Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo and M. Loper, eds.

HIGH-QUALITY MASKS REDUCE COVID-19 INFECTIONS AND DEATH IN THE US

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ABSTRACT

The objective is to evaluate the widespread adoption of masks on community transmission of SARS-CoV2. We employed an agent-based stochastic network simulation model and a variant of a SEIR disease model with one million agents in census tracts representing a population of 10.5 million. We evaluated scenarios with 25% to 90% mask-related reduction in viral transmission (mask efficacy). An individual wears a mask with a discrete probability values in [0-100%] (mask adherence). A mask order was initiated 3.5 months after the first confirmed case, with temporary state-wide distancing and voluntary quarantining of households. If 50% of the population wears masks that are 50% effective, this decreases the cumulative infection attack rate (CAR) by 27%, the peak prevalence by 54%, and the population mortality by 29%. If 90% wear masks that are 50% effective, this decreases the CAR by 38%, the peak prevalence by 75%, and the population mortality by 55%.

1 INTRODUCTION

In the United States, by August 2020, the SARS-CoV-2 virus that causes Covid-19 was widely circulating in many communities, especially throughout the South and Midwest (NYT 2020a). There was much speculation over the role of masks or face coverings with the CDC Director Robert Redfield stating that if people would wear masks for a few weeks that community transmission could be stopped (Statnews 2020). While there is growing evidence that masks can be effective at greatly reducing disease spread or severity (Chu et al. 2020; Fischer et al. 2020), it was not well understood how effective they are in stopping the outbreak when community transmission is already in existence.

This study describes a simulation model that was built to project the impact of face coverings at the state level and across urban, suburban, and rural counties under different population adherence and mask effectiveness levels in the absence of the availability of vaccine. The simulation is an agent-based network model of more than 1 million agents, with virus transmission occurring in households, workplaces and schools, and communities. In this article, we describe the simulation that was developed to study the impact

978-1-6654-3311-2/21/$31.00 ©2021 IEEE

of masks and face coverings. The simulation has also been used to study other mitigation and response decisions such as school closures, vaccine distribution and prioritization, and equity. For those the reader is referred to other articles (e.g., Eylul Oruc et al. 2021; Patel et al. 2021; Rosenstrom et al. 2021).

2 METHODS

We employ an agent-based stochastic network model with an SEIR framework for the progression of SARS-CoV-2 (Baxter et al. 2020; Keskinocak et al. 2020; Patel et al. 2020), as has been done for other pandemic viruses (Ekici et al. 2014; Shi et al. 2010a; Shi et al. 2010b). This analysis was performed for North Carolina (NC). The population of 10.5 million people is proportionately represented with 1,017,720 agents. Agents digitally represent people with defined characteristics, behaviors, and interaction patterns. We simulate interactions among a network of agents, where transmission can occur daily in households, workplaces and schools, and community settings, with day/night differentiation in interactions. This study uses publicly available de-identified data and did not require IRB approval.

Figure 1 summarizes the structure of agents across the network. Data values to generate individual agents were drawn from the US Census at the census tract level (U.S. Census 2010; U.S. Census 2017). Agents belong to one of five age brackets: age 0 to 4; age 5 to 9; age 10 to 19; age 20 to 64; age 65 and greater. Agents are assigned to a household with size following the distribution of households in the census tract. Children are present in the household following the census tract level proportion of presence of children. All agents interacted with households at night. During the day, all agents 5 to 19 were allowed interactions in their assigned peer groups ("schools"), and agents 19 to 64 interacted in their assigned peer groups ("work") according to commuting patterns. Commuting patterns were determined from workflow data (U.S. Census 2016), which indicates the people who live in a given census tract and the percentage who work in each of the other census tracts. All agents interact in the community setting which corresponds to the census tract.

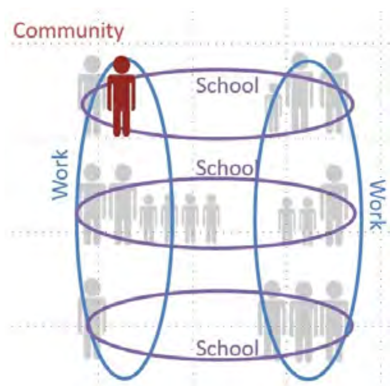

Figure 1: Network of agents allows for interactions and transmission in households, peer groups such as work or school, and communities.

The underlying model of disease spread was assumed to be a variant of a Susceptible-Exposed-Infectious-Recovered (SEIR) model; see Figure 2. At a given point in time, each individual is in exactly one state: susceptible (S), exposed (E), pre-symptomatic (IP), asymptomatic (IA), symptomatic (IS), hospitalized (H), recovered (R), or dead (D), and all individuals begin as susceptible. The probability of hospitalization and death are dependent on the age of the agent.

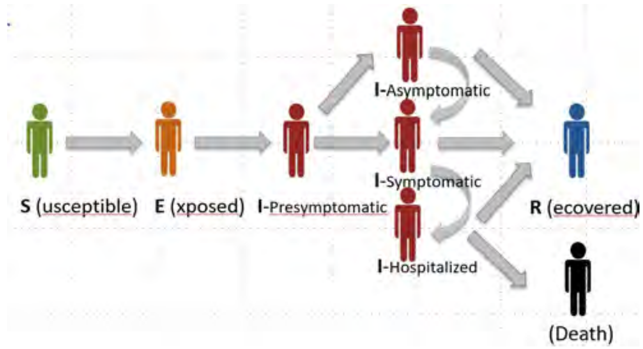

Figure 2: SEIR-type model represents the progression of Covid-19 for an individual.

Several parameters determine the length of time within each state in the SEIR including the mean and standard deviation of the time before an exposed patient becomes pre-symptomatic, the average length of time of the pre-symptomatic phase, the distribution of time within the symptomatic (S) stage, the distribution of the length of hospitalization, and the ratio of the duration of the symptomatic and asymptomatic states. Parameters related to the transmission between states include the probability of moving to symptomatic (from IP), the probability of hospitalization (from IS), and the probability of death (from H); probabilities out of a state must sum to 100%. The overall infection fatality rate (i.e., the probability that an exposed person will die) resulting from the simulation is just under 0.5%.

The infectivity of the virus at the beginning of the outbreak without interventions is summarized by reproductive rate R0 (2.4 without interventions), and the transmission rate (denoted as β) (Baxter et al. 2020). The proportion of transmissions that occur at either the IP or IA stage is τ, and the proportion of infections generated by individuals who are never symptomatic is θ. In the absence of interventions, the proportion of transmission that occurs outside households is ω, and the proportion of transmission outside households that occur in the community is δ.

One of the important differences in comparison to the values used for influenza (Ekici et al. 2014), is that the proportion of transmissions that can occur by people without symptoms is much higher. To reflect transmission in North Carolina, the community infection hazard parameter was set to 0.23, which was lower than GA as described in Keskinocak et al. (2020). δ is a little higher in comparison to the values used for the state of Georgia (Keskinocak 2020). For this paper we also take the import rate of cases to be lower (45 compared to 100) based on factors such as the airport size, commuting in or out of the state, etc. A list including input parameters, transition rates, and associated references is provided in the appendix in Table S1. Additional details such as equations are available in the supplements of Ekici et al. 2014 and Keskinocak et al. 2020.

The model captures the likelihood an adult agent stays home over time using SafeGraph data (SafeGraph 2020) aggregated by month and census tract. SafeGraph data captures the presence of devices in homes or other settings over time and across census blocks, which we aggregated into tracts grouped by urbanicity (urban, rural, suburban) and median household income (4 quartiles statewide). An adult will work from home on a given day according to a probability drawn from their census tract's rate. For interactions with the community by age group, we assume the rate follows the same pattern as the workplace mobility data but with a smaller reduction compared to workplace (e.g., a 40% reduction in work attendance is associated with a 12% reduction in community interaction). This is consistent with our comparisons of workplace mobility with other types of mobility (SafeGraph 2020, Google 2020). We assume mobility rates stabilize at month six levels. We do not assume a link between mobility and population infections as we did not see it consistently across locations when comparing mobility data and infections. The mobility data captures the fact that many people stayed home shortly after cases began rising (consistent with shelter-at-home orders given in NC and many other states) and mobility continues to be lower than pre-pandemic rates. We assume that households with a symptomatic Covid-19 infection will voluntarily quarantine, in line with the low quarantining rates from Keskinocak et al. (2020). Schools are virtual or closed initially, opening on month six with students rotating every other day. Anyone who is symptomatic stays home from school and away from work peer groups.

Unlike Keskinocak et al. (2020), a proportion of the population wears masks. The rate increases approximately monthly days 6-94, corresponding to the state mask order in NC), linearly from 0 to the final adherence probability of (0, 40, 60, 80, or 100%). We assume the rate is homogeneous across the population, as supported by initial data (NYT 2020b). In sensitivity analysis, we allow mask adherence to vary by urbanicity, [85%,75%,65%] or [85%,70%,55%] based on the November 2020 surveys conducted by Facebook (2020). According to some experimental analysis (Fischer et al. 2020), in the baseline mask cases we assume masks reduce the infectivity to others and susceptibility of self by 50% each. We compare the baseline mask effectiveness with scenarios where higher quality masks are employed and are more effective (e.g., 80+% reduction in transmission and susceptibility risk, like surgical or N95 masks). For our no-intervention control, we assume there are no interventions throughout the pandemic and mobility is as normal; there is also a scenario with 0% mask adherence that has changes in mobility. The simulation is run for 365 virtual days. For each scenario, 15 replications of the simulation are run.

The simulation is seeded (day 1) with cumulative cases as of March 24, 2020 (NYT 2020a), where the cases are multiplied by 10 to account for underreporting (Havers et al. 2020) and scaled to the number of agents in the simulation. Infections were assigned to census tracts randomly according to the population within each tract in the county using the Huntington-Hill method. The primary sources of randomness for these simulations include four types: (i) the structure of network, i.e., the random assignment of agents to households and peer groups (ii) the individual agents who are infected with the seed infections; (iii) whether an infected individual will transmit the virus to another person in the household, peer group, and/or community at a point in time; and (iv) the duration within a disease state. All simulation output values are adjusted to the true population of 10.49 million. The model is validated against reported hospitalizations and deaths in NC as of 11/1/2020, where the validation accounts for the fact that not all positive cases are lab-reported (NYT 2020a) and hospitalizations (NCDHHS 2020).

We compute the infection attack rate (IAR) or the proportion of the population cumulatively infected over the time horizon, the peak percentage of the population simultaneously infected, peak count of hospitalizations, and the mortality of the total population. We quantify the mean and standard deviation values over the 15 replications. In comparing scenarios, we quantify either the percentage change from the comparison, or the number of percentage points of the difference. We provide values at the state level, by county and stratified by urban/suburban/rural status, where urban corresponds to Rural-Urban-Commuting-Area (RUCA) codes of 1,2; rural of 6,7,8,9,10; and the remainder for suburban (USDA 2010).

3 RESULTS

Even at low levels of effectiveness, mask-wearing reduces cumulative infections, peak infections, hospitalizations, and mortality for COVID-19 (Table 1). If 75% of individuals wear 50% efficacious masks (population-level effectiveness of 37.5%), the IAR, peak infection, and deaths are reduced by 37%, 68%, and 47%, respectively, vs. no mask use, even in the setting of effective physical distancing measures.

Higher mask adherence leads to improvement in each metric, and the improvement is not necessarily linear. Increasing adherence from 50% to 75% has a higher incremental improvement in IAR points (5.4) than increasing from 0 to 25% or 25% to 50% (3.6 and 4.3, respectively). A similar improvement is seen in the number of deaths, which drops by 25.8% when adherence increases from 50% to 75%.

Notably, in the best scenario we studied where 90% of people wear a mask that is 50% efficacious, this results in an almost 50% reduction in IAR to 13.7% (compared to 21.7% with 50% adherence); additionally, peak hospitalizations decrease by 51% and deaths by 36.7% in this scenario.

If higher quality masks are worn, then all metrics improve. As with mask adherence, the incremental improvement is nonlinear. For example, the IAR decreases incrementally by 7, 8.4, and 2.9 percentage points over the previous value as mask efficacy increases (from 25% to 50%, then to 75%, then to 90%, respectively, all with adherence of 70%). The incremental reduction in the number of deaths is also highest as efficacy increases from 50 to 75%.

Table 1: The results of mask adherence and effectiveness are shown for IAR, peak prevalence rate, peak hospitalizations, and deaths for a state population of 10.5 million with mean (stdev) displayed.

Mask Adherence	**Mask Effectiveness**	**IAR**	Peak Prevalence Rate	Peak Hospitalizations	Deaths (in population of 10.5M)
Mask Adherence Experiments (Initial Shelter, Low Voluntary Quarantine throughout, School canceled)					
0%, Overall	N/A	29.6% (0.20%)	0.74% (0.07%)	8,387	29.6% (0.20%)
25%	50%	26.0% (0.21%)	0.547% (0.058%)	6,195 (645)	12,316 (447)
50%	50%	21.7% (0.22%)	0.38% (0.030%)	4,335 (418)	10,351 (544)
75%	50%	16.3% (0.22%)	0.237% (0.035%)	2,741 (463)	7,681 (483)
90%	50%	13.7% (0.22%)	0.184% (0.019%)	2,106 (280)	6,548 (544)
Mask Efficacy Experiments (Initial Shelter, Low Voluntary Quarantine throughout, School canceled)					
70%	25%	24.9% (0.21%)	0.494% (0.04%)	5,711 (537)	12,009 (480)
70%	50%	17.9% (0.22%)	0.279% (0.030%)	3,257 (404)	8,630 (468)
70%	75%	9.5% (0.20%)	0.117% (0.016%)	1303 (265)	4,461 (431)
70%	90%	6.6% (0.18%)	0.094% (0.024%)	1,022 (187)	3,143 (241)
Control case with no interventions					
From the beginning: No masks, no mobility changes, yes school. Usual status.		58% (0.14%)	4.76% (0.2%)	49,142 (1,379)	27,982 (483)
Geographical Analysis					
		Urban, IAR	Suburban, IAR	Rural, IAR	Overall, IAR
Cases by March 24		0.003%	0.00025%	0.00027%	0.0023%
0% masks (Initial shelter, Low VQ, schools canceled)		29.07% (0.05%)	32.81% (0.14%)	30.03% (0.23%)	29.6% (0.20%)
25%	50%	25.7% (0.31%)	28.1% (0.26%)	26.3% (0.4%)	26.0% (0.21%)
50%	50%	21.5% (0.15%)	23.59% (0.3%)	21.62% (0.25%)	21.7% (0.22%)
75%	50%	16.16% (0.54%)	17.82% (0.69%)	16.23% (0.26%)	16.3% (0.22%)
90%	50%	13.63% (0.19%)	15.07% (0.37%)	13.64% (0.32%)	13.7% (0.22%)

For all scenarios, community transmission continues to occur after the mask order, with the peak day of infection occurring approximately day 190.

If higher quality masks are worn, then all metrics improve. With 70% of people wearing masks, increasing the mask effectiveness from 50% to 90% is better than the scenario with 90% adherence where masks are 50% effective (see Figure 3, which shows results over time).

The results vary somewhat by RUCA county type, see Table 1. Note that mobility differences across area types (shown in the Supplemental Appendix) indicate that urban areas have stayed home at higher rates than other areas, d with rural areas remaining the most mobile. In the baseline scenario (50% adherence): the IAR for suburban areas is about two points higher than that of urban and rural areas (23.59% versus 21.5% and 21.62%). The difference between urban and rural areas is biggest with 0% mask adherence (25.7% versus 26.3%) and smallest with 90% adherence (13.63% and 13.64%).When mask adherence differs across geographies as seems indicated in recent data, then the IAR tends to be highest for rural areas.

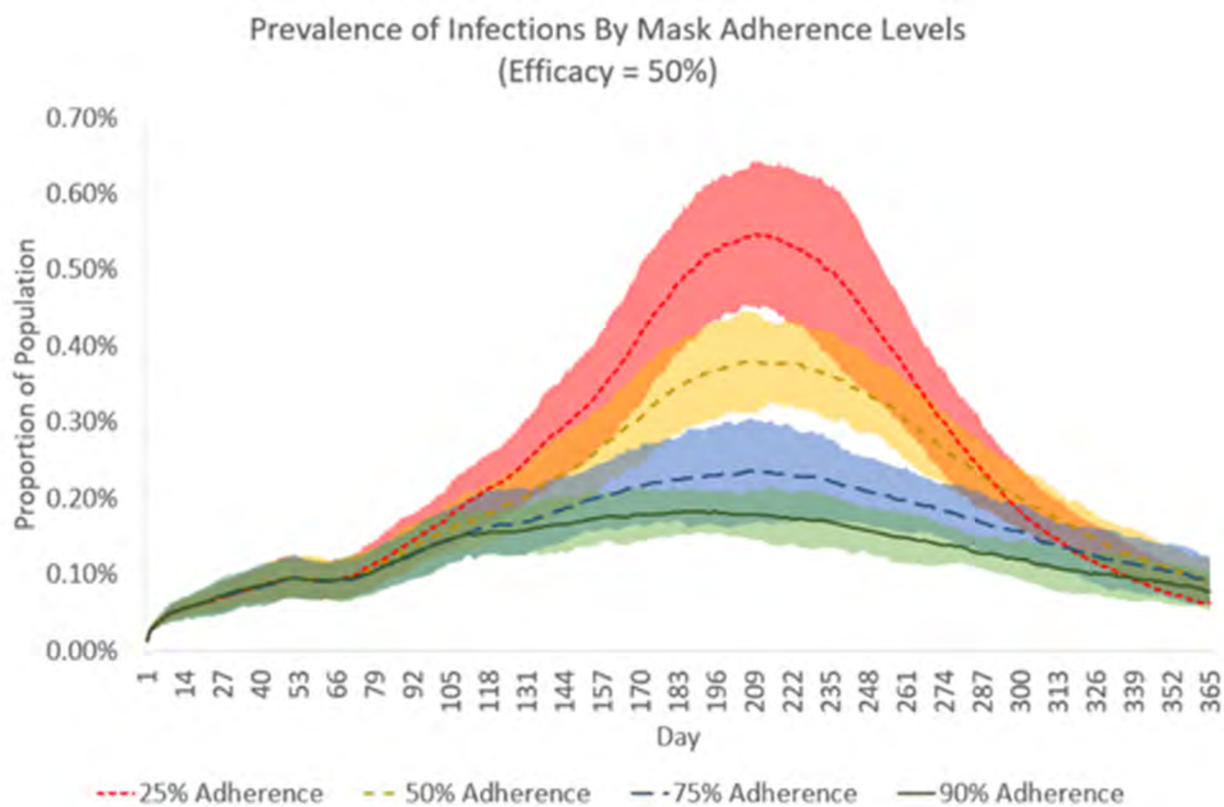

Figure 3: Prevalence of infectious people over time for four mask scenarios where the band is ± 2 standard deviations around the mean.

4 DISCUSSION

Widespread usage of masks decreases the impact of the pandemic, consistent with a deterministic aggregate model of disease spread (Eikenberry et al. 2020) and empirical findings using publicly reported data from states April 1 to May 21 (Lyu et al. 2020). The impact can 40% or higher reductions in infections and mortality, over and above the interventions in place. This leads to a flattening of the disease curve and would prevent the overutilization of hospitals which would save lives. However, even if 90% of people wore masks, this would not stop community transmission. It remains critical for other non-pharmaceutical interventions to be in place, such as distancing, closures of some community settings.

The finding that rural and suburban areas are at risk for high IAR is consistent with the recent spread of COVID-19 well beyond urban areas1. It is somewhat surprising that suburban areas are at higher risk in some scenarios, although these locales have relatively high population density compared to rural areas and their mobility changes have been less than in urban areas.

Masking is a critical behavior prior to the widespread availability of vaccines. Masks only offset disease spread while they are worn. If the population were to take them off, they would be susceptible to disease spread. Masks should be worn until an individual is vaccinated, which would be able to permanently protect the individual from infection. The greater the mask adherence prior to widespread vaccine availability, the more cases, hospitalizations, and deaths that can be averted by the vaccine.

Improving the quality of masks worn also has the potential to improve population health, e.g., by shifting people from neck gaiters or bandanas to masks with multiple fabric layers or special filtration material like surgical or N95 masks. As the supply of high-quality masks increases, messaging campaigns should used to encourage their use versus the alternative. As access to masks could be restricted for some portions of the population, it would also be worth while to consider sending them to everyone in the population, to ensure everyone has access.

There are several types of future research questions that can be answered by building upon this simulation model. An important area to consider is the impact of different types of vaccines (Kim 2021) and the allocation of a limited supply (Fujimoto 2021). It would also be useful to understand the causes of unequal burden of Covid-19 in the population and what interventions could reduce the inequities. Finally, it is important to continue engaging with decision makers and health agencies, to better understand how modeling can meet their needs (Johnson et al. 2021).

ACKNOWLEDGMENTS

This research was supported in part by the National Center for Advancing Translational Sciences (NCATS)/National Institutes of Health (NIH), through Grant Award Number UL1TR002489 and by the North Carolina Translational and Clinical Science Institute (NC TRACS) award number C192019 and the North Carolina State University (NCSU) Office of Research and Innovation. The work was also supported by a grant from the Council of State and Territorial Epidemiologists and the Centers for Disease Control and Prevention through Cooperative Agreement NU38OT000297. In addition, the research was partially supported by the Allison Distinguished Professorship at NCSU and by the William W. George endowment and the following benefactors at Georgia Tech: Andrea Laliberte, Joseph C. Mello, Richard "Rick" E. & Charlene Zalesky, and Claudia & Paul Raines. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH, CSTE, CDC, or the universities employing the researchers. The funding agreement ensured the authors' independence in designing the study, interpreting the data, writing, and publishing the report. All of the authors are employed by the state universities associated with the sponsorship.

A APPENDIX OF PARAMETERS

Table S1: Displays key model parameters and references. Many parameters are also summarized in the supplemental material of Keskinocak et al. 2020.

PARAMETER	ESTIMATES	REFERENCES
Exposed (E) Duration	Weibull with mean 4.6 days	Ferguson et al. 2020 and Linton et al. 2020
Pre-symptomatic (IP) Duration	0.5 days	Ferguson et al. 2020
Hospitalized (H) Duration	Exponential with mean 10.4 days	Ferguson et al. 2020 and Weitz et al. 2020
Symptomatic (S) Duration	Exponential with mean 2.9 days	Riou et al. 2020
Symptomatic-Asymptomatic Duration Ratio	1.5	Ferguson et al. 2020
Probability of Symptomatic (from IP)	0.50-0.82	Mizumoto et al. 2020, Andrei 2020, Day 2020, Mandavilli 2020 and Nishiura et al. 2020
Probability of Hospitalization (from IS)	0.016 for age 0-19; 0.18 for age 20-64; 0.30 for age 65+	CDC Covid-Response Team 2020
Probability of Death (from H)	0 for age 0-19; 0.0515 for age 20-64; 0.3512 for age 65+	CDC Covid-Response Team 2020
R0	2.4	Li et al. 2020, Walker et al. 2020 and WHO 2020
β transmission rate	1.12	Li et al. 2020
θ (probability IP to IA)	0.48	Ganyani et al. 2020
ω (proportion infections by IA)	0.24	Ganyani et al. 2020
γ (proportion of transmission that occur outside households)	30%	Ekici et al. 2014, Keskinocak et al. 2020
δ (proportion of infections outside households that occur in community)	0.23	Keskinocak et al. 2020 and calibration
FlatImportRate	45	Keskinocak et al. 2020 and calibration
Infection Fatality Rate	0.46%	Results from model transitions with other parameters

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