ticks in the model. Each week will show us the total number of positive cases, deaths, people that have recovered, and asymptomatic cases.

1.2.3 Environment

The model initializes by having all the healthy agents present in the environment. The environment includes all of the agents presented in the state variable column of Table 1.

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At each time step (a week), two things can happen:

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2. Every agent that is part of the *S* stage will infect the *H* stage right away, unless the *H* agent is practicing social distancing and/or is wearing a mask.
3. Almost every agent in the *A* state will end back up in the *H state.* Though in some cases, they might end up being a part of *S* state.

2 Design Concepts

2.1 Basic Principles

At its core, the model is designed to provide an understanding of COVID-19 preventative measures. After consulting various sources, our model uses prior knowledge of the effectiveness of masking and social distancing, sourced from the CDC; this prior knowledge, combined with our data, is used to affirm beliefs in masking policies and social distancing measures.

2.2 Emergence

The key outcome from this model comes from comparing the effectiveness of mask-wearing and social distancing practices.

2.3 Adaptation

This model implements adaptation in the case where agents will change their social interactions as the number of cases will increase to bring down the number of daily/ weekly cases in the future. Some prime examples of this can be school shutdowns, lockdowns, and stay at home orders.

2.4 Memory

This model does not implement memory.

2.5 Learning

This model does not implement learning.

2.6 Prediction

The agents do not engage in prediction.

2.7 Sensing

This model does not implement sensing.

2.8 Interactions

In this model, agents interact through the general population. If a healthy person interacts with an asymptomatic person or someone who has tested positive, they can contract the virus. This is how infections are transmitted.

2.9 Stochasticity

In this model, the disease progress is stochastic with probabilities that vary with the amount of time each agent has spent in a specific status. A prime example of this would be the progress of an agent who is in the S stage and will go to each H or D state over time. Same applies for A with a higher chance of going to the *H* stage. Transmission of disease is stochastic. It is used in initializing the amounts of each agent.

2.10 Collectives

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2.11 Observation

There are several outputs being observed by the model:

(1) The total number of people who contract COVID-19
(2) Percentage of overall population that contract COVID-19
(3) Percentage of non-mask-wearers who contract COVID-19, as compared to their mask-wearing counterparts

These statistics evolve as the model runs; hard values, such as total numbers, will show a monotonic increase of values, but our percentages may increase or decrease based on how long we run the simulation and how we toggle the user-input switches, i.e. increasing the amount of people who wear masks or social distance.

3 Details

3.1 Implementation

The model is implemented in Netlogo 6.2.0, using Python and SQL for data cleanup.

3.2 Initialization

Through user input, the model can be initialized with a varying infection-rate (1-10%), amount of people (0-1000), social-distancing toggles, and masking toggles.

3.3 Input Data

There is one external data source that is used as input for this model. The CDC presents probabilities of disease transmission when one uses prevention measures. These statistics are coded within our model, and these probabilities drive the simulation.

3.4 Submodels

3.4.1 Attributes

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go: This function is used to run the model. Once the user clicks on this button, the user will be able to see the simulation based on the settings they chose.
next-week: This button will move the simulation forward by one week.

show-dead: user toggled to identify whether the portion of the population that dies is visible, defaulted invisible

3.4.2 Strategy

Not Wearing a mask, No Social Distancing: This strategy would be set as the default setting. Users can choose to either keep this setting or change to another strategy before running the model.
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