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INCORPORATING FACE MASK USAGE IN AGENT-BASED MODELS USING PERSONAL BELIEFS AND PERCEPTIONS: AN APPLICATION OF THE HEALTH BELIEF MODEL

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ABSTRACT

The modelling of human behavior is a critical component of any simulation tool that aims to represent the spread of an infectious disease throughout a population. However, few modeling approaches attempt to incorporate protective behaviors using models grounded in theories from the behavioral sciences. Here, we demonstrate how to incorporate human behavior accounting for personal beliefs and perceptions by using a commonly known behavioral framework. We implemented the proposed model within an agent-based simulation to drive the agent's decision related to wearing a face mask. We used survey data to characterize a synthetic population, and investigate the effect of policies that aim to modify beliefs with the goal of promoting face mask usage. Our results highlight the importance of incorporating the individual drivers of behavior to better represent adoption of protective actions against health threats, enhancing the ability of simulation tools to quantify the impact of policy interventions.

1 INTRODUCTION

Human behavior is an essential component of simulation models that aim to represent infectious diseases. Specifically, protective behaviors, such as face mask usage, social distancing and handwashing, can play a significant role in slowing the spread of the disease throughout the population. Face mask usage was one of the most common measures promoted during the latest COVID-19 pandemic due to its high cost-effectiveness in reducing the risk of contracting respiratory diseases (NIOSH 2023). During this time, several policies were in place to either enforce or recommend these practices. In the US, the application of face mask mandates and high adherence with recommendations to wear them was associated with a significant decrease in potential cases (Fischer et al. 2021; Lyu and Wehby 2020). However, compliance within the population varied greatly. Individual behavior was greatly influenced by personal beliefs and perceptions, which differ between demographic groups (Tang et al. 2021; Shi et al. 2021; O'Connell et al. 2023). As we seek to develop more accurate tools to support policy interventions, incorporating personal attributes to determine behavior can help to better represent heterogeneity in groups.

As human behavior is complex, understanding the process behind decisions and actions is not a straightforward task. Nonetheless, the behavioral sciences field provides a rich literature that attempts to explain behaviors from a cognitive perspective. Behavioral theories are theoretical frameworks that aim to understand and predict human behavior by proposing a set of psychological constructs as the main catalysts of action. These theories hypothesize how constructs interact with each other, and how they lead an individual to undertake a certain behavior. As constructs represent cognitive processes the person has, these can be measured (e.g. through survey questions) to estimate their significance in predicting the target behavior. Several studies empirically evaluated the determinants of face mask usage during COVID-19 using behavioral theories (White et al. 2022; Irfan et al. 2021; Barile et al. 2021; Wismans et al. 2022; Sun et al. 2021). Among the numerous behavioral theories that have been proposed to explain protective behaviors against health threats, the Health Belief Model (HBM) has relevant importance in the literature (Zewdie et al. 2022). Proposed by Rosenstock (2005) as one of the first behavioral theories that addressed health-related threats, the HBM considers that a person is motivated to perform a protective behavior based on their perception of the threat, and their evaluation of the net benefit of performing the target action. Therefore, in the context of a disease outbreak, a person is more prone to undertake a protective behavior if they regard the infectious disease as a risky threat and if they perceive that the benefit of performing the action outweighs the cost of it.

On the other hand, Agent-based models (ABMs) have proven to be useful tools to model infectious diseases due to their flexibility to represent interactions between agents. In general, the spread of a disease through a community of agents can be modeled by considering susceptible agents having contact with infected ones with the chance of getting infected. Moreover, agents may engage in protective behaviors (e.g. use a face mask) to avoid contagion, among other activities that they may perform. This suitability to represent individuals and their interactions fostered the development of ABMs to simulate the spread of COVID-19 among communities (Kerr et al. 2021; Rosenstrom et al. 2024; Rodríguez et al. 2022; Reveil and Chen 2022; Hinch et al. 2021). However, the implementation of behavior based on a person's beliefs and perceptions is scarce, and the few studies that exist used population-level data to calibrate the behavioral model instead of individual-level data (Durham and Casman 2011). Overall, the usual implementation of behaviors such as face mask usage was generally simplified by modeling agents behavior assuming some sort of population-level variables to determine action (Lombardo et al. 2022; Yin et al. 2021; Rosenstrom et al. 2024). Although these modelling approaches represent the desired population-level mask usage, by not considering individual-level drivers of decision most of the heterogeneity expected in individual behavior is not represented in the model. This could potentially lead to different infection dynamics, specially in a diverse population. Moreover, the inclusion of human cognitive processes can enable the exploration of the potential impact of interventions aimed to influence beliefs and perceptions to promote behavioral change.

Our goal in this study is to provide a practical modeling approach to incorporate human behavior into an epidemiological ABM by using the HBM. We leveraged this theoretical framework by accounting for the beliefs and perceptions a person has in relation to COVID-19 and face mask usage to determine an agent's decision to wear a mask. We showcase the benefits of considering human cognitive processes by comparing our approach with using a homogeneous random probability for each age group, and explore the differences in transmission dynamics and estimated outcomes. We then make use of the behavioral model to investigate the impact of policy interventions that aim to modify the perceptions associated with face mask usage, illustrating the gain of considering perceptions within a theory-based framework to aid policy-makers during an infectious disease outbreak.

The rest of the paper is structured as follows: Section 2 provides an overview of how to incorporate face mask wearing into an ABM by using the HBM as a framework. In Section 3 we showcase a case study to shed light on the usefulness of our modelling approach. Finally, in Section 4 we discuss the main findings and propose future extensions.

2 BEHAVIOR MODELING

In the following section, we provide an overview of the HBM and how its constructs are measured to explain the use of face mask to prevent infection from COVID-19. Then, we present a practical implementation of this model in an ABM. We further provide details of the logic and parameters used for the agent-based simulation.

2.1 Health Belief Model

The HBM initially proposed that a person's decisions to perform an action were determined by the cognitions in relation to the health threat and the ones related to the protective behavior. These perceptions were further described in terms of psychological constructs (see Figure 1). Perceived severity (how severe the consequences of the disease are) and perceived susceptibility (how likely it is to get ill from the disease) are the components of the health threat, whereas the behavior perceptions consist on the perceived benefits (how beneficial the action is in preventing the disease) and perceived barriers (how difficult it is to perform the action). Later on, self-efficacy (how capable someone is in performing the behavior) and cues to action (events that trigger someone to perform the behavior) were added as additional constructs to the model. In this study, we will focus on the simpler initial model and its constructs to explain the use of face mask during COVID-19.

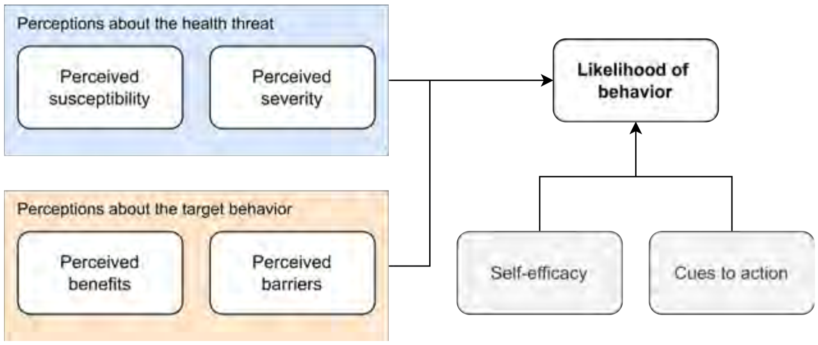

Figure 1: The health belief model.

2.2 Survey Data

As constructs are generally abstract definitions of a person's cognition, it is a difficult task to quantify the effect each construct has on predicting behavior. Survey questions are a useful and common tool to measure these concepts. From July 2020 to March 2021, MIT and Facebook conducted the Preventive Health Survey: COVID-19 Beliefs, Behaviors & Norms Survey (Collis et al. 2022) which measured people's beliefs and perceptions in relation to COVID-19 and protective behaviors. We selected the survey questions shown in Table 1 that measured the specific constructs from the HBM model. As the perceived barriers for wearing a face mask was not explicitly measured in the survey, we assumed that the cost of wearing a face mask is constant across all the population. The survey also measured self-reported face mask usage as one of the measures taken to prevent the spread of COVID-19, among other actions.

Table 1: Survey questions that measure the constructs of the HBM.

Construct	Question	Answers
Perceived susceptibility	How likely is it that someone of the same age as you in your community becomes sick from COVID-19?	5 levels: Not at all likely, Slightly likely, Moderately likely, Very likely, Extremely likely
Perceived severity	How serious would it be if you became infected with COVID-19?	3 levels: Not at all serious, Somewhat serious, Very serious
Perceived benefit	How effective is wearing a face mask for preventing the spread of COVID-19?	5 levels: Not effective at all, Slightly effective, Moderately effective, Moderately effective, Extremely effective
Behavior	What measures have you taken to prevent infection from COVID-19 in the past week? Wearing a face mask or covering	Binary: 1=option selected, 0=option shown but not selected

Given the nature of the data available, we used logistic regression to assess the effect of each variable in predicting face mask usage. The convenience of using a logistic function to model behavior relies on its ability to translate an individual's beliefs into a probability of using a face mask. Moreover, the model's parameters are simple to compute and have a relatively high interpretability. We later discuss the benefits and limitations of such an approach.

2.3 Agent-based Model

We designed a network-based agent-based framework that simulates the spread of an infectious disease through a community. The model replicates the spread of a disease by representing agents with nodes and the connections between them as arcs in a network. The network comprises several layers that represent each dimension of a community: households, community, schools, workplaces, among others. The disease spreads through the community when an infectious agent has contact (a connected arc) with a susceptible one. As each arc represents a contact, all the contacts that a susceptible agent had with an infectious one during the day are considered to calculate the probability of infection, with new infections being updated on a daily basis. Agent attributes include demographic variables, and perceptions towards COVID-19 and face mask usage. Interventions are simulated as simulation events and are used to modify population attributes, disease attributes, and the probability of infection.

The model is parameterized with a probability of infection per contact per day (β), which is assumed as the base probability of infection between two agents i and j (β_{ij}). We represent the impact of interventions and protective actions (i.e. wearing a face mask) as reductions in this probability. The reduction consists of the proportion probability is reduced to and is defined in terms of the mask usage of both agents, with one of the agents wearing a mask $r_{i\vee j}$ or both of them wearing one $r_{i\wedge j}$. Hence, we have that $\beta \times r_{ij} = \beta_{ij}$, with $r_{ij} \in \{r_{i\vee j}, r_{i\wedge j}, 1\},\ 0 \leq r_{i\wedge j} < r_{i\vee j} < 1$.

We implemented the extended SEIR compartmental model proposed in Rosenstrom et al. (2024) to represent the progression of COVID-19. The disease states include susceptible, exposed, pre-symptomatic, symptomatic and asymptomatic, recovered, hospitalized and dead. The change of the disease states is modeled using sequential continuous events defined by the same parametrized distribution used in Rosenstrom et al. (2024). For this study, we adapted the model so that new infections are generated from a discrete process (daily step) rather than a continuous stochastic process based on the force of infection. Figure 2 depicts the general logic of the simulation.

3 CASE STUDY

In the following section, we examine the effect of using the HBM framework to model face mask wearing in the context of a COVID-19 outbreak in North Carolina. We compared the proposed model with a masking-at-random policy that replicates the same proportion of agents that mask in each age group by assuming a constant probability. Moreover, we showcase the usefulness of using the estimated behavioral model to assess the impact of different interventions that aim to modify people's perceptions.

We simulated a COVID-19 outbreak and its effects over a period of 180 days, running a set of 30 replications for each experiment. To represent the population, we created a synthetic population of 10,000 agents using demographic data from the 2017-2021 American Community Survey (Ruggles et al. 2024). Four layers were used to generate the population network: schools, workplaces, community, and households. Households and workplaces were generated by considering household composition by age and industry related data (Ruggles et al. 2024). The schools layer was generated by randomly assigning children to schools and using an age-dependent contact matrix, while the community layer was generated using the Erdos-Renyi algorithm (Erdős and Rényi 2022). For the simulation parameters, we used $\beta = 0.05$ similar to Kerr et al. (2021), and assumed $r_{i\vee j} = 0.5, r_{i\wedge j} = 0.3$ to represent a simplified reduction in the probability of infection presented in Catching et al. (2021). We also assumed that agents update their decisions to wear masks every seven days. We implemented the described ABM in Python.

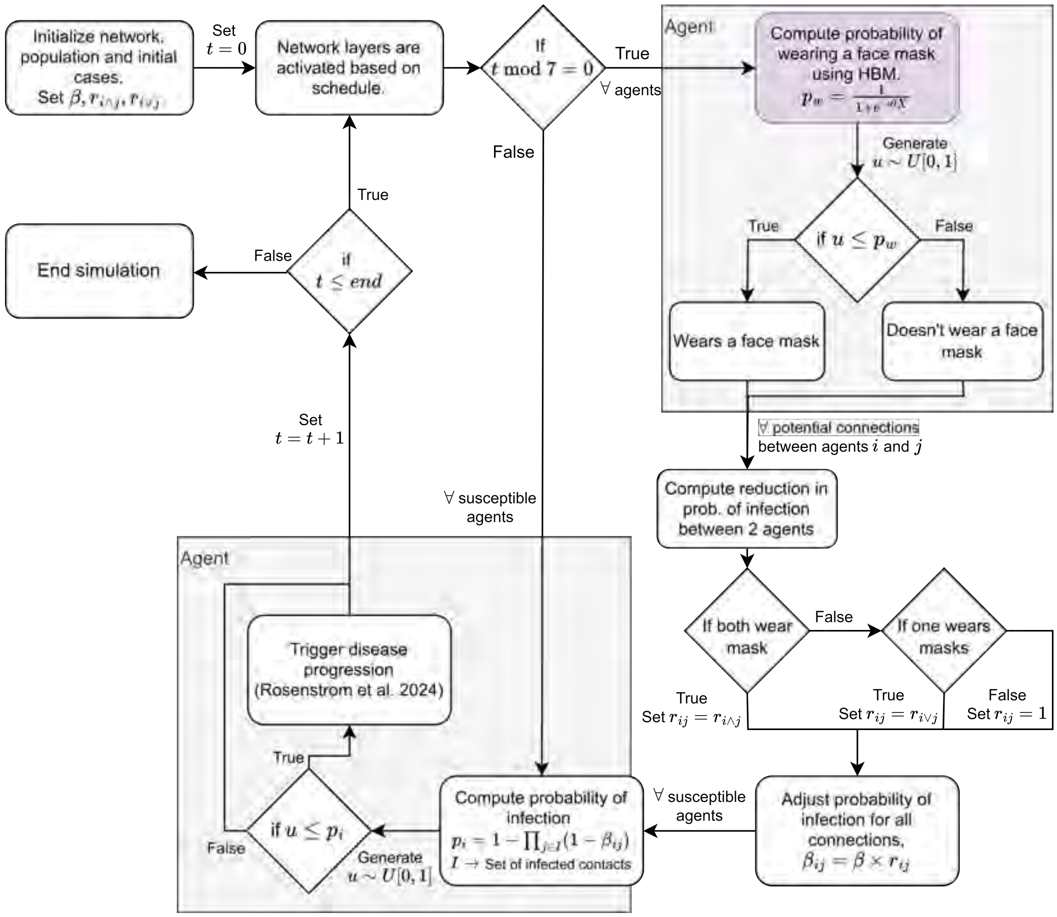

Figure 2: Flowchart depicting the ABM simulation logic.

We included perceptions about COVID-19 and face mask wearing by estimating the joint density of beliefs from the survey data using survey demographic weights. The survey contains 566 respondents with residence in North Carolina that answered all behavior and perceptions questions. Based on the availability of demographic data in the survey, the age groups used to estimate beliefs were Under 20, 20-40, 41-60, and Over 60 year-olds. Figure 3 shows the estimated weighted distribution of beliefs for each age group, illustrating the differences in perceptions between demographic subpopulations.

3.1 Behavioral Model Fitting

We fitted a logistic regression model using individual perceptions as independent variables and self-reporting of face mask usage as the dependent variable (see Table 2). Perceived benefits and perceived severity coefficients resulted to be statistically significant, whereas none of the perceived susceptibility categories were. Despite this, we included the latter variable in the behavioral model to maintain consistency with the theoretical framework, as it is considered an important predictor of protective behavior in the HBM. We further explore the impact of this perception in face mask usage and cases.

Although the resulting model is useful to represent probability of wearing a face mask for a specific individual, it relies on self-reporting data, which generally overestimates actual face mask usage. Based on the estimates of non-pharmaceutical adherence provided by Crane et al. (2021) for November 2020, we defined an alternative model that adjusts the population face mask usage to be between 60% and 70%. To achieve this, we scaled the estimated logistic function to match the population-level masking level,

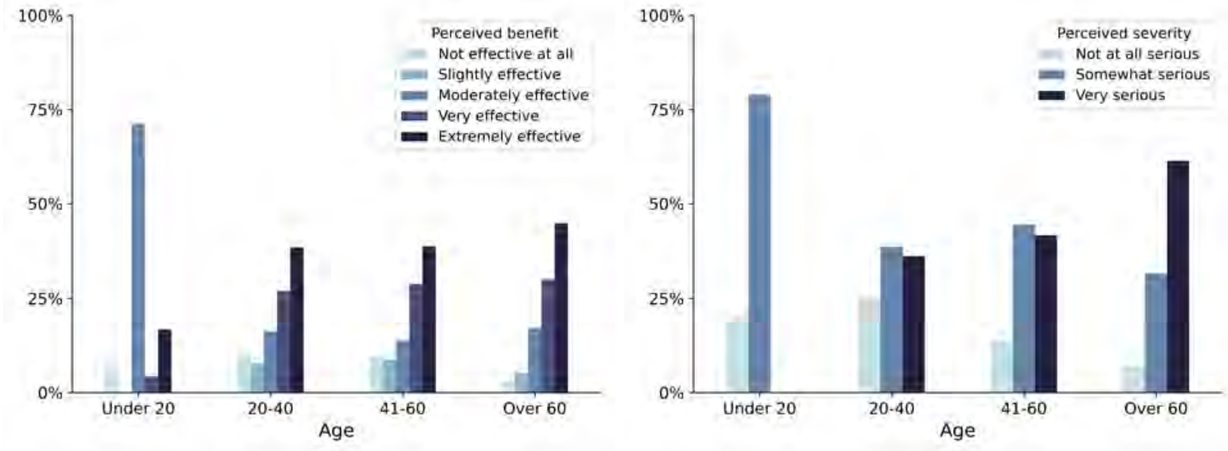

Figure 3: Estimated weighted distribution of perceptions of face mask benefits and COVID-19 severity by age group from survey data.

Table 2: Estimated coefficients of logistic regression.

Variable	Estimate	p-value
Intercept	-2.0852	0.0528
Perceived benefits - Slightly effective	1.6422	0.0193*
Perceived benefits - Moderately effective	4.0229	< 0.001***
Perceived benefits - Very effective	5.438	0.0193*
Perceived benefits - Extremely effective	3.4119	< 0.001***
Perceived severity - Somewhat serious	1.3088	0.0385*
Perceived severity - Very serious	1.527	0.0484*
Perceived susceptibility - Slightly likely	0.7428	0.4884
Perceived susceptibility - Moderately likely	0.9011	0.3934
Perceived susceptibility - Very likely	0.8964	0.4614
Perceived susceptibility - Extremely likely	1.104	0.3775

retaining the interactions estimated in the original model. Table 3 presents the two masking scenarios to be analyzed and the corresponding mean face mask usage for each age group.

3.2 Mask Wearing Using the HBM

We investigate the effect of using the HBM model to implement a perceptions-based masking behavior by comparing it against a masking-at-random policy. The latter consists of a procedure where agents decide to wear a mask based on an age group probability. To be consistent in our results, these age-dependent probabilities were computed from the average masking level resulting from the HBM model simulation.

Results show that there is no significant difference between both modeling approaches in the population incidence, as seen in Figure 4. The scenario with self-reported masking level exhibits practically the same

Table 3: Mean face mask usage by age group.

Scenario	Under 20	20-40	41-60	Over 60
Self-reported	96.3%	87.3%	90.4%	94.6%
Adjusted	57.9%	61.7%	67.6%	70.9%

level of infections for both masking behaviors, whereas in the adjusted scenario, the mean infections are slightly less when using the HBM compared to masking-at-random. The similarity in the mean average results for the population estimates can be expected, as the masking-at-random mimics the same average masking level for each age group. We further investigate the effect in demographic groups, analyzing the difference in incidence per each group between simulation replications. Figure 5 shows that for the scenario with high mask usage, both modeling approaches are equivalent. For the adjusted scenario, the use of HBM as a behavioral model tends to results in less cases through all age groups, although this difference is not statistically significant.

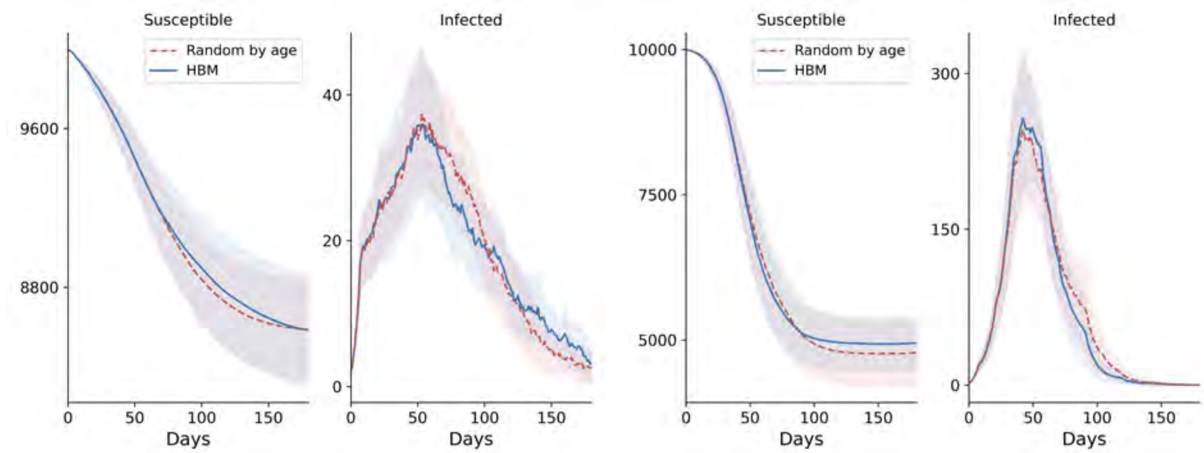

Figure 4: Simulation results for self-reported face mask wearing (left) and adjusted scenarios (right).

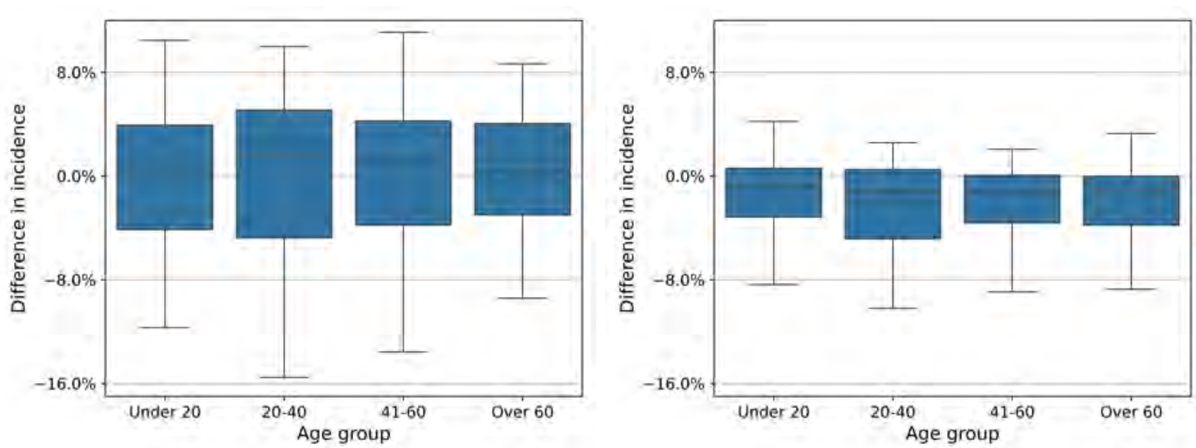

Figure 5: Difference in incidence between the HBM and masking-at-random for self-reported masking scenario (left) and adjusted scenario (right).

From a modeling standpoint, when incorporating theory-based behavior, we are interested in finely representing face mask usage as a structured process and gain insights on the differences in incidence of cases due to contrasting beliefs. Therefore, we expect that individuals that do not perceive COVID-19 as a health threat or don't consider face mask effective will wear masks less frequently, and in consequence, will be more vulnerable to getting ill. Figure 6 shows that individuals in the lowest level of each perception (e.g."Not effective at all") tend to have higher incidence compared to masking-at-random. Note that for this scenario, these results are not statistically significant. On the other hand, Figure 7 shows a greater difference between perception groups exists when masking level is lower. This could be explained by the fact that, when adoption of face masks is not as high as in the previous scenario, the decision of who wears a mask is more crucial given the higher infectivity setting. Results show that for all the age groups except the Under-20, there is a statistically significant difference between incidence levels for those with the lowest versus highest levels of each perception. When comparing with the masking-at-random incidence, agents over 20 years-old that believe face masks are not effective (perceived benefit) will have a statistically significant higher incidence. Moreover, agents in the Over 60 years-old age group that have a low perceived severity also have a significantly higher incidence, although agents with this perception represent less than 10% of this demographic group. Overall, results show that by modeling face mask wearing using the HBM, agents who have low perceptions (and therefore tend to mask less) have higher risk of infections, which is not reflected by a masking-at-random model.

As it is expected that a more elaborated model is able to capture a wider variability within a population, the advantage of using a theory-based behavioral model such as the HBM lies in the ability to represent who is more likely to wear a face mask. Depending on the distribution of beliefs and perceptions, the level of face mask usage, and the demographic composition of a population, the differences highlighted in our results can potentially influence both the estimation of cases within a subgroup and at a population level.

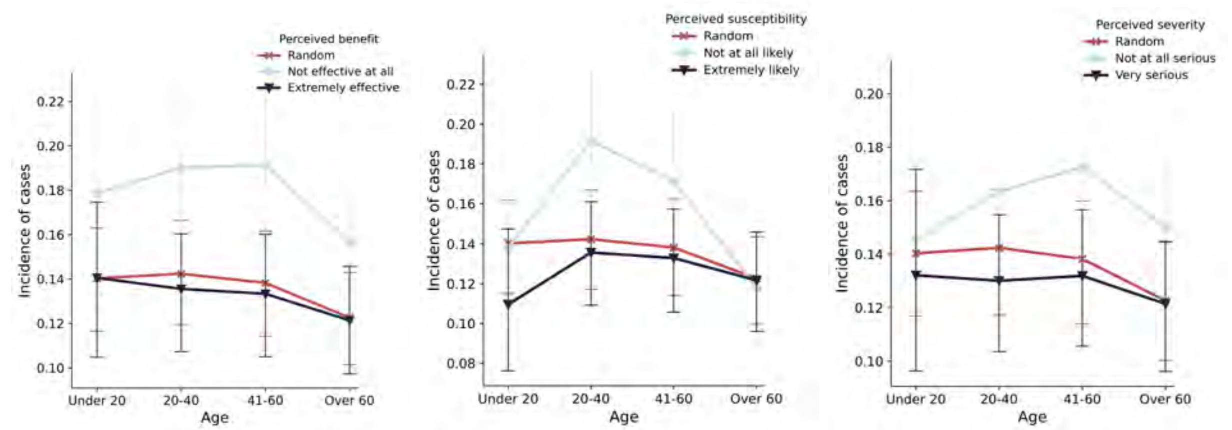

Figure 6: Incidence results for self-reported face mask wearing for each perception by age group. Error bars show the 95% confidence interval.

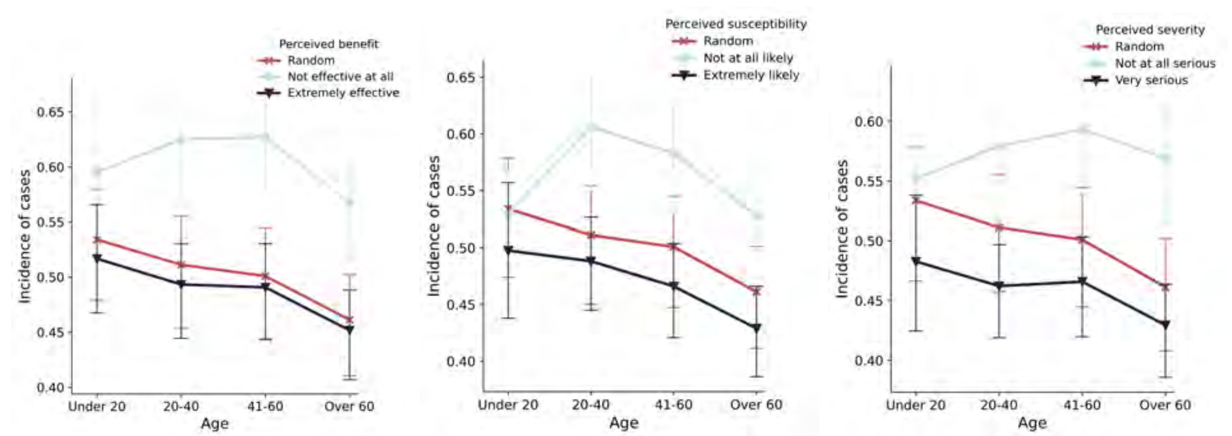

Figure 7: Incidence results for adjusted face mask wearing for each perception by age group. Error bars show the 95% confidence interval.

3.3 Interventions that Change Perceptions

We illustrate the usefulness of incorporating theory-based behavior by quantifying the impact of an intervention focused on modifying people's perceptions to promote protective behaviors. This type of intervention could be seen as public messaging directed to raise awareness about the severity of COVID-19, provide information about the active cases in a community, or provide education about the usefulness of wearing a face mask as a primary action to prevent contagion. We assumed that these policies increases in one level the perception someone has (i.e. from believing risk infection is slightly likely to moderately likely), and that they are effective in causing a change in perceptions only on the lowest levels (i.e. for perceived benefits the intervention targets those who think masking is not effective at all to moderately effective).

Figure 8 shows the results of applying these policies for the adjusted scenario, which we defined as the baseline for this experiment. The greatest reduction in incidence is achieved by the intervention targeting the perceived benefits of wearing a face mask across all age groups, with this decrease being statistically significant in relation to the rest of interventions. On the other hand, both health threat perceptions have a minor decrease in cases compared to the baseline. These results are driven by both the estimated coefficients for each perception and the distribution of beliefs through age groups (see Figure 3). As the Under 20 year-old group has the greatest proportion of people believing masks are not at all effective to moderately effective, the reduction in cases is relatively greater than in older age groups. On the other hand, the incidence in the youngest age group is more susceptible to decrease due to a change in the perception of the severity of COVID-19 compared to a change in the perception of the likelihood of getting ill. This effect is different in the rest of age groups, where interventions directed to modify the health threat perceptions have similar results.

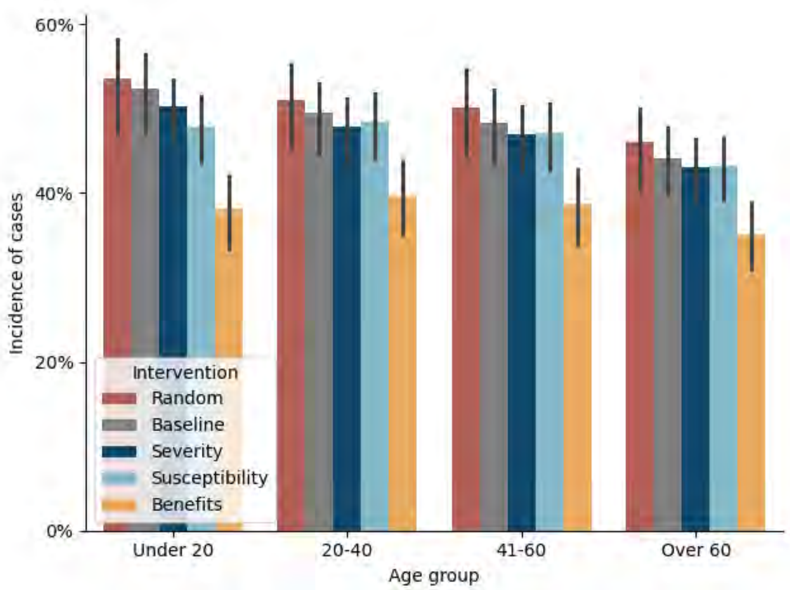

Figure 8: Incidence by age group when conducting interventions targeting different perceptions. Error bars show the 95% confidence intervals.

4 DISCUSSION

In this study, we presented a modeling approach to incorporate theory-based behavior by considering survey data to model face mask wearing. We investigated the benefits of modeling an individual's decision to wear a mask using this approach by comparing it with a commonly used random probability assumption that represent aggregate level behavior. Our insights on the presented case study show that incorporating a refined approach to represent individual actions has an impact on subgroups' estimated incidence results, which is greater when masking level is lower. Furthermore, the addition of individual perceptions based on demographic variables as attributes of agents improves representativity of the population, with agents having low risk perceptions and low perceived benefits masking less than the those with higher perceptions. Combined with the distribution of beliefs across a population, this adds a layer of realism to the ABM, enabling a better assessment of the behavior of different demographic groups and the impact this has on the spread of the disease. This enhancement in the modeling of cognitive processes comes with little computational cost, as statistical models can be efficiently implemented in most programming languages. As nowadays there is a growing interest in achieving equity goals when evaluating policy interventions, it is crucial to accurately model these interactions for simulation tools to be valid.

Behavioral theories such as the HBM are well-studied frameworks that provide a rich theory-based background to understand behavior. We showed that the addition of them in ABMs can help quantify the impact of interventions that aim to modify individual perceptions to promote protective behaviors. Given the underlying behavioral framework that explains the interactions between perceptions and action, policy-makers can use the proposed tool to analyze the impact of different interventions and assess which groups to target to achieve better outcomes. In our example, results show that a policy designed to improve the perception of how effective mask are has a greater impact in preventing cases than a policy focused on raising awareness of how dangerous or risky COVID-19 is.

Limitations to our proposed modeling approach exist. The logistic regression model estimated probability of masking is not monotonically increasing with covariates levels (i.e. one should expect that someone believing it is Extremely likely to catch COVID-19 would have a greater probability of masking than someone believing it is Moderately Likely). This may be caused by the limited number of samples in the survey data. Moreover, the inclusion of non-significant covariates in the model is not recommended. As behavioral theories are used mostly as explanatory models, the inclusion of such variables depends on the importance researchers give to them based on their knowledge and expert opinion. Our simulation results show that an intervention targeting perceived susceptibility or perceived severity do not produce a statistically significant reduction in cases. However, only the former was assessed as not statistically significant in the estimated regression model. As not only the behavioral model drives results but also the distribution of beliefs across the population, further experimentation must be conducted to assess the impact of including non-significant variables in the proposed modeling approach. Alternatively, other statistical models can be used to improve accuracy while maintaining certain interpretability (e.g. decision trees). On the other hand, other behavioral theories that explain health protective behavior exist and may better explain face mask wearing in the context of an infectious disease outbreak.

Additional extensions to our study include incorporating other demographic variables that can be relevant (e.g. urbanicity, gender, race/ethnicity) to explain behavior. Although behavioral models require the availability of individual level data to estimate their validity in explaining behavior, the addition of more demographic variables can be done by either generating the synthetic population age distribution considering them, or by including them as covariates in the statistical model. Moreover, we studied the usefulness of the behavioral model in a static context where individual beliefs remain constant (unless an intervention happens) and, therefore, are independent of their context. An extension of our study is to include dynamic changes to beliefs based on an agent's simulation context and external cues to action (such as a surge in cases).

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