# Non-Pharmaceutical Herd Immunity using Homemade Masks

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**Abstract.** The Coronavirus disease 2019 global pandemic in the United States is without a vaccine or cure to prevent its spread. Social distancing and stay at home orders have created financial turmoil while mandatory mask requirements have created other controversies. This paper presents a simple agent-based SEIR model developed to explore the use of homemade masks of various quality in a representative United States population. The goal of the model is to determine if a non-pharmaceutical herd immunity can be achieved using homemade masks. Doing so without vaccines can lower even the small risk posed by an eventual vaccination. The model demonstrates that at high levels of adoption even a mix of questionable quality homemade masks can "flatten the curve" for the pandemic and could do so without the immediate, sever economic cost of staying at home. The model suggests it is possible for a herd immunity effect to cause an early end to the pandemic resulting in fewer affected individuals.

**Keywords:** COVID-19, disease modeling, homemade masks, agent-based model.

## 1 Introduction

The Coronavirus disease 2019 (COVID-19) is a respiratory infection that is a global pandemic which originated in the People's Republic of China and spread to multiple continents including North American and the United States (US) in 2020. Those infected with COVID-19 can be asymptomatic without visible signs of the disease, or symptomatic where there are obvious indications they are infected [1]. It is transmitted between people in close contact through droplets exhaled from an asymptomatic or symptomatic person to a susceptible person [2]. Social distancing [3], by which people stay 6 or more feet (1.8 meters) from each other, was an early US recommendation. Some state and local governments in the US extended the social distancing concept to stay at home orders where the population was instructed not to go out except for essential purposes [4]. While there are benefits to this, there has also been an obvious impact of job loss and financial hardship [5].

This is not the first pandemic the US has faced and probably will not be the last [6,7,8,9]. Previous pandemics and epidemics have led some researchers to assume that professional and medical quality masks would not be available to the general population and explore the use of homemade masks. In the US, the Centers for Disease Control and Prevention (CDC) reversed an early recommendation against the wearing of masks by the public to one in favor of wearing masks [1]. However, any requirement to wear homemade masks by the general population creates controversies similar to those who resist vaccines. Achieving a high level of vaccination among a population is a goal of health officials, as a sufficient number of vaccinated individuals creates "herd immunity" that impacts the ability of the disease to sustain itself and can cause an epidemic or pandemic to end earlier than it might do otherwise. Unfortunately, there is no vaccine for COVID-19 and development of vaccines is generally a multi-year process. Vaccines are not without risk, as there is always some chance for an adverse medical reaction by the individual [10]. Wearing masks in sufficient quantities may provide herd immunity through non-pharmaceutical means and without the risk of medical issues while waiting for vaccine development. In the remainder of the paper Section 2 provides some background in previous studies of the efficacy of homemade masks. The model, method, and mask data are described in Section 3. In Section 4 the results are presented with some discussion. Finally, Section 5 provides some concluding remarks.

## 2 Background

Researchers have ranked three categories of masks with N95 respirators as the best, followed by surgical/medical masks, then homemade masks [11]. The N95 respirators were studied by Balazy, et al. [12] and Johnson, et al. [13]. They discovered they lived up to their name with an efficacy, their ability to block viruses, of 95%, though Konda, et al. [14] found them to be slightly less effective. Surgical and medical masks have also been tested, often in comparison with masks from the other categories, with results ranging from very bad to N95 equivalency [12,15,14,16,17]. In response to the H1N1 pandemic of 2009 [9], Davies, et al. [15] questioned if improvised masks used by the untrained general public would provide any protection from an infected wearer. They concluded it would be better than no protection, but should only be used as a last resort. MacIntyre, et al. [16] examined the common use of cloth masks among health care workers in some parts of the world. They cautioned against their use for protection of health care workers. Responding to the COVID-19 pandemic, Konda, et al. [14] studied a variety of materials that could be used to construct a homemade mask, finding it was possible to create significant protection for the wearer, but only if the mask was made with high quality, layered materials (see Table 1 for more information regarding mask efficacies).

A rapid means for exploring the use of these homemade masks is through simulation. Epidemiology investigations can include simulations using models of virus spread in populations. One such model is a Susceptible-Exposed-Infected-Recovered (SEIR) approach where people start in the first of those four compartments (states) and move in sequence to the last of the states. SEIR models can be deterministic, making use of differential equations to calculate the number of people in each state [18,19,20], or stochastic [21,22] where chance controls the movement between states. Modeling homemade mask use in a population has not been a focus of many researchers. However, in response to COVID-19 a compartment SEIR mathematical model of homemade mask use concluded an 80% adoption of moderately effective homemade masks could significantly reduce death rates in two studied US states [23].

## 3 Model and Methodology

A SEIR model was developed to explore the use of homemade masks in a representative United States population. The model used in this paper is a stochastic agent-based model (ABM) [24] and was developed using the NetLogo (version 6.1) [25] framework. Agents who are asymptomatic are considered “exposed’ while symptomatic agents are “infected.” The execution flow of the model is shown in Fig. 1 and described in the following paragraphs. The model and Overview, Design concepts, and Details (ODD) protocol [26] are available at https://tinyurl.com/y2dvu8df.

**Model Initialization**. The ABM contains 3,298 agents with each agent representing 100,000 people, approximately the population of the United States on 3 June 2020 [27]. All agents are placed in a 101x101 two-dimensional toroidal grid with locations drawn from a continuous uniform random distribution. The agents are set to a susceptible state, except for four who are set to exposed. Each agent's age is randomly drawn from a distribution based on the United States 2019 census [28] so that all agents collectively represent that distribution. Each agent is assigned a mask category (i.e., N95, Medical, Homemade, or none) based on probabilities assigned by the user. A mask type is assigned based on a random uniform distribution selection of available types from the assigned mask category (see Table 1 – Mask Type). The precise mask efficacies assigned to the agent is based on a continuous random normal distribution using the mean ($\mu$) and standard deviation ($\sigma$) for the mask category and type as shown in Table 1. Data was rarely available for both ingress and egress efficacies so an agent may be assigned different mask types for ingress and egress.

**Model Execution.** The model begins execution and continues until there are no longer exposed or infected agents. Each loop through the code is a single tick (a NetLogo term) equivalent to a single day (see blue dashed box in Fig. 1). During each tick, each agent moves one grid cell in a random, generally forward direction. An agent takes one of four paths. Agents in a recovered or susceptible state simply mode randomly. If the agent is in an exposed or infected state and there are other susceptible agents in its new location, it checks to see if it has infected the other agents (see Infection of Other Agents). Model execution ends when there are no longer any exposed or infected agents.

*Infection of Other Agents.* Based on the infectiousness of the virus (see Table 2), the infecting agent checks to see if co-located susceptible agents can be exposed. If so, the infecting agent's mask's egress efficacy is checked to see if the mask blocked the virus.

Finally, the susceptible agent's mask's ingress efficacy is checked to see if their mask blocked the virus. The two efficacy values were assigned during Model Initialization from randomly assigned masks drawn from Table 1. If the virus makes it through these

**Table 1.** Ingress (protects wearer) and egress (protects from wearer) efficacy for various category and mask types. Mask Types are labels created to provide unique references within the model's code. In most cases, researchers examined either ingress or egress efficacy resulting in N/A values for missing data.

| Category | Mask Type | Ingress Efficacy | | Egress Efficacy | | Source |
|---|---|---|---|---|---|---|
| | | μ | σ | μ | σ | |
| **N95** | Balazy A | 95.60% | 0.600% | N/A | N/A | [12] |
| | Balazy B | 94.40% | 0.500% | N/A | N/A | [12] |
| | Johnson | 95.00% | 0.00% | 95.00% | 0.00% | [13] |
| | Konda | 85.00% | 15.00% | N/A | N/A | [14] |
| **Medical** | MacIntyre | 44.00% | 0.00% | N/A | N/A | [16] |
| | Davies | N/A | N/A | 89.52% | 2.65% | [15] |
| | Oberg A | 9.80% | 0.86% | N/A | N/A | [17] |
| | Oberg B | 47.10% | 4.80% | N/A | N/A | [17] |
| | Oberg C | 22.80% | 2.40% | N/A | N/A | [17] |
| | Oberg D | 94.02% | 0.60% | N/A | N/A | [17] |
| | Oberg E | 62.60% | 0.80% | N/A | N/A | [17] |
| | Oberg F | 71.10% | 1.40% | N/A | N/A | [17] |
| | Oberg G | 89.56% | 1.60% | N/A | N/A | [17] |
| | Oberg H | 96.04% | 0.40% | N/A | N/A | [17] |
| | Oberg I | 68.40% | 2.20% | N/A | N/A | [17] |
| | Balazy A | 15.00% | 0.10% | N/A | N/A | [12] |
| | Balazy B | 80.00% | 0.20% | N/A | N/A | [12] |
| | Konda | 50.00% | 7.00% | N/A | N/A | [14] |
| **Homemade** | MacIntyre | 3.00% | 0.00% | | | [16] |
| | Davies A | N/A | N/A | 50.85% | 16.81% | [15] |
| | Davies B | N/A | N/A | 48.87% | 19.77% | [15] |
| | Davies C | N/A | N/A | 57.13% | 10.55% | [15] |
| | Davies D | N/A | N/A | 61.67% | 2.41% | [15] |
| | Davies E | N/A | N/A | 54.32% | 29.49% | [15] |
| | Konda A | 83.00% | 9.00% | N/A | N/A | [14] |
| | Konda B | 67.00% | 16.00% | N/A | N/A | [14] |
| | Konda C | 57.00% | 8.00% | N/A | N/A | [14] |
| | Konda D | 96.00% | 2.00% | N/A | N/A | [14] |
| | Konda E | 82.00% | 19.00% | N/A | N/A | [14] |
| | Konda F | 79.00% | 23.00% | N/A | N/A | [14] |
| | Konda G | 38.00% | 11.00% | N/A | N/A | [14] |
| | Konda H | 9.00% | 13.00% | N/A | N/A | [14] |

three checks, the susceptible agent's state is changed to exposed and they are assigned a days-until-infected counter based on a discrete random uniform distribution between the values min-exposed-period and max-exposed-period initially set by the user (see Table 2).

*Agent Death*. If an agent is in an infected state, the probability it has died is checked using an age-based probability distribution. If dead, the agent is removed from the simulation.

*Check for Infected to Recovered State Change*. An agent in an infected state has its days-until-recovered counter decremented by one. If the counter has reached zero, the agent's state is changed to recovered. It can no longer be exposed or infected.

*Check for Exposed to Infected State Change*. Agents in an exposed state have its days-until-infected counter decremented by one. If the counter has reached zero, the agent's state is changed to infected and they are assigned a days-until-recovered counter based on a discrete random uniform distribution between the values min-infected-period and max-infected-period initially set by the user (see Table 2).

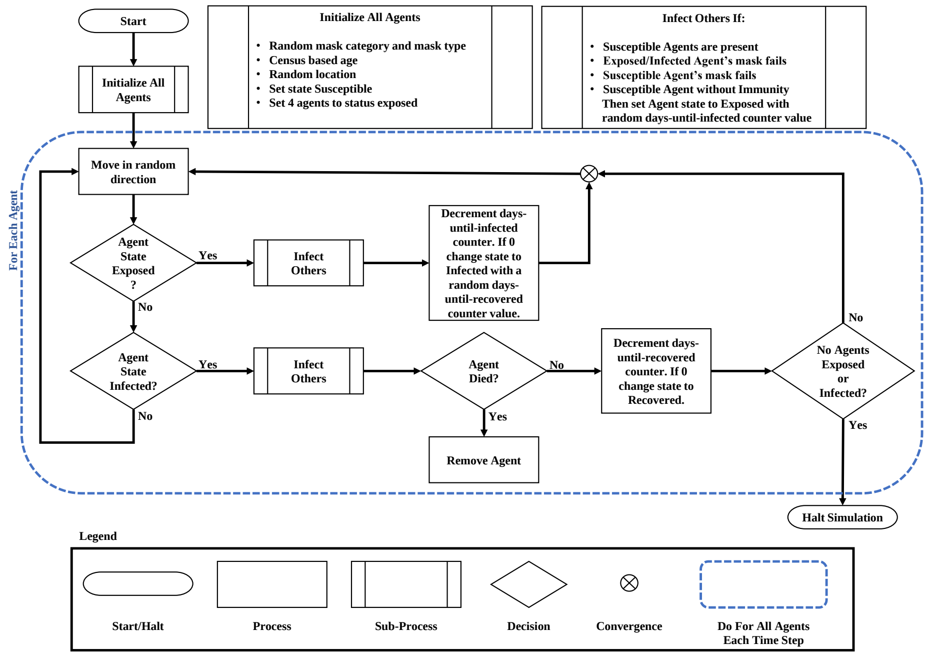


**Fig. 1.** High level view of model execution flow.

**Methodology**. To test the effect of homemade mask adoption at various adoption levels, the other two mask categories were set to constant values of 1% for N95 and 4% for Medical. Other initial values for each model run are shown in Table 2. Homemade mask adoption ranged from 0% to 95% in increments of 5%. Five-hundred model runs for each of these twenty adoption values was conducted with results collected using the NetLogo tool BehaviorSpace. Mean and standard error values for all results were calculated for the five-hundred simulations and data graphics were created with a Python program developed for this purpose.

**Table 2.** Initial user changeable parameter values selected for simulation.

| Parameter | Value |
|---|---|
| infectiousness | 99% |
| min-exposed-period | 2 Days |
| max-exposed-period | 14 Days |
| min-infected-period | 10 Days |
| max-infected-period | 14 Days |

## 4 Results and Discussion

Collective use of homemade masks in the simulation demonstrated a positive difference in high adoption scenarios. As homemade mask adoption increases, the total number of asymptomatic agents (exposed) and symptomatic agents (infected) on each day decreases and the peak day moves further away from the beginning of the pandemic (see Fig. 2A and Fig. 2B). This has a similar effect to social distancing in “flattening the curve.”

Examining the maximum number of agents affected on the worse day (combining asymptomatic and symptomatic states) demonstrates a monotonically decreasing number of agents as homemade mask adoption increases (see Fig. 3A). The number of days into the pandemic that the worse day occurs increases as part of the effect of flattening the curve until adoption reaches 85%, then decreases during the remaining two adoption percentages (see Fig. 3B). The data graphics in Fig. 4 provide two views of pandemic length. Fig. 4A show pandemic length increasing monotonically as mask adoption increases until adoption reaches 85%, then decreasing after that. Fig. 4B tracks the maximum length (the end of each plot) and daily mean number of susceptible agents for all mask adoption scenarios. This demonstrates even the maximum pandemic lengths decease at high homemade mask adoptions.

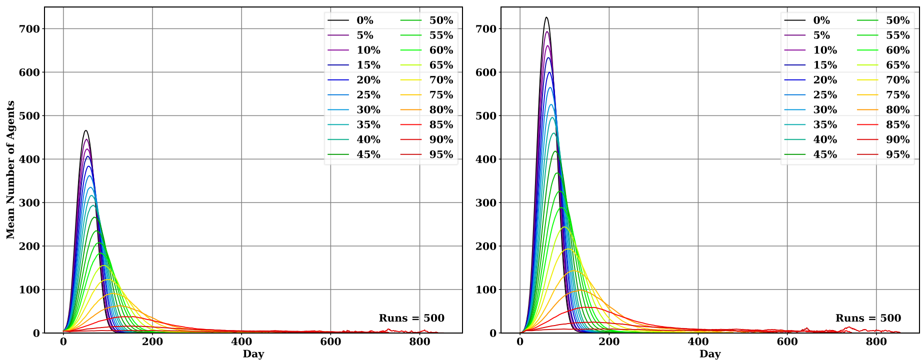


**Fig. 2.** The left figure (A) shows the mean number of agents exposed (asymptomatic) each day while the right figure (B) shows the same for agents infected (symptomatic) each day. The legend indicates the percent of agents using homemade masks. The means are calculated over five-hundred model runs.

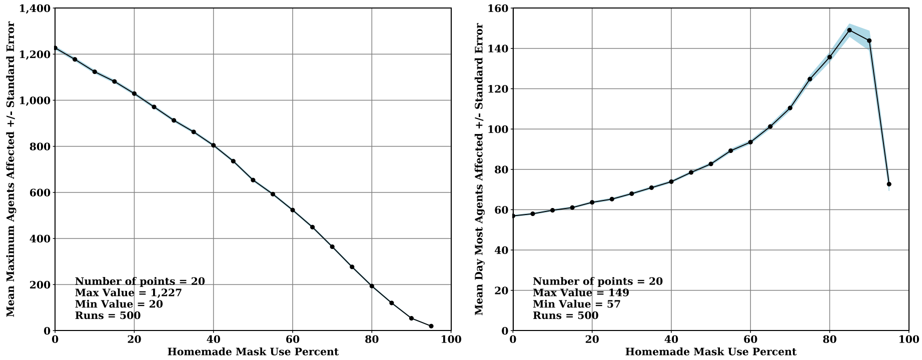


**Fig. 3.** The mean maximum agents affected on the worse day is shown in the left figure (A). The right figure (B) shows the mean day on which the mean maximum number of agents were affected. Standard error for the y-axis is shown in light blue. The means are calculated over five-hundred model runs.

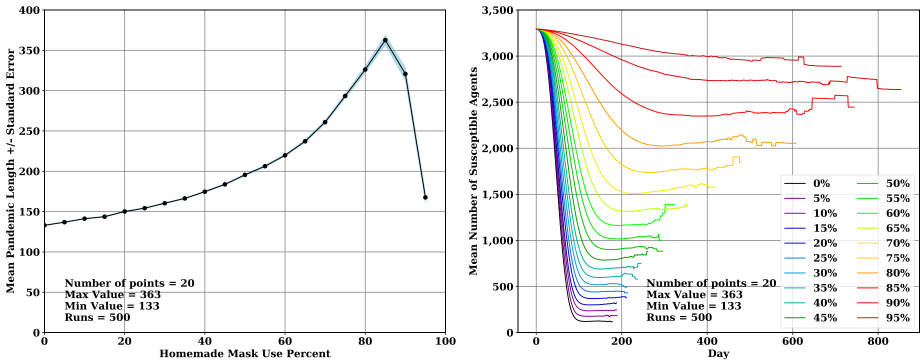


**Fig. 4.** The left figure (A) shows the mean number of days the pandemic lasted for each homemade mask adoption percentage with standard error for the y-axis in light blue. The right figure (B) shows the number of susceptible agents each day for each homemade mask adoption percentage with the end point showing the maximum length of any run. The legend for B indicates the percent of agents using homemade masks. All means are calculated over five-hundred model runs.

## 5 Conclusion

Using a simulated population in a simple environment, this paper is intended to contribute to the ongoing discussion regarding the use of homemade masks by an untrained, general population. Individually, homemade masks made from a wide variety of materials [14,16,15] range from ineffective to potentially equivalent to the N95 mask. As demonstrated in Section 4, a collection of mixed efficacy masks at high adoption levels can decrease the maximum number of affected agents on the worse day by slowing the pace at which the virus spreads. This flattens the curve, but does so without the immediate, sever economic cost of staying at home. It is also possible for an early end to the pandemic with fewer affected agents if the virus is unable to find new hosts in a susceptible, but well masked, population. This achieves a goal of herd immunity by non-pharmaceutical means at an adoption percent of 85%. Unfortunately, this positive outcome takes place only at levels of adoption that may not be possible to achieve.

Like all models, this one can be improved or extended. For example, different types of social networks could be added. Social networks that included family members, coworkers, fellow students, and friends would limit agent-to-agent contact in a manner more realistic than random motion in a large box. A second extension could recognize that humans move with purpose and not at random [29] thus limiting or extending the reasons that the agents come into contact. Finally, social distancing could be added to study the effect of combining homemade masks and social distancing.

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## References

1. **Centers for Disease Control and Prevention.** Recommendation Regarding the Use of Cloth Face Coverings, Especially in Areas of Significant Community-Based Transmission. *Centers for Disease Control and Prevention.* [Online] 2020. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/cloth-face-cover.html.
2. —. How COVID-19 Spreads. *Coronavirus Disease 2019 (COVID-19).* [Online] 2020. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/how-covid-spreads.html.
3. —. Social Distancing. *Coronavirus Disease 2019 (COVID-19).* [Online] 2020. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html.
4. **Wikipedia.** Stay-at-home order. *Wikipedia.* [Online] 2020. https://en.wikipedia.org/wiki/Stay-at-home_order.
5. *The Benefits and Costs of Using Social Distancing to Flatten the Curve for COVID-19.* **Thunström, Linda, et al.** s.l. : Cambridge University Press, 2020, Journal of Benefit-Cost Analysis, pp. 1-17.
6. **Centers for Disease Control and Prevention.** 1918 Pandemic (H1N1 virus). *Centers for Disease Control and Prevention.* [Online] 2019. https://www.cdc.gov/flu/pandemic-resources/1918-pandemic-h1n1.html.
7. —. 1957-1958 Pandemic (H2N2 virus). *Centers for Disease Control and Prevention.* [Online] 2019a. https://www.cdc.gov/flu/pandemic-resources/1957-1958-pandemic.html.
8. —. 1968 Pandemic (H3N2 virus). *Centers for Disease Control and Prevention.* [Online] 2019b. https://www.cdc.gov/flu/pandemic-resources/1968-pandemic.html.

9. —. 2009 H1N1 Pandemic (H1N1pdm09 virus). *Centers for Disease Control and Prevention.* [Online] 2019c. https://www.cdc.gov/flu/pandemic-resources/2009-h1n1-pandemic.html.

10. **Anderson, Roy M and May, Robert M.** Vaccination and herd immunity to infectious diseases. *Nature.* 1985, Vol. 318, 6044, pp. 323–329.

11. *Professional and Home-Made Face Masks Reduce Exposure to Respiratory Infections among the General Population.* **van der Sande, M, Teunis, P and Sabe, l R.** 7, 2008, PLOS ONE, Vol. 3.

12. *Do N95 respirators provide 95% protection level against airborne viruses, and how adequate are surgical masks?* **Balazy, Anna, et al.** 2, 2006, American Journal of Infection Control, Vol. 34, pp. 51-57.

13. *A Quantitative Assessment of the Efficacy of Surgical and N95 Masks to Filter Influenza Virus in Patients with Acute Influenza Infection.* **Johnson, D F, et al.** 2, 2009, Clinical Infectious Diseases, Vol. 49, pp. 275-277.

14. *Aerosol Filtration Efficiency of Common Fabrics Used in Respiratory Cloth Masks.* **Konda, Abhiteja, et al.** 5, 2020, ACS Nano, Vol. 14, pp. 6339–6347.

15. *Testing the Efficacy of Homemade Masks: Would They Protect in an Influenza Pandemic?* **Davies, Anna, et al.** 4, 2013, Disaster Medicine and Public Health Preparedness, Vol. 7, pp. 413-418.

16. *A cluster randomised trial of cloth masks compared with medical masks in healthcare workers.* **MacIntyre, Raina, et al.** 4, 2015, BMJ Open, Vol. 5.

17. *Surgical mask filter and fit performance.* **Oberg, Tara and Brosseau, Lisa M.** 2008, American Journal of Infection Control, pp. 276-282.

18. *Time series modelling of childhood diseases: a dynamical systems approach.* **Finkenstädt, Bärbel F and Grenfell, Bryan T.** 2, Coventry, UK : Journal of the Royal Statistical Society: Series C (Applied Statistics), 2000, Vol. 49, pp. 187-205.

19. *A contribution to the mathematical theory of epidemics.* **Kermack, William Ogilvy and McKendrick, Anderson G.** London, UK : Proceedings of the Royal Society of London. Series A, 1927. Vol. 115, pp. 700-721.

20. *Stability Analysis Susceptible, Exposed, Infected, Recovered (SEIR) Model for Spread Model for Spread of Dengue Fever in Medan.* **Side, S, et al.** 1, s.l. : Journal of Physics: Conference Series, 2018, Vol. 954, p. 012018.

21. *Statistical inference in a stochastic epidemic SEIR model with control intervention: Ebola as a case study.* **Lekone, Phenyo E and Finkenstädt, Bärbel F.** 4, s.l. : Biometrics, 2006, Vol. 62, pp. 1170-1177.

22. *Stationary distribution and extinction of a stochastic SEIR epidemic model with standard incidence.* **Liu, Qun, et al.** s.l. : Physica A: Statistical Mechanics and its Applications, 2017, Vol. 476, pp. 58-69.

23. *To mask or not to mask: Modeling the potential for face mask use by the general public to curtail the COVID-19 pandemic.* **Eikenberry, Steffen E, et al.** 2020, Infectious Disease Modelling, Vol. 5, pp. 293-308.

24. *How to Build and Use Agent-Based Models in Social Science.* **Gilbert, Nigel and Terna, Pietro.** 1, 2000, Mind & Society, Vol. 1, pp. 57 - 72.

25. **Wilensky, Uri.** NetLogo. Evanston : Center for Connected Learning and Computer-Based Modeling, Northwestern University, 1999.

26. *The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism.* **Grimm, V, et al.** 2029, Journal of Artificial Societies and Social Simulation.

27. **United States Census Bureau.** U.S. and World Population Clock . *United States Census Bureau.* [Online] 2020. https://www.census.gov/popclock/.

28. —. US Census 2019 age distribution by age (Table 1). *United States Census Bureau.* [Online] 2020. https://www.census.gov/data/tables/2019/demo/age-and-sex/2019-age-sex-composition.html.

29. **Kennedy, William G.** Modelling Human Behaviour in Agent-Based Models. [ed.] Alison J Heppenstall, et al. *Agent-Based Models of Geographical Systems.* New York, New York, USA : Springer Netherlands, 2012, pp. 167-179.