EXPLORING VACCINE HESITANCY DYNAMICS THROUGH THE HEALTH BELIEF MODEL: A SYSTEM DYNAMICS MODELING APPROACH

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ABSTRACT

This study employs a combination of the Health Belief Model (HBM) and System Dynamics (SD) modeling to investigate the dynamics of COVID-19 vaccine acceptance in the United States. Utilizing survey data from the CHASING COVID study from April 2020 to December 2021, our model explores relationships between HBM constructs and vaccination intentions. The system is dominated by three feedback loops, where increased vaccination positively impacts perceived benefits (*Reinforcing Loop 1*) and lowers perceived barriers (*Reinforcing Loop 2*), accelerating vaccine acceptance, and decreased perceived threat due to declining infection rates (*Balancing Loop 1*) hinders vaccine acceptance. Compared to their White counterparts, young Black adults exhibited unique behavior with higher perceived barriers and prolonged vaccination timelines, leading to lower vaccine acceptance. This analysis highlights the utility of the HBM and SD modeling in comprehending and addressing vaccine hesitancy, offering insights applicable beyond pandemics to improve responses during public health emergencies.

Keywords: health belief model, COVID-19, vaccine hesitancy, systems dynamics modeling.

1 INTRODUCTION

In 2019, before the emergence of the COVID-19 pandemic, The World Health Organization (WHO) listed vaccine hesitancy as one of the top ten greatest threats to global health [1]. Since the onset of the pandemic, anti-vaccine sentiment has substantially grown. Vaccine hesitancy levels increased globally in response to news stories about the rapid vaccine development in various media outlets [2]. The lack of trust in vaccine development and the proliferation of misinformation surrounding COVID-19 on social media impeded vaccination uptake [3]. Additionally, the politicization of the COVID-19 pandemic and of its subsequent public health vaccination campaigns negatively impacted COVID-19 health outcomes [4, 5]. As a result, acceptance of the COVID-19 vaccine was alarmingly low, even among health care personnel [6]. A full year after the vaccine became widely available, only 61% of the United States population was fully

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vaccinated [7]. Further, the high transmissibility of various variants of the SARS-CoV-2 virus required a higher proportion of vaccination uptake in the population to reach herd immunity [8].

The causes of vaccine hesitancy are complex and subjective, varying greatly from person to person. An individual's decision not to get vaccinated can be shaped by several psychosocial factors, such as complacency, barriers to access, and perceptions of vaccine safety and disease risk [1]. These factors have been shown to vary based on demographic characteristics such as race and ethnicity, political affiliation, education level, and age [9]. To better understand the multitude of influences on an individual's decision-making process regarding vaccination, several experts have suggested applying the Health Belief Model (HBM) as a theoretical framework for understanding how subjective perceptions and beliefs influence individual health behaviors [10-12].

1.1 The Health Belief Model

We utilize the HBM theoretical framework to understand how COVID-19 vaccination intentions changed over time across different racial and ethnic populations of different ages during the first year of the pandemic. The HBM framework suggests that people's health behaviors are driven by their perceptions, self-efficacy, and cues to action [13, 14]. Through the lens of the HBM, an individual will get vaccinated against COVID-19 if they regard themselves as susceptible to COVID-19 (*Perceived Susceptibility*), if they believe COVID-19 could cause them serious harm (*Perceived Severity*), if they believe the vaccine would reduce their disease severity or susceptibility (*Perceived Benefit*), and if they perceive little to no obstacles to obtaining a vaccine (*Perceived Barriers*) [13, 14]. We have adopted a simplified version of the HBM in which *Perceived Susceptibility* and *Perceived Severity* form the construct *Perceived Threat*.

1.2 Systems Dynamics Modeling

System dynamics (SD) modeling refers to a tradition of dynamic, nonlinear simulation modeling which has been utilized to study complex social, environmental, and health systems. SD models are characterized by interacting causal feedback loops which capture the nonlinear interactions between endogenous variables within the model, generating dynamic model behavior. Reinforcing feedback loops cause exponential growth or decay, while balancing feedback loops cause the system to approach equilibrium. Over the course of a simulation, different feedback loops may dominate the system, determining the model's emergent behavior. In this paper, we operationalize and simulate a SD model of COVID-19 vaccine hesitancy to understand the underlying causal mechanisms fueling vaccine resistance, hesitancy, and acceptance in the United States.

2 METHODS

2.1 Data Source

To calibrate the model, we used survey data from the nationwide study "Communities, Households and SARS-CoV-2 Epidemiology (CHASING) COVID" (https://cunyisph.org/chasing-covid/) [15] led by the City University of New York (CUNY) Institute for Implementation Science in Population Health and the CUNY School of Public Health. This was a longitudinal cohort study with over five thousand diverse participants located across the US, with data collection occurring every three months since the beginning of the pandemic in March 2020. Participants provided answers to questions on a variety of topics that were asked during each survey iteration, tracking changes in the cohort over time. Survey topics included demographic information (e.g., race, ethnicity, age), beliefs about the COVID-19 vaccine and the SARS-CoV-2 virus, and individual behaviors (e.g., masking and social distancing). Our model utilizes survey data from April 2020 – December 2021. Because the survey was not created using the HBM framework, we identified questions that acted as proxies for five HBM constructs: *Perceived Susceptibility, Perceived Severity, Perceived Threat, Perceived Benefits,* and *Perceived Barriers* (Table 1).

For the construct *Perceived Susceptibility*, we chose the maximum response from the two questions listed in Table 1 (Row 1), which were assessed using a four-category Likert scale (None = 0; Low = 1; Medium = 2; and High = 3). Similarly, for *Perceived Severity* we selected the maximum response from the two questions relevant to beliefs about severity of COVID-19 (Table 1, Row 2). For *Perceived Threat*, we chose the median value between the values determined for *Perceived Severity* and *Perceived Susceptibility,* as well as a third question regarding familial death from COVID-19, which was recoded to a value of either 0 (do not have family or friends who passed away from COVID-19) or 3 (do have family or friends that passed away from COVID-19) (Table 1, Row 3). During the first five rounds of the survey, *Perceived Benefits* was equal to 0 if the participant answered "No" to receiving a flu vaccine in the 12 months before the study baseline, or 1 if the participant answered "Yes". In December 2020 and on, additional questions on motivations and influence for vaccination which were relevant to *Perceived Benefits* of vaccination were asked. As a result, we formulated the value for *Perceived Benefits* for remaining time points by subtracting the count of reasons given to delay vaccination (drawn from multiple answers to questions on motivation and influence for vaccination) from the count of reasons to accept vaccination, and re-scaled this value to match the four-category Likert scale (0-3) used in the other HBM constructs (Table 1, Row 4). Finally, if a participant selected any of the possible barriers to vaccination, the value of *Perceived Barriers* was set to 1. If no barriers were selected, *Perceived Barriers* was set to 0 (Table 1, Row 5).

Table 1: HBM constructs and the identified proxy responses from the CHASING COVID survey

Perceived Susceptibility	Maximum between the answers to two questions: *a) How worried are you about getting sick from the new coronavirus?* *b) How worried are you about getting sick from the new coronavirus again?*
Perceived Severity	Maximum between the answers to two questions: *a) How worried are you about your loved ones getting sick from the new corona-virus?* *b) How worried are you about the new coronavirus overwhelming hospitals?*
Perceived Threat (Susceptibility + Severity)	Median between **Perceived Susceptibility**, **Perceived Severity**, and the answer to the following question: *Since you completed your last survey, do you personally know anyone who has died from the new coronavirus?*
Perceived Benefits	For the first four rounds of the survey, the answer to the following question: *During the past 12 months, have you had either a flu vaccine that was sprayed in your nose or a flu shot injected into your arm?* For the remaining survey rounds, selected answers to the following questions: *a) Which of the following influence your decision to get a vaccine?* *b) What motivates you to get the vaccine?*
Perceived Barriers	Selected answers (from the option list) in response to the following question: *Did you have difficulty with the following aspects of getting a test?*

2.2 Model

Figure 1 depicts a simplified version of the model, with three key feedback loops highlighted. The model population is divided into three distinct categories: vaccine acceptant, vaccine hesitant, and vaccine resistant. Vaccine acceptant individuals are divided into two stocks, those who are not yet vaccinated but plan on getting a vaccine [*Adults who Decide to Get Vaccinated (Acceptant)*], and those who have already been vaccinated [*Adults who are Vaccinated*]. The vaccine resistant population is also composed of two stocks. Individuals in the *Adults who Do Not Intend to Get Vaccinated (Resistant)* might change their mind and flow to the hesitant stock [*Adults who are Undecided (Hesitant)*]. From there, these individuals might change their perceptions again and decide to get vaccinated. Alternatively, some individuals in the resistant stock might choose to never get vaccinated, in which they will flow into the *Adults who Never Get*

Vaccinated stock. Once an individual chooses to never take the vaccine, they cannot flow back into the *Adults who Do Not Intend to Get Vaccinated (Resistant)* stock.

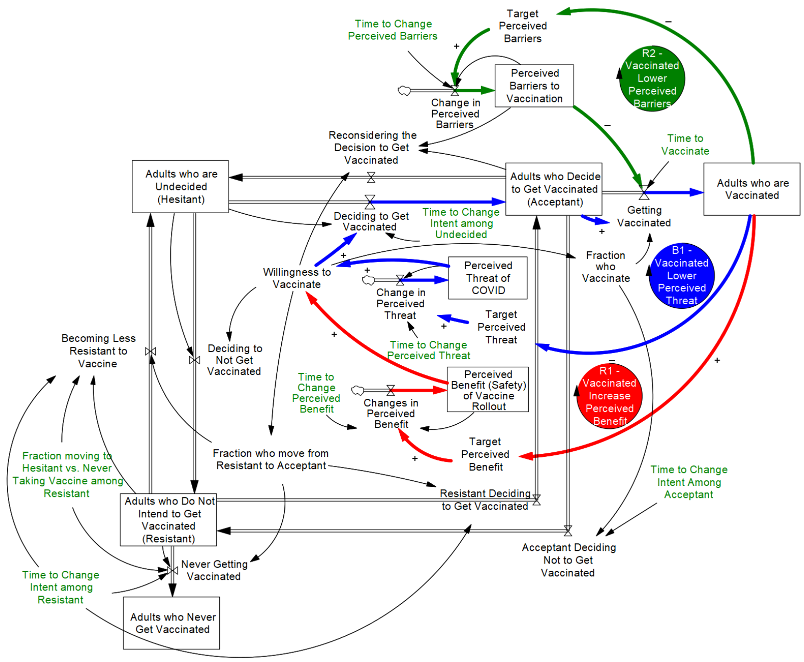

Figure 1: Simplified model.

The reinforcing loop "R1 – Vaccinated Increase Perceived Benefit" (in red) demonstrates how an increase in the number of *Adults who are Vaccinated* leads to an increase in the *Perceived Benefit (Safety) of Vaccine Rollout* through a goal gap structure. As perceived benefits increase, *Willingness to Vaccinate* increases. Willingness fuels two key variables including the rate by which undecided people become vaccine acceptant [*Deciding to Get Vaccinated*] and the rate by which vaccine acceptant people receive the vaccine [*Getting Vaccinated*]. This reinforcing loop demonstrates that as more individuals get vaccinated, their confidence in the safety and benefit of the vaccine increases, thus increasing people's willingness to get vaccinated, and increasing the subsequent vaccination rate in the population.

The second reinforcing loop, "R2 – Vaccinated Lower Perceived Barriers" (in green) depicts the path through which the increase in the number of vaccinated individuals [*Adults who are Vaccinated*] causes *Perceived Barriers to Vaccination* to decrease through a goal gap structure, thereby increasing the rate by which vaccine acceptant people receive their vaccine [*Getting Vaccinated*]. As more individuals get vaccinated, perceptions of barriers to receiving the vaccine such as availability, transportation, and cost decrease, leading to more willingness to get vaccinated, and consequently, a higher vaccination rate. Balancing loop "B1 – Vaccinated Lower Perceived Threat" (in blue) depicts the path through which an increase in the *Adults who are Vaccinated* stock leads to a decrease in *Getting Vaccinated* through changes in perceived threat. As more people get vaccinated, COVID-19 infections and subsequent deaths decrease. As a result, *Perceived Threat of COVID* decreases, and vaccination rates follow a similar decline.

Vaccinated individuals are still at risk of contracting COVID-19. These cases are referred to as breakthrough infections, and they often influence public perception of the vaccine [16]. If an individual believes they will still contract COVID-19 after being vaccinated, their perceived benefits of the vaccine will be low. Conversely, perceived threat of COVID-19 may increase if the virus is transmissible enough to infect even those who are vaccinated. To address this, we have defined a breakthrough infection mechanism within the model. For simplicity, we have assumed a constant breakthrough infection rate of 0.01% of the stock of vaccinated people per day (or 3.65% per year). This rate is in line with published breakthrough infection rates early in the COVID-19 pandemic (2020-2021) [17, 18]. This assumption allows us to capture the influence of breakthrough infections on vaccine perceptions; although we recognize that this is an over-simplification (breakthrough infection rates vary over time due to a variety of factors which are beyond the current scope of this model).

2.1 Model Calibration

The model was calibrated towards the HBM construct data over time derived from the CHASING COVID survey using a maximum likelihood estimation approach employing Powell's algorithm in Vensim® (Ventana Systems, Inc.) [19]. Since vaccination perceptions differ substantially across subgroups, we utilized data which was stratified by age and race/ethnicity within model array structures. In this analysis, we report comparative simulation results for four groups of interest: young (age 18-34) Black adults, older (age 55+) Black adults, young White adults, and older White adults.

3 RESULTS

Figure 2 depicts the percentage of vaccine acceptant individuals stratified by age (18 to 34) and (55+), and race (Black and White) from the simulation base run. At the start of the simulation (April 2020), Black adults began less acceptant of the vaccine compared to White adults. Similarly, older adults began the simulation less acceptant of the vaccine compared to their younger counterparts. In January 2021, older Black adults and both groups of White adults experienced a surge in vaccine acceptance corresponding to the roll-out of the COVID-19 vaccine during this time. This shift was further fueled by the two reinforcing feedback loops "R1- Vaccinated Increase Perceived Benefit" and "R2 – Vaccinated Lower Perceived Barriers", which became activated once the vaccine became available. As more people got vaccinated and infections in the population began to decrease, perceived benefits of the vaccine subsequently increased, and perceived barriers to vaccination decreased, causing more people to move from vaccine hesitant or resistant to vaccine acceptant. Domination of these two reinforcing feedback loops after the initial rollout of the vaccine caused a brief period of exponential growth in vaccine acceptance among these three groups (December 2020 to April 2021).

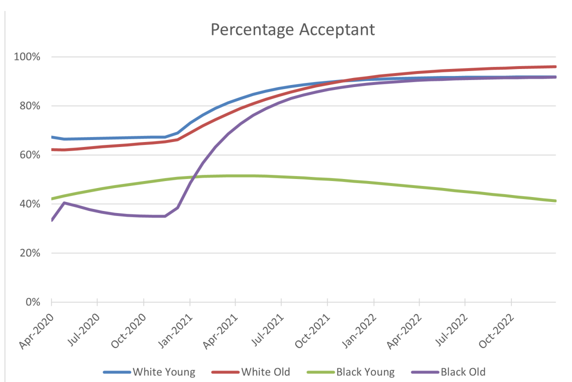

Figure 2: Simulated percentage of vaccine acceptant individuals over time.

Eventually, the rapid growth of vaccine acceptance among young and older White adults and older Black adults was slowed by the balancing loop "B1 – Vaccinated Lower Perceived Threat". Although perceived benefit of the vaccine increased as infections decreased, perceived threat of infection also began to decline. In other words, individuals perceived COVID-19 as less harmful when infection and death rates declined as a result of more vaccinations being administered. A drop in perceived threat resulted in a subsequent decline in vaccine acceptance across all age groups. Vaccine acceptance gradually leveled when perceived threat declined within the population and the balancing feedback loop that captures this HBM construct (B1) pulled the system towards equilibrium. Further, as the stock of unvaccinated individuals diminished, the flow from unvaccinated to vaccinated declined, and the vaccine acceptant population leveled.

Across both racial groups, young adults started with a higher acceptance compared to their older counterparts. This dynamic shifted by the end of the simulation, and older adults exceeded younger adults in their acceptance. During initial vaccine rollout, age restrictions prohibited younger adults from receiving the vaccine. As older adults began to get vaccinated at higher rates than their young counterparts, R1 and R2 feedback loops became more influential among older adults. As a result, the dynamic reversed by the end of the simulation.

Young Black adults exhibited unique system behavior when compared to the other subgroups. Model calibration resulted in young Black adults taking 600 days on average to get vaccinated compared to 1 day for young White adults and 1.7 days for older Black adults. The slight increase in acceptance near the beginning of the simulation was likely because a small proportion of young Black adults had a much shorter time to vaccinate, and therefore got vaccinated and moved into the *Adults who are Vaccinated* stock. However, because the average time to vaccinate was so long, there was an insufficient number of vaccinations to activate R1 and R2 within this population in the same way that these loops became activated in the older Black, young White, and older White populations. Therefore, young Black adults were the only subgroup to end the simulation run with declining vaccine acceptance.

Figure 3 depicts the changes in perceived benefits to vaccination and perceived barriers to vaccination over time. These two variables have an inverse relationship with one another. Perceived benefits to vaccination began to rise, and perceived barriers began to fall around January 2021 when the vaccine became widely available. This behavior is indicative of the effects of R1 and R2 loops dominating the system around this time. Young Black adults maintained the lowest perceived benefits and the highest perceived barriers for most of the simulation run, culminating in decreased vaccine acceptance towards the end of the simulation compared to the other groups discussed, which experienced a flattening in vaccine acceptance towards the end of the simulation (Figure 2).

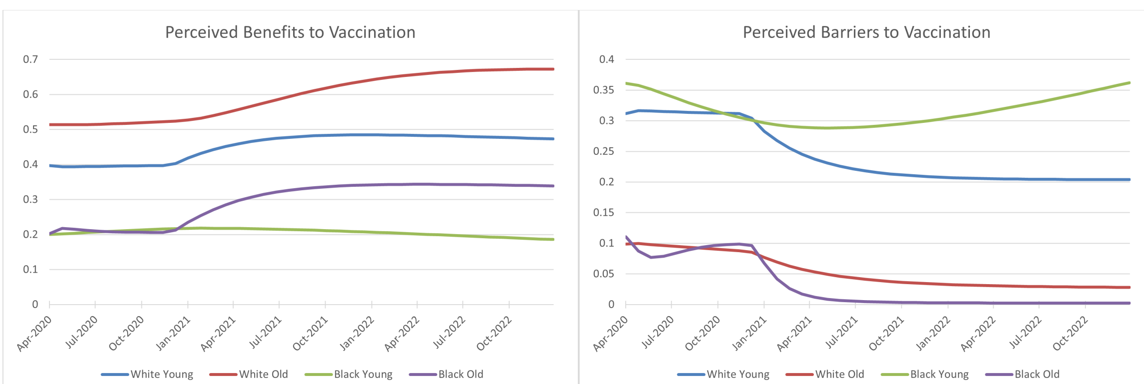

Figure 3: Simulated changes in perceived benefits and perceived barriers over time.

4 DISCUSSION

In this study, we have demonstrated the use of the Health Belief Model and System Dynamics modeling to investigate the shifting dynamics of COVID-19 vaccine acceptance in the United States. The results of our analysis showcase the utility of the HBM and systems modeling in understanding how perceptions influence health behaviors, offering insights applicable beyond pandemics to improve responses to public health emergencies. Furthermore, we have demonstrated how SD modeling can shed light on differences in health beliefs by race and age, the results of which can inform the development of targeted interventions for vulnerable populations to utilize finite resources more efficiently during public health emergencies.

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