A Framework for Simulating Emergent Health Behaviors in Spatial Agent-Based Models of Disease Spread

Emma Von Hoene[1], Amira Roess[2] , Shivani Achuthan[3] &Taylor Anderson[1]

[1]Department of Geography and Geoinformation Science, George Mason University, Virginia, USA

[2]Department of Global and Community Health, George Mason University, Virginia, USA

[3] James Madison High School, Virginia, USA

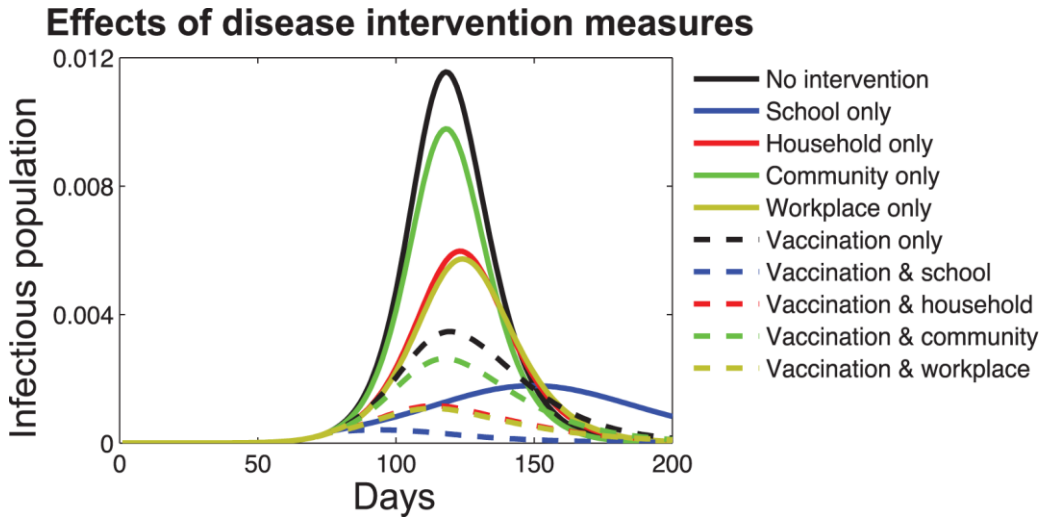
GeoSimulation (GeoSim) Workshop

31st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems

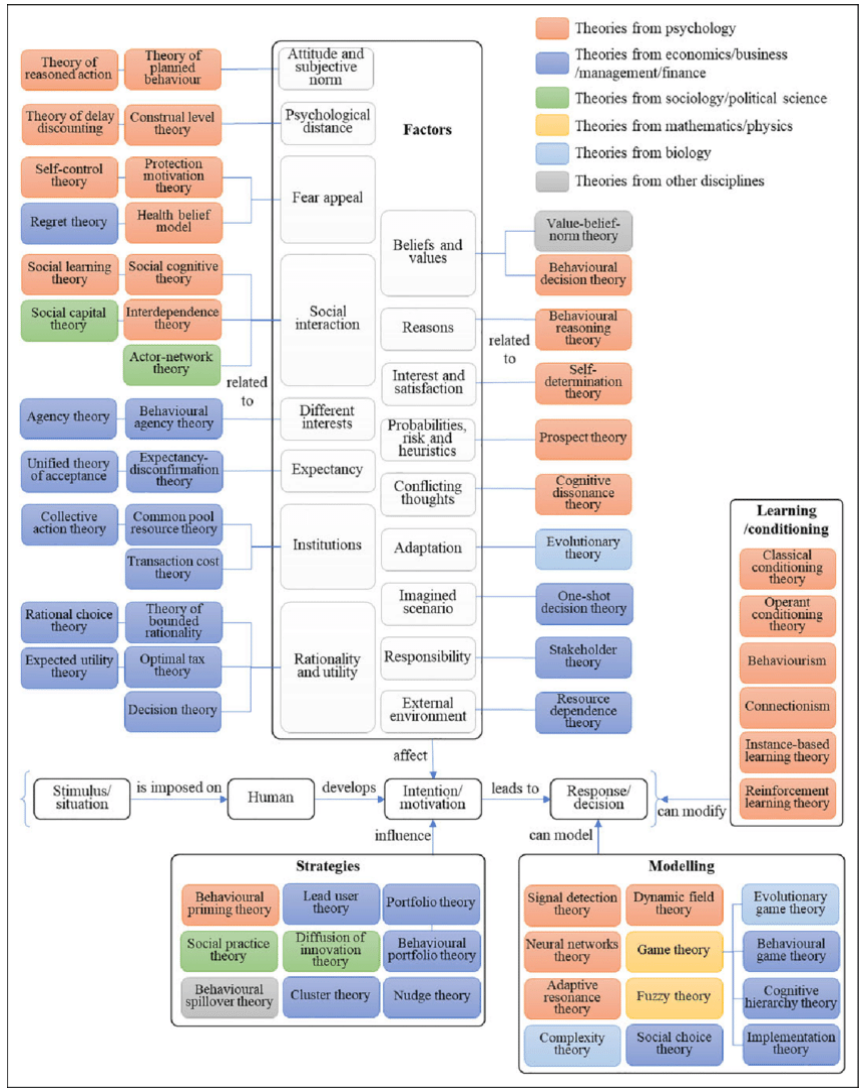
November 13th, 2023

Introduction

- **Health behaviors** are key drivers of disease trajectories
- ABMs from a range of applications traditionally *ignore* or and continue to *oversimplify* the human behavior component



Infectious disease dynamics with vaccination and varying contact reduction measures (Xia et al., 2013).



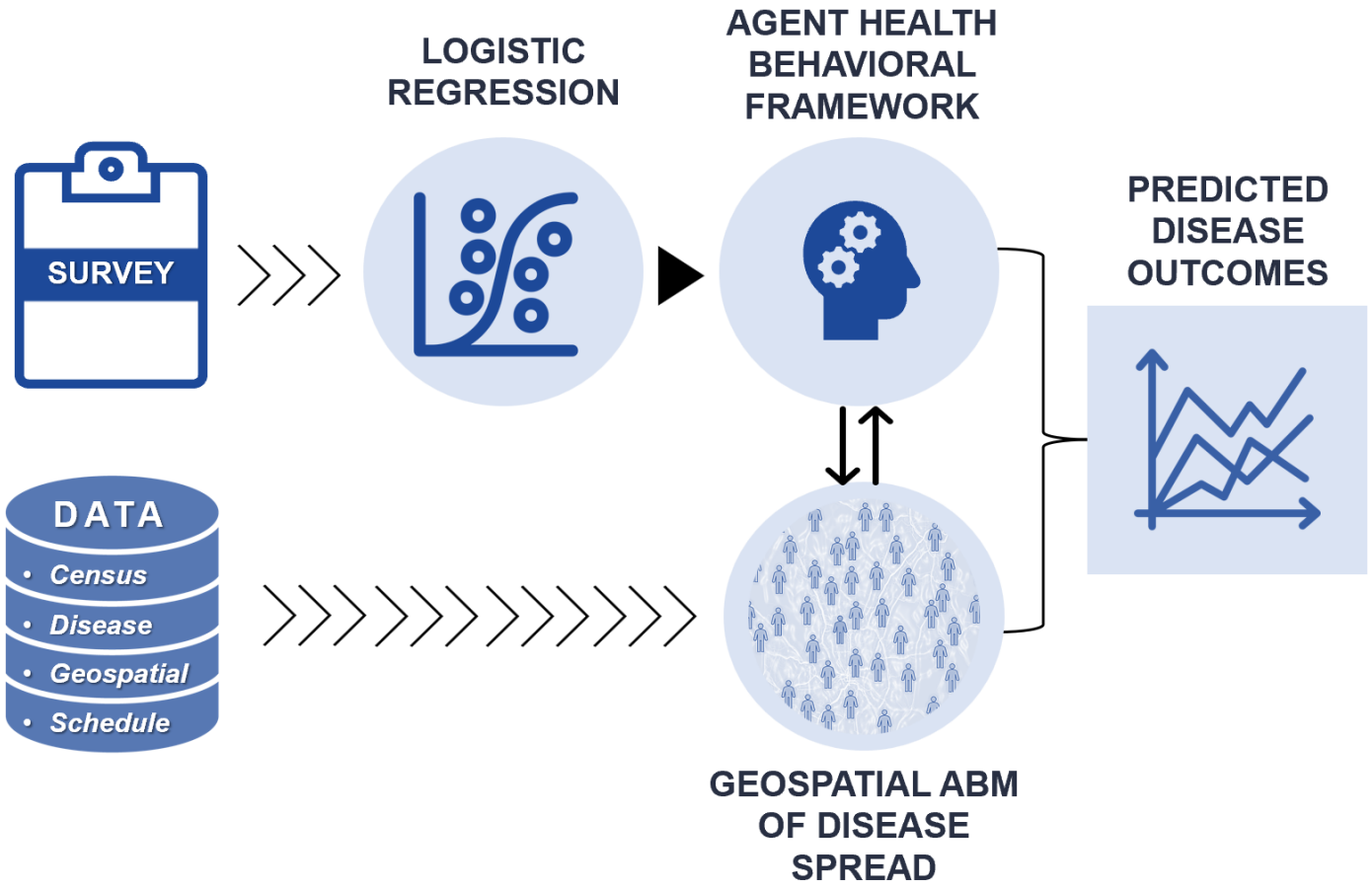
Map of general theories and disciplines of human behavior (Kwon & Silva, 2019).

Objective

*Develop and implement a **data-driven agent decision framework** for simulating emergent health behaviors in **geospatial ABMs** of infectious disease spread*



Methods Overview



Agent Health Behavioral Framework

- Determines how agents in a geospatial ABM make decisions about whether or not to adopt a specific health behavior

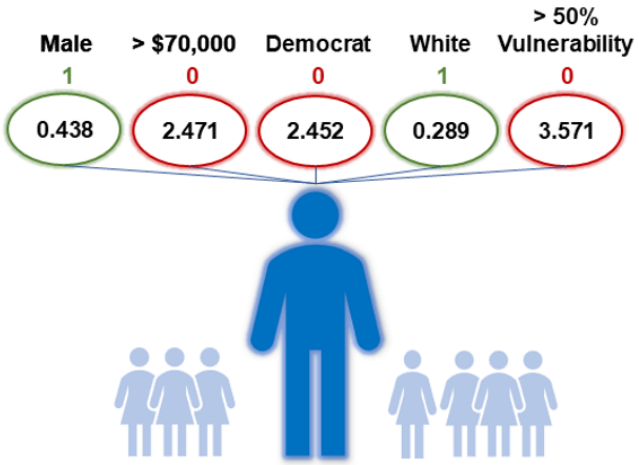
$$p_t(mask) = \frac{OR_0 * \Pi_i OR_i^{X_{i,t}}}{1 + OR_0 * \Pi_i OR_i^{X_{i,t}}}, i = 1, \ldots n$$

Logistic regression model equation.
Adapted from **Durham and Casman (2012)**.

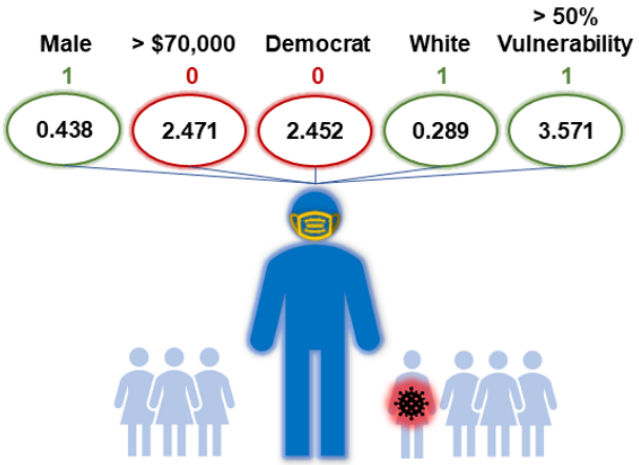
Variables	Odds-Ratio	P-Value
Gender: Male	0.43	0.026
Income: > $70,000	2.47	0.032
Party: Democrat	2.45	0.015
Race: White	0.29	0.035
Vulnerability: > 50%	3.57	0.006
Intercept: 4.54		

Calculated odds-ratios from the utilized survey conducted by **Rabin and Dutra (2021)**.

Agent Health Behavioral Framework







$$p_t(mask) = \frac{4.540 * (0.438^1 * 2.471^0 * 2.452^0 * 0.289^1 * 3.571^0)}{1 + 4.540 * (0.438^1 * 2.471^0 * 2.452^0 * 0.289^1 * 3.571^0)} = \mathbf{0.365}$$

There is a 36.5% chance I wear a mask!

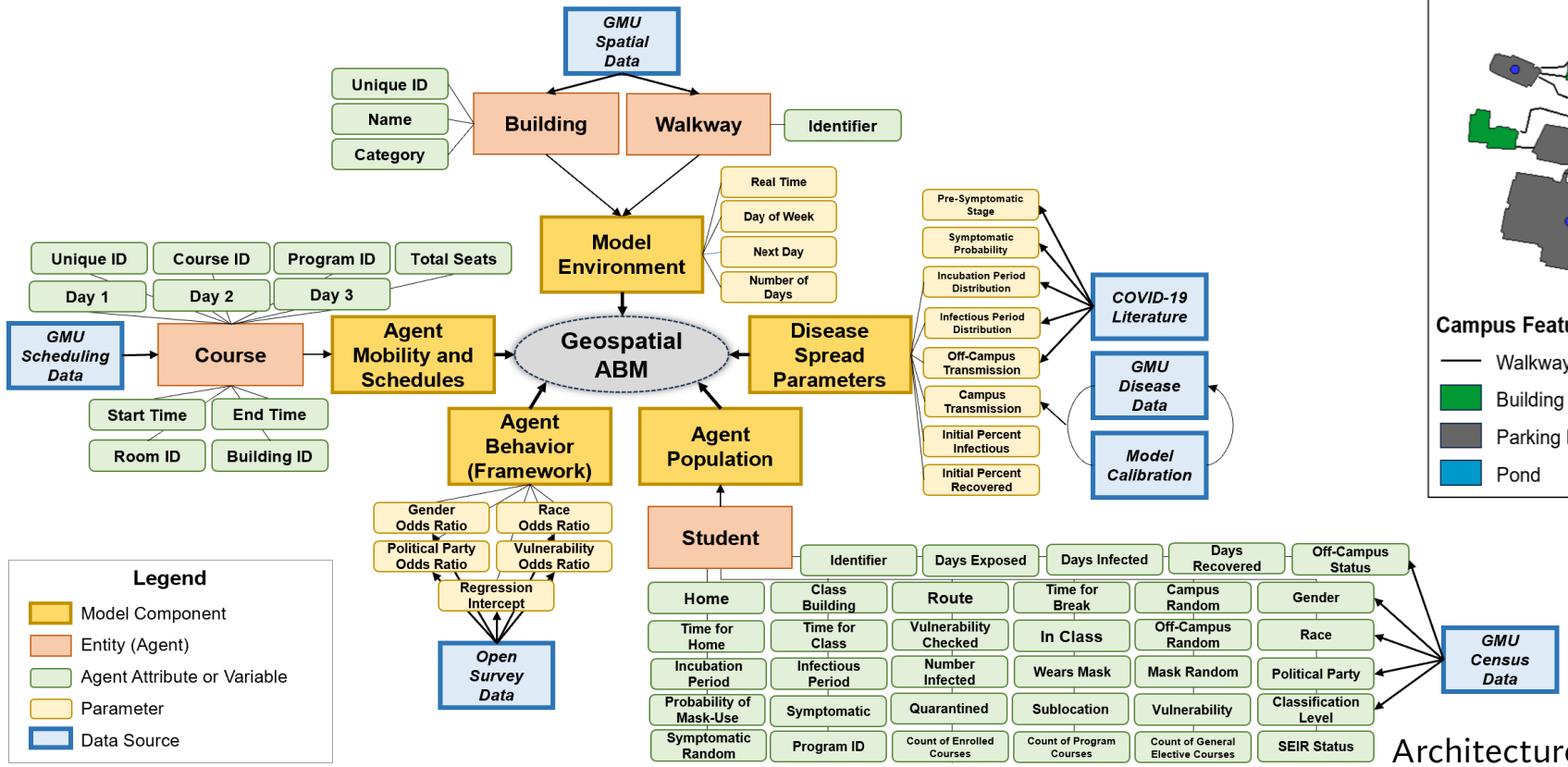
$$p_{t+n}(mask) = \frac{4.540 * (0.438^1 * 2.471^0 * 2.452^0 * 0.289^1 * 3.571^1)}{1 + 4.540 * (0.438^1 * 2.471^0 * 2.452^0 * 0.289^1 * 3.571^1)} = \mathbf{0.672}$$

There is a 67.2% chance I wear a mask!

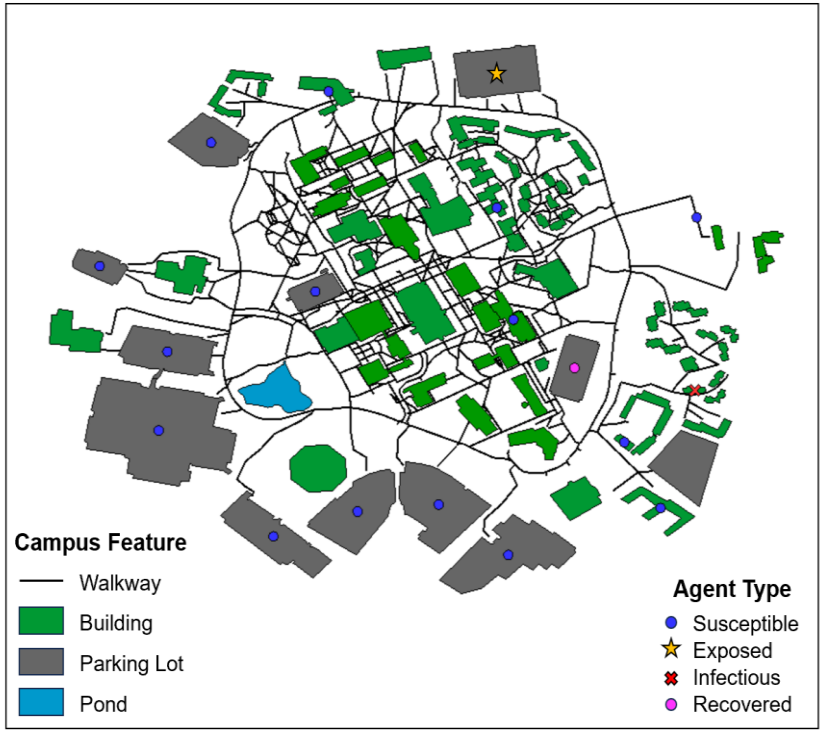
Example of the functionality of the proposed agent behavioral framework.

Geospatial ABM of Disease Spread

- Simulates the spread of COVID-19 and masking behavior among the undergraduate population at GMU in Fall 2021



Architecture diagram of the geospatial ABM.



Model environment of GMU's campus in Repast Simphony (Malleson, 2012).

Geospatial ABM of Disease Spread

- Simulates the spread of COVID-19 and masking behavior among the undergraduate population at GMU in Fall 2021



Transition between SEIR disease stages.

Parameters used to simulate COVID-19

PARAMETER	VALUE	SOURCE
Campus Transmission Rate, Without Masks	0.08 (probability from 0-1)	Calibrated from (Alvarez & Ford, 2021),(Gressman, & Peck, 2020)
Campus Transmission Rate, With Mask	0.04 (probability from 0-1)	(Gressman, & Peck, 2020)
Off-Campus Transmission Rate	0.25 (probability from 0-1)	(Gressman, & Peck, 2020)
Symptomatic Rate	0.85 (probability from 0-1)	(Ogata, et al., 2022)
Exposed Period	Normal Distribution of (4.41,0.5) days	(Wu et al., 2022)
Pre-symptomatic Period	2 days	(Reveil & Chen, 2022)
Infectious Period	Normal distribution of (8.0,1) days	(He et al., 2020)
Recovered Period (days)	90 days	(CDC, 2020)
Infectious Agents at Initialization	0.5%	(Brodsky et al., 2021) and GMU Internal Data
Recovered Agents at Initialization	3.5%	(Fall 2021 COVID-19 Archive, n.d.)

Experiments

IMPOSED HEALTH BEHAVIOR

Agents were ***assigned*** a specific percentage that randomly determines their mask-use behavior



There is a 0% chance I wear a mask!



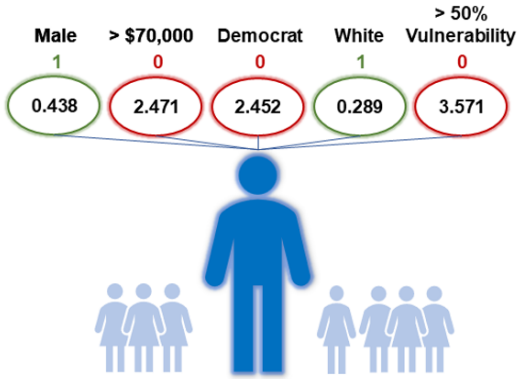
There is a 50% chance I wear a mask!



There is a 100% chance I wear a mask!

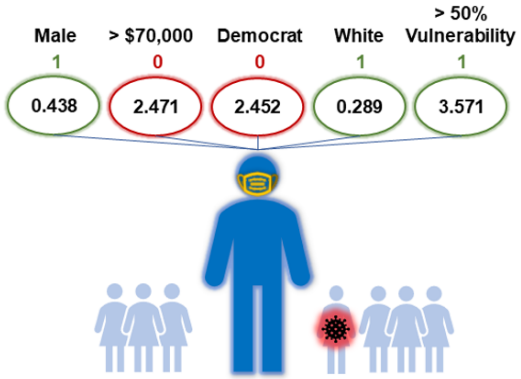
EMERGENT HEALTH BEHAVIOR

Agents can ***adapt*** their mask-use behavior based on their socio-demographics and perception of vulnerability to disease



$$p_t(mask) = \frac{4.540 * (0.438^1 * 2.471^0 * 2.452^0 * 0.289^1 * 3.571^0)}{1 + 4.540 * (0.438^1 * 2.471^0 * 2.452^0 * 0.289^1 * 3.571^0)} = \mathbf{0.365}$$

There is a 36.5% chance I wear a mask!

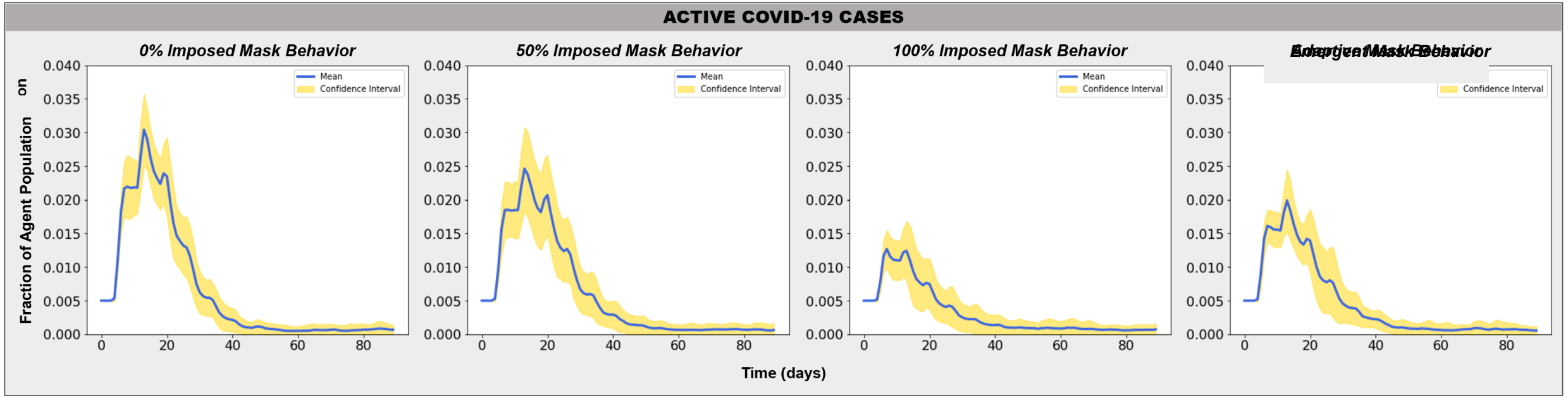


$$p_{t+n}(mask) = \frac{4.540 * (0.438^1 * 2.471^0 * 2.452^0 * 0.289^1 * 3.571^1)}{1 + 4.540 * (0.438^1 * 2.471^0 * 2.452^0 * 0.289^1 * 3.571^1)} = \mathbf{0.672}$$

There is a 67.2% chance I wear a mask!

Results

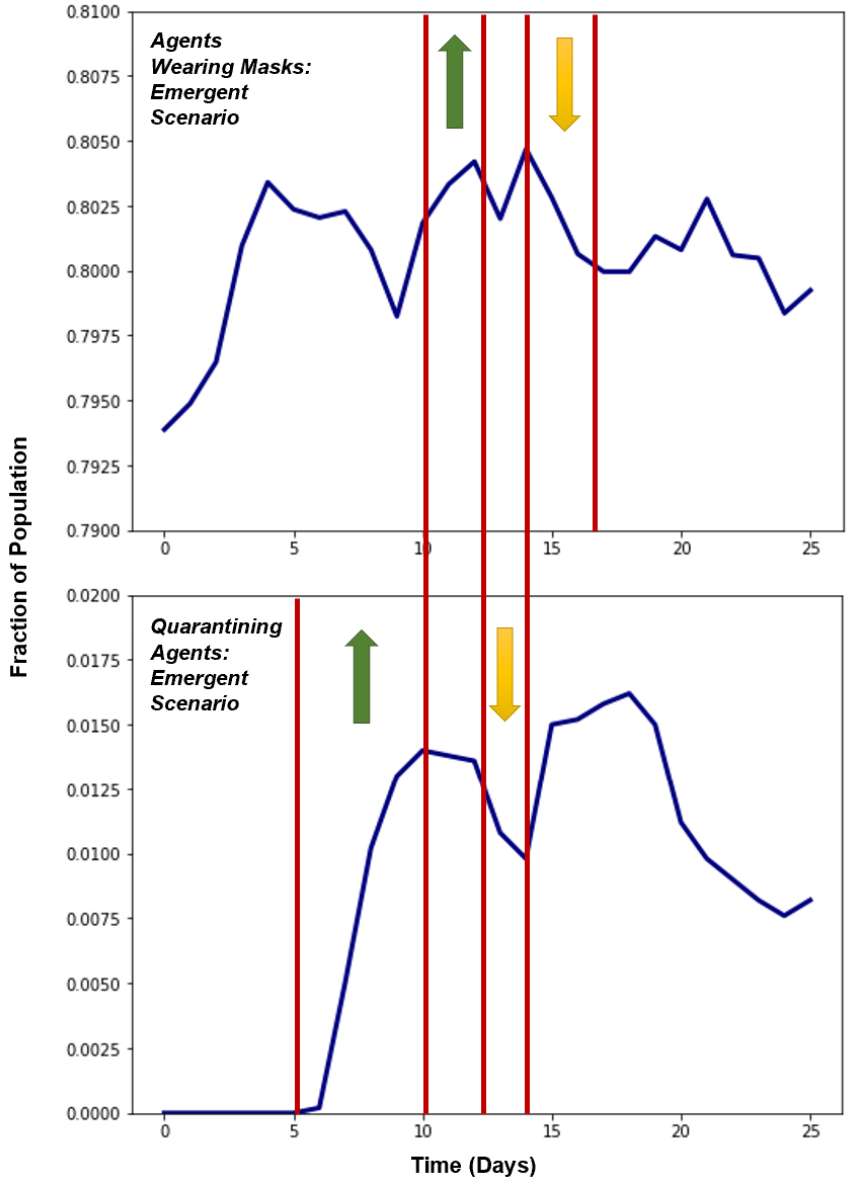
- The ABM was executed 40 times to address randomness
- Executed with 5000 agents and simulated for 90 days



Average percent of infectious agent population across 40 simulation runs.

Discussion & Conclusion

- This study leverages the advantageous features of ABMs
- The proposed approach allows us to assess the feedback between health behaviors and disease outcomes
- Using a logistic regression model offers flexibility, interpretability & collaboration
- Future work will explore a new study area and the emergence of health behaviors over geographic space



Comparing feedback mechanisms between disease outcomes and masking behavior with the emergent scenario.

References

- Alvarez Castro, D., & Ford, A. (2021). 3D agent-based model of pedestrian movements for simulating COVID-19 transmission in university students. ISPRS International Journal of Geo-Information, 10(8), 509.
- Brodsky, A., Tadakamalla, A., Brodsky, S., & Roess, A. A. (2021). Toward COVID-19 Decision Support: Modeling of Transmission Dynamics Extended with a Comprehensive Mitigation Protocol to Predict Health, Cost and Productivity Outcomes. In 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC). https://doi.org/10.1109/smc52423.2021.9658935
- CDC. (2020, February 11). Reinfection : Clinical considerations for care of children and adults with confirmed COVID-19. Centers for Disease Control and Prevention. https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-care/clinical-considerations-reinfection.html
- Durham, D. P., & Casman, E. A. (2012). Incorporating individual health-protective decisions into disease transmission models: a mathematical framework. Journal of the Royal Society Interface, 9(68), 562-570.
- Fall 2021 COVID-19 Archive. (n.d.). George Mason University. https://www.gmu.edu/fall-2021-covid-19-archive
- Gressman, P. T., & Peck, J. R. (2020). Simulating COVID-19 in a university environment. Mathematical biosciences, 328, 108436
- He, X., Lau, E.H.Y., Wu, P. et al. Temporal dynamics in viral shedding and transmissibility of COVID-19. Nat Med 26, 672–675 (2020). https://doi.org/10.1038/s41591-020-0869-5
- Huang, G., & Guo, F. (2022). Loss of life expectancy due to respiratory infectious diseases: findings from the global burden of disease study in 195 countries and territories 1990–2017. Journal of Population Research, 39(1), 1–43. https://doi.org/10.1007/s12546-021-09271-3
- Kwon, H. R., & Silva, E. A. (2019). Mapping the Landscape of Behavioral Theories: Systematic Literature Review. Journal of Planning Literature, 35(2), 161–179. https://doi.org/10.1177/0885412219881135
- Malleson, N. (2012). RepastCity. Google Code Archive. https://code.google.com/archive/p/repastcity/wikis/RepastCity3.wiki
- Rabin, C., & Dutra, S. J. (2021). Predicting engagement in behaviors to reduce the spread of COVID-19: the roles of the health belief model and political party affiliation. Psychology Health & Medicine, 27(2), 379–388. https://doi.org/10.1080/13548506.2021.1921229
- Reveil, M., Chen, YH. Predicting and preventing COVID-19 outbreaks in indoor environments: an agent-based modeling study. Sci Rep 12, 16076 (2022). https://doi.org/10.1038/s41598-022-18284-8
- Ogata, T., Tanaka, H., Irie, F., Nozawa, Y., Noguchi, E., Seo, K., & Tanaka, E. (2022). A low proportion of asymptomatic COVID-19 patients with the Delta variant infection by viral transmission through household contact at the time of confirmation in Ibaraki, Japan. Global health & medicine, 4(3), 192–196. https://doi.org/10.35772/ghm.2021.01116
- Xia S, Liu J, Cheung W (2013) Identifying the Relative Priorities of Subpopulations for Containing Infectious Disease Spread. PLoS ONE 8(6): e65271. https://doi.org/10.1371/journal.pone.0065271
- Wu Y, Kang L, Guo Z, Liu J, Liu M, Liang W. Incubation Period of COVID-19 Caused by Unique SARS-CoV-2 Strains: A Systematic Review and Meta-analysis. JAMA Netw Open. 2022;5(8):e2228008. doi:10.1001/jamanetworkopen.2022.28008

Thank you!
Questions?

Contact Us:
Emma Von Hoene (evonhoen@gmu.edu)
Amira Roess (aroess@gmu.edu)
Shivani Achuthan
Taylor Anderson (tander6@gmu.edu)



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