Integrating Behavioral Theories and Agent-Based Models of Disease Spread

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Perspectives on GeoComputation Approaches for Urban and Regional Systems I

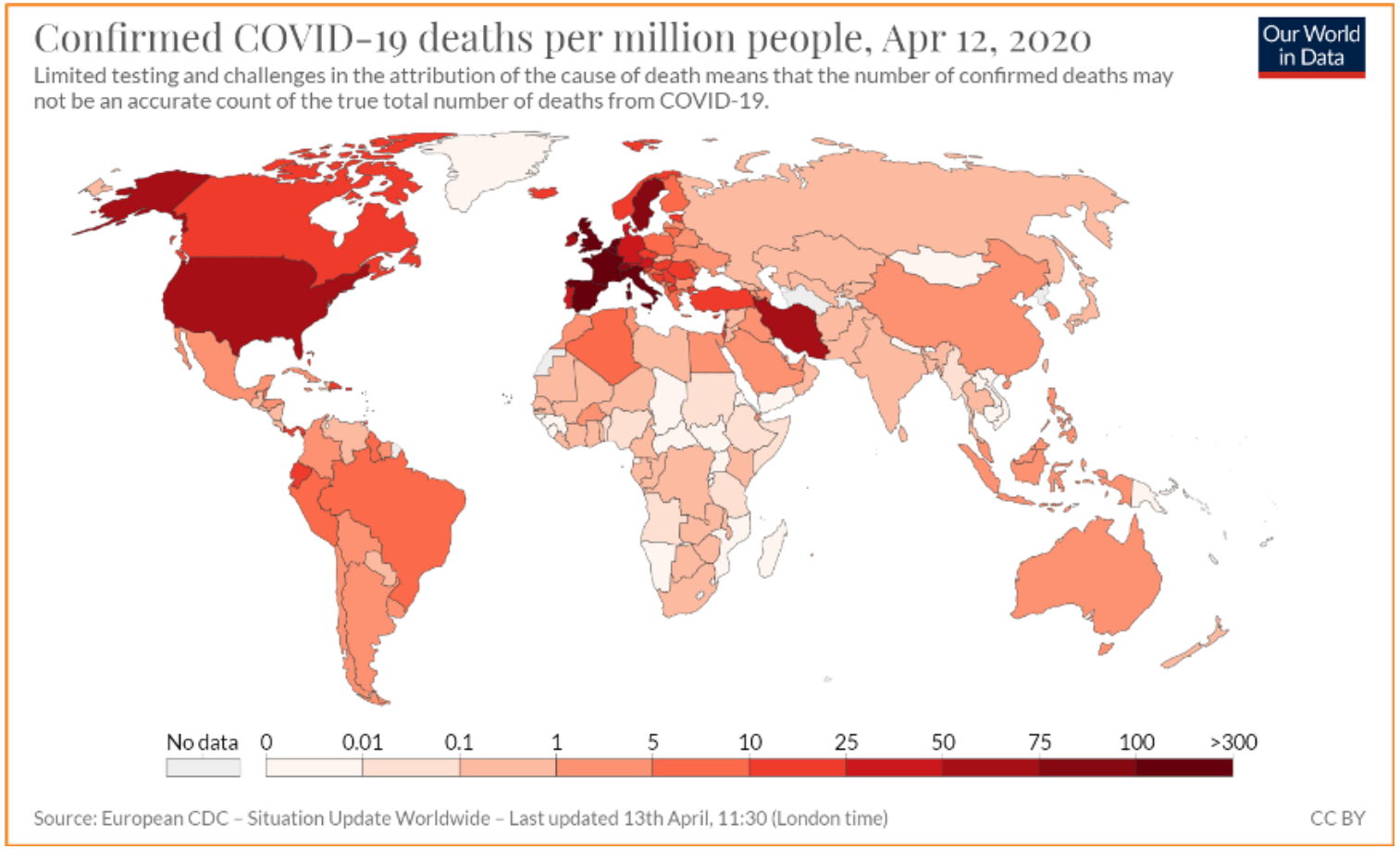
69th Annual North American Meetings of the Regional Science Association International

November 11, 2022

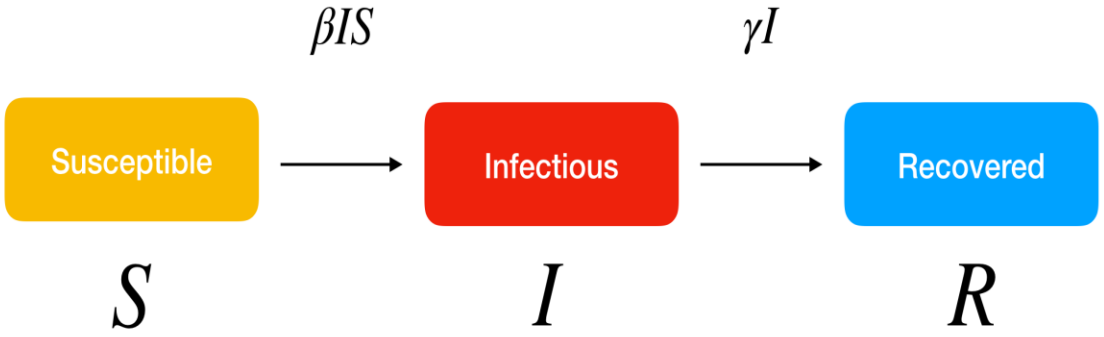
Introduction

- Infectious respiratory diseases pose a critical threat to global health

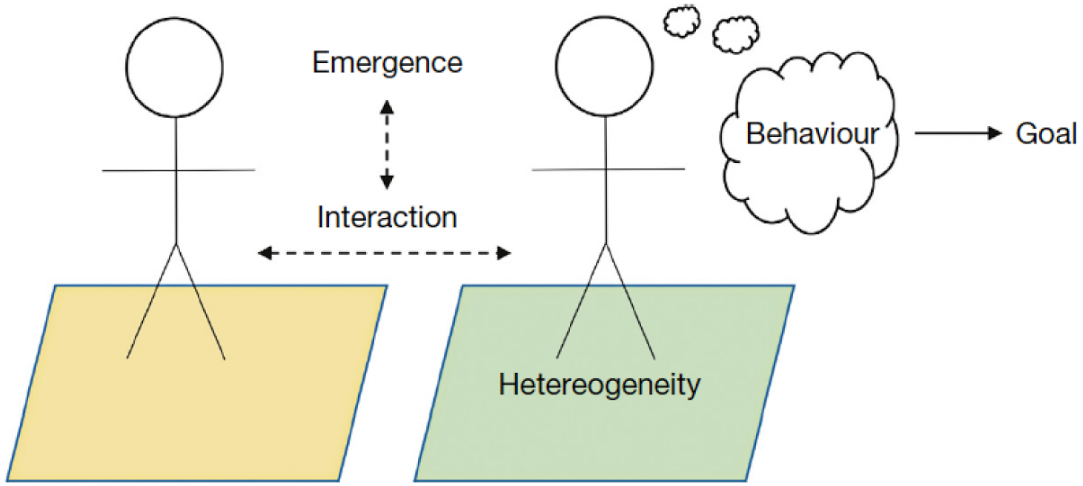
- Epidemiological models are vital tools for policymakers



Disease Modelling Approaches



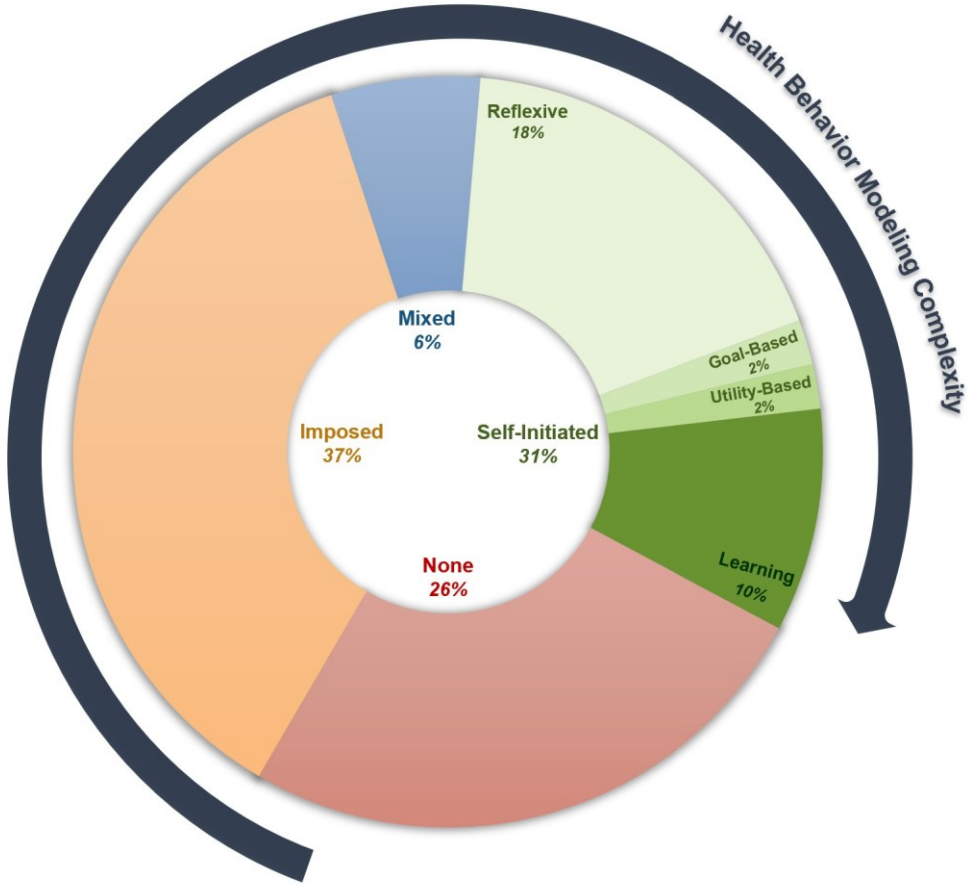
Compartmental Model



Agent-based Model

Motivation

- Existing ABMs often overlook or oversimplify health behaviors due to several challenges



Anderson et al., In Revision

Research Objective

Improve representations of health behavior in ABMs infectious respiratory disease spread through integrating a flexible and data-driven agent decision-making framework with a spatial ABM.

Methods Overview

1. **Constructing agent decision framework** that leverages behavioral theories and data to capture health behaviors of individuals
2. **Develop a spatial ABM** to simulate the spread of COVID-19 among the student population at George Mason University
3. **Integrating the agent decision framework and the spatial ABM** to estimate the effect of masks (*future work)



Agent Decision-Making Framework

- Capable of leveraging behavioral theories and data to conceptualize agent decision making on adopting health behaviors
- Involves a standard logistic regression model expressed in the terms of odd ratios (Durham & Casman, 2012)

$$p(mask) = \frac{OR_0 * \Pi_i OR_i^{X_i}}{1 + OR_0 * \Pi_i OR_i^{X_i}}, i = 1, \ldots 3$$

Logistic Regression Model

- Represents variables that explain health behavior
  - Any variables that describe human behaviors can be used
  - This makes the framework applicable for a range of health behaviors and supports various forms of variables, including behavioral theories and data

$$p(mask) = \frac{OR_0 * \Pi_i OR_i^{X_i}}{1 + OR_0 * \Pi_i OR_i^{X_i}}, i = 1, \ldots 3$$

Logistic Regression Model

- Binary form of the variable representing the state
  - High → 1
  - Low → 0
  - Continuous variables are reclassified by researcher

$$p(mask) = \frac{OR_0 * \Pi_i OR_i^{X_i}}{1 + OR_0 * \Pi_i OR_i^{X_i}}, i = 1, \ldots 3$$

Logistic Regression Model

- A constant that defines the probability when all of the binary variables are low
  - The intercept that is calculated with the odds ratios

$$p(mask) = \frac{OR_0 * \Pi_i OR_i^{X_i}}{1 + OR_0 * \Pi_i OR_i^{X_i}}, i = 1, \ldots 3$$

Logistic Regression Model

- Value of the relative odds ratios for each variable
  - Measures the strength of association between two events

$$p(mask) = \frac{OR_0 * \Pi_i OR_i^{X_i}}{1 + OR_0 * \Pi_i OR_i^{X_i}}, i = 1, \ldots 3$$

Logistic Regression Model

- A threshold used to determine the agent's adoption of a health behavior
  - The fraction of respondents with the corresponding predicted behaviors are then extrapolated to the agent population

$$p(mask) = \frac{OR_0 * \Pi_i OR_i^{X_i}}{1 + OR_0 * \Pi_i OR_i^{X_i}}, i = 1, \ldots 3$$

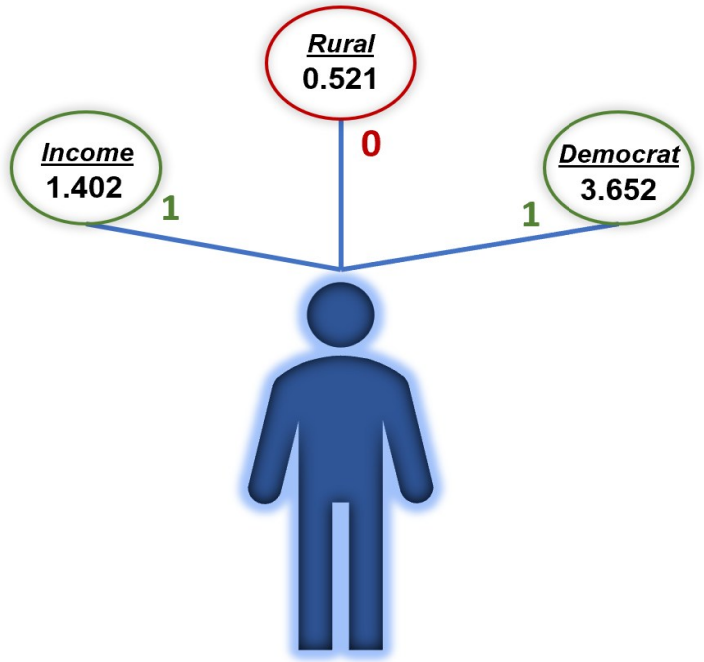
Applying the Decision Framework

- Currently using socio-demographic and mask usage data from a national survey
- Using gender, ethnicity, income, location and party affiliation as variables
- Odds ratios were calculated for each of the variables

Variables	Odds-Ratio	P-Value
Wore a mask 3 or more times		
Gender: Male	0.8984822	0.281
Race: Black	1.458916	0.056
Income: $20k-40k	1.401515	0.013
Location: Rural	0.5210687	0.000
Party: Democrat	3.652081	0.000
Base Outcome: Wears a mask 0 times		
Intercept: 1.415093		

Applying the Decision Framework

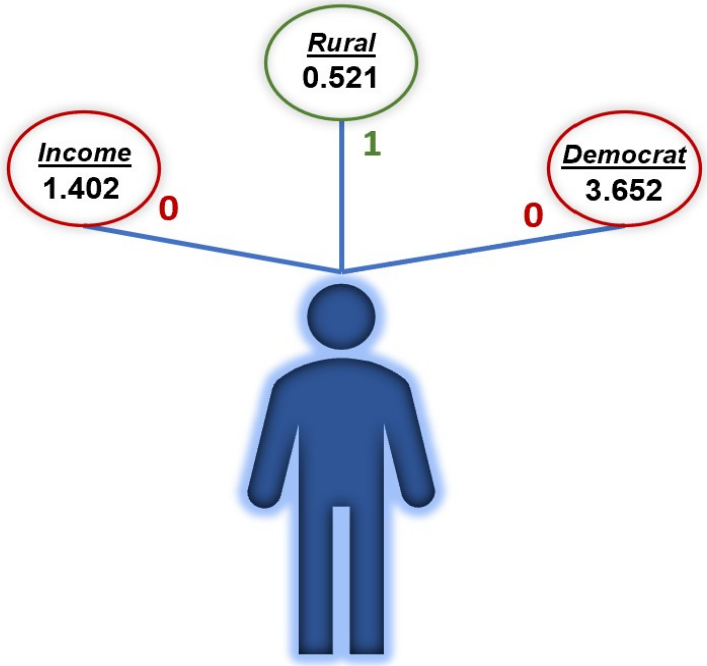
- Enter the values of the odd ratios into the logistic regression equation
  - Captures the association between socio-demographic data and mask use → predicts the probability of the agent with the given attributes



$$p(mask) = \frac{1.415 * (1.402^1 * 0.521^0 * 3.652^1)}{1 + 1.415 * (1.402^1 * 0.521^0 * 3.652^1)} = 0.879$$

Applying the Decision Framework

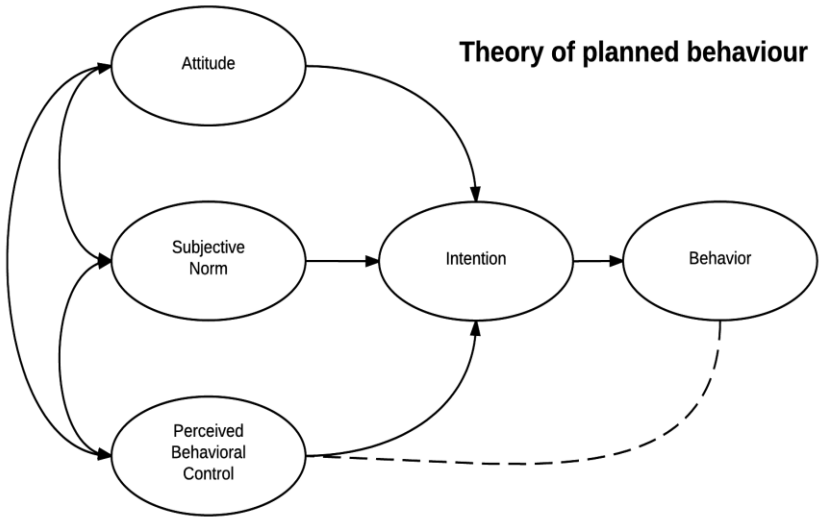
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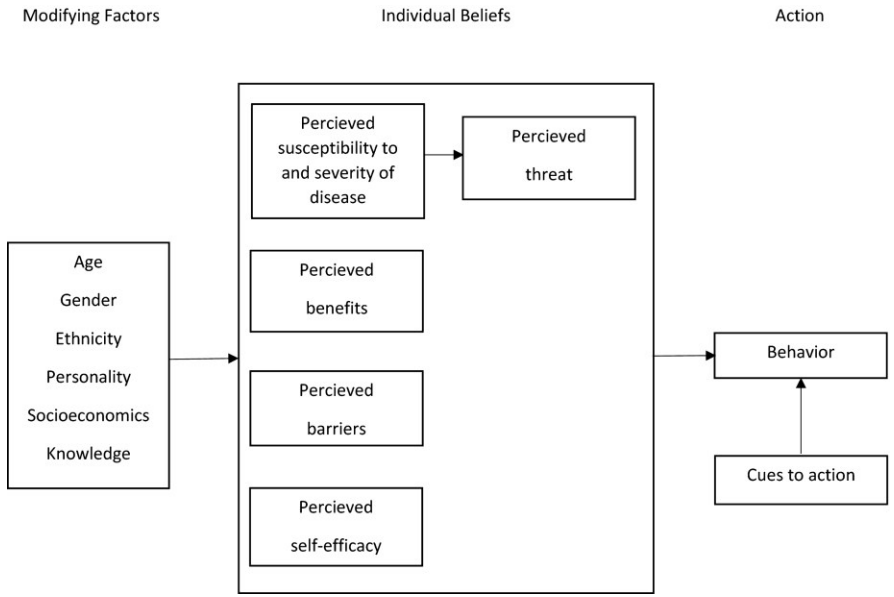
$$p(mask) = \frac{1.415 * (1.402^0 * 0.521^1 * 3.652^0)}{1 + 1.415 * (1.402^0 * 0.521^1 * 3.652^0)} = 0.420$$

Integrating Behavioral Theories

- Many theories guide with selecting variables



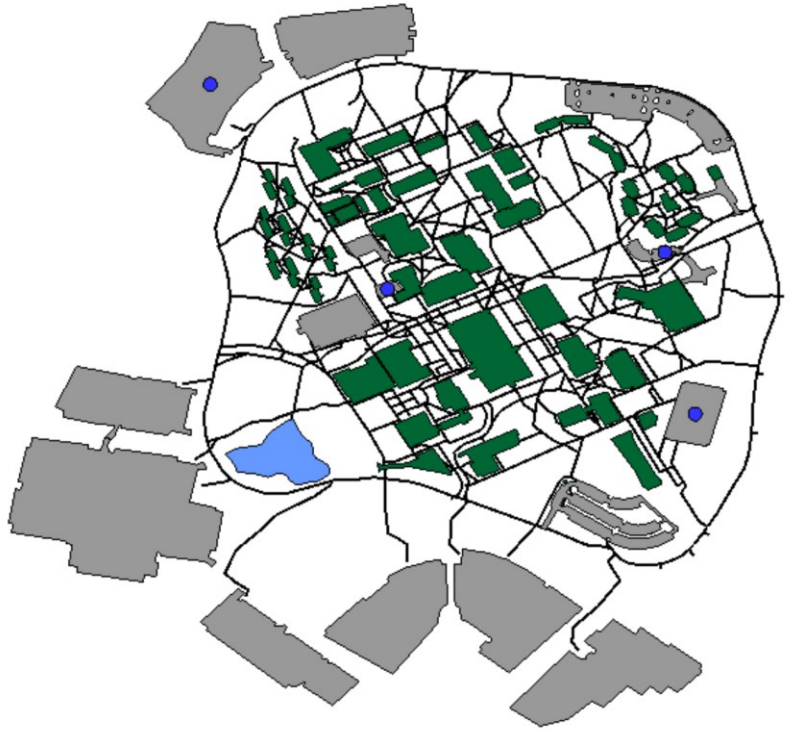
Theory of Planned Behavior



Health Belief Model

Geospatial ABM of Infectious Disease

- Expands upon ‘RepastCity’ (Malleson, 2012)
- Models COVID-19 and mask usage at GMU
- Undergraduate commuter Geography students
- Simulates days with a one second interval



Scheduling

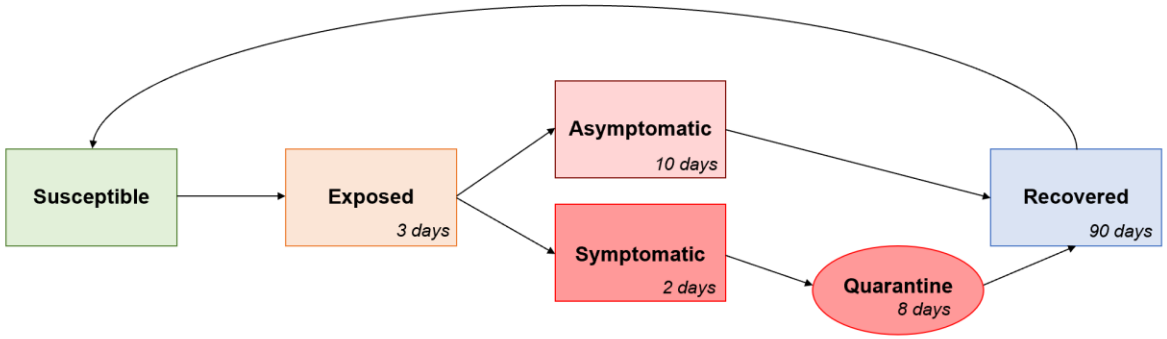
- Students follow a schedule representative of undergraduate commuter Geography students
  - Agents are randomly assigned buildings and sublocations at initialization

TIME	SCHEDULED EVENT
8:45	Agent starts walking to their first class
9:00	Agents have arrived at their first class (either in the Planetary Hall or Exploratory Hall)
10:15	Class ends and agents begin walking to the library to study (either in A wing or B wing)
1:00	Agents leave the library and walk to lunch (either in Student Union or Johnson Center)
2:45	Agents leave lunch and start walking to their second class
3:00	Agents have arrived at their second class (either in the Planetary Hall or Exploratory Hall)
4:15	Class ends and agents go back to the parking lot to go home

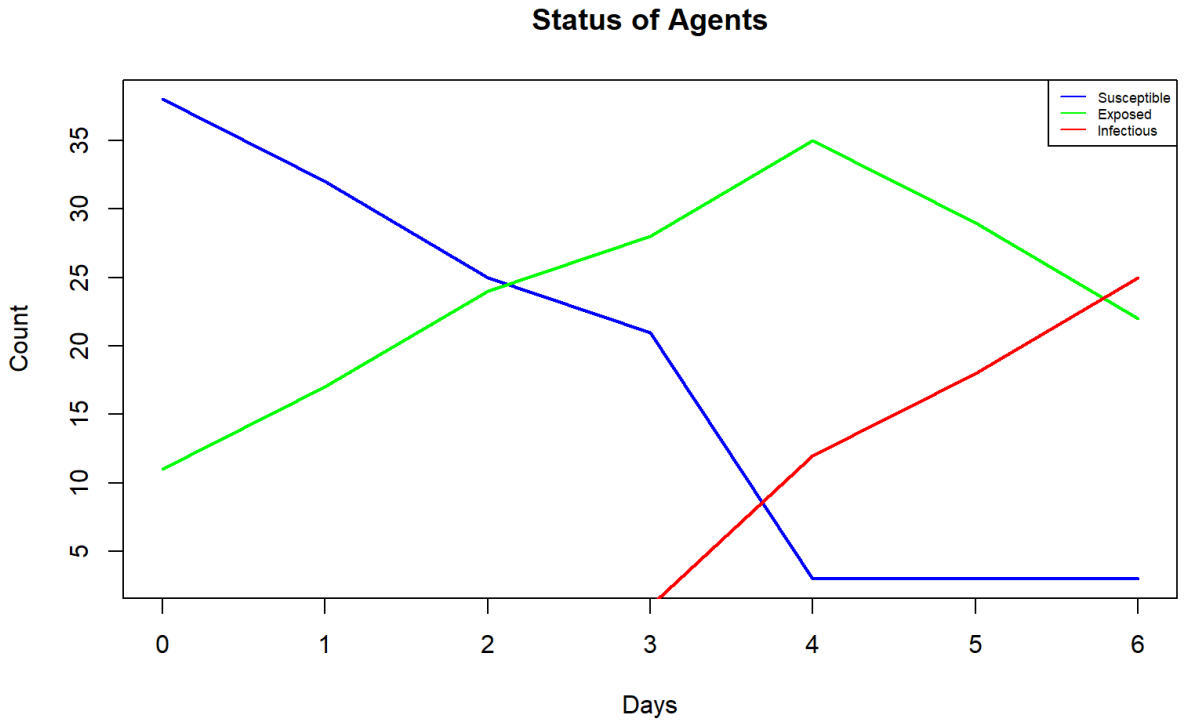
Disease Transmission

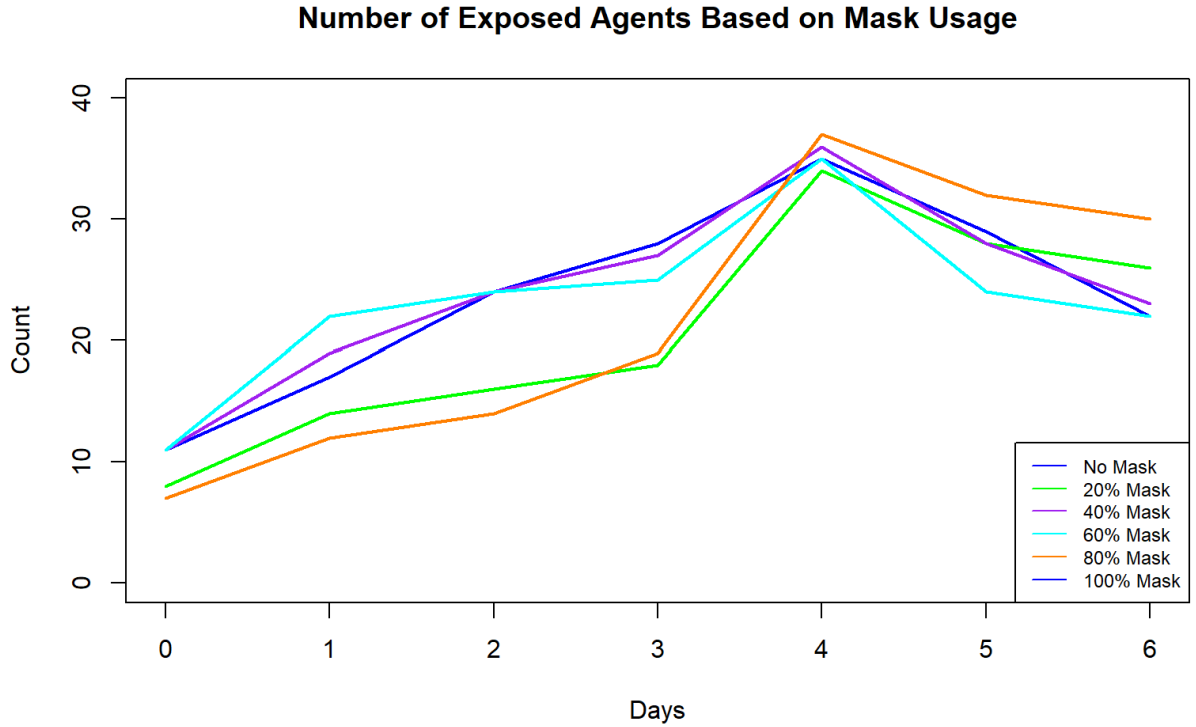
- Applies the SEIRS model
- Direct interaction leads to infection
- Agents can become exposed on campus or off-campus
- Mask behavior is initially imposed

Parameter	Value	Source
Transmission Rate	0.05	Alvarez et al. (2021); Gressman et al. (2020)
Transmission Rate with Mask	0.025	Gressman et al. (2020)
Off-campus Transmission Rate	0.25	Gressman et al. (2020)
Symptomatic Rate	0.60	Reveil et al. (2022); Kerr et al. (2021)
Exposed Period	3 days	Reveil et al. (2022)
Infectious Period	10 days	Reveil et al. (2022)
Quarantine Period	8 days	Reveil et al. (2022)
Recovered Period	90 days	CDC (2020)



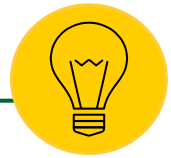
Results


Status of Agents
Susceptible
Exposed
Infectious
Count
5
10
15
20
25
30
35
0
1
2
3
4
5
6
Days


Number of Exposed Agents Based on Mask Usage
Count
0
10
20
30
40
0
1
2
3
4
5
6
Days
No Mask
20% Mask
40% Mask
60% Mask
80% Mask
100% Mask

Conclusion

- Constructed an agent decision-making framework and a spatial ABM of COVID-19
- Future work will involve integrating the framework with the ABM
- Refining the ABM and using behavioral theories to define variables will address limitations
- Improves the representation of health behaviors in ABMS of infectious respiratory disease spread



Questions?

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Acknowledgements:

This research is funded by the National Science Foundation (Award #2030685 and #2109647).