What Can We Learn from Simple Computational Models of Health Behavior Change?

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Abstract. Simple computational models designed to appropriately represent hypothesized mechanisms of health behavior change may be valuable given the challenges of behavior modeling. We developed a simple approach drawn from research on the psychology of health to assesses adoption of health-protective behavior according to (i) its efficacy in reducing disease risk, (ii) the influence of others who themselves differ in the likelihood of behavior change, and (iii) the threshold of perceived threat needed for behavior change. Simulations vary the efficacy of behavior adoption for reducing disease risk, the influence of others on threat perception, and the level of threat associated with behavior change. Face validity of model dynamics is confirmed by the greater number of behavior adopters when expected efficacy of disease reduction is higher. Likewise, a greater number adopt protective behavior when threat thresholds are lower within each disease risk reduction scenario. Social influence had its greatest effect in scenarios of low expected efficacy of disease risk reduction with a high threshold for behavior change. Only in this scenario did high protective behavior influence from social contacts substantially increase behavior adoption. Observational and experimental efforts will allow a test of this finding and parameters for more sophisticated models.

Keywords: Behavior models, epidemics, health psychology.

1 Introduction

The substantial effort invested in developing computational models of health behavior change in epidemic conditions has produced mixed results. Conclusions from a number of these efforts suggest important challenges in developing agent-based epidemic models designed to incorporate individual behavior, which changes with disease incidence and in turn affects incidence. The models attempt to implement broad concepts from health psychology, but often data for key components -- such as attitudes and social norms, how these may change in the face of epidemic disease threats, and how the elements interact to produce behavior change -- are unavailable.

For example, consider conclusions from perhaps the most sophisticated of these attempts, the TELL ME (Transparent communication in Epidemics: Learning Lessons from experience, delivering effective Messages, providing Evidence) European consortium on influenza modeling (Badham & Gilbert 2015). TELL ME implemented key elements of behavior change theories (attitudes, social norms, epidemic threat) but concluded that “ultimately, the TELL ME model was not suitable for detailed communication planning because there was insufficient understanding of the behaviour being modelled to support that purpose, and insufficient data to overcome that gap” (Bedlam 2018). “Fit was generally poor” (Badlam & Gilbert 2015). An attempt to implement TELL ME in the setting of the COVID pandemic was also unsatisfying. “We found the TELL ME behavioural rule to be associated with a moderate to high error rate in representing the adoption of behaviours, indicating that parameter values are not constant over time and that other key variables influence individual decisions” (Martin-Lapoirie, d’Onofrio, McColl, Raude 2023).

The attempt to implement models of this type could be valuable, however. For example, the COVID TELL ME model showed that an attitudinal variable, perceived efficacy of change in behavior to avert disease, had the highest weight for computation of behavior change, while perceived barriers and perceived threat had much lower weights. The authors suggest that “the adoption of protective behaviours is mainly based on perceived efficacy, i.e., how improved hygiene measures and social distancing are perceived as effective in preventing COVID-19 infection.” (Martin-Lapoirie 2023). By contrast, epidemic threat, and especially discounted prior incidence, had a much smaller impact.

Still, should we be confident with this result? It is unclear how much the priority of the attitudinal variable is driven by model assumptions, calibration efforts, or actual behavior-disease dynamics.

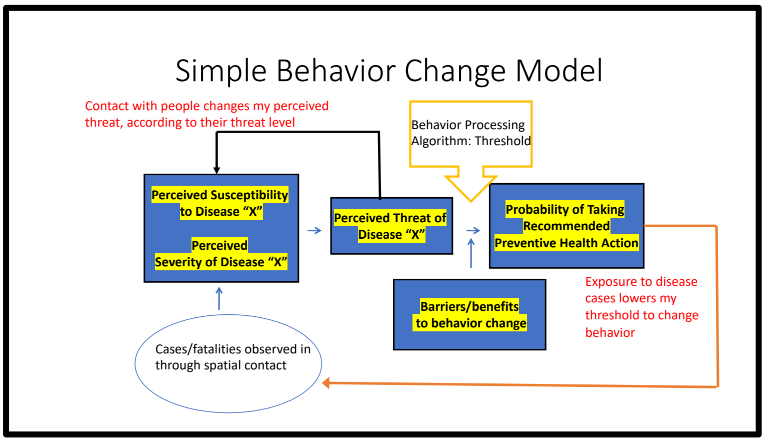
It may be worth stepping back from efforts to validate model predictions and return to simpler models. Simple models designed to appropriately represent hypothesized mechanisms of behavior change, rather than assess the validity of predictions, may be valuable given the challenges of behavior modeling. They allow us to determine if a proposed mechanism or behavior rule provides a plausible explanation of some behavior. Here we do not seek to establish real world values for hypothesized psychological elements or thresholds that predict adoption of behavior, but rather to determine which mechanisms are likely to be most salient for behavior and epidemic dynamics.

A simple approach drawn from research on the psychology of health is that behavior change is likely to differ according to (i) its efficacy in reducing disease risk, (ii) the influence of others who themselves differ in the likelihood of behavior change, and (iii) the threshold of perceived threat needed for behavior change. In this approach, three parameters are of interest: the expected efficacy of behavior change in reducing disease risk, social influences on perceived threat, and the threshold of threat necessary for behavior change. Restricting ourselves to this admittedly simplified approach, we can use simulation to investigate a number of important but unresolved questions. Under what conditions will the influence of others have the most effect on behavior change? How much of an increase in behavior adoption do we see under different assumptions of efficacy in reducing disease risk? We can assign a range of high and low values for each of the three parameters to assess the relative salience of each factor as determined by the incidence of behavior change and course of a simulated epidemic. This was our goal in developing a simple model of health behavior change under epidemic conditions.

2. Model Elements

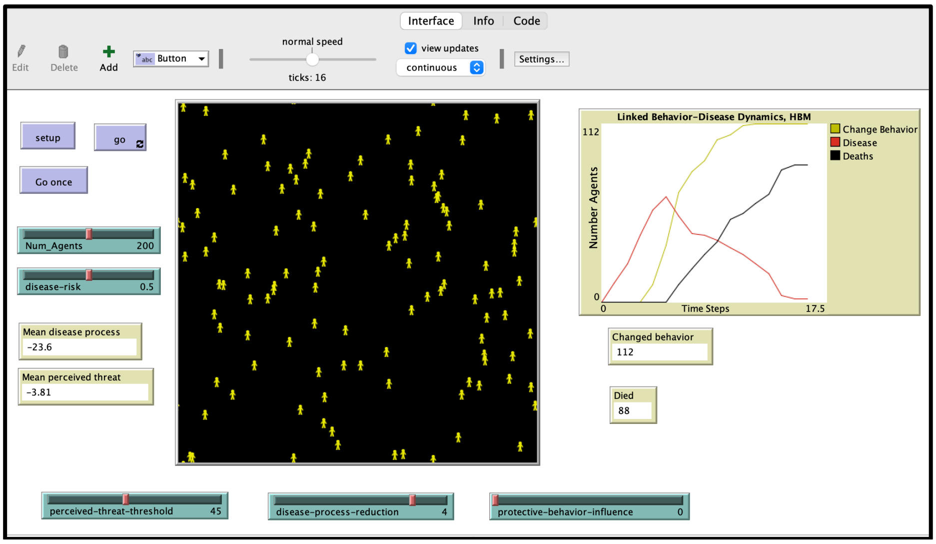
Figure 1 shows the conceptual model used for the simulation.

Figure 1. Model Specification



We implemented the model in Netlogo 6.1.0. A screenshot of the user interface is shown in Figure 2. Simulations can vary the efficacy of behavior adoption for reducing disease risk (*disease_process_reduction*), the influence of others on threat perception (*protective-behavior_influence*), and the level of threat associated with behavior change (*perceived_threat_threshold*). Initial threat and disease risk are drawn from random distributions.

Figure 2. Netlogo User Interface



Updating involves the following relationships. Under the assumption of epidemic pathogen spread**,** disease risk increases 1 unit each timestep and agents die when their disease value is above a threshold. Perceived threat increments based on the increasing disease risk in the locality: *set perceived-threat (disease-process + perceived-threat)*. Agents adopt protective behavior when (i) they encounter a sick agent in a Moore neighborhood and (ii) their threat level exceeds the threshold needed for behavior change. When they adopt protective behavior, their disease risk decrements by the efficacy measure (*disease-process-reduction).* Agents increment threat by *protective-behavior-influence* when they encounter agents with lower threat levels, again in a Moore neighborhood.

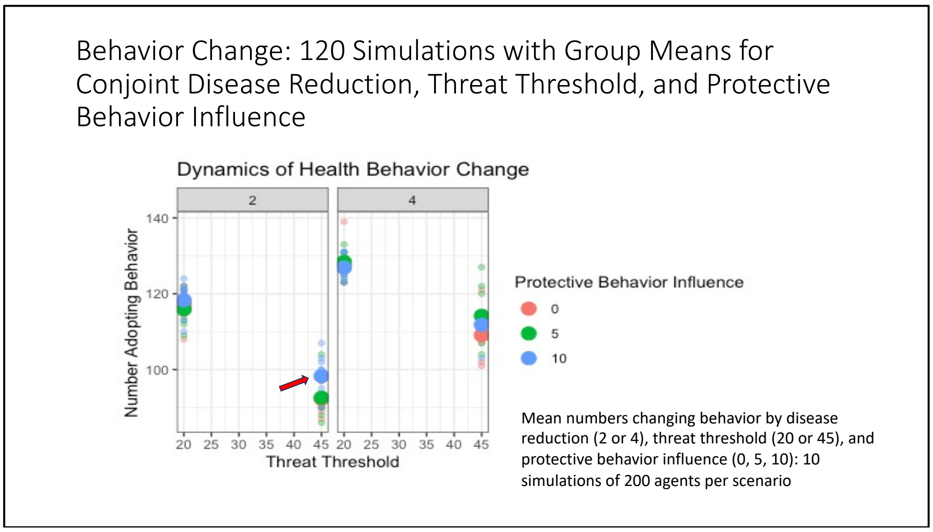
We used populations of 200 and 400 agents and used the Netlogo BehaviorSpace tool to produce 120 model simulations (10 for each parameter), varying efficacy by arbitrarily high and low values of disease risk reduction (-2 and -4 units), threat threshold (25 and 40), and protective behavior influence through spatial contact (0, 5, 10). The model produced predictions for number adopting behavior as well as number with disease and dying over the course of the epidemic. Netlogo results were imported into R for ggplot graphing.

3. Results from the Simulation

Model predictions examining the effect of high and low values for disease risk reduction (-2 and -4 units), threat threshold (25 and 40), and protective behavior influence (0, 5, 10) are shown in Figure 3a,b for values at the end of the simulation for an initial population of 200. The face validity of model dynamics is confirmed by the greater number of behavior adopters when expected efficacy of disease reduction is higher, controlling for level of threat threshold required for behavior change. Likewise, a greater number adopt the protective behavior when threat thresholds are lower within each disease reduction scenario.

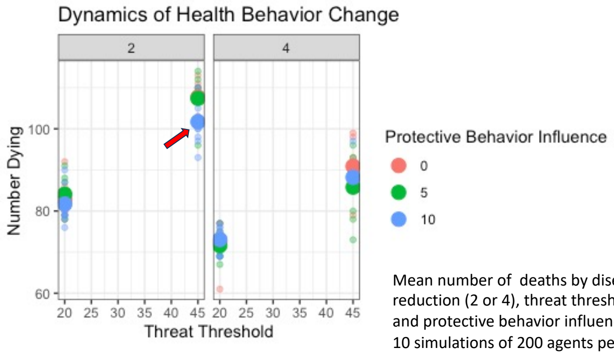
As shown in Figure 3a, an important and perhaps less expected result is evident for the effect of social influence. Social influence has its greatest effect in scenarios of low expected efficacy in disease risk reduction (-2) with a high threshold for behavior change (45). In this scenario, and only in this scenario (indicated by arrow), high protective behavior influence (10) from social contacts (light blue color) substantially increases behavior adoption, moving the mean number adopting from ~70 to ~95. High protective behavior influence has no such effect in the other three scenarios.

Figure 3. Model Predictions
a. Health Behavior



b. Deaths

Deaths and Behavior Change: 120 Simulations with Group Means for Conjoint Disease Reduction, Threat Threshold, and Protective Behavior Influence

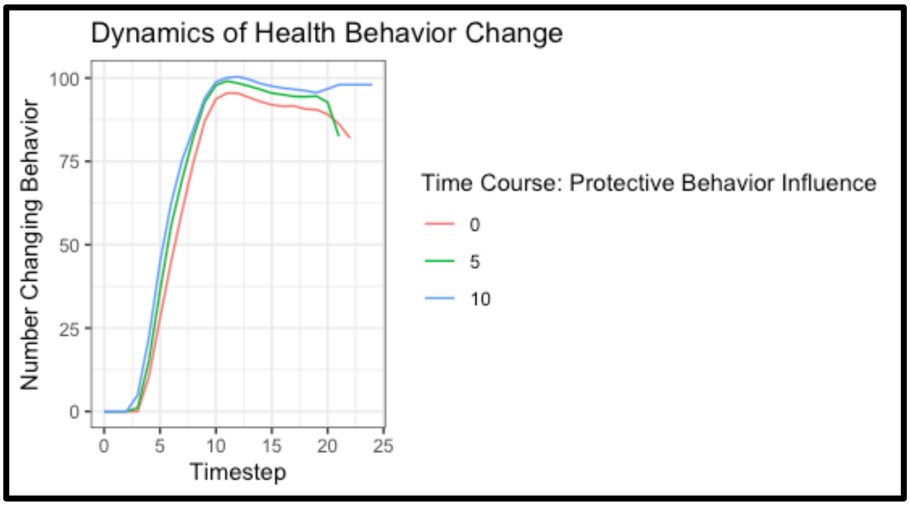


Mean number of deaths by disease reduction (2 or 4), threat threshold (20 or 45), and protective behavior influence (0, 5, 10): 10 simulations of 200 agents per scenario

Deaths over the course of the epidemic follow the same pattern, as shown in Figure 3b. Mortality is highest when efficacy in reducing disease risk is low and the threshold to change behavior is high. But in the scenario with the greatest mortality (efficacy in reducing disease risk =2, threshold to change behavior =45), and only in this scenario, a greater influence of social contacts for raising perceived threat lowers mortality substantially.

Finally, the time course of behavior adoption shows that higher influence of contacts in raising levels of perceived threat (protective_behavior_influence = 5 or 10 vs. 0) in this most challenging disease dynamics scenario leads to earlier adoption of behavior, as shown in Figure 4. Uptake and persistence of behavior change, and avoidance of disease (and death), is highest when social influence is highest. Note that the model allows behavior change to fail, which usually occurs late in the epidemic. In such cases disease risk continues to increase, agents no longer encounter cases of disease to promote or reinforce behavior change, and they contract disease and may die.

Figure 4. Time Course of Behavior Adoption



4. Conclusions

This simple model of the dynamics of health behavior change has nonetheless produced an important finding that is potentially valuable for public health and health communication. Increasing the influence of social contacts through media campaigns or other health communication efforts will likely be most effective in situations where the expected efficacy of behavior change on disease risk is low and barriers to changing behavior are high. Rather than increasing behavior adoption across all four scenarios, as we might have expected, we see the effect only in this particular condition. We see a similar pattern for mortality. The particular salience of social influence in raising threat levels only in this condition is thus an emergent property of the model.

The proposed model is simple and makes no pretense of predicting behavior change in a recent or current epidemic. In this we have developed a model seeking “plausibility rather than realism, [with] an intuitive connection to the real world rather than representing a detailed theoretical behaviour mechanism” (Badham 2018). Other approaches combining epidemic compartment models and psychologically valid agents may offer more sophisticated approaches for assessing behavior change in epidemic settings (Pirolli, Bhatia, Mitsopoulos, Lebiere, Orr 2020). Still, the approach has produced an important mechanistic finding that could be tested in experimental settings. Is the influence of social contacts more potent for behavior change in situations of low expected efficacy and high barriers to change?

An important caveat in this model specification is the overly simple linked disease-behavior dynamics. While each agent is assigned a disease risk and perceived threat level randomly, disease risk increases constantly over time and is used to update perceived threat directly. This broadly follows an approach used by Yang and Diez-Roux (2013). One component of their model adds attitude toward walking and the distance to be travelled to predict whether children will walk to school. A second caveat is our specification of protective_behavior_influence. In the current model, agents with higher perceived threat increase their perceived threat when they encounter agents with lower threat. This would be the equivalent of increasing mask wearing upon encountering someone not wearing a mask. Other specifications of this relationship are clearly possible and worth testing.

In short, this simple model suggests that the influence of social contacts is most potent in situations where the expected efficacy of behavior change for disease risk is low and barriers to behavior change are high. Observational and experimental efforts will allow a test of this hypothesis and parameters for more sophisticated models (Durham & Casman 2012, Durham, Albert, Casman 2012).

References

Badham J, Chattoe-Brown E, Gilbert N, Chalabi Z, Kee F, Hunter RF. Developing agent-based models of complex health behaviour. Health and Place 2018; 54: 170-177.

Badham J, Gilbert N. TELL ME Design: Protective Behaviour During an Epidemic. CRESS Working Paper 2015:2, University of Surrey. URL ⟨http://cress.soc.surrey.ac.uk/web/publications/working-papers/tell-me-design-protective-behaviour-duringepidemic⟩.

Durham DP, Casman EA. Incorporating individual health-protective decisions into disease transmission models: a mathematical framework. J R Soc Interface 2012; 9(68): 562-70. doi: 10.1098/rsif.2011.0325.

Durham DP, Albert SM, Casman EA. Deriving behavior model parameters from survey data: Self-protective behavior adoption during the 2009–2010 Influenza A (H1N1) pandemic. Risk Analysis, 32(12): 2020-2031, 2012.

Martin-Lapoirie D, d'Onofrio A, McColl K, Raude J. Testing a simple and frugal model of health protective behaviour in epidemic times. Epidemics 2023; 42: 100658.

Pirolli P, Bhatia A, Mitsopoulos K, Lebiere C, Orr M. Cognitive modeling for computational epidemiology. 2020 International Conference on Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling and Simulation (SPB-BRIMS 2020)

Yang Y, Diez-Roux A. Using an agent-based model to simulate children's active travel to school. International Journal of Behavioral Nutrition and Physical Activity 2013; 10: 67.