Health Risk Perception for Household Trips and Associated Protection Behavior During an Influenza Outbreak

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ABSTRACT

This project deals with exploring 1) travel-related health risk perception, and 2) actions taken to mitigate that health risk. Ordered logistic regression models were used to identify factors associated with the perceived risk of contracting influenza at work, school, daycare, stores, restaurants, libraries, hospitals, doctor's offices, public transportation, and family or friends' homes. Based on the models, factors influencing risk perception of contracting influenza in public places for discretionary activities (stores, restaurants, and libraries) are consistent but differ from models of discretionary social visits to someone's home. Mandatory activities (work, school, daycare) seem to have a few unique factors (e.g., age, gender, work exposure), as do different types of health-related visits (hospitals, doctors' offices). Across all of the models, recent experience with the virus, of either an individual or a household member, was the most consistent set of factors increasing risk perception. Using such factors in examining transportation implications will require tracking virus outbreaks for use in conjunction with other factors.

Subsequently, social-health risk mitigation strategies were studied with the objective of understanding how risk perception influences an individual's protective behavior. For this objective, this study analyzes travel-actions associated with two scenarios during an outbreak of influenza: 1) A sick person avoiding spreading the disease and 2) A healthy person avoiding getting in contact with the disease. Ordered logistic regression models were used to identify factors associated with mitigation behavior in the first scenario: visiting a doctor's office, avoiding public places, avoiding public transit, staying at home; and in the second scenario: avoiding public places, avoiding public transit, staying at home. Based on the models for Scenario 1, the factors affecting the decision of avoiding public places, avoiding public transit, and staying at home were fairly consistent but differ for visiting a doctor's office. However, Scenario 2 models were consistent with their

counterpart mitigation models in Scenario 1 except for two factors: gender and household characteristics. Across all the models from Scenario 1, gender was the most significant factor, and for Scenario 2, the most significant factor was the ratio of household income to the household size.

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GENERAL AUDIENCE ABSTRACT

Transmission of a communicable disease depends on the social interactions of the members of society. Generally, individuals associate their health-protection behavior to the perception of health risk associated with that activity. Hence, individuals with high health-risk perception are likely to participate in a protective action to reduce the threat of getting infected with influenza. However, in some cases, even if a high health risk is perceived, an individual might have a decreased likelihood to take actions to mitigate that risk. This behavior could be associated with their inability to carry out recommendations, such as vaccination (due to the cost of vaccination) or adopting protective behaviors such as social isolation (switching from public transit to personal vehicle due to the associated cost). This behavior, of either adopting or rejecting protective action, can be explained by protection motivation theory. This theory explains the individual's perception of the severity of an event (i.e., threat appraisal), and individual's expectancy of carrying out recommendations (risk mitigation strategies) to reduce threat (i.e., coping appraisal). Both, health risk perception and risk-mitigation strategies are studied for changes in travel decisions.

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CHAPTER 1 INTRODUCTION

1.1. BACKGROUND

Seasonal influenza viruses circulate and cause disease in humans every year, which impacts productivity and the economy *(1)* with potential economic losses of $6.4 million in a quarter of US counties (75th percentile) *(2)*. In temperate climates, influenza tends to occur seasonally during the winter months, spreading from person-to-person through sneezing, coughing, or touching contaminated surfaces. Seasonal influenza viruses can cause mild to severe illness, and for high-risk individuals, even death *(3)*.

Individuals come into contact with potential carriers of the virus at various locations based on their everyday activities. Examples include visits to a workplace, school, daycare, stores, restaurants, libraries, hospitals, doctor's offices, public transportation (bus, train, etc.) and family or friends' homes. During a disease (communicable) outbreak, actions such as social isolation can reduce contact rates in the population. This action, combined with properly treating the sick and reducing the risk to the susceptible population (via vaccination), helps to contain the transmission of the virus. Mathematically, to contain a communicable disease, the average number of secondary cases generated by a typical primary case has to be less than 1 *(1, 2)*.

This study focuses on identifying factors associated with (1) the risk perception of contracting influenza at typical everyday locations, (2) the travel-related actions that reduce exposure, and (3) the travel-related actions to get treatment or prevent the spread of disease.

Data for this study came from a health survey of 2168 respondents across the U.S. Self-reported perceived risk of contracting influenza by visiting (a) work locations, (b) schools, (c) day care, (d) stores, (e) restaurants, (f) libraries, (g) hospitals, (h) doctors' offices, (i) family and friends' homes, and (j) using public transit was measured on a three-factor scale: low risk (not likely), medium risk (somewhat likely) and high risk (very likely). These risk perception variables served as the dependent variables in ordered logit models with characteristics of the individuals (e.g., knowledge and experience with influenza, insurance, and socio-demographics) as explanatory variables. Understanding the risk perception for contracting influenza at various locations is the first step in understanding actions individuals may take to protect themselves, such as canceling trips, avoiding public transit, and avoiding public places, as well as being vaccinated. The first three of these protective actions affect a person's travel, destination, and mode choices.

This study incorporates the influence of risk perception into travel-related risk mitigation models. It can be anticipated that risk perception would influence the protection behavior based on protection motivation theory *(4, 5)*. This study provides insight into the way regular household trips or work-related travel would be affected by an influenza outbreak.

Risk mitigation actions are likely to vary for every individual not only based on their risk perception but also on their social interaction. Stochastic patterns of social interaction make it difficult to comprehend the transmission of the virus between an infectious and a susceptible individual. Hence, assessing factors influencing the protection behavior of a susceptible individual becomes a complex task *(6)*.

Risk perception level responses and other parameters (including demographics, comprehension of the disease, etc.) were used as independent variables for the ordered logit model. The frequencies of travel-related actions that mitigate the associated health-risk (i.e., actions to prevent the spread of the disease when sick or adopt social isolation when not sick) were used as dependent variables in the models. The models to prevent the spread of disease predict (a) how likely the respondent is to visit a doctor when sick; (b) how likely the respondent is to avoid public places when sick with influenza; (c) how likely the respondent is to avoid public transit when sick with influenza; (d) how likely the respondent is to stay home when sick with influenza. The models for actions taken to avoid contracting influenza include: (e) how likely the respondent is to avoid public places to protect oneself from getting sick during an Influenza outbreak; (f) how likely the respondent is to avoid public transit to protect oneself from getting sick during an influenza outbreak; (g) how likely the respondent is to stay at home to protect oneself from getting sick during an influenza outbreak. The self-reported likelihoods for these activities were "never," "sometimes," and "always."

1.2. CONTRIBUTION OF THESIS

The objectives of this study include identifying factors which are associated with (1) risk perception of contracting influenza at typical everyday locations, (2) travel-related actions that reduce exposure, and (3) travel-related actions to obtain treatment or to prevent the spread of disease. The tie between travel plans (or likelihood thereof) and influenza has received little attention to date. However, participation in activities (e.g., school, work, shopping) provides social contact allowing contagious diseases to spread, and travel itself (e.g., through public transit) can also expose people to the virus. Furthermore, travel is required to obtain medical care when sick. Outcomes of this study can inform models of disease transmission, a parameter that incorporates exposure and mitigation as a part of social interaction involved in travel-related activities.

1.3. ORGANIZATION OF THE THESIS

The remainder of this thesis is organized into six additional chapters. Chapter 2 provides the literature review on influenza and studies conducted on the association of risk perception and public health interventions. Chapter 3 represents an overview of the data used in the study, followed by the analysis methodology in Chapter 4. The subsequent chapters present the analysis and results for the Risk Perception (Chapter 5) and the Risk Mitigation models (Chapter 6). Finally, Chapter 7 presents the conclusions.

CHAPTER 2 LITERATURE REVIEW

The influenza virus has been identified as a major health threat to humans. Three types of influenza affect human health: seasonal, Zoonotic or variant, and pandemic influenza *(3)*. Seasonal influenza is predominant during winter months, in regions with a temperate climate. Due to its evolving behavior, seasonal influenza can affect individuals multiple time in their lifetimes. Zoonotic or variant forms of influenza are spread by the interaction between humans and animals and have been recorded several times in the past century *(3).* Whereas, influenza is pandemic when the virus is not previously circulated amongst humans and creates significant outbreaks (for example, H1N1 influenza (2009) pandemic) *(3).* The Influenza virus results in respiratory morbidity (respiratory illnesses: asthma, chronic or acute bronchitis, emphysema, chronic airway obstruction, etc.) and mortality (deaths due to respiratory illness) across diverse species including humans *(7, 8).*

2.1. EPIDEMIC MODELS

Dynamics of the spread of influenza could be studied based on mathematical models. In the past, most of the previous research works focused on developing and extending the K-M model *(9),* initially constructed by Kermack and Mckendrick in 1927 *(10).* The K-M model was based on the assumption that 1) all members of the society are susceptible to a disease, 2) every susceptible individual develops a complete immunity from the disease, and no infected person would be amongst the susceptible group once immune, and 3) there is no inherited immunity in any individual in the society *(10).* Hence, from the assumptions, the only way a susceptible individual leaves the susceptible group is by being infected. Further, the only way a person can leave the infected group is after recovering completely from the infection and would never return to the susceptible group.

For the K-M model, the population is divided into three distinct classes: S (the susceptible), - individuals prone to being infected by the epidemic; I (the infected), - Individuals who act as disease carriers; and R (the removed), - individuals who have had the disease and are now immune to the infection (or removed from the further propagation of the disease) *(10)*. Schematically, the individual goes through consecutive states S → I → R. Such models are often called the SIR models. SIR models apply to a closed population (i.e., no births deaths or migration) *(10).* The SIR model is of the differential form, as given below:

$$\frac{dS_t}{dt} = -\alpha S_t I_t$$

$$\frac{dI_t}{dt} = \alpha S_t I_t - \rho I_t \tag{1}$$

$\alpha = \alpha 1 \times \alpha 2$

where,

$\alpha 1$ = Rate at which an individual comes into contact with any other individual;

$\alpha 2$ = Probability that a susceptible individual upon contact with an infected individual contracts the disease

ρ = Rate of recovery of infected individuals

I_t = Number of infected individuals at time t

S_t = Number of susceptible individuals at time t *(10)*

The above equation (1) represents the classic K-M model (also known as an SIR model). This model is more of a mathematical model to estimate the termination of an epidemic for a certain population, which has a known number of susceptible society members, based on the assumptions stated previously.

Adding to the classic K-M model, researchers introduced the basic reproduction number *(11)* Ro, which quantifies the transmissibility of any pathogen. Ro is the average number of secondary cases generated by a typical primary case in an entirely susceptible population *(12);* hence, to contain the transmission of a disease, Ro should be less than 1. Practically, this is achievable by incorporating various risk mitigation measures such as reducing the contact rates in the population, proper treatment of the infected individual, or reducing the susceptibility of the non-infected individual (e.g., through vaccination).

This study deals with the perceived threat of the communicable disease and the associated mitigation actions, rather than developing a mathematical model to trace the spread of disease. Hence, it is essential to understand the social health behavior across various social groups. Social health behavior could be understood by the social cognitive models *(13)*, which are discussed in the next sub-section.

2.2. THEORIES OF PROTECTIVE HEALTH ACTIONS

With the Social Cognition Model (SCM), the focus is on the cognitive or thought processes that persuade an individual to differ from the course of action based on the risk perception

(Action considered by an individual with a desire to be healthy) and adopt a different behavior (Action considering outside media influences) in real-world situations *(14).* SCM assumes that behavior is a function of people's perceptions of the event. Additionally, it establishes on self-regulation research. Self-regulation can be defined as "mental and behavioral processes by which people enact their self-conceptions, revise their behavior, or alter the environment to bring about outcomes in it in line with their self-perceptions and personal goals" *(14, p. 181).*

The Health Belief Model is the oldest and most widely used Social Cognition Model in health psychology and is considered useful to predict health behavior *(15, 16).* There are two aspects of health behavior representation in the Health Belief Model: how the threat/risk is perceived and health interventions to this threat. Other health psychology models also indicate that risk perceptions are critical drivers of health behaviors *(17-21).*

Later, Rogers *(22, 23),* postulated the Protection Motivation Theory (PMT), which links the risk perception with engagement in protection behavior (to avoid contacting disease) of an individual. PMT builds on the Health Belief Model *(24),* with an emphasis on two cognitive processes: Threat appraisal and Coping appraisal.

Threat appraisal is related to the perception of the severity of the event and maladaptive response reward. Maladaptive response reward is the perceived benefit gained by not engaging in health protection behavior (to avoid getting sick) *(23, 25).* Moreover, threat appraisal is the estimation of the chance of contracting the disease, i.e., vulnerability, and estimation of the seriousness of a disease, i.e., severity *(22, 23, and 26)*.

"The coping appraisal process evaluates the components that are related to the evaluation of coping responses. These components are individual's expectancy that carrying out recommendation can remove the threat (response efficacy) and the belief in one's ability to execute recommended courses of action successfully (self-efficacy)." *(26, p. 98).* Hence based on response-efficacy and self-efficacy, an individual can either adopt or reject protective action. For instance, an individual who is a regular public transit user and perceives high health-risk traveling in public transit during an influenza outbreak is likely to discontinue commuting to work using public transit. Despite the high perceived health-risk, some individuals may continue to travel using public transit due to external factors, such as unavailability of personal vehicle, or paying for tolls or parking. Hence, some individuals have less likelihood to follow recommended measures (i.e., discontinuing the use of public transit) due to two reasons: 1) lack of resources required to carry out recommendations and 2) perceived importance associated with the trip.

2.3. HEALTH RISK PERCEPTION AND MITIGATION

Risk perception and mitigation strategies can explain a lot about an individual's behavior during a health epidemic. The two identified principal strategies for containing serious human outbreaks of influenza are therapeutic countermeasures (e.g., vaccines and medications) and public health interventions (e.g., social separation and isolation) *(27).* Public health interventions include an individual's decision whether to travel or not and which mode of transportation to use. Further, as per Social Cognition Models, individuals base their decisions on risk perception and risk mitigation.

Several studies in the past have focused on connecting risk perception and risk mitigation. In a study on the Australian population, Barr et al. *(28)* found that respondents with higher levels of health-risk perception reported more willingness to comply with public health interventions during influenza outbreaks. Similar results were found in Hong Kong *(29),* Italy *(30),* and Australia *(7),* where respondents with increased perception of risk were more likely to engage in risk-reducing behaviors. Our study investigates factors associated with risk perception for various locations involving travel.

Risk perception and risk mitigation behavior are influenced by various demographic factors, such as age, income, household characteristics, etc. However, it is also evident that there are various parameters other than the demographic characteristics and social interactions (i.e., parameters influencing the comprehension of the health-threat associated with involvement in any activity), which affect risk perception and protection behavior. Efforts in this study have been made to identify these factors.

2.3.1. Parameters Affecting Comprehension of Severity: Risk Perception/Mitigation

Experience with influenza, its communicability, and health consequences, likely increases risk perception *(7, 8, and 31).* Hence, this parameter is likely to influence the threat appraisal component based on the comprehension of the spread of the disease. Further, this increased risk perception attributes to an individual's understanding of the communicability associated with influenza *(32-34)*.

2.3.2. Demographic: Risk Perception/Mitigation

Several demographic characteristics are likely to be associated with different health perception/mitigation behavior. According to a study on the Canadian population, women, individuals without a bachelor's degrees, and low-income respondents had high social health risk perception *(36)*. Demographic studies by *(32- 34, and 37),* suggest a higher level of risk perception of getting sick with influenza within women when compared to men.

Additionally, household characteristics (such as children in the household, and household size) could also be anticipated to affect mitigation behavior. Cauchemez *(12),* conducted a study for the spread of seasonal influenza in schools and concluded that children between the age of 6-10 years had the highest number of cases of the flu. The age group of 2-5 years had the next highest number of influenza cases.

2.3.3. Social Interaction: Risk Perception/Mitigation

Children are more susceptible to respiratory illnesses in comparison to adults *(38-45),* which could increase parents' (or other elder household members') risk perception for travel-related actions. This would happen as the parents' (or other elder household members') would not want to be the potential carrier of the influenza virus, which could be transmitted to the children in the household. This indicates certain household characteristics, e.g., presence of children in a household, would likely influence health-risk actions. Lau et al. *(46),* studied influenza dynamics within the household and concluded that the transmissibility of influenza decreases between two members of a household with the increase of household size. Therefore, household size could influence the protection behavior of an individual.

Modeling and statistics have been useful in capturing social network structure, socio-demographics, and biological factors affecting the transmission (of influenza) in small communities such as household, hospitals or schools *(46-48).* However, these models capture only the microscopic transmission, i.e., confined to the premises of small communities, and fail to capture interactions during other routines. It is essential to capture a holistic network of social interactions, involving various household trips, to understand the protection behavior.

Tracking of social interactions could help assess the spread of influenza *(56)*. However, a very fine level of data is required to reflect social interaction, since the social network varies across each member of society. Candia et al.*(49)*, Gastner and Newman*(50)*, Schintler et al.*(51)*, Erath et al.*(52)*, Wang et al.*(53)*, González et al. *(54, 55)* incorporated a fine level of tracking social interaction for a better understanding of the spread of communicable diseases. They performed spatial analyses of transportation and communication networks to track social interactions. Researchers expect to construct social network models using social networking platforms like Facebook, Twitter, etc. *(56)*.

Furthermore, few researchers explored advances in public transit modeling to provide detailed contact patterns including temporal patterns (e.g., bus travel time), and spatial patterns (a function of the vehicle size and passenger volume) *(57, 58).*

Employing technological advances could be useful for a better comprehension of the health behavior. For instance, using travel data from social networking platforms could capture changes in travel patterns during an event involving health risks *(59).*

CHAPTER 3 DATA

3.1. DATA COLLECTION

For this study, the GfK Group (formerly Knowledge Networks) conducted a survey developed by Virginia Tech researchers. The survey was conducted using a sample from GfK's KnowledgePanel®, a probability-based web panel designed to be representative of the United States. The sample consisted of general population English-language survey-takers, aged 18 and over residing in the United States. From the total of 3604 fielded participants, 2168 participants (close to 60%) completed the survey. It took them 11 minutes (median) to complete the entire survey.

As per GfK Group's conducted survey, the recorded demographic parameters included:

- Gender (Male/Female)
- Age (18–29, 30–44, 45–59, and 60+)
- Race/Hispanic ethnicity (White/Non-Hispanic, Black/Non-Hispanic, Other/Non-Hispanic, 2+ Races/Non-Hispanic, Hispanic)
- Education (Less than High School, High School, Some College, Bachelor and beyond)
- Census Region (Northeast, Midwest, South, West)
- Household income (under \$10k, \$10K to <\$25k, \$25K to <\$50k, \$50K to <\$75k, \$75K to <\$100k, \$100K+)
- Homeownership status (Own, Rent/Other)
- Metropolitan Area (Yes, No)
- Internet Access (Yes, No)

The remaining survey consisted of 50 questions. The purpose of the survey was to 1) learn about the influenza awareness of the respondents, 2) determine risk perceived in various routine activities, 3) identify health protection behavior to avoid spread/contacting influenza, 4) gather information about vaccination and health insurance, 5) identify case specific mitigation behaviors, and 6) obtain information (routine trips, health insurance, health conditions, mitigation responses etc.) for other household members.

3.2. DATA OVERVIEW

Respondents for this survey were located across the USA. The sample size from each state is reported in Table A1. Figure 1 represents the heat map, which depicts the location of respondent households. The majority of the respondents were based in California (11.21%), followed by Texas (6.73%), New York (7.29%) and Florida (6.23%). States were also grouped into nine regions (Figure 2). These nine regions include: 1) New England, 2) Mid Atlantic, 3) East-North Central, 4) West-North Central, 5) South Atlantic, 6) East-South Central, 7) West-South Central, 8) Mountain, 9) Pacific. The percentage of responses recorded from each of the regions is shown in Table A1 (Appendix A). Additionally, for the risk mitigation models, seven of the states were labeled as expensive states/places to live. These in the decreasing order of the expense-index are 1) Hawaii; 2) District of Colombia (not state); 3) New York; 4) Alaska; 5) New Jersey; 6) California; 7) Connecticut *(60).* All of the states have different climatic parameters and different socio-economic characteristics, which could be associated with different behaviors.

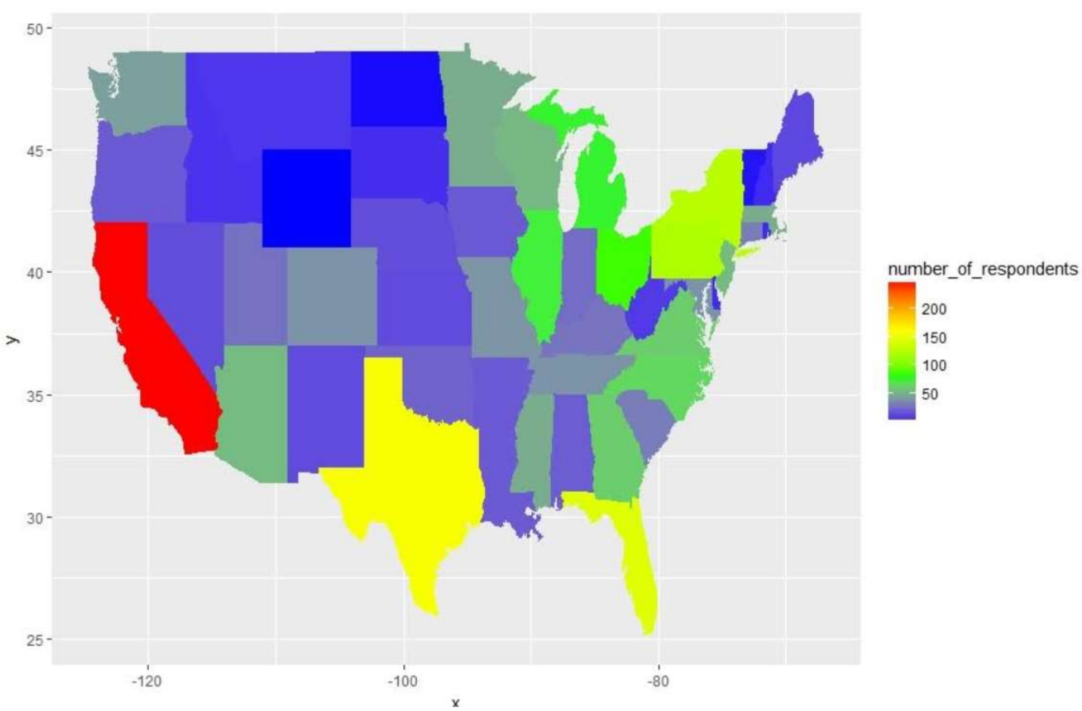

Figure 1: Representation of Respondents percent wise

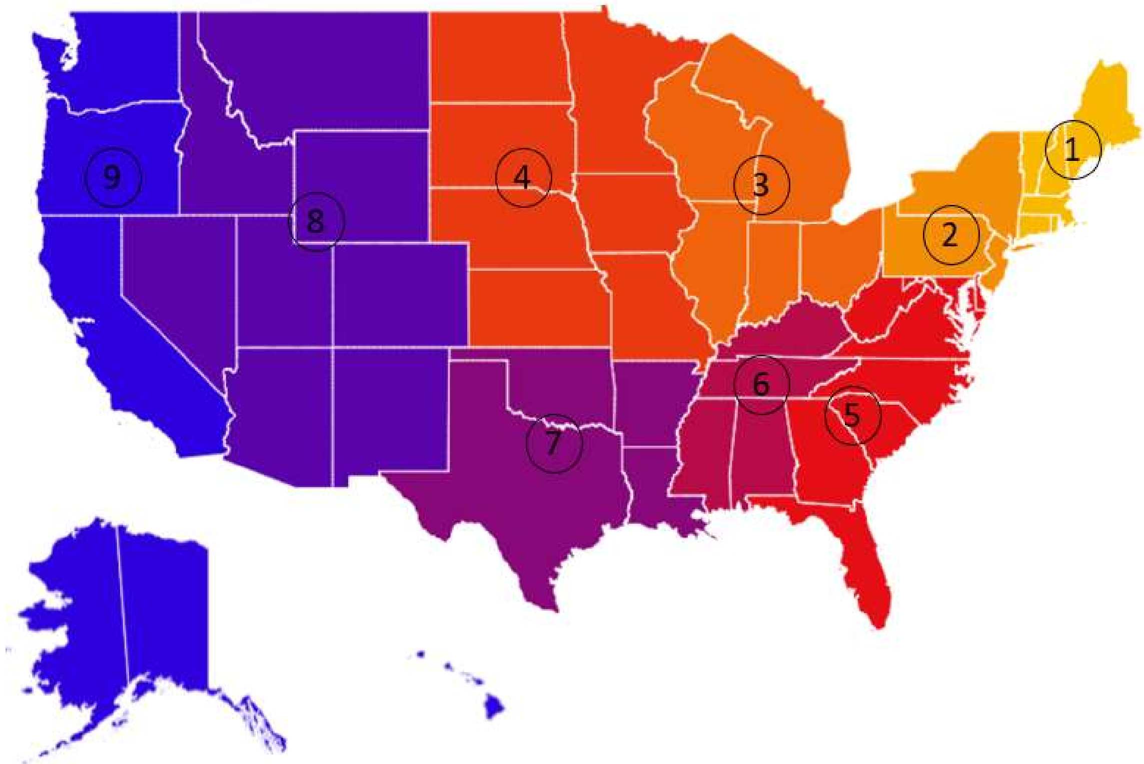

Figure 2: Representation of states based on their geographic location

Table 1 shows the demographic distribution of the study population and their use of public transit. As shown in Table 1, for a total of 2153 participants (15 less than 2168, as those 15 skipped the question asking if they were regular transit users), 72% self-identified as White-Non Hispanic, which was higher than the 61.5% for the US national statistics *(61)*. The gender split was nearly even: 49% male and 51% of female, consistent with national statistics.

Table 1: Demographic distribution of the study population and their use of public transit.

Age	Gender	Sample Size	Race/Ethnicity: White, Non-Hispanic	Black, Non-Hispanic	Other, Non-Hispanic	Hispanic	2+ Races Non-Hispanic	Use public transport
18-24	Male	86	67%	8%	3%	16%	5%	20%
	Female	86	55%	9%	6%	27%	3%	20%
25-34	Male	117	61%	9%	7%	17%	6%	14%
	Female	175	70%	10%	4%	10%	6%	11%
35-44	Male	178	62%	11%	8%	15%	4%	8%

	Female	146	73%	9%	6%	7%	5%	6%
45-54	Male	191	71%	8%	5%	13%	3%	11%
	Female	194	73%	9%	3%	11%	4%	9%
55-64	Male	249	74%	11%	4%	7%	4%	9%
	Female	247	74%	11%	3%	9%	3%	5%
65+	Male	237	84%	5%	3%	7%	1%	3%
	Female	247	79%	8%	3%	6%	3%	9%

As per Census statistics, 5.2% of the US population uses public transit *(61).* For the data collected, 9% of the sample used public transportation, which is slightly higher than the national average. Based on the national statistics, the population has a median age of 37.8 years and a median income of $55,775 *(61).* The respondents in the survey had a median age of 53 years and median income of $67,500, both of which were higher than the general population.

Table 2 presents household characteristics of the sample by income group. The sample had a nearly normal pattern across income groups, i.e., higher numbers of respondents in the middle-income groups. For the sample, the average household size is higher for the higher income group participants, with the maximum average household size observed for the income group $150,000-$175,000. Possibly, more household members were working as the household size increased as well. The number of children in the household increased with increasing household income but was less than one for all income categories, potentially related to the age distribution shown in Table 1. This suggests, only a few households were recorded to have children in them.

Table 2: Household characteristics by income group of the sample population

Income	Percent of Households	Average Household Size	Average Number of Children in the Household
< $10,000	4%	2.12	0.24
$10,001-$25,000	11%	2.23	0.38
$25,001-$50,000	21%	2.44	0.36
$50,001-$75,000	19%	2.60	0.44
$75,001-$100,000	14%	2.88	0.55
$100,001-	21%	2.88	0.56
$150,001-	4%	3.07	0.59
More than	6%	2.94	0.60

The relationships of education level to knowledge and recent experience with influenza, vaccination rates, and health insurance are shown in Table 3. A little more than a third of the sample had an education level of a Bachelor's degree or more. This is consistent with Census estimates *(62)* as the education level of a Bachelor's degree or more for individuals above 25 years of age is 33.4%.

Vaccination rates increased with an increase in the level of education; potentially, the risk perception also increased with education level. The percentage of respondents having health insurance increased with education level; however, some of the respondents with health insurance did not vaccinate themselves regularly against influenza.

Table 3: Level of education in relation to other parameters

Education level of the participant		Knows difference between stomach flu and influenza	Participant had influenza	Participant's HH member had influenza	Vaccination taken	No vaccination was taken	Have Health Insurance
Less than High School	7%	70%	24%	20%	57%	43%	76%
High School	29%	72%	17%	16%	57%	43%	94%
Some College	28%	83%	21%	22%	61%	39%	94%
Bachelor's degree or higher	36%	84%	20%	20%	70%	30%	98%

For risk perception models, the dependent variables were captured using the survey responses for an individual's risk perception of influenza for various types of household trips/activity locations. Risk perception was recorded for different activities and household trips and is summarized in Figure 3. As shown in Figure 3, a higher number of respondents perceived high health-risk when using public transit, visiting health facilities (doctors' offices and hospitals), and completing child-related mandatory trips (daycare and schools), in comparison to other locations.

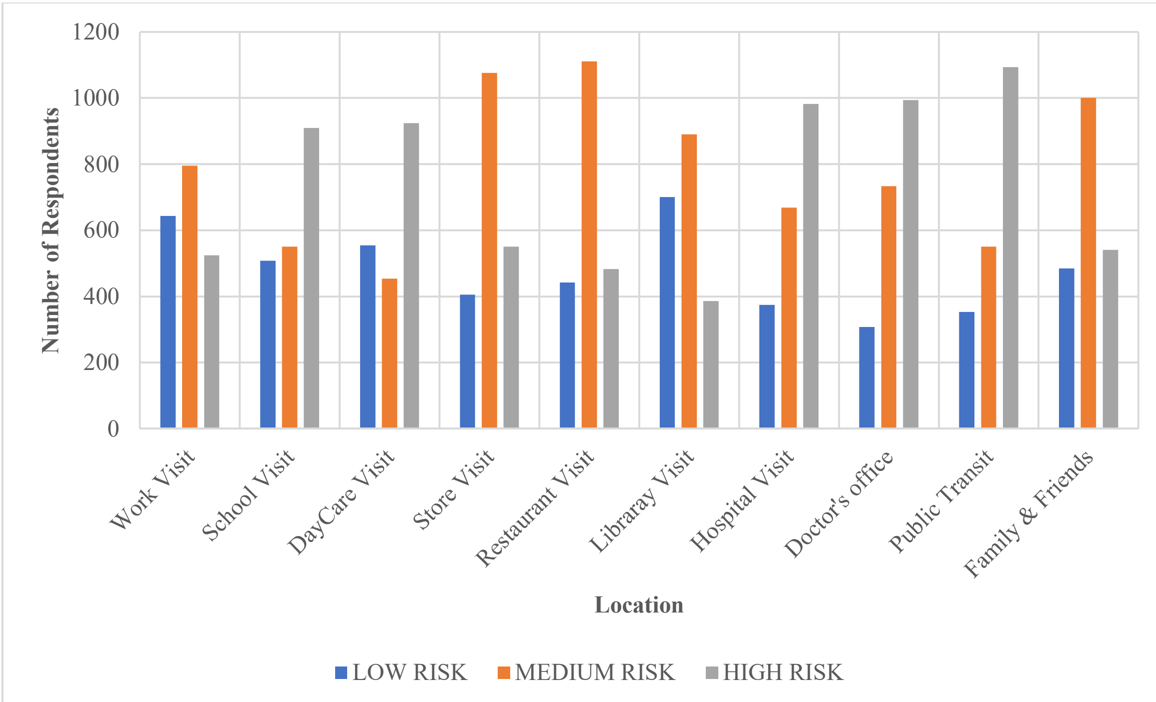

Figure 3: Risk perception of contracting influenza for various activities

Subsequently, actions of the individuals were modeled for risk mitigation during influenza. Travel behavior, when sick with flu, was modeled for four different dependent variables: (a) how likely the respondent is to visit a doctor when sick; (b) how likely the respondent is to avoid public places when sick with influenza; (c) how likely the respondent is to avoid public transit when sick with influenza; (d) how likely the respondent is to stay home when sick with influenza. The models for actions taken to avoid contracting influenza include: (e) how likely the respondent is to avoid public places to protect oneself from getting sick during an Influenza outbreak; (f) how likely the respondent is to avoid public transit to protect oneself from getting sick during an influenza outbreak; (g) how likely the respondent is to stay at home to protect oneself from getting sick during an influenza outbreak. The mitigation dependent parameters had 3 scaled responses: “Never,” “Sometimes,” “Always.”

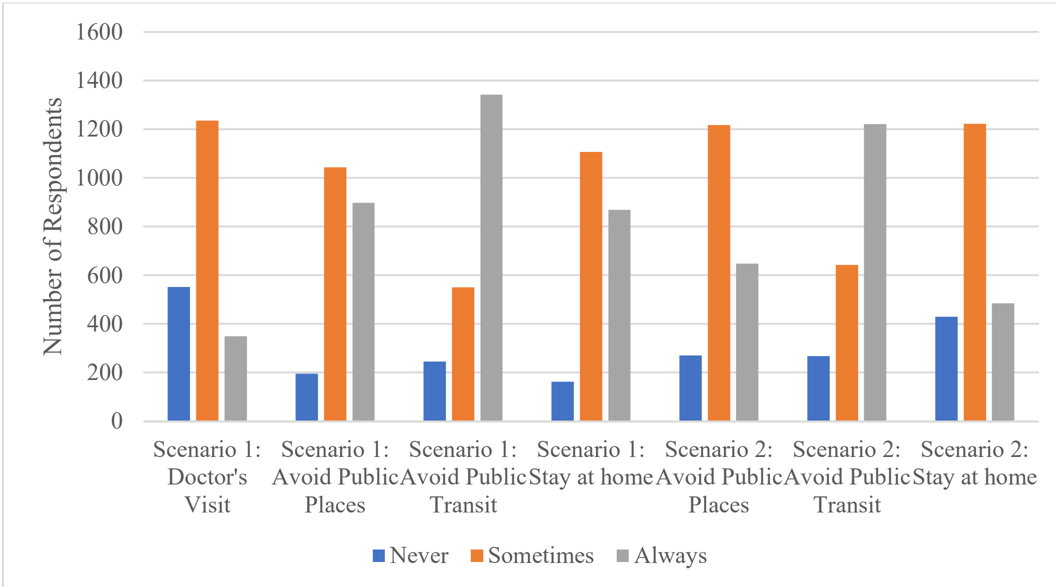

Figure 4: Protective action behavior during influenza outbreak

As observed from Figure 3, respondents perceived a higher risk of getting sick with influenza for public transit travel. This was consistent with responses recorded for the risk mitigation variables as observed from Figure 4.

Table 4: Parameter Definitions and Coding

Variable Name	Parameter Definition
PPAGE	Participant's age in years, Variable type- Continuous
PPGENDER	Gender of the participant, Variable type- Binary: Coded "0" for female and "1" for male
INCOME	Household income of participant, Variable type- Continuous: Responses were recorded for 19 levels of income, which were converted into continuous variable by averaging the bounds of the responses levels
Bachelor's or higher degree	If the participant has a bachelors' degree, Variable type- Binary: Coded as "1" for participants with a bachelor's or higher degree, and "0" otherwise
NUMKIDS	Count of children in household, Variable type- Continuous: Count of children (under 18) in the household
NUMKIDS<5	Count of children less than 5 years old in household, Variable type- Continuous: Count of children under 5 years old in the household
Without Bachelors	If the participant doesn't have a bachelors' degree, Variable type- Binary: Coded as "1" for participants without a bachelor's or higher degree, and "0" otherwise

DIFF_STMCH_FLU	If the participant knows the difference between "stomach flu" and influenza, Variable type- Binary: Coded as a "1" if the participant knew the difference between "stomach flu" and influenza and "0" otherwise
PPFLU_6MNTS	If participant had influenza, six months prior to survey, Variable type- Binary: Variable coded as a "1" if the participant had influenza in the last six months and "0" otherwise
HHMFLU_6MNTS	If participant's HH member influenza, six months prior to survey, Variable type- Binary: Variable coded as a "1" if a participant's household member had influenza in the last six months and "0" otherwise
EXPOSURE_WORK	If the participant's job involves working with the public, Variable type- Binary: Variable coded as a "1" if the participant's job involves working with the public and "0" otherwise
If_Kids	If kids are present in the household, Variable type- Binary: Variable coded as '1' for kid present in HH, '0' otherwise
If_Work	If the participant is working, Variable type- Binary: Variable coded '1' if the respondent is working, '0' otherwise
Risk perception_work_High	High-risk perception for workplace visit, Variable type- Binary: Variable coded '1' for High health risk perception for a work trip, '0' otherwise
Risk perception_work_medium	Medium risk perception for workplace visit, Variable type- Binary: Variable coded '1' for Medium health risk perception for a work trip, '0' otherwise
Risk perception_store_high	High-risk perception for store visit, Variable type- Binary: Variable coded '1' for high health risk perception for a trip to store, '0' otherwise
Risk perception_store_medium	Medium risk perception for store visit, Variable type- Binary: Variable coded '1' for medium health risk perception for a trip to store, '0' otherwise
Risk perception_Store_High_Medium	High-Medium level of risk perception for store visit, Variable type- Binary: Variable coded '1' for high/medium health risk perception for a store visit, '0' otherwise
Risk perception_PublicTransit_High_Medium	High-Medium level of risk perception for travel using public transit, Variable type- Binary: Variable coded '1' for high/medium health risk perception for a trip using public transit, '0' otherwise
Risk perception_public transit_high	High-risk perception for travel using public transit, Variable type- Binary: Variable coded '1' for high health risk perception for the use of public transit, '0' otherwise
Risk perception_public transit_medium	Medium risk perception for travel using public transit, Variable type- Binary: Variable coded '1' for medium health risk perception for the use of public transit, '0' otherwise

Health insurance	Participant has health Insurance, Variable type- Binary: Variable coded '1' if respondent has health insurance, '0' otherwise
Influenza vaccine	Participant has influenza vaccine: Everyear or some years, Variable type- Binary: Variable coded as '1' if respondent has influenza every year or some years, '0' otherwise
Residence- New England	Region of Residence- New England, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
Residence- Mid Atlantic	Region of Residence- Mid Atlantic, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
Residence- East-North Central	Region of Residence- East-North Central, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
Residence- West-North Central	Region of Residence- West-North Central, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
Residence- South Atlantic	Region of Residence- South Atlantic, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
Residence- East-South Central	Region of Residence- East-South Central, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
Residence- West-South Central	Region of Residence- West-South Central, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
Residence- Mountain	Region of Residence- Mountain, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
Residence- Pacific	Region of Residence- Pacific, Variable type- Binary: Variable coded '1' if a resident, '0' otherwise
If kids in HH less than 12 yrs	If at least one child less than 12 years in HH, Variable type- Binary: '1' If at least one child is under age 12 years old in the household, '0' otherwise
If kids in HH less than 5 yrs	If at least one child less than 5 years in HH, Variable type- Binary: '1' If at least one child is under age 5 years old in the household, '0' otherwise
race_white	Race of the participant, Variable type- Binary: Variable coded '1' if the respondent is White Non-Hispanic, '0' otherwise
Income/HHSIZE	Ratio between household income(/10000) and household size, Variable type-Continous: Variable ratio between household income(/10000) and household size

Table 5: Descriptive statistics of model parameter

Parameters	Count	Mean	Median	Standard Deviation	Minimum	Maximum
PPAGE (participant's age in years)	2168	50.4	53	16.84	18	93
PPGENDER (coded "0" for female and "1" for male)	2168	0.5	0	0.5	0	1
INCOME	2168	75,540	67,500	47,895	2,500	175,000
Bachelor's or higher degree (coded as "1" for	2168	0.1	0	0.42	0	3

participants with a bachelor's or higher degree, and "0" otherwise)						
NUMKIDS (number of children (under 18) in the household)	2168	0.5	0	0.92	0	6
NUMKIDS<5 (number of children under 5 years old in the household)	2168	0.4	0	0.48	0	1
Without Bachelors (coded as "1" if respondent has no bachelor's degree)	2168	0.65	1	0.48	0	1
DIFF_STMCH_FLU (coded as a "1" if the participant knew the difference between "stomach flu" and influenza and "0" otherwise)	2152	0.8	1	0.42	0	1
PPFLU_6MNTS (coded as a "1" if the participant had influenza in the last six months and "0" otherwise)	2149	0.2	0	0.39	0	1
HHMFLU_6MNTS (coded as a "1" if a participant's household member had influenza in the last six months and "0" otherwise)	1991	0.2	0	0.39	0	1
EXPOSURE_WORK (coded as a "1" if the participant's job involves working with the public and "0" otherwise)	1371	0.5	1	0.5	0	1
If_Kids (Binary Variable coded as '1' for kid present in HH, '0' otherwise)	2168	0.260	0	0.439	0	1
If_Work (Binary Variable coded '1' if the respondent is working, '0' otherwise)	2150	0.638	1	0.481	0	1
Risk perception_work_High (Binary Variable coded '1' for High health risk perception for a work trip, '0' otherwise)	1962	0.267	0	0.443	0	1
Risk perception_work_medium (Binary Variable coded '1' for Medium health risk	1962	0.405	0	0.491	0	1

perception for a work trip, '0' otherwise)						
Risk perception_store_high (Binary Variable coded '1' for high health risk perception for a trip to store, '0' otherwise)	2032	0.271	0	0.445	0	1
Risk perception_store_medium (Binary Variable coded '1' for medium health risk perception for a trip to store, '0' otherwise)	2032	0.530	1	0.499	0	1
Risk perception_Store_High_Medium (Binary Variable coded '1' for high/medium health risk perception for a store visit, '0' otherwise)	2032	0.801	1	0.400	0	1
Risk perception_PublicTransit_High_Medium (Binary Variable coded '1' for high/medium health risk perception for a trip using public transit, '0' otherwise)	1962	0.672	1	0.470	0	1
Risk perception_Store_High_Medium (Binary Variable coded '1' for high/medium health risk perception for a store visit, '0' otherwise)	2032	0.801	1	0.400	0	1
Risk perception_public transit_high(Binary Variable coded '1' for high health risk perception for use of public transit, '0' otherwise)	1997	0.547	1	0.498	0	1
Risk perception_public transit_medium (Binary Variable coded '1' for medium health risk perception for use of public transit, '0' otherwise)	1997	0.276	0	0.447	0	1
Health insurance (Binary Variable coded '1' if respondent has health insurance, '0' otherwise)	2148	0.928	1	0.258	0	1

Influenza vaccine (Binary Variable coded '1' if has influenza everyear or someyears, '0' otherwise)	2150	0.619	1	0.486	0	1
(Continious variable: Ratio of (Income/10000) to size of household)	2168	3.418	2.75	2.640	0.05	17.5
Residence- New England (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.000	0	0.000	0	0
Residence- Mid Atlantic (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.141	0	0.348	0	1
Residence- East-North Central (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.149	0	0.356	0	1
Residence- West-North Central (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.072	0	0.259	0	1
Residence- South Atlantic (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.201	0	0.401	0	1
Residence- East-South Central (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.050	0	0.218	0	1
Residence- West-South Central (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.103	0	0.304	0	1
Residence- Mountain (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.083	0	0.275	0	1
Residence- Pacific (Binary Variable coded '1' if yes, '0' otherwise)	2168	0.148	0	0.355	0	1
If kids in HH less than 12 yrs (Binary Variable coded '1' if household has at least one child less than 12 years old '0' otherwise)	2168	0.178	0	0.383	0	1
If kids in HH less than 5 yrs(Binary Variable coded '1' if household has atleast one child less than 5 year old '0' otherwise)	2168	0.096	0	0.295	0	1

race_white (Binary Variable coded '1' if the respondent is White Non-hispanic, '0' otherwise)	2168	0.723	1	0.447	0	1
Income/HHSIZE(Continuous Variable ratio between houehold income(/10000) and household size)	2168	3.418	2.75	2.640	0.05	17.5

Tables 4 and 5 present the parameters which were used in the models. The first column depicts the variable name and explains its coding. All of the independent parameters were converted to a binary format, except for the continuous variables.

For instance, race and ethnicity had five different options, 1) race white: non-Hispanic, 2) race black: non-Hispanic, 3) race other: non-Hispanic, 4) race Hispanic, 5) more than 2 races. These options were recorded on a scale of one through five. However, since these numbers had no significance in themselves, all race variables later were converted into five different binary variables. For converting such a variable into a binary variable, e.g., if the race of a respondent is white, then 'race_white' would be coded as '1' and the other races would be coded '0'. Similar variable coding was followed for the educational level of the participant, region of residence and the risk perception categories to be used as the independent parameters in the risk mitigation models.

Household income and the age of participant were used as continuous variables. For the income parameter, the participants were asked to respond with a different level of income. Hence, these levels were converted into the continuous variable by coding each level of responses as the midpoint value of the upper and lower level of responses. Whereas, for the highest level (household income more than $175,000), the lower bound, i.e., $175,000 was considered as the response for that level.

Additionally, the ratio of household income to household size was used in the risk mitigation model. This ratio could be thought of normalizing the household income by the number of members living in the household. Therefore, if the income was high for a household, but the household size is high, then that household would not be similar to the household with the same income but fewer household members. It was identified as a significant variable in most of the risk mitigation model discussed in chapter 6.

Apart from the socio-demographic characteristics, the survey recorded individuals' responses to reflect their comprehension of the disease. Two factors which reflected comprehension were experience and knowledge of the difference between stomach flu and influenza. Experience with influenza was assessed from the responses recorded for: (1) the respondent having the flu in the past six-months and (2) any household member suffering from influenza in the past six months.

CHAPTER 4 METHODOLOGY

4.1. MODELING APPROACH

Since this project is based on the survey data, the parameters assessed in the study were continuous, binary, or in the ordered form. An example for ordered variables includes responses on a Likert scale (High, Medium, Low). Although these variables do not have a mathematical equivalent, they have a monotonic order (increasing/ decreasing) in which they could be represented. Hence, they were represented mathematically by assigning 1 to Low, 2 to Medium, and 3 to High, or even vice-versa as per requirements of the problem.

In this study, dependent parameters were used in an ordered form (Low (1) /Medium (2) /High (3) risk, or Never (1) /Sometimes (2) /Always (3)). However, each independent parameter was either continuous or converted into binary form if it was previously recorded in an ordered form. Afterwards, ordered logit models were developed using R-Studio.

Before modeling, each potential independent variable from the survey was checked for correlation using the Spearman correlation test with the other independent variables and the risk perception/mitigation (dependent variables) response. The Spearman correlation test was used since the dependent variables had ordered responses, and Spearman correlation can be used with parameters with ordered responses *(63)*. Independent variables with high correlations (rho value of 0.4) were not considered in the same model. Independent variables with a p-value (from the Spearman test) of 0.25 or better for the correlation with risk perception/mitigation, in addition to the hypothesis variables, were considered for the multi-variable modeling context.

As a first step to the model building process, hypotheses variables were identified based on literature and logical explanation. Subsequently, backward model building methodology was used for the risk perception models, and forward model building methodology was used for the risk mitigation models.

4.1.1. Backward Model Approach

The process for developing the ordered logit models for Risk perception (Chapter 5) was done using the backward approach is depicted in Figure 5. The explanatory variables chosen for modeling were either influencing, rationally, the dependent variable or shown to be significant based on previous studies. Only if the parameters had an association of (Spearman correlation) p-value < 0.25 *(64)* with the dependent variable, were they retained in a pool of non-hypothesis parameters to be tested in the model. These variables were then pooled together and checked for correlation (Pearson correlation, since no independent variable had ordered responses) amongst themselves. If two variables were correlated, then those variables were not considered in the model together. Out of the two correlated variables, the variable which was more significant (p-value from the Spearman correlation test) for predicting dependent variable was chosen. Significance of these variables were obtained from the correlation between the dependent variables.

Subsequently, all of these explanatory non-hypothesis variables were regressed with risk perception responses (dependent variable: ordered variable) to estimate the ordered logit model. From the ordered logit model statistics, the most insignificant (i.e., p-value > 0.05) explanatory variable was removed and subsequently, risk perception response was re-modeled with the remaining parameters. This step was repeated until all the parameters in the model were significant to the 0.05 (p-value) level of significance. However, hypothesis variables were retained in the model during the process, until all the insignificant non-hypothesis variables were removed from the model. Finally, the model with all the hypothesis variables and significant non-hypothesis variables were reported.

4.1.2. Forward Model Approach

The forward model approach (Figure 6) was used to model the risk mitigation responses (Chapter 6). Similar to the Backward Model Approach, the explanatory variables chosen for modeling were either influencing, rationally, the dependent variable or shown to be significant based on previous studies. These variables were then pooled together and checked for correlation (Spearman correlation) amongst themselves. The survey included parameters that had categorical responses. Hence, the Spearman correlation test was used, which checks the correlation amongst the variables *(64)*. Spearman correlation was used for all kind of variables (continuous, binary or ordered). “When analyzing both Pearson’s and Spearman’s coefficients, one could logically expect that the significance of one would imply the significance of the other.” *(64, p. 92)*. Subsequently, the model building process was started by picking the most significant hypothesis-parameter, based on the p-value from the Spearman correlation test with the dependent variable. This parameter was modeled with the risk mitigation response. Subsequently, along with this parameter, the next most significant parameter was regressed with the risk mitigation response. Before developing the model, it was checked that no two parameters in the model were correlated to rho value (Spearman correlation) of 0.4. If two hypothesis variables were correlated, then the parameter with a greater significance (Spearman correlation p-value) was used for further analysis. Similarly, remaining hypothesis parameters were added one by one in their order of significance (Spearman correlation p-value). This step continued until all of the hypothesis parameters were regressed with the risk mitigation response. A model with only hypothesis parameters as (non-correlated) independent variables in the model was obtained by the end of this step.

The next task in this approach was to identify the non-hypothesis parameter which would have a logical tie to the dependent parameter. For this task, initially, the pool of non-hypothesis independent variables was checked for correlation with the dependent parameter. Only if the parameters had an association of (Spearman correlation) p-value < 0.25 *(63)* with the dependent variable, were they retained in a pool of non-hypothesis parameters to be tested in the model.

Before testing a variable in the model, the correlation of that variable was checked with other variables present in the model, to avoid multicollinearity. Thereafter, similar to the modeling hypothesis parameters, all of the variables were sequentially regressed with the dependent variable. In addition to checking for correlation, every time after a variable was added to the model, it was checked for any improvement in the model fit, using the nested likelihood ratio test. If the variable was significant (model parameter p-value < 0.05) and improved the model (based on the nested test; refer section 4.4), it was retained. If the variable was significant to the level of 0.1 and improved the model based on the nested likelihood ratio test, it was retained in the model. However, if the variable was neither significant nor improved the model, then this variable was dropped. Subsequently, the next significant non-hypothesis parameter, along with other significant parameters, was regressed with the dependent variable. This task was continued until all of the remaining independent variables (including interactions between variables and transformed variables) were checked for significance based on the nested likelihood ratio test.

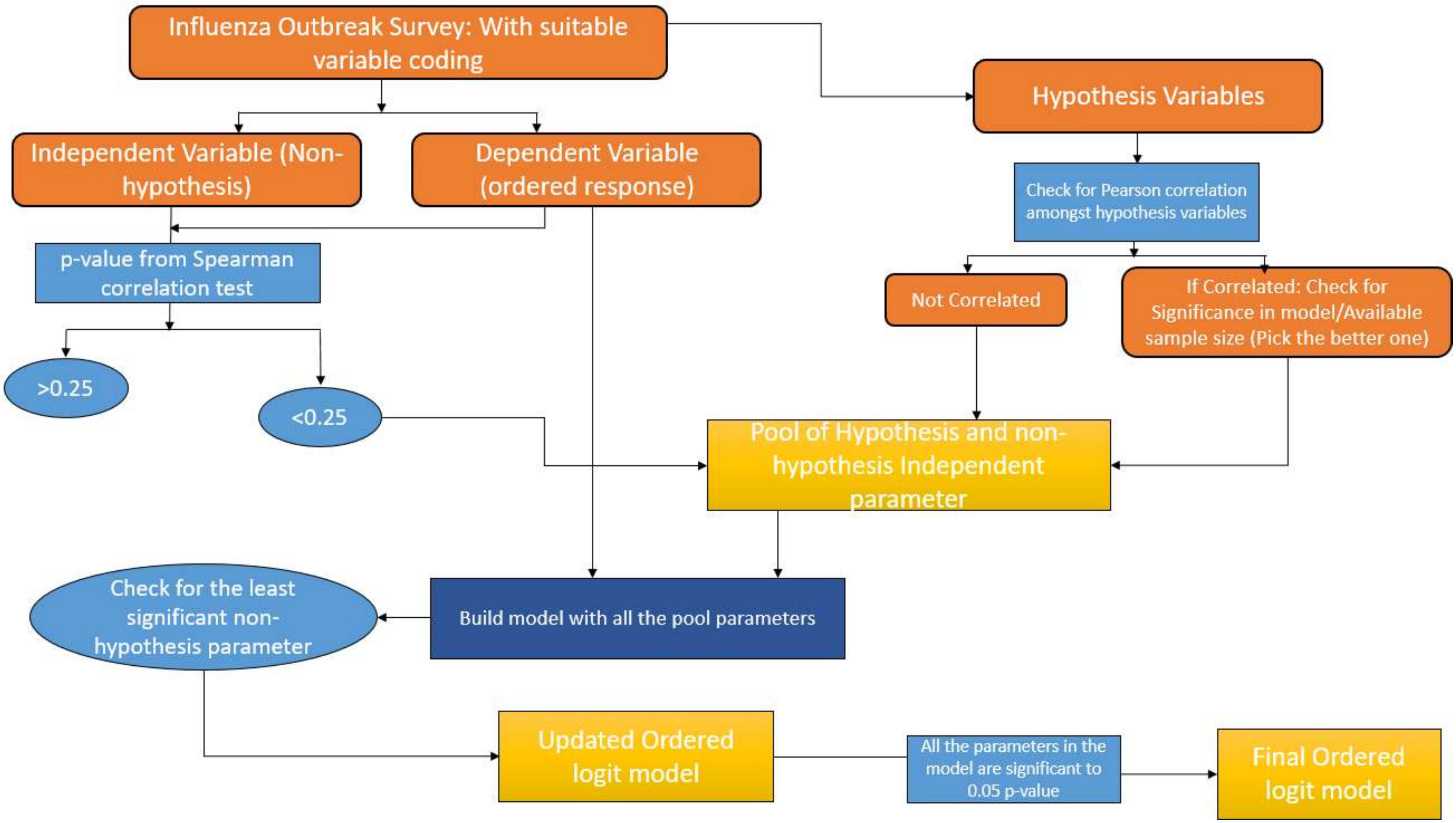

Figure 5: Methodology for backward modeling approach

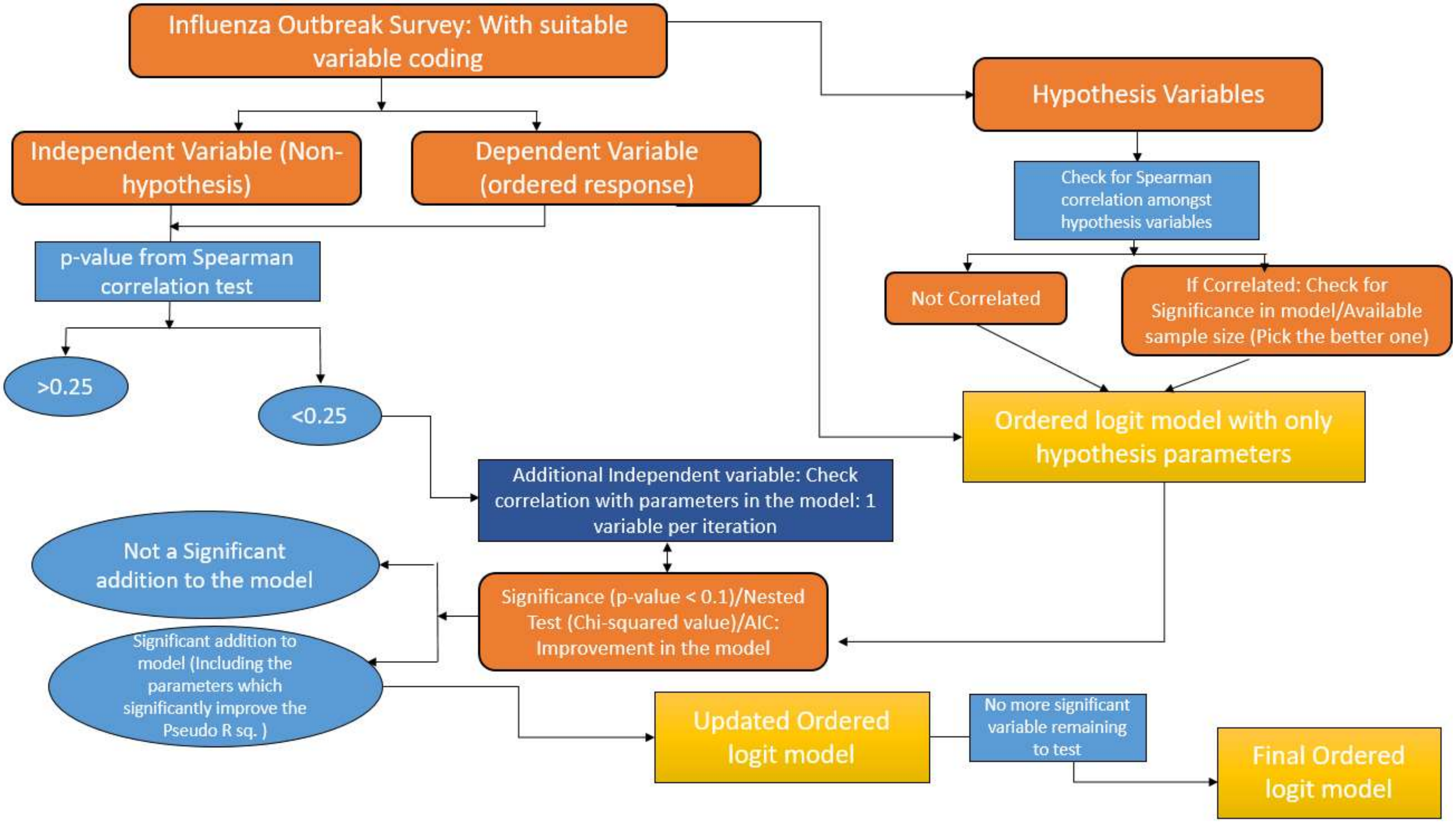

Figure 6: Methodology for forward modeling approach

4.2. ORDERED LOGIT MODEL

Risk perception was indicated on a three-factor scale: low risk (not likely), medium risk (somewhat likely) and high risk (very likely). Similarly, for the risk mitigation model, protective actions had a three-factor scale: Never, Sometimes and Always. These responses have an order but no mathematical equivalent representation. For instance, if the responses are coded as 1 for low risk, 2 for medium risk, and 3 for high risk, it does not mean that medium risk perception is equivalent to twice the low risk, or high risk is thrice the low-risk perception. Additionally, the difference in the transition between low risk to medium risk, and medium risk to high risk (similar analogy for risk mitigation responses) are similar. Hence, to model these responses, the ordered logit model was selected.

Mathematically, the ordered logit model is based on the cumulative probabilities of the responses which are assumed to be a linear function (y^*- underlying latent function) of the covariates with regression coefficients constant across response categories *(65, 66).* The ordered logit model is as shown in equation (2) *(67, 68)*.

$$y^* = \in_j + \sum_{i=1}^{k} (\beta_i * X_i) \tag{2}$$

Where, $\in_j$ = L(μ|υ) {L represents the Logistic CDF which has a logistic random distribution with variance equal to υ, that accounts for the measurement error}

$$\in_j = \text{L}(\mu) = e^{\mu}/1 + e^{\mu} \tag{3}$$

μ= Threshold diving different categories of responses.

β_i = Regression coefficients,

X_i = Model independent parameters,

k = Number of independent parameters in model, and

j = index for the response categories that ranges from 1 to the number of categories minus 1 (i.e. Number of risk perception responses – 1) *(67, 68)*.

Given the nature of the responses, it is assumed for the ordered model that the dependent variable is in order.

> "Another important assumption of this model is the "proportional odds" assumption, which states that the effects of any (and all) independent variables are the same regardless of what two groups are being compared. This assumption is

important because the goal of ordinal logistic regression is to create a single estimate that predicts the probability of being in the next higher group as a function of a change in the independent variable(s) regardless of which group transition. The ordinal logistic regression model attempts to model the latent underlying continuous variable rather than a variable that has a series of groups or transitions." *(69, p. 410)*

The Brant test was used to check the assumption of "proportional odds." The Brant test estimates the logit coefficients for underlying binary logistic regressions and provides the chi-square test *(70)*. R-studio's "brant" package was used to perform this test. If the null hypothesis of this test, i.e., parallel regression assumption holds, then using ordered logistic regression is justified.

4.3. INTERPRETING ORDERED LOGIT MODEL

The ordered logit model (from equation (2) in Section 4.2) defines the relationship between the dependent variable and the explanatory variables by using a latent continuous variable (y^*). This latent continuous variable is defined by threshold points ($\mu1$, $\mu2$) as described in equation (2). Dependent variables in the ordered logit model have more than two responses, which are ordinal. The objective is to model these ordered responses as functions of explanatory variables. If the dependent variable has 'n' responses, there would be 'n-1' thresholds. For instance, if the dependent variable has three responses: Low, Medium, and High, for modeling purposes, it shall be converted into two thresholds: Low|Medium ($\mu1$) and Medium|High ($\mu2$). These threshold cutoff parameters ($\mu1$, $\mu2$) represent the transition between the three categories of responses. In general, these thresholds have no direct implications themselves. However, these are used to compute predicted probability for model interpretation (as discussed in the section 4.3.1).

Independent parameters are assumed to have the same effect on different categories of responses (assumption of proportional odds). Therefore, the estimate values for these independent parameters remain constant across all the responses. The sign of the coefficient of the parameters explains the direction of effect, i.e., increasing/decreasing the likelihood of a response. The magnitude of the coefficients cannot be interpreted because they differ by a scale factor for each variable. For instance, the estimated value for income (continuous variable with high order value: range – $2500 to $175,000) would be much less in comparison to gender (binary Variable: 0 or 1), which would not define the significance of either parameter. Moreover, these coefficients are in log-odds units, and estimation requires converting the parameter estimates into the marginal effect *(68)*. In this study, the marginal effect for different level of responses are presented.

Interpreting the parameter's sensitivity towards different responses (low, medium or high) could be understood from the sign and magnitude of the marginal effect values associated with each response. These marginal effects can be understood as the probability of change in the likelihood of the dependent variable (always, sometimes, or never,) for one unit change in the independent variable (keeping other variables constant). For instance, suppose the marginal effect of the age parameter with respect to high risk is 0.50% (Always), -0.02% (Sometimes) and -0.48% (Never). The marginal effect value reflects 0.50% increase in the probability of an 'always' response if the age of the participant is increased by one unit. Similarly, the higher the magnitude of the marginal effect, the more sensitive is the outcome (dependent variable) to change in the independent variable. Also, it should be noted that the marginal effect values for all the levels always add up to '0'.

4.3.1. Example of Model Interpretation

Verification of the model obtained from the analysis was done using an archetypal individual. This 'individual,' is characterized by a set of values (presented below in this section) defined to interpret the model under consideration. The model for "Avoiding public transit when sick" was used for verification.

Next, predicted probability is computed for this representative sample (archetypal individual) based on the obtained model parameter estimates presented in Table 11 (we get these parameter estimates from the final ordered logit models presented in this study). Mathematically, the predicted probability of response 'j' is computed from equations listed below *(68)*:

$$\text{P(j < threshold 1)} = e^{(\mu 1 - \sum_{i=1}^{k}(\beta_i * X_i))} / (1 + e^{(\mu 1 - \sum_{i=1}^{k}(\beta_i * X_i))}) \quad (4)$$

$$\text{P(j < threshold 2)} = e^{(\mu 2 - \sum_{i=1}^{k}(\beta_i * X_i))} / (1 + e^{(\mu 2 - \sum_{i=1}^{k}(\beta_i * X_i))}) \quad (5)$$

$$\text{P(j} \geq \text{threshold 2)} = 1 - e^{(\mu 2 - \sum_{i=1}^{k}(\beta_i * X_i))} / (1 + e^{(\mu 2 - \sum_{i=1}^{k}(\beta_i * X_i))}) \quad (6)$$

$$\text{P(threshold 1} \leq \text{j < threshold 2)} = \text{P(j} \geq \text{threshold 2)} - \text{P(j < threshold 1)} \quad (7)$$

The probability for an 'always' response corresponds to the P(j ≥ threshold 2), the 'sometimes' response corresponds to the P(threshold 1 ≤ j < threshold 2) and the 'never' response corresponds to the P(j < threshold 1).

Hence, from the above equations, the probability for the three responses could be predicted. Table A4 shows the code used to obtain the predicted probabilities for the representative sample.

Model: Avoiding public transit when sick- Scenario 1(c)

For the model for avoiding public transit when sick, the archetypal individual has to be a regular transit user. Based on Table 11, there are only two parameters that are significant, i.e., the age of the participant and the gender of the participant. The coefficients for the model parameter are: $\beta male = -0.725$ and $\beta age = 0.022$. Further, the threshold cut-off values (from Table 11), are - $\mu 1 = -1.098$ and $\mu 2 = 1.577$.

Now, using equations (4-7), with the input values provided above, the predicted probability is estimated for a woman of age 32 (given this individual is a regular transit user), to avoid public transit (Please refer to Figure A4 for the code used for this example).

The results suggest that this archetypal 32-year-old woman would have a 14.55% probability of never avoiding public transit, a 56.64% probability of sometimes avoiding public transit and a 28.80% probability of always avoiding public transit.

Similarly, an archetypal 32-year-old man was considered. This "individual," would have a 25.99% probability of never avoiding public transit, a 57.60% probability of sometimes avoiding public transit and a 16.39% probability of always avoiding public transit. This result is consistent with the discussion of the model for avoiding public transit when sick, as the man is more likely always to avoid public transit in comparison to a woman.

4.4. TESTING THE ORDERED LOGIT MODEL

In this study, two checks were applied after every iteration involving adding a variable to/removing a variable from the model: 1) Adjusted McFadden's pseudo R2 and 2) the Nested Likelihood Ratio test. Both of these log likelihood-based statistical tests were incorporated simultaneously, to check if the parameter included in the model improves the prediction in the model.

Although there are various pseudo R2 tests in literature, McFadden *(71)* suggested an alternative, known as "likelihood ratio index," comparing a model without any predictor to a model including all predictors. It is one minus the ratio of the log likelihood for the null model and the log likelihood for the complete model. If the slope parameters (betas for each parameter) are all 0, McFadden's pseudo R2 is 0, but it is never 1, suggesting that McFadden's pseudo-R2 has very low values, and should not be interpreted as general R2 for the linear regression. Previous researchers *(65,66)* using ordered logistic regression models have typically reported low values (0.012 to 0.075) for the pseudo R squared. Equation (8) shows the mathematical computation of the adjusted McFadden's pseudo R2 ($\bar{\rho}_o^2$) *(71)*.

$$\bar{\rho}_o^2 = 1 - \frac{LL(\beta)-K}{LL(0)} \qquad (8)$$

Where,

$LL(\beta)$	is the likelihood of the model with all the parameters
$LL(0)$	is the likelihood of the null model
K	is the number of parameter in the model *(71)*

The nested likelihood ratio test was used to check if there was a significant improvement in the model prediction with the introduction of additional parameter(s). The null hypothesis for this test states that there is no improvement in the restricted model with the introduction of additional parameter(s). Improvement in the model is checked with the chi-squared distribution for a defined level of significance. Hence, if the chi-squared value indicates an improvement in the significance of the model, only then is the null hypothesis is rejected. For the current study, a significance level of 95% was assumed. If the model is able to reject the null hypothesis, then the unrestricted model shall be considered significant. Equation 9, shows the mathematical formulation for nested likelihood ratio test *(72)*.

H_o = Restricted model = Unrestricted
Reject H_o if -2 * $[LLr - LLu] > critical\ value\ from\ \chi^2_{NR,\alpha}$ distribution (9)

Where,

LLr	is the likelihood of the restricted model
LLu	is the likelihood of the unrestricted model
NR	is the number of restrictions
α	is the significance level *(72)*

CHAPTER 5 RISK PERCEPTION OF CONTRACTING INFLUENZA FOR COMMON HOUSEHOLD TRIPS

5.1. INTRODUCTION

Seasonal influenza viruses circulate and cause disease in humans every year, which impacts productivity and the economy *(1)* with potential economic losses of $6.4 million in a quarter of US counties (75th percentile) *(2)*. In temperate climates, influenza tends to occur seasonally during the winter months, spreading from person-to-person through sneezing, coughing, or touching contaminated surfaces. For some high-risk individuals, seasonal influenza viruses can cause mild to severe illness and even death *(3)*. Individuals come into contact with each other at a variety of locations based on their everyday activities. Examples include work, school, daycare, stores, restaurants, libraries, hospitals, doctor's offices, public transportation (bus, train, etc.) and family or friends' homes.

This chapter's objective was to identify the factors associated with the degree of risk perception of contracting influenza at these locations using survey data from 2168 respondents across the U.S. Self-reported perceived risk was measured on a three-factor scale: low risk (not likely), medium risk (somewhat likely) and high risk (very likely). This information was used in an ordered logit model to identify influential factors. Understanding the risk perception for contracting influenza at various locations is the first step in understanding actions individuals may take to protect themselves, such as canceling trips, avoiding public transit, and avoiding public places, as well as being vaccinated. The first three of these protective actions affects travel, destination, and mode choices as well as traffic in general.

The remainder of this chapter is divided into five sections. The first provides background on influenza and studies of the association of risk perception and public health interventions. The second discusses the hypotheses investigated in this study. The hypotheses of this study are discussed in the third section, followed by the risk perception models. Finally, the fifth section presents the conclusions.

5.2. BACKGROUND

Recently, influenza virus has been identified as a major health threat to the humans. Three types of influenza affect human health: seasonal, Zoonotic or variant influenza, and pandemic. Seasonal influenza is predominant in winter months, in regions with a temperate climate. Due to its evolving behavior, seasonal influenza could affect individual multiple times in their lives. Zoonotic or variant forms of influenza are spread by the interaction between humans and animals and have been recorded several times in the past century *(3).* Influenza virus results in respiratory morbidity and mortality across diverse species including humans *(7, 8).*

The two identified principal strategies for containing serious human outbreaks of influenza are therapeutic countermeasures (e.g., vaccines and antiviral medications) and public health interventions (e.g., social separation and isolation) *(27).* This study deals with the public health interventions. Public health interventions include an individual's decision to make the travel or conveyance choice. To help understand the effect on transportation behaviors and mode choices when a health epidemic strikes, risk perception was examined which could reflect a personal assessment of the probability of being infected from an individual's perspective.

In previous studies, the health belief model, which is the oldest and most widely used social cognition model in health psychology, was considered useful to predict health behavior *(15, 16).* The health belief model is based on two aspects of health behavior representation: how the threat/risk is perceived and health interventions to this threat. Other health psychology models also indicate risk perceptions are key drivers of health behaviors *(17-21).*

The importance of these drivers was further supported by additional studies. For instance, with the Australian population, Barr et al. *(28)* found that respondents with higher levels of risk perception reported more willingness to comply with public health interventions during influenza outbreaks. Similar results were found in Hong Kong *(29),* Italy *(30),* and Australia *(7),* where respondents with increased perception of risk were more likely to engage in risk-reducing behaviors. This study investigates factors associated with risk perception for various locations involving household related travel. Conforming with the previous study, the risk perception parameter was hypothesized to influence the mitigation behavior.

Individuals come into contact with each other at a variety of locations based on their everyday activities. Examples include work, school, daycare, stores, restaurants, libraries, hospitals, doctor's offices, public transportation (bus, train, etc.) and family or friends' homes.

This chapter's objective was to identify the factors associated with the degree of risk perception of contracting influenza at these locations using survey data from 2168 respondents across the U.S. Self-reported perceived risk was measured on a three-factor scale: low risk (not likely), medium risk (somewhat likely) and high risk (very likely). This information was used in an ordered logit model to identify influential factors. Understanding the risk perception for contracting influenza at various locations is the first step in understanding actions individuals may take to protect themselves, such as canceling trips, avoiding public transit, and avoiding public places, as well as being vaccinated. The first three of these protective actions affects travel, destination, and mode choices as well as traffic in general.

5.3. HYPOTHESES

For this study, five hypotheses were constructed to identify the factors influencing risk perception for various locations.

Hypothesis 1: Having knowledge of the difference between stomach flu and influenza is positively correlated with an individual's risk perception of contracting influenza at (a) work, (b) school, (c) daycare, (d) stores, (e) restaurants, (f) libraries, (g) hospitals, (h) doctors' offices, (i) on public transit, and (j) at friends/family members' homes. Greater awareness of the disease, its communicability, and health consequences, probably results in an increase in risk perception *(7, 8, and 31).* This increased risk perception could be attributed to an individual's understanding of the communicability associated with influenza *(32-34).*

Hypothesis 2: Respondents who had influenza within six months of the survey (personal self-experience) have higher risk perceptions for all of the locations investigated in the study: (a) work, (b) school, (c) daycare, (d) store, (e) restaurant, (f) library, (g) hospital, (h) doctor's office, (i) on public transit, and (j) at friends/family members' homes. This personal experience was expected to increase the respondent's awareness of the virus and its health effects. If an individual has knowledge and understanding of the spread of a disease, it influences the individual's risk perception *(7,8, and 31).*

Hypothesis 3: Respondents who had a household member who contracted influenza in the six months prior to the survey have higher risk perception for all of the locations considered in this study: (a) work, (b) school, (c) daycare, (d) store, (e) restaurant, (f) library, (g) hospital, (h) doctor's office, (i) on public transit, and (j) at friends/family members' homes. Similar to the previous hypothesis, if the respondent was more aware of the virus and its health effects, then he/she could have an understanding of the spread and the severity of the disease.

Hypothesis 4: Having interaction with the public as part of one's job is positively associated with higher risk perception for contracting influenza at work. For a working individual, if the workplace requires a lot of social interaction, then that individual is at risk of contracting influenza through the public *(73).* The authors anticipated such respondents would be aware of this exposure potential.

Hypothesis 5: Households with greater numbers of children have a greater perceived risk for contracting influenza at school/daycare. A greater number of children implies a greater number of potential carriers and thus greater household exposure. Furthermore, children are more susceptible to respiratory illnesses in comparison to adults *(38-45),* which could increase parents' risk perception.

5.4. RISK PERCEPTION MODELS

Socio-economic and demographic parameters along with the knowledge/awareness and exposure information were used to model the risk perception responses. For the final risk perception model, the parameters which were significant are shown in Table 4. All of the risk perception models shown in Tables 5 and 6 were checked for the assumption of parallel regression in R-studio, and the results supported the parallel regression assumption.

(a) Work

Since only the employed population makes this type of trip, the model was developed with only the respondents who indicated that they were working. As shown in Table 6, the significant parameters for this model were the age of the participant, gender of the participant, knowledge of the difference between stomach flu and influenza, recent personal experience with influenza, recent experience of a household member with influenza, and having a job requiring contact with the public. The most significant and sensitive parameter (marginal effect) was exposure to people at work. The positive value of the coefficient indicates that if the participant's work involved interaction with the public, it was 31.63% more likely for the individual to perceive higher risk, supporting *hypothesis 4*. However, medium risk perception depicted a decrease of 1.88% if the participant's work involved interaction with the public. *Hypotheses 1(a), 2(a),* and *3(a)* were also supported; knowledge of and recent experience with the disease increased respondents' risk perception for contracting influenza at work. Also, people with higher age perceived lower risk, whereas, if the participant was female, higher risk was perceived, consistent with previous studies *(74)*.

(b) School

The model for school was developed based on the sample that reported having school-aged children (6-18 years old). Table 6 shows the factors significant in this model. Supporting *hypothesis 2(b) and 3(b),* recent experience with the disease increased the perception of risk of contracting influenza at school. According to the marginal effects, these were the most sensitive parameters. If the participants themselves or their household members had influenza in the past six months, they were 21.09% and 20.30%, respectively, more likely to perceive high risk than the population who had not had the same experience. However, medium risk perception depicted a decrease of 10.42% and 10.02% if they themselves or their household members had influenza in the past six months, respectively. In this model, the importance of experience overshadowed the knowledge of the difference between stomach flu and influenza and the number of children. Both of these variables were insignificant, rejecting *hypothesis 1(b) and 5(a)*.

(c) **Daycare**

This model was developed based on the population who had young children (less than 5 years old). Table 6 shows the variables significant to the model and hypotheses. As with the model for school, knowledge of the difference between stomach flu and the number of appropriately aged children (less than 5 years old) were insignificant, rejecting *Hypotheses 1(c)* and *5(b)*. However, the recent experience variables did not meet the significance threshold (0.05) in this model, rejecting *Hypotheses 2(c)* and *3(c)* as well. However, an education term was significant; respondents with educational levels less than a bachelor's degree perceived lower risk. The marginal effect value for this parameter indicates that for respondents with educational levels less than a bachelor's degree, it was 23.31% less likely for the individual to perceive high risk. However, medium risk perception depicted an increase of 11.73% for respondents with educational levels less than a bachelor's degree.

(d) **Stores**

Table 8 indicates the variables significant to this model. For this model, *hypothesis 1(d)* was rejected, knowledge of the difference between stomach flu and influenza was insignificant. However, recent experience (self or a household member) was significant, supporting *Hypotheses 2(d)* and *3(d)*. According to the marginal effects, these were the most sensitive parameters. If the participants themselves or their household members had influenza in the past six months, they were 10.87% and 6.31%, respectively, more likely to perceive high risk than the population who had not had the same experience. However, medium risk perception depicted a decrease of 2.03% and 1.18% if they themselves or their household members had influenza in the past six months, respectively. Having a higher educational degree increased the likelihood of lower perceived risk. Also, as the number of children in the household increased, the perceived risk for shopping also increased, perhaps due to an increased number of household members touching goods.

(e) Restaurants

Table 8 indicates the variables significant to this model. Similar to the model for stores, *hypothesis 1(e)* was rejected while *Hypotheses 2(e)* and *3(e)* were supported. According to the marginal effects, these (recent experience: self or a household member) were the most sensitive parameters. If the participants themselves or their household members had influenza in the past six months, they were 9.50% and 5.38%, respectively, more likely to perceive high risk than the population who had not had the same experience. However, medium risk perception depicted a decrease of 0.42% and 0.24% if they themselves or their household members had influenza in the past six months respectively. Also, similar to the model for stores, those with higher education degrees tended to perceive lower risk for a restaurant visit.

(f) Libraries

Table 8 indicates the variables significant to this model. The variables' significance and direction of effect for the library model were similar to that of restaurants. *Hypothesis 1(f)* was rejected, while hypotheses *2(f)* and *3(f)* were supported. According to the marginal effects, these (recent experience: self or a household member) were the most sensitive parameters. If the participants themselves or their household members had influenza in the past six months, they were 5.80% and 4.58%, respectively, more likely to perceive high risk than the population who had not had the same experience. Moreover, medium risk perception also depicted an increase of 2.92% and 2.31% if they themselves or their household members had influenza in the past six months, respectively. The higher education degree population tended to perceive lower risk for a library visit.

(g) Hospitals

Table 7 indicates the variables significant to this model. *Hypothesis 1(g)* was rejected while *hypotheses 2(g)* and *3(g)* were supported. According to the marginal effects, these (recent experience: self or a household member) were the most sensitive parameters. If the participants themselves or their household members had influenza in the past six months, they were 6.83% and 9.75%, respectively, more likely to perceive high risk than the population who had not had the same experience. Moreover, medium risk perception also depicted an increase of 2.81% and 4.02% if they themselves or their household members had influenza in the past six months respectively. In this context, the experience was the only influential type of factor.

(h) Doctors' Offices

Table 7 indicates the variables significant to this model. Similar to the other health-related location (hospitals), *hypothesis 1(h)* was rejected while *hypotheses 2(h)* and *3(h)* were supported; recent experience with influenza was important. According to the marginal effects, these (recent experience: self or a household member) were the most sensitive parameters. If the participants themselves or their household members had influenza in the past six months, they were 10.00% and 6.11%, respectively, more likely to perceive high risk than the population who had not had the same experience. However, medium risk perception depicted a decrease of 5.00% and 3.06% if they themselves or their household members had influenza in the past six months, respectively. Knowledge of disease differences was insignificant in the model. Additionally, gender was also significant in this model, with women more likely to perceive higher risk at doctors' offices. The gender influence could reflect household roles with women, on average, still being more likely to conduct child chauffeuring activities (see for example *(75)* and references therein) which include visiting a doctor's office. Hence, for their more involvement with the health trip for children they, generally, have higher risk perception as compared to men *(32-34 and 37)* for this location. Hospitals may represent a more emergent health issue, negating perception differences due to gender.

(i) Public Transit

Table 9 indicates the variables significant to this model. *Hypothesis 1(i)* was rejected in this context while *hypotheses 2(i)* and *3(i)* were supported; recent experience with influenza increased risk perception for contracting it on public transit. According to the marginal effects, this (recent self-experience) were the most sensitive parameters. If the participants themselves had influenza in the past six months, they were 9.95%, more likely to perceive high risk than the population who had not had the same experience. However, medium risk perception depicted a decrease of 4.28% if they themselves had influenza in the past six months respectively. Knowledge of disease differences was insignificant in the model. Additionally, gender was also significant in this model, with women more likely to perceive higher risk at doctors' offices. As the age of the participant increased, they were more likely to perceive lower risk for public transport. As shown in Table 2, a larger percentage of the younger age groups used transit compared to older respondents. Potentially, not using the mode would reduce the risk perception. However, in direct contrast, as the household income rose, respondents were more likely to perceive higher risk traveling using public transit. Income and transit use has been historically inversely related.

(j) Family and Friends' Homes

The significant parameters for this model are shown in Table 9. *Hypothesis 1(j)* was rejected while *hypotheses 2(j)* and *3(j)* were supported; recent experience increased risk perception. According to the marginal effects, these (recent experience: self or a household member) were the most sensitive parameters. If the participants themselves or their household members had influenza in the past six months, they were 15.76% and 6.10%, respectively, more likely to perceive high risk than the population who had not had the same experience. However, medium risk perception depicted a decrease of 1.34% and 0.52% if they themselves or their household members had influenza in the past six months, respectively. Knowledge of disease differences was insignificant in the model. Additionally, age and income were also significant in this model, i.e., with an increase in age or income, increases the likelihood of lower risk perception. This direction of effect for income was different from that for the public transit model.

Table 6: Risk Perception Models for Mandatory Trips

Variables	Work				School				Daycare			
	Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)	Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)	Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)
PPAGE	-0.01*	-0.16%	0.01%	0.15%								
PPGENDER	-0.24*	-4.21%	0.26%	3.97%								
DIFF_STMCH_FLU	0.33*	5.80%	-0.35%	-5.46%	0.4(.)	9.86%	-4.87%	-5.00%	0.37	9.58%	-4.82%	-4.77%
PPFLU_6MNTS	0.71***	12.71%	-0.76%	-11.96%	0.85*	21.09%	-10.41%	-10.69%	0.83(.)	18.29%	-9.21%	-9.10%
HHMFLU_6MNTS	0.39*	6.95%	-0.42%	-6.54%	0.82*	20.30%	-10.02%	-10.29%	0.53	14.02%	-7.06%	-6.97%
EXPOSURE_WORK	1.77***	31.63%	-1.88%	-29.76%								
NUMKIDS					0.09	2.10%	-1.04%	-1.07%				
NUMKIDS<5									0.15	2.41%	-1.22%	-1.20%
EDU_Low									-0.94*	-23.31%	11.73%	11.59%
Threshold Low|Medium	-0.36				-0.93**				-1.45**			
Threshold Medium|High	2.14***				0.89**				0.02			
Model Fit												
Number of Observations	1225				393				180			
AIC	2300				776				340			
McFadden Pseudo R square	0.12				0.05				0.06			
-2 Log Likelihood (final)	570.41				190.46				80.96			
Residual Deviance	2281.62				761.84				323.8			

Note: Significance. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 7: Risk Perception Models for Health-Related Trips

Variables		Hospital				Doctor's Office			
		Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)	Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)
PPAGE									
PPGENDER						-0.25**	-6.20%	3.10%	3.11%
DIFF_STMCH_FLU		0.2(.)	5.26%	-2.17%	-3.10%	0.18(.)	4.46%	-2.23%	-2.24%
PPFLU_6MNTS		0.27*	6.83%	-2.81%	-4.02%	0.41**	10.00%	-5.00%	-5.01%
HHMFLU_6MNTS		0.39**	9.75%	-4.02%	-5.75%	0.25(.)	6.11%	-3.06%	-3.07%
EXPOSURE_WORK									
NUMKIDS									
NUMKIDS<5									
EDU_Low									
Threshold	Low|Medium	-1.23***				-1.61***			
	Medium|High	0.34**				0.18			
Model Fit									
Number of Observations		1887				1884			
AIC		3827				3744			
McFadden Pseudo R square		0.01				0.01			
-2 Log Likelihood (final)		953.65				932.5			
Residual Deviance		3814.6				3730			

Note: Significance. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 8: Risk Perception Models for Discretionary Trips

Variables	Stores				Restaurants				Libraries			
	Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)	Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk	Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)
PPAGE												
Bachelor's or higher degree	-0.42***	-7.94%	1.48%	6.46%	-0.39***	-6.81%	0.30%	6.52%	-0.27**	-3.98%	-2.00%	5.98%
DIFF_STMCH_FLU	0.02	0.27%	-0.05%	-0.22%	-0.07	-1.22%	0.06%	1.17%	-0.02	-0.29%	-0.15%	0.44%
PPFLU_6MNTS	0.57***	10.87%	-2.03%	-8.85%	0.55***	9.50%	-0.42%	-9.09%	0.39**	5.80%	2.92%	-8.72%
HHMFLU_6MNTS	0.33*	6.31%	-1.18%	-5.13%	0.31*	5.38%	-0.24%	-5.15%	0.31**	4.58%	2.31%	-6.88%
NUMKIDS	0.1*	1.88%	-0.36%	-1.53%								
INCOME												
Public_Transit_Regular												
Threshold Low|Medium	-1.18***					-1.34***				-0.58***		
Threshold Medium|High	1.3***					1.2***				1.49***		
Model Fit												
Number of Observations	1882				1882				1828			
AIC	3737.62				3730				3790			
McFadden Pseudo R square	0.02				0.02				0.01			
-2 Log Likelihood (final)	930.91				928.43				944.3			
Residual Deviance	3723.62				3714.3				3777.3			

Note: Significance. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 9: Risk Perception Models for Discretionary Trip and Public Transit

Variables		Family/Friends' Home				Public Transit			
		Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)	Parameter estimates β	Marginal Effect (high risk)	Marginal Effect (medium risk)	Marginal Effect (low risk)
PPAGE		-0.22*	-4.22%	0.38%	4.05%	-0.014***	-0.30%	0.13%	0.17%
Bachelor's or higher degree									
DIFF_STMCH_FLU						0.141	11.78%	-5.07%	-6.72%
PPFLU_6MNTS		0.82***	15.76%	-1.34%	-14.46%	0.463***	9.95%	-4.28%	-5.68%
HHMFLU_6MNTS		0.32*	6.10%	-0.52%	-5.60%	0.429**	-0.30%	0.13%	0.17%
NUMKIDS									
INCOME		-0.02*	-0.36%	0.03%	0.31%	0.023**	0.55%	-0.24%	-0.31%
Public_Transit_Regular						-0.073	0.55%	-0.24%	-0.31%
Threshold	Low|Medium		-1.13***				-1.84***		
	Medium|High		1.14***				-0.437*		
Model Fit									
Number of Observations		1879				1884			
AIC		3834				3597			
McFadden Pseudo R square		0.03				0.02			
-2 Log Likelihood (final)		955				895			
Residual Deviance		3818				3590			

Note: Significance. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

5.5. DISCUSSION AND RESULTS

This section presented ordered logit models to identify the factors associated with survey respondents' qualitative assessment of the risk of contracting influenza by participating in various travel inducing activities: attending (a) work, (b) school, (c) daycare; visiting (d) stores, (e) restaurants, (f) libraries, (g) hospitals, and (h) doctors' offices; (i) traveling on public transit; and (j) visiting friends/family members' homes. More respondents ranked public transit as high risk than any of the other locations, followed by health-related locations and schools and daycare centers. The models for work, school, and daycare were developed based on a sub-sample of the data so that only respondents who would participate in those activities were reflected.

The outcomes of the hypothesis testing of variables initially believed to influence risk perception are summarized below.

Hypothesis 1: Knowledge of the difference between stomach flu and influenza is positively correlated with an individual's risk perception of contracting influenza at each of the locations. This hypothesis was supported for (a) work but was rejected for all of the other locations at the 0.05 significance level.

Hypothesis 2: Respondents who had influenza within six months of the survey (personal self-experience) have higher risk perceptions for each of the locations. This hypothesis was supported for (a) work, (b) school, (d) stores, (e) restaurants, (f) libraries, (g) hospitals, (h) doctors' offices, (i) on public transit, and (j) at friends/family members' homes, but was rejected for (c) daycare.

Hypothesis 3: Respondents who had a household member who contracted influenza in the six months prior to the survey have higher risk perception for each of the locations. This hypothesis was supported for (a) work, (b) school, (d) stores, (e) restaurants, (f) libraries, (g) hospitals, (i) on public transit, and (j) at friends/family members' homes, but was rejected for (c) daycare and (h) doctors' offices.

Hypothesis 4: Having interaction with the public as part of one's job is positively associated with higher risk perception for contracting influenza at work. This hypothesis was supported, as one comes into contact with greater numbers of people, exposure and perceived risk naturally increase.

Hypothesis 5: Households with greater numbers of children have a greater perceived risk for contracting influenza at (a) school and (b) daycare. This hypothesis was not supported, the number of children was not significant in these models. The sample could have been biased in terms of the count of children; the household sizes were generally less than three, and the average and median respondent age implied children older than daycare age, in general. The effect of the number of children could be further explored in future research with a sample with larger household sizes.

Considering the activities as mandatory (work, school, and daycare), discretionary (stores, restaurants, libraries, and family/friends), health-related (hospitals and doctors' offices), and public transit, some similarities, and differences arose. The work trip model was fairly distinct. It was the only one influenced by knowledge of the disease, and unlike the other mandatory activities, was influenced by age and gender. Even the school and daycare models had some differences. The recent experience variables were not significant in the daycare model but were for the school model, which could have been a result of the relatively small sub-sample of respondents with daycare aged children. The school model was more similar to the discretionary trips for the effects of knowledge and recent influenza experience. The different types of discretionary trips were consistent in the significance of recent experience and insignificance of knowledge of the difference between influenza and stomach flu. The models for stores, restaurants, and libraries all had a significant education variable; respondents with a bachelor's degree or higher were less likely to consider these public places high-risk areas. Although the family/friends' home model did not include the education variable, it did have the often correlated income variable with a similar direction of effect. The model for stores was one model that indicated the number of children as a significant factor, possibly this reflected greater exposure in stores either for more frequent trips or a greater amount of contact with public surfaces. However, the family/ friends' home visit model depicted reverse effect for the number of children parameter. The model for hospitals was similar to that of discretionary activities in terms of the significance (or lack thereof) for knowledge and recent experience. However, for the doctors' office model, recent experience for a household member became insignificant while gender was significant, with women being more likely to perceive higher risk. Public transit, while not an activity, shared similarities with the discretionary trips in terms of the importance (or lack thereof) of knowledge and experience of influenza. Similar to the work trip and visiting friends/family, age was significant with increased age generally perceiving lower risk, perhaps due to vaccination practices or confidence in their immune systems. For the public transit model, income was influential, but in the opposite direction to that of income in the friends/family model.

Based on the models developed in this study, it appears that factors influencing risk perception of contracting influenza in public places for discretionary activities (stores, restaurants, and libraries) are fairly consistent, but differ from models of discretionary social visits to someone's home. Mandatory activities seem to have a few individual factors, as do different types of health-related visits. Additional factors should be investigated in the future for all of the locations. The implications for these risk perception models will be explored in future research, particularly how they are associated with public health interventions, such as social isolation, which involves canceling some trips. With the significance of recent experience with influenza more so than consistent socio-demographic and economic factors, it may be beneficial to track influenza infection rates from year to year to get information for this risk perception variable for use in risk mitigation models.

CHAPTER 6 TRAVEL-RELATED HEALTH-PROTECTION BEHAVIOR DURING AN INFLUENZA OUTBREAK

6.1. INTRODUCTION

This chapter focuses on identifying factors (including risk perception levels) influencing health protection behavior. Various researchers, in the past, across numerous disciplines, have focused on studying the tie between risk perceived by individuals to the degree individuals will act to mitigate any given risk *(76-81).* This tie between risk perception and mitigation could be understood from the basics of Protection Motivation Theory. Considering a higher health-risk associated with a household trip (i.e., high severity component of threat appraisal) could be anticipated to result in canceling a trip or a change in the mode of travel (for instance changing from public transit to personal vehicle to reduce threat). This chapter identifies how risk perception relates to risk mitigation and the tie to changes in travel behavior.

Further, this study attempts to identify factors associated with (1) travel-related actions that reduce exposure, and (2) travel-related actions to obtain treatment or prevent the spread of disease. Outcomes of this study could inform models of disease transmission that incorporates individual activities as part of the exposure and mitigation.

The remainder of this chapter is divided into four sections. The first provides background on influenza and studies of the association of risk perception and public health interventions. The second discusses the hypotheses investigated in this study, followed by the discussion of the risk mitigation models. Finally, the fourth section presents the conclusions.

6.2. BACKGROUND

The two identified principal strategies for containing serious human outbreaks of influenza are therapeutic countermeasures (e.g., vaccines and antiviral medications) and public health interventions (e.g., social separation and isolation) *(27).* This chapter specifically examines the public health interventions. Public health interventions include an individual's decision to travel/cancel trips and choice of travel mode. Further, these travel behaviors could be anticipated to have an association with the perception of risk associated to travel.

Previously, theoretical efforts (e.g., Protection Motivation Theory (PMT) *(15, 16)*) have linked risk perception to the response strategies at an individual level. PMT was built on the Health Belief Model *(17)* and is based on two cognitive processes: Threat appraisal and Coping appraisal.

Threat appraisal is related to the perception of the severity of the event and maladaptive response reward. Maladaptive response reward is the perceived benefit gained by not engaging in health behavior *(16, 18).* Therefore, threat appraisal could be more pressing with higher risk perception, varying for different individuals. Hence, as an objective of the study, efforts have been made to check for a tie between risk perception and mitigation actions undertaken.

"The coping appraisal process evaluates the components that are related to the evaluation of coping responses. These components are individual's expectancy that carrying out recommendations can remove the threat (response efficacy) and the belief in one's ability to execute recommended courses of action successfully (self-efficacy)." *(26, p. 98).* Hence based on response-efficacy and self-efficacy, an individual can either adopt or reject a protective action. For instance, an individual who is a regular public transit user and perceives high health-risk traveling in public transit during an influenza outbreak is likely to discontinue commuting to work using public transit. Despite the high perceived health-risk, some individuals may continue to travel using public transit due to external factors, such as unavailability of personal vehicle, or paying for tolls or parking. Hence, some individuals have a reduced likelihood to follow recommended measures (i.e., discontinuing the use of public transit) due to two reasons: 1) lack of resources required to carry out recommendations and 2) perceived importance associated with the trip.

There are two scenarios considered in the study. The first scenario presents the measures (social interaction behavior) taken by the respondent to protect themselves from contracting influenza. Whereas, the second scenario pertains to activities undertaken by an individual suffering from influenza. Ordered logit models were developed using survey data from 2168 respondents across the U.S. Risk mitigation actions anticipated during an influenza outbreak were measured on a three-factor scale: always, sometimes, and never.

6.3. HYPOTHESES

For this study, eight hypotheses were constructed to help identify the factors influencing travel-related risk mitigation. These hypotheses apply to some or all of the seven different models:

1. Scenario 1: Actions when sick with influenza
    a. Model for visiting a doctor's office when sick.
    b. Model for avoiding public places when sick.
    c. Model for avoiding public transit when sick.
    d. Model for staying at home when sick.
2. Scenario 2: Actions to avoid getting sick with influenza
    e. Model for avoiding public places to avoid getting sick with influenza.
    f. Model for avoiding public transit to avoid getting sick with influenza.
    g. Model for staying at home to avoid getting sick with influenza.

Hypothesis 1: Males are less likely to (a) visit a doctor's office when they show symptoms of influenza, (b) avoid public places, (c) avoid public transit, or (d) stay home to avoid spreading influenza. Similarly, men are less likely to (e) avoid public places, (f) avoid public transit or (g) stay home, to avoid contracting influenza during an outbreak. This hypothesis is based on previous studies indicating that men usually perceive lower social health risk in comparison to women *(32-34, and 37).* Further, the tie between the risk perceived and the degree to which an individual would act to mitigate that risk implies that males should be less involved in risk mitigation behavior for less perceived risk.

Hypothesis 2: Respondents with a higher ratio of household income to household size, are more likely to take protective actions to avoid exposure to influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during an influenza outbreak. This ratio is expected to present normalized income for a household, i.e., household income per household member. A household with high income and more household members are likely to have a different effect than a household with similar income but fewer household members. For a household with fewer members and high income, the likelihood of protective actions, such as regular vaccination, would be high (because of the ability to afford medical bills). Whereas, the household with the same income and a higher count of members might not have the same likelihood of adopting the protective behavior (because that income might not be sufficient for such a household). Hence, the use of this ratio would differentiate between the two cases discussed above.

Hypothesis 3: If a household has children of the age less than 12 years, then respondents are more likely to take protective action to avoid getting sick with influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. This behavior could be anticipated from the conclusions of a study based on a survey which was done on a school population by Cauchemez et al. *(48).* It was found that there were high infection rates reported for children between the ages of 6 and 10 years, followed by children of the ages between 2 and 5 years. Being the vulnerable population in the household, the presence of children less than ten years of age in the household could increase the likelihood of adults to engage in the protective behavior, based on the protection motivation theory. Involvement of adults in protective behavior could be because other household members could perceive themselves as potential carriers of disease, thereby increasing the likelihood of infecting the children in the household.

Hypothesis 4: Knowledge of the difference between stomach flu and influenza positively correlates with actions to avoid getting sick with influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. Greater awareness of the disease, its communicability, and health consequences, is likely to increases risk perception *(7, 8, and 31).* Having an awareness of the disease would enable an individual to assess the severity of the scenario (travel) based on the health-risk perceived. Hence, based on the protection motivation theory, the threat component associated with health risk (during travel) would increase the likelihood of an individual to adopt protective behavior.

Hypothesis 5: Respondents who had influenza or had a household member who contracted influenza within six months before the survey are more likely to (a) visit a doctor's office when sick with influenza. Also, they would avoid exposure to influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. If an individual had influenza or any member of the household has experienced influenza in the past, it would imply that the individual is aware of the spread of that disease, which would influence the individual's risk perception *(7, 8, and 31).* Hence, having an experience with the disease could enable an individual to develop a perception of health-risk associated with travel. Further, based on the protection motivation theory, the threat component associated with travel decisions could increase the likelihood of individuals to engage in the protective behavior.

Hypothesis 6: Respondents perceiving a higher risk of contracting influenza at 1_work, 2_school, 3_daycare, 4_stores, 5_restaurants, 6_libraries, 7_hospitals, 8_doctor's offices, 9_public transportation (bus, train, etc.) and 10_family or friends' homes during an influenza outbreak, are more likely to take protective actions to avoid exposure to influenza either by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. Risk perception for a household trip relates to the assessment of severity of health risk associated with that trip. Since the threat component of protection motivation theory is based on the severity assessment of an event, it would involve protective behavior.

Hypothesis 7: Respondents, who obtain influenza vaccines, are more likely to visit a doctor's office when infected with influenza. These respondents are likely to be health conscious and recognize the advantages of prevention and treatment. This is because an individual takes influenza vaccine to protect oneself from influenza *(35)*.

Hypothesis 8: Respondents, who have insurance, are more likely to visit a doctor's office when suffering from influenza. Having health insurance might be an assurance of covering the medical bills and, perhaps, the ability to execute the recommendations to take a protective action.

6.4. RISK MITIGATION MODELS

Actions to avoid spreading or to insulate oneself from influenza were modeled based on the aforementioned hypotheses. For the final risk perception model, the parameters which were significant are shown in Tables 10 - 13. Socio-economic and demographic parameters along with the parameters explaining the comprehension of the disease were used to model the risk mitigation responses. Additionally, various parameters, like having health insurance and the influenza vaccination, were taken into consideration based on the support from literature and relevance to the context. Risk perception parameters were also considered. The forward modeling methodology presented in section 4.1.2 was followed to develop the risk mitigation models for two scenarios of action in this study, i.e., 1) actions the respondents would take when they have influenza (avoiding exposure to the general public) and 2) actions the respondent would take to reduce exposure during an influenza outbreak (protective behavior for oneself).

Scenario I: When Respondent is sick with Influenza

(a) Doctor's office visit

In this model, the dependent variable was the likelihood (Never, Sometimes, Always) of respondents visiting a doctor's office when they are sick with influenza. As shown in Table 10, the significant parameters for this model were the following: having health insurance, having influenza vaccine, respondent's region of residence, an interaction term between an expensive state of residence and living in a metropolitan area, and if the participant is white, non-Hispanic. The most sensitive parameter (marginal effect) in the model was having health insurance. If participants have health insurance, the likelihood of always visiting a doctor's office when sick increases by 12.01%, supporting *hypothesis 8,* since insurance covers their medical bills. Further, for an individual with health insurance, there is an increase of 4.9% in the likelihood of sometimes visiting a doctor's office. Similarly, *hypothesis 7(a)*, i.e., having the influenza vaccine, was supported, suggesting that people who were vaccinated (every year or some years) have an increased likelihood of visiting a doctor's office when sick. *Hypothesis 1(a)* (gender of the participant) and *hypothesis 5(a)* (experience with influenza) were not supported to the significance level of 0.05. Irrespective of the gender of the participant, having health insurance or influenza vaccine influences the individual for visiting a doctor's office, explaining the insignificance of gender parameter. Furthermore, the parameter of experience with influenza is associated with having a lesser concern for health risk. People who had influenza in the past may have successfully used self-treatments (i.e., over the counter medication or home remedies), which reduces their likeliness to visit a doctor's office. The significance of the region parameters could be associated with different lifestyles and different mitigation behaviors. The marginal effects indicate that the residents in region 4 (West-North Central) more frequently visit a doctor's office when sick. Weather in most of the states of West-North Central is very cold in comparison to other regions (i.e., the average temperature stays very low with a mean temperature of less than 40°F) *(82)*. Hence, if the people living in that region do not visit a doctor's office, they are highly likely to exacerbate their illness, because of the extreme climatic conditions in that region. Further, the interaction term between a metropolitan region of residence and a state with a high living expense was a significant parameter, suggesting that people residing in the metropolitan regions of the expensive states are less likely to visit a doctor's office. This observation could be due to two possible reasons: 1) Time invested in visiting a doctor's office and 2) Expense associated with the treatment. In an expensive state of residence, which is also a metropolitan region (dense population), traffic would be more compared to other locations, resulting in an increased commute time. Additionally, for such regions, travel cost would also be high, i.e., high fare for transit users due to high demand and high parking cost for personal vehicle users. The model depicts that the likelihood of white, non-Hispanic individuals visiting a doctor's office is lower; perhaps they perceive less health risk (threat component). This result is consistent with a study by Bish et al. *(83)* for health behavior associated with a global flu pandemic. Hence, based on the protection motivation theory, the white, non-Hispanic population are less likely to adopt protective behavior.

(b) Avoid public places

In this model, the dependent variable was the likelihood (Never, Sometimes, Always) of respondents avoiding public places when they are sick. As shown in Table 10, the significant parameters (p-value < 0.1) for this model were the following: the gender of the respondent, knowledge of the difference between stomach flu and influenza, recent experience with influenza, the age of the participant, and work status of the participant. A higher p-value, i.e., 0.1 level, was allowed for the age parameter since it improved the model based on the nested likelihood ratio test. The most sensitive parameter (marginal effect) was the gender of the participant. Male participants are 9.08% less likely to always avoid public places when they are sick, supporting *hypothesis 1(b)*. Whereas, the likelihood of sometimes avoiding public places depicted an increase of 7.23% for male respondents. Knowledge of the difference between stomach flu and influenza depicted an increase in respondents' likelihood to avoid public places. This is because awareness (knowledge of the difference between stomach flu and influenza) relates to having knowledge of how influenza is spread, which influences the assessment of health risk associated with exposure during travel and thereby increasing the likelihood of an individual to avoid visiting public places when sick. Although the parameter of experience with influenza (respondent or other household member had influenza within six months of the survey) was significant, the direction of effect suggests that having experience decreases the likelihood of respondents avoiding public places. This could be because individuals place less importance for the spread of influenza with them as carriers of the disease compared to the importance of trips (such as work and discretionary trips) they are required to make. Hence, based on the protection motivation theory, failure to carry out recommendation influences individuals to have decreased likelihood of involving in protective behavior, which explains this opposite effect of experience parameter. Age of participants suggested that as individuals grow old, they are more likely to avoid public places when sick. As people age, they tend to have poorer physical abilities to deal with any health ailment and require proper medical attention. Hence, their vulnerability to influenza (threat appraisal component) influences them to make the decision to avoid public places (taking protection behavior). Further, an employed individual depicts a lower likelihood of avoiding public places, potentially due to prioritizing mandatory activities which involve public interaction (e.g., trip to a workplace where there is exposure to the public).

(c) Avoid public transit

In this model, the dependent variable was the likelihood (Never, Sometimes, Always) of respondents avoiding public transit when they are sick. Since the model deals with travel using public transit, only the regular transit users were used as samples in this model. As shown in Table 11, the significant parameters for this model were the following: the gender and the age of the participant. The most sensitive parameter (marginal effect) was the gender of the participant. A negative value of the coefficient for this parameter indicates that male participants are 14.5% less likely to always avoid public transit always when they are sick, supporting *hypothesis 1(c)*. Whereas, the likelihood of sometimes avoiding public transit depicted an increase of 5.13% for male respondents. The coefficient of the age parameter suggested that, as individuals age, they are more likely to avoid public transit when sick, i.e., younger individuals are less likely to avoid public transit. Generally, the younger age group individuals are more involved in the mandatory trips (work or school: which involves travel using public transit) compared to their counterparts. Hence, in a health epidemic event, they are less likely to change their mode of transportation, as they are regular transit users. This is because they might not own a private vehicle or might be reluctant to pay for tolls or parking. Hence, the younger age group population is less likely to comply with the recommendations to reduce the threat, resulting in the decrease in the likelihood of avoiding public transit.

(d) Stay at home

In this model, the dependent variable was the likelihood (Never, Sometimes, Always) of respondents staying at home when they are sick. As shown in Table 11, the significant parameters for this model were the following: gender, knowledge of the difference between stomach flu and influenza, recent experience with influenza, the age of the participant, the ratio of household income to household size, and work status of the participant. The most sensitive parameter (marginal effect) was the gender of the participant. A negative value of the coefficient for this parameter indicates that male participants are 9.98% less likely to always stay at home when they are sick, supporting *hypothesis 1(d)*. However, the likelihood of sometimes avoiding public place depicted an increase of 7.38% for male respondents. Additionally, an employed individual is 13.38% less likely to always stay at home when they are sick since making a work trip is more important. Whereas, the likelihood of sometimes staying at home increased by 9.98% for employed respondent. This behavior of the working population could be associated with not being able to comply with recommendations, i.e., cancel mandatory trips, to reduce the threat due to the importance of trip. Knowledge of the difference between stomach flu and influenza, increased the respondents' likeliness to stay at home. This is because awareness (knowledge of the difference between stomach flu and influenza) relates to having knowledge of how influenza is spread, which influences the assessment of health risk associated with exposure during travel and thereby increasing the likelihood of an individual to stay at home. Further, it was observed that as the age of individuals increase, they are more likely to stay at home when sick. Older age individuals have less involvement in mandatory trips (work). Hence, they prefer to stay at home when sick. Additionally, as people age, they tend to have poorer physical abilities to deal with any health ailment and require proper medical attention. Hence, when they are sick, they are more likely to stay at home (taking protection behavior). Although the parameter of experience with influenza (respondent or other household member had influenza within six months of the survey) was significant, the direction of effect suggests that having experience decreases the likelihood of the respondent to stay at home. This could be because, the perceived importance for making trips, such as work, is more than the consideration for the spread of influenza with them as carriers of the disease. Furthermore, the ratio of household income to household size was significant and depicted that a higher ratio decreased the likelihood of the respondent staying at home. This suggests that the respondent from a household with a reduced household size or with a higher household income is less likely to adopt this protective behavior. This is because, for high-income households, there could be more work trips, which are important and individuals are less likely to avoid such trips. Although there would be fewer trips generated from a household with a smaller household size, the individuals from such a household would still prioritize their mandatory trip (work). Hence, they would have less likelihood of canceling the trip to stay at home.

Scenario II: Protective actions to avoid getting sick with Influenza

(e) Avoid public places

In this model, the dependent variable was the likelihood (Never, Sometimes, Always) of respondents avoiding public places as a protective action to avoid getting sick with influenza. As shown in Table 12, the significant parameters for this model were the following: the gender of the respondent, at least one child less than 12 years old in the household, higher health risk perception for the store visit, work, and public transit, and the ratio of the household income to household size. The most sensitive parameter (marginal effect) was the parameter of 'higher health risk perception for a store visit.' A positive value of the coefficient for this parameter indicates that participants perceiving higher health risks for a store visit have 10.96% more likelihood to always avoid public places, supporting *hypothesis 6(e_4)*. Also, the likelihood of sometimes avoiding public places increased by 5.82% for employed respondents. *Hypothesis 6(e_4)* is supported because of the protection motivation theory and suggests that higher health-risk perception would be associated with the protective behavior to mitigate that risk. Similarly, *hypothesis 6(e_9),* i.e., for high health-risk perception for using public transit was supported. However, *hypothesis 6(e_1)* was not supported, as higher or medium risk perception for a work trip decreased respondents' likelihood to avoid public place. This reverse effect could be associated with the importance of work trips. Employed individuals commuting to the workplace (involving public interaction) have less likelihood to cancel/avoid a work trip, resulting in the decrease of the likelihood of involvement in protective behavior. *Hypotheses 3(e)* was also not supported, as having a child (less than 12 years) in the household decreased the respondents' likelihood to avoid public places. With children in the household, different discretionary trips increase. Hence respondents from such a household are less likely to avoid public places. This results in the failure of adopting these protective behaviors. Furthermore, the ratio of household income to household size was significant and depicted that a higher ratio decreased the likelihood of a respondent to avoid public places, rejecting *hypothesis 2(e)*. This suggests that respondents from a household with a lower household size or with a higher household income are less likely to adopt protective behavior. This is because households with high income have more work trips (more individuals are working). Given the importance of these trips, individuals are less likely to avoid such trips, even if they involve public interaction. Despite fewer trips generated from a household with a smaller household size, the individuals from such a household would still prioritize their mandatory trips (work). Hence, they have a reduced likelihood of avoiding public places.

(f) Avoid public transit

In this model, the dependent variable was the likelihood (Never, Sometimes, Always) of respondents to avoid public transit as a protective action to avoid getting sick with influenza. Since the model deals with travel using public transit, only the regular transit users were included in this model. As shown in Table 12, the significant parameters for this model were the following: the age of respondent, respondents without a bachelors' degree, high and medium health risk perception for public transit, and the ratio of household income with household size. The most sensitive parameter (marginal effect) was high health risk perceptions for using public transit. Respondents who perceive high health risk for using public transit, are 11.83% (supporting *hypothesis 6(f_9)*), more likely to always avoid public transit, and only 0.49% less likely to sometimes avoid public transit. This hypothesis is supported because the protection motivation theory suggests that higher health-risk perception would associate with the protective behavior to mitigate that risk. *Hypotheses 4(f) and 5(f)* were not supported as it was reflected that knowledge of the difference between stomach flu and influenza (*hypotheses 4(f)*) and recent experience with influenza *hypothesis 5(f)*) were not significant to 0.05 level of significance. Although awareness (knowledge of the difference between stomach flu and influenza) and experience with influenza increase concerns of getting infected with influenza, priority is given to making important trips (particularly mandatory: work or school) which might involve the use of public transit. Hence, these parameters lose their significance in the model. Similarly, *Hypothesis 3(f),* was rejected as it reflected if the household had at least one child less than 12 years, was not significant to 0.05 level. Similar to *hypotheses 4(f) and 5(f),* rejection of *hypothesis 3(f)* (having a child of less than 12 years old in the household) could be associated with the importance of the trip. *Hypotheses 1(f),* was rejected, as gender was not significant to the level of 0.05. From the survey data, it could be observed that most of the regular public transit users are employed individuals (i.e., both male and female). Hence, they would likely travel irrespective of the risk associated with getting sick due to the importance of the work trip. Since both male and female population might prioritize work trip equally, the gender parameter would lose its significance. Furthermore, the ratio of household income to household size was significant and depicted that a higher ratio decreased the likelihood of the respondent avoiding public transit, i.e., rejecting *hypothesis 2(e).* This suggests that the respondent from households with a smaller household size or with a higher household income are less likely to adopt this protective behavior. This is because households with high income have more work trips, which are important and individuals are less likely to avoid such trips unless they have a safe alternative mode to commute. Given these respondents are regular transit users, it is less likely for them to change modes to an alternative mode, i.e., personal vehicle. Despite fewer trips generated from a household with a smaller household size, the individuals from such a household could still prioritize their mandatory trip (work). Hence, they have a reduced likelihood of avoiding public transit. The age parameter suggested that as the ages of individuals increase, they are more likely to avoid public transit when sick, i.e., younger individuals are less likely to avoid public transit. For lower values of the participant's age, i.e., younger individuals, the involvement in the mandatory trips (work or school: which involves travel using public transit) is more than their counterparts. For these trips, they are less likely to change to a different mode (as they might not own a vehicle), given they are regular transit users. Additionally, as observed from the model results, the individuals without a bachelor's degree depicted a higher likelihood of avoiding public transit. This result is consistent with the high-risk perception of people with a lower education *(39).* Hence, based on the protection motivation theory, lower risk perception relates to less likelihood of adopting the protective behavior, i.e., avoiding public transit.

(g) Stay at home

In this model, the dependent variable was the likelihood (Never, Sometimes, Always) of respondents to stay at home as a protective action to avoid getting sick with influenza. As shown in Table 13, the significant parameters for this model were age, education (without a bachelors' degree), working status, higher and medium health risk perception for public transit and work trips, race (white non-Hispanic), if New England ($p\text{-value} < 0.1$) is the residence of the respondent, if East-South Central ($p\text{-value} < 0.1$) is the residence of the respondent, and the ratio of the household income to the household size. A higher p-value, i.e., 0.1 level, was allowed for the location parameter since it had significance in the model based on the nested likelihood ratio test. The most sensitive parameter (marginal effect) was the working status of the participant. Based on the model results, employed participants are 12% less likely to always stay at home, as they give more importance to working than the health risk associated with either travel to the workplace or exposure at the workplace itself. A positive value of the coefficient for this parameter indicates that the participants perceiving higher or medium health risk for a store visit, are more likely to stay at home, supporting *hypothesis 6(g_4)*. This hypothesis is supported by the protection motivation theory and suggests that higher health-risk perception would associate with the protective behavior to mitigate that risk. *Hypotheses 3(g)* (at least one child less than 12 years old in the household) *, 4(g)* (knowledge of the difference between stomach flu and influenza)*, and 5(g)* recent experience (self/other household member had influenza within six months of the survey) with the disease, were rejected at the significance level of 0.05 and direction of effect. Although awareness (knowledge of the difference between stomach flu and influenza) and experience with influenza raise the concern of getting infected with influenza, priority is given to making an important trip (particularly mandatory: work or school) rather than to cancel the trip. Similar to *hypotheses 4(g) and 5(g),* rejection of *hypothesis 3(g)* (having a child of less than 12 years old in the household) could be associated with the importance of the trip. Additionally, the model depicts that white, non-Hispanic individuals are less likely to stay at home to avoid getting sick with influenza. This result is consistent with a study by Bish et al. *(83)* for health behavior associated with the global flu pandemic. Furthermore, the model reflects that if the respondents live in the East-South Central region, they are more likely to stay at home. However, if the respondents live in New England, they are less likely to stay at home. This could be since New England includes states having commercial regions suggesting a high median income *(61)*, hence work trips have more economic importance when compared to other low median income regions. Whereas, the East-South Central region includes states with prominent agricultural regions, and have a lower median income. Hence, work trips here have less economic importance when compared to other high median income regions. Therefore, people would more likely consider to cancel a work trip and stay at home. It is observed from the model results that, individuals without a bachelor's degree are more likely to stay at home to protect oneself from getting sick with influenza. This is consistent with the high-risk perception behavior of people with a lower education *(36)*.

Furthermore, the ratio of household income to household size was significant and depicted that a higher ratio decreased the likelihood of the respondent to stay at home, i.e., rejecting *hypothesis 2(g)*. This suggests that respondents from the household with a smaller household size or with a higher household income are less likely to adopt this protective behavior. This is because households with high income have more work trips, which are important and individuals are less likely to cancel trips. Despite fewer trips generated from a household with a smaller household size, individuals from such a household would still prioritize their mandatory trip (work). Hence, they have less likelihood of canceling trips.

Table 10: Risk Mitigation Model: Scenario I (Travel-related actions to obtain treatment or prevent the spread of disease)

Scenario 1 Models		Doctor's Visit				Avoid Public Place			
Variables		Parameter estimates β	Marginal Effect (Always)	Marginal Effect (Sometimes)	Marginal Effect (Never)	Parameter estimates β	Marginal Effect (Always)	Marginal Effect (Sometimes)	Marginal Effect (Never)
Gender(male)		-0.126	-1.63%	-0.71%	2.34%	-0.42***	-10.28%	7.23%	3.05%
Age of the Participant						0.008.	0.18%	-0.13%	-0.05%
If working						-0.36***	-8.94%	6.29%	2.65%
Health insurance		0.864***	11.22%	4.90%	-16.11%				
Influenza vaccine		0.603***	7.84%	3.42%	-11.25%				
Race_White non hispanic		-0.45*	-5.85%	-2.55%	8.40%				
Knowledge						0.24**	5.84%	-4.11%	-1.73%
Experience		-0.087	-1.13%	-0.49%	1.62%	-0.34***	-8.41%	5.92%	2.49%
Region 1 (New England & Mid Atlantic)		0.842***	10.94%	4.77%	-15.71%				
Region 3 (East-North Central)		0.568*	7.38%	3.22%	-10.60%				
Region 4 (West-North Central)		0.433***	5.63%	2.46%	-8.08%				
Region 6 (East-South Central)		1.087**	14.13%	6.16%	-20.29%				
Region (South Atlantic & West-South Central)		0.942.	12.23%	5.34%	-17.57%				
Region 8 (Mountain)		0.568	7.38%	3.22%	-10.60%				
Expensive_State*Metro		0.331***	4.29%	1.87%	-6.16%				
Threshold	Never|Sometimes	0.441				-2.615***			
	Sometimes|Always	3.255***				0.138.			
MODEL FIT									
Number of Observations		1961				1958			
McFadden Pseudo R square		0.035202				0.02075			
(-2) Log Likelihood (AIC)		3683.129				3544.954			
Residual Deviance		3653.129				3528.954			
Adj. McFadden Pseudo R square		0.028864				0.017975			

Note: Significance. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 11: Risk Mitigation Model: Scenario I (Travel-related actions to obtain treatment or prevent the spread of disease)

Scenario 1 Models		Avoid Public Transit				Stay at Home			
Variables		Parameter estimates β	Marginal Effect (Always)	Marginal Effect (Sometimes)	Marginal Effect (Never)	Parameter estimates β	Marginal Effect (Always)	Marginal Effect (Sometimes)	Marginal Effect (Never)
Gender(male)		-0.725*	-14.50%	5.13%	9.37%	-0.408***	-9.89%	7.38%	2.51%
Age of the Participant		0.022**	0.44%	-0.16%	-0.28%	0.011***	0.25%	-0.18%	-0.06%
If working						-0.552***	-13.38%	9.98%	3.39%
Income/HHSIZE						-0.052**	-1.24%	0.92%	0.31%
If kid in HH less than 12 yrs old									
Knowledge						0.302**	7.31%	-5.46%	-1.85%
Experience						-0.341***	-8.26%	6.17%	2.10%
Threshold	Never|Sometimes	-1.098**				-2.717***			
	Sometimes|Always	1.577***				0.285			
MODEL FIT									
Number of Observations		191				1958			
McFadden Pseudo R square		0.038425				0.034282			
(-2) Log Likelihood (AIC)		372.118				3414.868			
Residual Deviance		362.118				3396.868			
Adj. McFadden Pseudo R square		0.022493				0.03087			

Note: Significance. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 12: Risk Mitigation Model: Scenario II (Travel-related actions that reduce exposure)

Scenario 2 Models	Avoid Public Place				Avoid Public Transit			
Variables	Parameter estimates β	Marginal Effect (Always)	Marginal Effect (Sometimes)	Marginal Effect (Never)	Parameter estimates β	Marginal Effect (Always)	Marginal Effect (Sometimes)	Marginal Effect (Never)
Gender(male)	-0.235*	-4.84%	2.62%	2.22%	0.097	1.58%	-0.07%	-1.51%
Age of the Participant					0.024*	0.39%	-0.02%	-0.37%
Race_white								
Without Bachelors					0.713.	11.63%	-0.48%	-11.15%
If work								
Income/HHSIZE	-0.107***	-2.21%	1.20%	1.01%	-0.135.	-2.20%	0.09%	2.11%
If kids in HH less than 12 yrs	-0.52***	-10.74%	5.82%	4.93%	0.157	2.55%	-0.11%	-2.45%
Knowledge	0.063	1.30%	-0.70%	-0.60%	0.129	2.09%	-0.09%	-2.00%
Experience	-0.085	-1.74%	0.94%	0.80%	0.192	3.13%	-0.13%	-3.00%
Region 1 (New England)								
Region 6 (East-South Central)								
Risk perception_work_high_medium	-0.394***	-8.14%	4.41%	3.73%				
Risk perception_public transit_High	0.396***	8.18%	-4.43%	-3.75%				
Risk perception_public transit_medium								
Risk perception_PublicTransit_High_Medium					0.725	11.83%	-0.49%	-11.34%
Risk perception_stores_High	0.53***	10.96%	-5.94%	-5.03%				
Risk perception_stores_medium								
Risk perception_store_High_Medium								
Threshold Never|Sometimes	-2.59***				0.541			
Threshold Sometimes|Always	0.417**				3.317***			
MODEL FIT								
Number of Observations	1753				166			
McFadden Pseudo R square	0.030816				0.065177			
(-2) Log Likelihood (AIC)	3162.917				331.1468			

Residual Deviance	3140.917	309.1468
Adj. McFadden Pseudo R square	0.025879	0.010747

Note: Significance. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 13: Risk Mitigation Model: Scenario II (Social Isolation to reduce exposure)

Scenario 2 Model		Stay at Home			
Variables		Parameter estimates β	Marginal Effect (Always)	Marginal Effect (Sometimes)	Marginal Effect (Never)
Gender(male)		-0.216*	-3.41%	0.20%	3.22%
Race_white		-0.407***	-6.45%	0.38%	6.07%
Without Bachelors		0.348***	5.52%	-0.32%	-5.20%
If work		-0.756***	-12.00%	0.70%	11.30%
Income/HHSIZE		-0.111***	-1.75%	0.10%	1.65%
If kids in HH less than 12 yrs		-0.126	-2.00%	0.12%	1.88%
Knowledge		-0.094	-1.48%	0.09%	1.40%
Experience		-0.052	-0.81%	0.05%	0.76%
Region 1 (New England)		-0.387.	-6.14%	0.36%	5.78%
Region 6 (East-South Central)		0.359.	5.69%	-0.33%	-5.36%
Risk perception_store_High_Medium		0.418***	6.62%	-0.39%	-6.24%
Threshold	Never|Sometimes	-2.548***			
	Sometimes|Always	0.35			
MODEL FIT					
Number of Observations		1870			
McFadden Pseudo R square		0.055377			
(-2) Log Likelihood (AIC)		3459.588			
Residual Deviance		3431.588			
Adj. McFadden Pseudo R square		0.049321			

Note: Significance. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

6.5. DISCUSSION AND CONCLUSIONS

The previous section presented ordered logit models to identify the factors associated with the likelihood of taking protective actions. The outcomes of the hypothesis testing of variables initially believed to influence risk mitigation responses are summarized below.

Hypothesis 1: Males are less likely to (a) visit a doctor's office when they show symptoms of influenza, (b) avoid public places, (c) avoid public transit, or (d) stay home to avoid spreading influenza. Similarly, men are less likely to (e) avoid public places, (f) avoid public transit or (g) stay home, to avoid contracting influenza during an outbreak. The hypotheses were supported in the first scenario: (b) Avoiding public place, (c) avoiding public transit, and (d) staying at home, but rejected for a visit to doctor's office at the significance level 0.05. Additionally, the hypotheses supported in the second scenario: (e) Avoiding public places and (g) staying at home, but rejected for (f) avoiding public transit at the significance level of 0.05.

Hypothesis 2: Respondents with a higher ratio of household income to household size, are more likely to take protective actions to avoid exposure to influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during an influenza outbreak. This hypothesis was rejected based on reverse effect for all the three models.

Hypothesis 3: If a household has children of the age less than 12 years, then, respondents are more likely to take protective action to avoid getting sick with influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. This hypothesis was rejected based on insignificance for (e) Avoiding public places, and (g) staying at home at significance level 0.05. Whereas, (f) 'avoiding public transit' model was rejected for depicting reverse effect.

Hypothesis 4: Knowledge of the difference between stomach flu and influenza positively correlates with actions to avoid getting sick with influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. The hypotheses were rejected for (e) avoiding the public places and (f) avoiding public transit at the significance level of 0.05, but was rejected for a reverse effect for (g) staying at home model.

Hypothesis 5: Respondents who had influenza or had a household member who contracted influenza within six months before the survey were more likely to (a) visit a doctor's office when sick with influenza. Also, they would avoid exposure to influenza by (e) avoiding public places, (f) *avoiding public transit or (g) staying at home, during the event of an influenza outbreak.* This hypothesis was rejected for (e) avoiding the public place and (g) staying at home model for Scenario 2 for opposite correlation. However, it was rejected for (f) avoiding public transit model at significance level 0.05.

Hypothesis 6: Respondents perceiving a higher risk of contracting influenza at 1_work, 2_school, 3_daycare, 4_stores, 5_restaurants, 6_libraries, 7_hospitals, 8_doctor's offices, 9_public transportation (bus, train, etc.) and 10_family or friends' homes during an influenza outbreak, are more likely to take protective actions to avoid exposure to influenza either by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. This hypothesis was only supported in the (e) avoiding public places model for the risk perception parameters associated to work visits, public transit trips, and store visits. Also, this hypothesis was supported in the (f) avoiding public transit model, for risk perception associated with public transit trips. Additionally, in the (g) stay at home model, this hypothesis was supported by the risk perception parameter for store visits. Whereas, it was rejected for risk perception for public transit trips in the, (g) staying at home model for depicting a reverse effect.

Hypothesis 7: Respondents who obtain influenza vaccines, are more likely to visit a doctor's office when infected with influenza. This hypothesis was supported by the first scenario's (a) doctors' office visit model.

Hypothesis 8: Respondents who have insurance, are more likely to visit a doctor's office when suffering from influenza. This hypothesis was supported by first scenario's (a) doctors' office visit model.

Considering Scenario 1, having health insurance and influenza vaccine were both good indicators in the model for (a) 'visiting a doctor's office when sick.' The region of residence was a significant factor in the model and depicted that willingness of participants to visit a doctor's office varied across different regions considered. Moreover, having a residence in a metropolitan area decreases the likelihood to visit a doctor's office. People residing in metropolitan regions of expensive states (Hawaii; District of Colombia (not state); New York; Alaska; New Jersey; California; Connecticut) depicted a reduced likelihood to visit a doctor's office. This could be due to two possible reasons: 1) Time invested in visiting the doctor's office (traffic in the metropolitan region would increase commute time), 2) higher medical expenses in the expensive state of residence.

Additionally, for Scenario 1, (b) avoiding public places (c) public transit or (d) stay at home models were fairly similar with the direction of effect of the significant parameters in the model. For these three models, the age of the respondent was significant and depicted that older individuals are more inclined to take protective action in avoiding the spread of influenza when they are sick. Normalization of the household income was tested using the ratio of household income to household size parameter in the model. Higher ratios indicate that the respondent would be less likely to (a) visit a doctor's office or (c) avoid public transit or (d) stay at home when sick. Similarly, the white non-Hispanic individuals are less likely to (a) visit a doctor's office when they are sick with influenza. Furthermore, the males were less likely to take a protective action when tested for Scenario 1.

Similar conclusions for the male population were made for avoiding public transit to avoid getting sick from influenza during an influenza outbreak, i.e., Scenario 2. Having knowledge of the difference between stomach flu and influenza was consistent with the assumed hypothesis, except for the (e) staying at home model to avoid getting sick from influenza. Moreover, similar to Scenario 1, a lower ratio of normalized income (ratio of household income to household size) depicted decrease in the likelihood of participation in protective action to avoid getting sick from influenza. Also, as concluded from the model results, an employed respondent is unlikely to (e, g) stay at home for both the scenarios. Further, higher health risk perception of visiting a store is related to (f) avoiding public places and (g) staying at home during influenza outbreak to avoid getting sick. Additionally, high-risk perception for contacting influenza in public transit implied involvement in adopting the protective behavior, i.e., avoiding public transit. Hence, these conclusions verify the tie between the risk perception and mitigation behavior. However, higher health risk perceived for workplace visit implied less involvement in mitigation behavior. This reverse effect was associated with the importance of the trip (i.e., work trip). From the model results, it is concluded that individuals without a bachelor's degree are likely to (f) avoid public transit and (g) stay at home to avoid getting sick during an influenza outbreak.

It can also be observed from the models in Scenario 1 and 2, that (b) and (e) avoiding public places models have almost the same parameter effects. Similar model parameter effects were observed for (d) and (g) staying at home models. This depicts that irrespective of the scenarios, the same significant parameters in either model influence the mitigation behavior with the same direction of effect.

CHAPTER 7 CONCLUSION

In this study, 17 different travel-related health risk perception and mitigation ordered logit models have been presented. In the process of describing these different models, the goal was to provide more clarity regarding the connections between factors found significant in the models with health risk perception and mitigation behavior.

For the risk perception models, ordered logistic regression models were used to identify factors associated with the perceived risk of contracting influenza at work, school, daycare, stores, restaurants, libraries, hospitals, doctor's offices, public transportation, and family or friends' homes. Parameters such as knowledge and awareness of the spread of influenza for an individual were found to influence the individual's risk perception.

Based on the risk perception models developed in the study, it appears that factors influencing risk perception of contracting influenza in public places for discretionary activities (stores, restaurants, and libraries) are fairly consistent, but differ from models of discretionary social visits to someone's home. Mandatory activities seem to have a few individual factors, as do different types of health-related visits. Additional factors should be investigated in the future for all of the locations.

The implications for these risk perception models were then explored to understand how they are associated with public health interventions, such as social isolation and canceling of household trips. For this, two scenarios were analyzed: 1) travel-related actions to obtain treatment or prevent the spread of disease, 2) travel-related actions that reduce exposure to avoid getting sick with influenza. Risk perception was checked for association with models for the second scenario, to be consistent with the protection motivation theory.

Based on the results of Scenario 1 models, having health insurance and the influenza vaccine were positively correlated for (a) visiting a doctor's office. Additionally, gender was a significant parameter, which suggests males are less likely to adopt protective actions for both the scenarios' tested. This was consistent with the conclusions from previous studies *(25, 84, and 85)*. Additionally, from the results of Scenario 2 models, higher risk perception (for work visit/ store visit/ use of public transit) influenced individuals to adopt protective behavior to mitigate risk *(76-81)*. It was also observed that both scenarios had similar significant factors influencing the responses for 'avoiding public places' models. Similarly, significant factors influencing the responses for 'stay at home' models for both scenarios were similar. This similarity indicates that irrespective of the scenarios considered, these factors influenced individuals to adopt similar protection behavior.

It can be concluded that certain demographic factors, such as gender, income, household size, race, and the age of the participant also influenced protective actions for both scenarios. Hence, in conclusion, demographic parameters in conjunction with other factors, such as those affecting the comprehension of the severity of influenza, would be essential to capture changes in travel behaviors during influenza.

7.1. HYPOTHESES

7.1.1. Risk Perception Model

Hypothesis 1: Knowledge of the difference between stomach flu and influenza is positively correlated with an individual's risk perception of contracting influenza at each of the locations. This hypothesis would be essential in explaining the risk perception associated with the workplace.

Hypothesis 2: Respondents who had influenza within six months of the survey (personal self-experience) have higher risk perceptions for each of the locations. This hypothesis would be essential in explaining risk perception associated to (a) work, (b) school, (d) stores, (e) restaurants, (f) libraries, (g) hospitals, (h) doctors' offices, (i) on public transit, and (j) at friends/family members' homes.

Hypothesis 3: Respondents who had a household member who contracted influenza in the six months before the survey have higher risk perception for each of the locations. This hypothesis would be essential in explaining risk perception associated to (a) work, (b) school, (d) stores, (e) restaurants, (f) libraries, (g) hospitals, (i) on public transit, and (j) at friends/family members' homes.

Hypothesis 4: Having interaction with the public as part of one's job is positively associated with higher risk perception for contracting influenza at work. This hypothesis would be essential in explaining risk perception associated to visit the workplace.

Hypothesis 5: Households with greater numbers of children have a greater perceived risk for contracting influenza at (a) school and (b) daycare. This hypothesis was not able to significantly explain the risk associated with any of the household trips considered in this study.

7.1.2. Risk Mitigation Model

Hypothesis 1: Males are less likely to (a) visit a doctor's office when they show symptoms of influenza, (b) avoid public places, (c) avoid public transit, or (d) stay home to avoid spreading influenza. Similarly, men are less likely to (e) avoid public places, (f) avoid public transit or (g) stay home, to avoid contracting influenza during an outbreak. This hypothesis was supported in the first scenario. For the first scenario, this hypothesis would be essentially influencing the travel decisions: (b) Avoiding public place, (c) avoiding public transit, and (d) staying at home. Additionally, for the second scenario, this hypothesis would be essentially influencing the travel decisions: (e) Avoiding public place, and (g) staying at home.

Hypothesis 2: Respondents with a higher ratio of household income to household size, are more likely to take protective actions to avoid exposure to influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during an influenza outbreak. This hypothesis depicted reverse effect for the models.

Hypothesis 3: If a household has children of the age less than 12 years, then respondents are more likely to take protective action to avoid getting sick with influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. This hypothesis was not supported.

Hypothesis 4: Knowledge of the difference between stomach flu and influenza positively correlates with actions to avoid getting sick with influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. For the first scenario, this hypothesis would be essentially influencing the travel decisions: (b) Avoiding public place, and (d) staying at home. Additionally, for the second scenario, this hypothesis would be essentially influencing only (g) staying at home model.

Hypothesis 5: Respondents who had influenza or had a household member who contracted influenza within six months before the survey are more likely to (a) visit a doctor's office when sick with influenza. Also, they would avoid exposure to influenza by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. This hypothesis was not supported by this study.

Hypothesis 6: Respondents perceiving a higher risk of contracting influenza at 1_work, 2_school, 3_daycare, 4_stores, 5_restaurants, 6_libraries, 7_hospitals, 8_doctor's offices, 9_public transportation (bus, train, etc.) and 10_family or friends' homes during an influenza outbreak, are more likely to take protective actions to avoid exposure to influenza either by (e) avoiding public places, (f) avoiding public transit or (g) staying at home, during the event of an influenza outbreak. This hypothesis was only supported by work, public transit, and store visit for (e) avoiding public place model. Whereas, for risk perception associated public transit trip, it was supported in (f) avoiding public transit model but rejected in (g) staying at home model with a contradictory correlation with protective action. However, for a (g) stay at home model, this hypothesis was supported by a store visit risk perception.

Hypothesis 7: Respondents, who obtain influenza vaccines, are more likely to visit a doctor's office when infected with influenza. This hypothesis was supported by first-scenario's (a) doctors' office visit.

Hypothesis 8: Respondents, who have insurance, are more likely to visit a doctor's office when suffering from influenza. This hypothesis was supported for (a) first-scenario's doctors' office visit.

7.2. CONTRIBUTION OF THESIS

This study presents factors statistically associated with (1) risk perception of contracting influenza at typical everyday locations, (2) travel-related actions that reduce exposure, and (3) travel-related actions to obtain treatment or prevent the spread of disease.

Where previous studies were focused on assessing factors affecting risk perception such as demographics and social interaction, this study explores additional factors which affect risk perception. This thesis focuses on capturing both demographic and social interaction parameters in addition to those affecting comprehension of the severity of the disease. Since it could be anticipated that different household trips have different importance, (for instance, work trip is more important than a recreation trip, as missing out on a work trip would lead to economic loss), and different social interaction, the risk is perceived differently and result in different protective behaviors. This necessitates modeling (1) risk perception based on the trip type. Hence, risk perception was modeled for trips associated to (a) work, (b) school, (c) daycare; visiting (d) stores,

(e) restaurants, (f) libraries, (g) hospitals, and (h) doctors' offices, (i) traveling on public transit, and (j) visiting friends/family members' homes.

This approach helps identify additional parameters affecting the health-risk perceived based on the trip types (broadly classified as Mandatory, Health, and Discretionary). Also, this study concludes that demographic parameters, social interaction parameters, and the parameters affecting the comprehension of disease resulted in different risk perceptions associated with each trip type differently.

In the latter part of the thesis, risk mitigations models for (2) travel-related actions that reduce exposure, and (3) travel-related actions to obtain treatment or prevent the spread of disease were studied. In the past, researchers have explored risk mitigation/protection behavior based on the Social Cognition Models. But, for this study, as an add-on, efforts were made to identify the additional factors which influence risk mitigation behavior. These factors identified in the study were logically tied to the parameters of demographics/ comprehension of severity/ transmission of influenza/ social interaction using the concepts of Social Cognition Models. Significant parameters in the models were reported and discussed. However, this model requires identification of more parameters which would further explain the protection behavior.

Similar efforts were made for (3) travel-related actions to obtain treatment or prevent the spread of disease with one additional parameter considered; namely, the tie between travel decisions (or likelihood thereof) and risk perception was analyzed as presented in this study. Based on the conclusions from the study, health risk perception for participation in activities involving contact with the contagious disease (work and shopping), and travel itself (i.e., through public transit), were statistically significant in influencing protection behavior.

Results from this thesis have implications which could be applied to the SIR model. Parameters of modeling transmission of disease in the SIR model are; the rate at which an individual comes into contact with any another individual ($\alpha 1$), the probability that a susceptible individual upon contact with infected individual contracts the disease ($\alpha 2$) and rate of recovery of infected individuals (ρ). The rate of recovery from infection (ρ) and the probability of getting infected when contacting an infected individual are all dependent on the health/medical characteristics of the population studied, which is out of the scope of this study.

However, this study provides a methodology to develop some insight on the α1 parameter, which relates to the risk mitigation models (travel-related actions that reduce exposure and travel-related actions to prevent the spread of disease). The α1 parameter is based on the understanding of the interaction of the susceptible population and infected population. Factors identified for travel-related actions that reduce exposure and prevent the spread of disease models could be used to determine the α1 parameter for a targeted population. Application of implications of this study to the SIR models could provide a greater understanding of the transmission of influenza within the targeted population.

7.3. RECOMMENDATIONS FOR FUTURE WORK

It is recommended to explore other behavioral characteristics which would influence the travel decisions during an outbreak, such as the possibility of an employed individual to work from home. This would be a good parameter to differentiate between two working individuals who choose to either stay at home or choose not to cancel the work trip. Moreover, factors such as frequency of an individual visiting different locations could be a factor which might influence health-risk perception associated with that place. Hence, more such factors should be explored for inclusion in the survey to enhance the prediction of health protection behavior.

Furthermore, a spatial analysis to assess the social interaction could provide a good basis to determine the protection behavior of an individual. Moreover, social networking platforms could be used to assess the location from where the individual is operating the app and could be used to provide a comparison of location-based data between two scenarios: 1) when an outbreak of influenza occurred and 2) for other normal days *(56)*. It is recommended to put into use this location data from the social networking platform to obtain a comprehensive spatial analysis which would help in capturing the change in travel patterns during an event of an outbreak *(56)*.

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APPENDIX

Table A1: Distribution of Respondents based on the geographical location

Location of State		STATE	Percent of Respondents
West	Pacific	Alaska	0.14%
		California	11.21%
		Hawaii	0.32%
		Oregon	0.97%
		Washington	2.12%
	Mountain	Arizona	2.58%
		Colorado	1.89%
		Idaho	0.42%
		Montana	0.46%
		New Mexico	0.74%
		Nevada	0.78%
		Utah	1.34%
		Wyoming	0.05%
Midwest	West-North Central	Iowa	0.97%
		Kansas	0.74%
		Minnesota	2.35%
		Missouri	1.94%
		North Dakota	0.09%
		Nebraska	0.78%
		South Dakota	0.37%
	East-North Central	Illinois	3.51%
		Indiana	1.25%
		Ohio	4.01%
		Michigan	3.60%
		Wisconsin	2.54%
South	West-South Central	Arkansas	0.97%
		Oklahoma	1.11%
		Texas	7.29%
		Louisiana	0.97%
	East-South Central	Alabama	1.01%
		Tennessee	1.89%
		Minnesota	2.35%
		Kentucky	1.38%
	South Atlantic	District of Columbia	0.23%
		Delaware	0.32%
		Florida	6.73%
		Maryland	1.89%
		Georgia	2.91%
		Virginia	2.91%

		North Carolina	3.09%
		South Carolina	1.52%
		West Virginia	0.51%
North East	Mid Atlantic	New Jersey	2.58%
		New York	5.86%
		Pennsylvania	5.63%
	New England	Connecticut	1.52%
		Massachusetts	2.35%
		Maine	0.69%
		New Hampshire	0.32%
		Rhode Island	0.32%
		Vermont	0.14%

Figure A1: Code in R-studio for developing correlation matrix

```
m1 = read.csv("~File location~/model_2.csv", header= TRUE)

## Load the Dataset
df = data.frame(m1[,1:172])

## Obtain the descriptive statistics of the dataset
desc = describe(df)

# converting the data set into dataframe
df_1 = as.data.frame(df)

# converting the data set into dataframe
d = data.frame(m1[,1:170])
df_1 = as.data.frame(d)

## corelation matrix

c1 = matrix( nrow = 172, ncol = 172)                    # Creating Null matrix for correlation value
d1 = matrix( nrow = 172, ncol =172)                     # Creating Null matrix for p-value

for (i in 1:172) {
  for (j in 1:172){
    v2 = df_1[ , j]
    v1 = df_1[ , i]
    cd1 = cbind(v1,v2)
    cd1_1= cd1[complete.cases(cd1), ]                   # Assigning blanks to non-numeric value
    cdf = na.omit(cd1_1)                                # Removing blanks
    cdf1 = as.data.frame(cdf)
    tb1 = table(cdf1$v1, cdf1$v2)                       # converting to a table format
    a = cor.test(cdf1$v1, cdf1$v2, method = 'spearman') # Spearman correlation Chi-squared value
    c1[i,j] = a$estimate
    d1[i,j] = a$p.value
  }
}

write.csv(c1, "~File location~/rho_value.csv")

write.csv(d1, "~File location~/p_value.csv")
```

Figure A2: Code in R-studio for building Ordered logit model

```
m1 = read.csv("~File location~/model_2.csv", header= TRUE)

df = data.frame(m1[,1:172])

dc1 = cbind(df$Q23_2_Ordered,df$PPGENDER, df$DIFF_STMCH_FLU,df$PPFLU_6MNTS , df$If_kids_12, df$age_2,df$If_work)

##removing the missing data_TO obtain a reduced dataset

df1_1 = na.omit(dc1)
df_1 = data.frame(df1_1)


## Converting the variables into workers category
y1 = as.matrix(df_1$X1)

#dependent and independent variable for ordered model

y1_1 = (factor(y1 ,label = c("Never", "Sometimes", "Always"), levels = c(1,2,3), ordered = is.ordered(df_1$X1)))

# Ordered Logit Model

polr.f = polr(y1_1 ~ df_1$X2+ df_1$X3+ df_1$X4+ df_1$X5+ df_1$X6+ df_1$X7,  Hess = TRUE)

## Checking the assumption of Proportional odds
pt = brant(polr.f)

## Marginal Effect model study
fin_mod = oglmx(y1 ~df_1$X2+ df_1$X3+ df_1$X4+ df_1$X5+ df_1$X6+ df_1$X7,link="logit", threshparam = NULL)

marginal_effect = margins.oglmx(fin_mod, ascontinuous = TRUE)

## Number of Rows
nrow(y1)

ll_model = as.data.frame(pR2(polr.f))
llh = ll_model[1,1]
llhnull = ll_model[2,1]
McFadden_adj = (1-(llh - (ncol(dc1)-1))/llhnull)
```

Model test results are shown in Table 10.

Figure A3: Result of Brant test {Proportional Odds Test}

```
--------------------------------------------
Test for            X2      df   probability
--------------------------------------------
Omnibus             21.91   6    0
PPGENDER            0.23    1    0.63
DIFF_STMCH_FLU      4.26    1    0.04
PPFLU_6MNTS         9.55    1    0
If_kids_12          2.38    1    0.12
age_2               2.15    1    0.14
If_work             3.17    1    0.07
--------------------------------------------

H0: Parallel Regression Assumption holds
```

Figure A4: R-studio code for predicted probability

```
cut1 <- -1.098
cut2 <- 1.577
beta <- c(-0.724, 0.021)
# 32 year old female
X    <- c(0, 32)
pred_cat1      <- exp(-1*(X%*%beta)+cut1)/(1+exp(-1*(X%*%beta)+cut1))            # result for response less than first threshold
pred_cat_less3      <-(exp(-1*(X%*%beta)+cut2)/(1+exp(-1*(X%*%beta)+cut2)))            # result for response less than third threshold
pred_cat3      <- 1-pred_cat_less3                                          # result for response greater than third threshold
pred_cat2      <- pred_cat_less3-pred_cat1                                      # result for response bet first and third threshold
predicted_distribution <- cbind(pred_cat1, pred_cat2, pred_cat3)
predicted_distribution
```

Table A2: Spearman correlation values for risk perception models (1)

Parameter	Model_Risk perception for a workplace visit (1)			Model_Risk perception for a School Visit (2)			Model_Risk perception for a Daycare visit (3)			Model_Risk perception for a Store visit (4)		
	Sample Size	rho value	p-value	Sample Size	rho value	p-value	Sample Size	rho value	p-value	Sample Size	rho value	p-value
Age of the participant	2168	-0.156	2.52E-13	2168	-0.148	4.00E-12	2168	-0.105	8.54E-07	2168	-0.010	6.36E-01
Male	2168	-0.075	5.12E-04	2168	-0.072	8.36E-04	2168	-0.061	4.73E-03	2168	-0.032	1.33E-01
Income	2168	0.069	1.28E-03	2168	0.094	1.06E-05	2168	0.114	1.09E-07	2168	0.004	8.65E-01
HH child between age 0-1	2168	0.013	5.48E-01	2168	0.045	3.71E-02	2168	0.082	1.23E-04	2168	-0.008	6.97E-01
HH child between age 2-5	2168	0.025	2.48E-01	2168	0.076	4.26E-04	2168	0.063	3.48E-03	2168	-0.001	9.63E-01
HH child between age 6-12	2168	0.027	2.08E-01	2168	0.064	2.66E-03	2168	0.047	2.83E-02	2168	0.012	5.81E-01
HH child between age 13-17	2168	0.053	1.38E-02	2168	0.047	3.00E-02	2168	0.027	2.09E-01	2168	0.017	4.23E-01
HH member over age 18	2168	0.069	1.37E-03	2168	0.087	5.45E-05	2168	0.073	6.80E-04	2168	0.086	6.63E-05
Edu_Less than high school	2168	-0.076	4.10E-04	2168	-0.056	8.54E-03	2168	-0.055	1.01E-02	2168	-0.037	8.58E-02
Edu_High school	2168	-0.062	3.60E-03	2168	-0.068	1.49E-03	2168	-0.071	9.03E-04	2168	0.041	5.46E-02
Edu_Some college	2168	-0.062	3.60E-03	2168	-0.068	1.49E-03	2168	-0.071	9.03E-04	2168	0.041	5.46E-02
Edu_Bachelor's or higher degree	2168	0.035	1.08E-01	2168	0.019	3.75E-01	2168	0.003	8.85E-01	2168	0.034	1.19E-01
Diff. Known b/w Stomach flu and Infuenza	2168	0.069	1.30E-03	2168	0.078	2.62E-04	2168	0.096	8.21E-06	2168	-0.051	1.86E-02
Had influenza since August 2015	2152	0.101	2.73E-06	2152	0.075	5.35E-04	2152	0.064	3.03E-03	2152	0.064	3.00E-03
HH member had influenza since August 2016	2149	0.153	9.73E-13	2149	0.165	1.19E-14	2149	0.153	1.05E-12	2149	0.157	2.72E-13
Not Working	1991	0.169	3.20E-14	1991	0.182	2.51E-16	1991	0.165	1.29E-13	1991	0.140	3.87E-10
Working	2168	-0.253	4.43E-33	2168	-0.119	3.13E-08	2168	-0.108	4.65E-07	2168	-0.092	1.67E-05
Car travel to work	1368	0.040	1.35E-01	1368	0.059	3.02E-02	1368	0.076	4.81E-03	1368	0.056	3.74E-02

Regular use of public transportation	2153	-0.022	3.02E-01	2153	-0.035	1.03E-01	2153	-0.048	2.72E-02	2153	-0.022	3.11E-01
Avoiding crowded place to avoid getting sick	2168	0.040	6.38E-02	2168	0.054	1.22E-02	2168	0.065	2.43E-03	2168	0.149	2.84E-12
Get an Influenza vaccine	2168	-0.057	7.93E-03	2168	-0.034	1.11E-01	2168	-0.042	5.18E-02	2168	-0.026	2.19E-01
Get avaccine: If people around get a vaccine	1331	-0.023	4.05E-01	1331	0.000	9.99E-01	1331	0.023	4.04E-01	1331	-0.035	1.96E-01
Get a vaccine: If people around don't get vaccine	1325	-0.039	1.55E-01	1325	0.021	4.41E-01	1325	0.019	4.83E-01	1325	-0.070	1.05E-02
Vaccine taken to Protect Myself	1324	0.000	9.96E-01	1324	-0.044	1.12E-01	1324	-0.018	5.05E-01	1324	-0.032	2.42E-01
Vaccine taken to Protect other	1324	0.029	2.87E-01	1324	0.002	9.52E-01	1324	0.008	7.69E-01	1324	-0.024	3.89E-01
Vaccine taken to Protect myself and other	1324	-0.008	7.71E-01	1324	0.043	1.22E-01	1324	0.016	5.66E-01	1324	0.038	1.64E-01
Rating of effectiveness of vaccine	2168	0.079	2.33E-04	2168	0.078	2.80E-04	2168	0.078	2.58E-04	2168	0.086	6.20E-05
Effectiveness of vaccine varies from season to season	2149	0.030	1.67E-01	2149	0.074	5.85E-04	2149	0.072	9.07E-04	2149	0.020	3.48E-01

Table A3: Spearman correlation values for risk perception models (2)

Parameter	Model_Risk perception for a store visit (5)			Model_Risk perception for visit to Restaurant (6)			Model_Risk perception for a Hospital Visit (7)		
	Sample Size	rho value	p-value	Sample Size	rho value	p-value	Sample Size	rho value	p-value
Age of the participant	2168	0.007	7.47E-01	2168	-0.044	4.18E-02	2168	0.003	9.06E-01
Male	2168	-0.038	7.51E-02	2168	-0.056	9.12E-03	2168	-0.060	5.05E-03
Income	2168	0.005	8.26E-01	2168	0.027	2.08E-01	2168	0.086	5.97E-05

HH child between age 0-1	2168	-0.018	3.96E-01	2168	0.014	5.16E-01	2168	0.035	1.08E-01
HH child between age 2-5	2168	-0.006	7.88E-01	2168	0.013	5.42E-01	2168	0.040	6.50E-02
HH child between age 6-12	2168	0.005	8.20E-01	2168	0.021	3.27E-01	2168	0.032	1.33E-01
HH child between age 13-17	2168	0.006	7.66E-01	2168	0.036	9.11E-02	2168	-0.002	9.23E-01
HH member over age 18	2168	0.056	8.57E-03	2168	0.073	6.59E-04	2168	0.022	3.13E-01
Edu_Less than high school	2168	-0.017	4.35E-01	2168	-0.035	1.01E-01	2168	-0.042	4.96E-02
Edu_High school	2168	0.030	1.65E-01	2168	-0.002	9.10E-01	2168	-0.044	4.23E-02
Edu_Some college	2168	0.030	1.65E-01	2168	-0.002	9.10E-01	2168	-0.044	4.23E-02
Edu_Bachelor's or higher degree	2168	0.020	3.56E-01	2168	0.016	4.44E-01	2168	0.027	2.09E-01
Diff. Known b/w Stomach flu and Infuenza	2168	-0.038	7.81E-02	2168	0.006	7.69E-01	2168	0.040	6.57E-02
Had influenza since August 2015	2152	0.045	3.59E-02	2152	0.047	2.88E-02	2152	0.101	2.59E-06
HH member had influenza since August 2016	2149	0.144	2.20E-11	2149	0.122	1.26E-08	2149	0.110	3.36E-07
Not Working	1991	0.125	2.26E-08	1991	0.113	4.80E-07	1991	0.115	2.91E-07
Working	2168	-0.072	8.34E-04	2168	-0.073	6.32E-04	2168	-0.105	9.66E-07
Car travel to work	1368	0.018	5.07E-01	1368	0.034	2.12E-01	1368	0.094	5.01E-04
Regular use of public transportation	2153	-0.009	6.79E-01	2153	0.002	9.14E-01	2153	-0.037	8.64E-02
Avoiding crowded place to avoid getting sick	2168	0.165	9.21E-15	2168	0.138	1.13E-10	2168	0.085	7.47E-05
Get an Influenza vaccine	2168	-0.023	2.80E-01	2168	-0.029	1.72E-01	2168	-0.066	2.24E-03
Get avaccine: If people around get a vaccine	1331	-0.027	3.27E-01	1331	-0.034	2.10E-01	1331	0.033	2.27E-01

Get a vaccine: If people around don't get vaccine	1325	-0.072	8.32E-03	1325	-0.072	9.14E-03	1325	-0.013	6.30E-01
Vaccine taken to Protect Myself	1324	-0.024	3.78E-01	1324	-0.031	2.60E-01	1324	0.012	6.56E-01
Vaccine taken to Protect other	1324	-0.026	3.51E-01	1324	0.001	9.83E-01	1324	-0.045	1.01E-01
Vaccine taken to Protect myself and other	1324	0.031	2.60E-01	1324	0.030	2.70E-01	1324	0.000	9.86E-01
Rating of effectiveness of vaccine	2168	0.094	1.28E-05	2168	0.089	3.54E-05	2168	0.108	4.37E-07
Effectiveness of vaccine varies from season to season	2149	0.002	9.31E-01	2149	0.001	9.71E-01	2149	0.058	7.28E-03

Table A4: Spearman correlation values for risk perception models (3)

Parameter	Model_Risk perception for a visit to Doctor's office (8)			Model_Risk perception for the use of Public Transit (9)			Model_Risk perception for a visit to family or friends (10)		
	Sample Size	rho value	p-value	Sample Size	rho value	p-value	Sample Size	rho value	p-value
Age of the participant	2168	0.000	9.97E-01	2168	-0.095	8.68E-06	2168	0.005	8.23E-01
Male	2168	-0.091	2.04E-05	2168	-0.052	1.60E-02	2168	-0.073	6.43E-04
Income	2168	0.084	9.04E-05	2168	0.122	1.11E-08	2168	0.029	1.82E-01
HH child between age 0-1	2168	0.045	3.76E-02	2168	0.046	3.22E-02	2168	0.000	9.99E-01
HH child between age 2-5	2168	0.040	6.21E-02	2168	0.035	1.02E-01	2168	0.005	8.09E-01

HH child between age 6-12	2168	0.013	5.54E-01	2168	0.034	1.17E-01	2168	0.015	4.73E-01
HH child between age 13-17	2168	-0.012	5.79E-01	2168	0.037	8.75E-02	2168	0.010	6.44E-01
HH member over age 18	2168	0.040	6.06E-02	2168	0.103	1.52E-06	2168	0.034	1.16E-01
Edu_Less than high school	2168	-0.050	1.93E-02	2168	-0.087	4.70E-05	2168	-0.013	5.46E-01
Edu_High school	2168	-0.036	9.11E-02	2168	-0.037	8.11E-02	2168	0.005	8.05E-01
Edu_Some college	2168	-0.036	9.11E-02	2168	-0.037	8.11E-02	2168	0.005	8.05E-01
Edu_Bachelor's or higher degree	2168	0.026	2.22E-01	2168	0.011	6.15E-01	2168	-0.019	3.73E-01
Diff. Known b/w Stomach flu and Infuenza	2168	0.038	7.90E-02	2168	0.074	5.71E-04	2168	0.020	3.48E-01
Had influenza since August 2015	2152	0.098	4.99E-06	2152	0.079	2.44E-04	2152	0.098	4.87E-06
HH member had influenza since August 2016	2149	0.122	1.54E-08	2149	0.140	8.11E-11	2149	0.204	1.03E-21
Not Working	1991	0.109	1.00E-06	1991	0.145	8.68E-11	1991	0.152	8.65E-12
Working	2168	-0.072	8.29E-04	2168	-0.126	4.00E-09	2168	-0.025	2.45E-01
Car travel to work	1368	0.058	3.21E-02	1368	0.038	1.63E-01	1368	0.055	4.30E-02
Regular use of public transportation	2153	-0.039	6.84E-02	2153	-0.002	9.36E-01	2153	-0.022	2.98E-01
Avoiding crowded place to avoid getting sick	2168	0.087	5.01E-05	2168	0.116	6.64E-08	2168	0.086	5.97E-05
Get an Influenza vaccine	2168	-0.069	1.32E-03	2168	-0.018	4.01E-01	2168	-0.090	2.83E-05

Get avaccine: If people around get a vaccine	1331	0.048	7.76E-02	1331	-0.021	4.51E-01	1331	-0.027	3.33E-01
Get a vaccine: If people around don't get vaccine	1325	-0.012	6.69E-01	1325	0.000	9.86E-01	1325	-0.048	7.91E-02
Vaccine taken to Protect Myself	1324	-0.001	9.78E-01	1324	-0.034	2.21E-01	1324	-0.038	1.68E-01
Vaccine taken to Protect other	1324	-0.066	1.60E-02	1324	-0.010	7.06E-01	1324	-0.035	2.04E-01
Vaccine taken to Protect myself and other	1324	0.019	4.87E-01	1324	0.036	1.91E-01	1324	0.047	8.70E-02
Rating of effectiveness of vaccine	2168	0.090	2.61E-05	2168	0.124	7.25E-09	2168	0.070	1.20E-03
Effectiveness of vaccine varies from season to season	2149	0.072	8.07E-04	2149	0.046	3.11E-02	2149	0.040	6.30E-02

Table A5: Spearman correlation values for Scenario 1 models

Parameter	Model_type1			Model_type2a			Model_type2b			Model_type2c		
	Sample Size	Rho value	p-value	Sample Size	Rho value	p-value	Sample Size	Rho value	p-value	Sample Size	Rho value	p-value
Age of the participant	2136	-0.001	9.74E-01	2137	0.123	1.32E-08	2137	0.171	1.81E-15	2138	0.147	8.32E-12
Male	2136	-0.039	6.93E-02	2137	-0.109	4.34E-07	2137	-0.096	8.72E-06	2138	-0.116	7.35E-08
Income	2136	-0.007	7.61E-01	2137	-0.002	9.23E-01	2137	0.009	6.65E-01	2138	-0.037	9.03E-02
Household size	2136	0.021	3.41E-01	2137	-0.015	4.76E-01	2137	-0.012	5.89E-01	2138	-0.030	1.68E-01
Without Bachelor's degree	2136	-0.002	9.38E-01	2137	0.021	3.31E-01	2137	0.014	5.03E-01	2138	0.038	8.05E-02
Diff. Known b/w Stomach flu and Infuenza	2128	0.007	7.30E-01	2129	0.082	1.49E-04	2129	0.083	1.29E-04	2129	0.089	3.61E-05
Had influenza since August 2015	2124	-0.020	3.62E-01	2125	-0.077	4.05E-04	2125	-0.041	5.63E-02	2125	-0.062	4.22E-03

HH member had influenza since August 2016	1972	-0.021	3.54E-01	1973	-0.058	9.98E-03	1973	0.000	9.90E-01	1973	-0.076	7.04E-04
If respondent works	2126	-0.011	6.26E-01	2127	-0.108	5.51E-07	2127	-0.087	5.62E-05	2127	-0.170	3.06E-15
Work has exposure to people	1354	-0.028	3.06E-01	1356	-0.049	7.26E-02	1356	-0.014	6.01E-01	1356	-0.023	3.91E-01
Regular use of public transportation	2129	0.005	8.03E-01	2130	-0.054	1.30E-02	2130	-0.200	9.94E-21	2131	-0.019	3.80E-01
Risk perception_work_High	1953	0.057	1.21E-02	1954	-0.006	7.77E-01	1954	-0.021	3.56E-01	1954	-0.010	6.69E-01
Risk perception_work_medium	1953	-0.026	2.53E-01	1954	-0.057	1.24E-02	1954	-0.035	1.24E-01	1954	-0.068	2.52E-03
Risk perception_work_Low	1953	-0.026	2.43E-01	1954	0.065	3.92E-03	1954	0.056	1.31E-02	1954	0.081	3.58E-04
Risk perception_school_High	1959	0.022	3.37E-01	1960	0.052	2.23E-02	1961	0.070	2.02E-03	1961	0.039	8.19E-02
Risk perception_school_medium	1959	-0.036	1.11E-01	1960	-0.062	5.75E-03	1961	-0.075	8.53E-04	1961	-0.073	1.25E-03
Risk perception_school_Low	1959	0.012	5.88E-01	1960	0.005	8.21E-01	1961	-0.002	9.21E-01	1961	0.030	1.85E-01
Risk perception_daycare_High	1923	0.019	4.09E-01	1924	0.047	3.93E-02	1925	0.056	1.44E-02	1925	0.034	1.36E-01
Risk perception_daycare_medium	1923	-0.036	1.11E-01	1924	-0.066	3.67E-03	1925	-0.059	9.16E-03	1925	-0.083	2.69E-04
Risk perception_daycare_Low	1923	0.013	5.60E-01	1924	0.010	6.59E-01	1925	-0.006	7.93E-01	1925	0.040	7.79E-02
Risk perception_stores_High	2022	0.075	7.90E-04	2023	0.060	7.38E-03	2024	0.078	4.77E-04	2024	0.040	7.32E-02
Risk perception_stores_medium	2022	-0.044	5.04E-02	2023	-0.040	7.53E-02	2024	-0.028	2.11E-01	2024	-0.041	6.54E-02
Risk perception_stores_Low	2022	-0.029	1.97E-01	2023	-0.017	4.49E-01	2024	-0.052	2.03E-02	2024	0.007	7.58E-01
Risk perception_restaurant_High	2027	0.083	1.84E-04	2028	0.069	1.93E-03	2029	0.066	2.91E-03	2029	0.030	1.81E-01
Risk perception_restaurant_medium	2027	-0.030	1.75E-01	2028	-0.026	2.49E-01	2029	-0.021	3.54E-01	2029	-0.019	3.90E-01
Risk perception_restaurant_Low	2027	-0.049	2.65E-02	2028	-0.040	7.16E-02	2029	-0.043	5.15E-02	2029	-0.008	7.32E-01
Risk perception_library_High	1967	0.052	2.13E-02	1967	0.078	5.74E-04	1968	0.057	1.22E-02	1968	0.029	1.98E-01
Risk perception_library_medium	1967	-0.008	7.34E-01	1967	-0.024	2.96E-01	1968	-0.018	4.14E-01	1968	-0.018	4.28E-01
Risk perception_library_Low	1967	-0.035	1.19E-01	1967	-0.040	7.73E-02	1968	-0.028	2.20E-01	1968	-0.005	8.09E-01
Risk perception_hospital_High	2014	0.011	6.34E-01	2015	0.077	5.40E-04	2015	0.084	1.56E-04	2015	0.051	2.19E-02
Risk perception_hospital_medium	2014	-0.004	8.46E-01	2015	-0.070	1.71E-03	2015	-0.060	7.35E-03	2015	-0.063	4.38E-03
Risk perception_hospital_Low	2014	-0.008	7.06E-01	2015	-0.014	5.16E-01	2015	-0.036	1.06E-01	2015	0.011	6.17E-01

Risk perception_doctor's office_High	2026	0.017	4.35E-01	2027	0.078	4.73E-04	2028	0.085	1.37E-04	2028	0.053	1.70E-02
Risk perception_doctor's office_medium	2026	0.013	5.48E-01	2027	-0.061	5.89E-03	2028	-0.060	7.00E-03	2028	-0.035	1.10E-01
Risk perception_doctor's office_Low	2026	-0.042	5.78E-02	2027	-0.026	2.37E-01	2028	-0.038	8.89E-02	2028	-0.026	2.35E-01
Risk perception_public transit_High	1988	0.046	4.12E-02	1989	0.113	3.91E-07	1990	0.143	1.63E-10	1990	0.062	5.85E-03
Risk perception_public transit_medium	1988	-0.040	7.80E-02	1989	-0.097	1.52E-05	1990	-0.148	3.16E-11	1990	-0.062	5.93E-03
Risk perception_public transit_Low	1988	-0.013	5.49E-01	1989	-0.035	1.22E-01	1990	-0.013	5.71E-01	1990	-0.008	7.09E-01
Risk perception_friend's or family's place_High	2015	0.057	1.08E-02	2017	0.035	1.17E-01	2017	0.010	6.48E-01	2017	0.057	1.09E-02
Risk perception_friend's or family's place_medium	2015	0.009	6.87E-01	2017	-0.031	1.60E-01	2017	-0.009	6.78E-01	2017	-0.065	3.71E-03
Risk perception_friend's or family's place_Low	2015	-0.069	1.81E-03	2017	0.001	9.82E-01	2017	0.000	9.89E-01	2017	0.017	4.49E-01
Do you have health insurance	2127	0.106	9.42E-07	2128	0.102	2.32E-06	2128	0.091	2.56E-05	2129	0.107	8.03E-07
If the respondent has influenza vaccine	2129	0.148	6.35E-12	2130	0.046	3.24E-02	2130	0.039	7.03E-02	2131	0.049	2.51E-02
Squared Age of the participant	2136	-0.001	9.74E-01	2137	0.123	1.32E-08	2137	0.171	1.81E-15	2138	0.147	8.32E-12
Income per household member	2136	-0.014	5.23E-01	2137	0.008	7.15E-01	2137	0.029	1.86E-01	2138	-0.014	5.23E-01
Region 1	2136	0.007	7.37E-01	2137	-0.002	9.36E-01	2137	-0.022	3.16E-01	2138	0.013	5.49E-01
Region 2	2136	0.052	1.63E-02	2137	-0.016	4.60E-01	2137	-0.078	3.02E-04	2138	-0.013	5.33E-01
Region 3	2136	-0.048	2.76E-02	2137	-0.014	5.18E-01	2137	0.006	7.87E-01	2138	-0.002	9.30E-01
Region 4	2136	-0.042	5.08E-02	2137	-0.023	2.92E-01	2137	-0.008	7.04E-01	2138	0.015	4.97E-01
Region 5	2136	0.064	3.25E-03	2137	0.034	1.13E-01	2137	0.028	1.94E-01	2138	0.009	6.77E-01
Region 6	2136	0.014	5.27E-01	2137	-0.007	7.35E-01	2137	0.038	7.83E-02	2138	0.005	8.13E-01
Region 7	2136	0.046	3.41E-02	2137	0.015	4.87E-01	2137	0.007	7.58E-01	2138	0.004	8.47E-01
Region 8	2136	-0.017	4.31E-01	2137	0.010	6.50E-01	2137	0.040	6.56E-02	2138	-0.016	4.48E-01
Region 9	2136	-0.083	1.21E-04	2137	-0.007	7.32E-01	2137	-0.002	9.42E-01	2138	-0.008	7.17E-01
Income greater than 50k	2136	-0.019	3.68E-01	2137	-0.014	5.10E-01	2137	0.016	4.51E-01	2138	-0.041	5.59E-02
Kids less than 12 years	2136	0.018	4.18E-01	2137	-0.046	3.27E-02	2137	-0.036	9.24E-02	2138	-0.045	3.80E-02
Kids less than 5 years	2136	-0.026	2.32E-01	2137	-0.047	2.92E-02	2137	-0.051	1.85E-02	2138	-0.028	1.92E-01
race_white	2136	-0.064	3.04E-03	2137	0.042	5.25E-02	2137	0.093	1.78E-05	2138	0.056	9.12E-03

marital_married	2136	0.025	2.47E-01	2137	0.056	1.02E-02	2137	0.096	7.98E-06	2138	0.038	7.98E-02
Expensive_state_Metro	2136	0.004	8.68E-01	2137	-0.034	1.15E-01	2137	-0.074	6.01E-04	2138	-0.022	3.02E-01

Table A6: Spearman correlation values for Scenario 2 models

S.No.	Parameter	Model_type3a			Model_type3b			Model_type3c		
		Sample Size	Rho value	p-value	Number of Values	Rho value	p-value	Number of Values	Rho value	p-value
1	Age of the participant	2135	0.089	4.01E-05	2132	0.166	1.28E-14	2135	0.084	1.01E-04
2	Male	2135	-0.064	3.26E-03	2132	-0.057	8.31E-03	2135	-0.086	6.99E-05
3	Income	2135	-0.116	8.01E-08	2132	-0.062	4.18E-03	2135	-0.196	6.27E-20
4	Household size	2135	-0.018	4.11E-01	2132	-0.023	2.88E-01	2135	-0.009	6.77E-01
7	Without Bachelor's degree	2135	0.104	1.44E-06	2132	0.100	4.08E-06	2135	0.164	2.06E-14
8	Diff. Known b/w Stomach flu and Infuenza	2127	0.026	2.36E-01	2124	0.059	6.59E-03	2127	-0.003	8.80E-01
9	Had influenza since August 2015	2123	-0.028	2.01E-01	2120	0.007	7.31E-01	2123	-0.005	8.35E-01
10	HH member had influenza since August 2016	1972	-0.003	8.82E-01	1970	0.030	1.83E-01	1972	-0.021	3.62E-01
11	If respondent works	2125	-0.067	1.86E-03	2122	-0.064	3.15E-03	2125	-0.197	4.24E-20
12	Work has exposure to people	1353	-0.077	4.43E-03	1350	-0.064	1.84E-02	1353	-0.019	4.77E-01
14	Regular use of public transportation	2128	-0.077	3.89E-04	2125	-0.213	3.12E-23	2128	-0.030	1.69E-01
15	Risk perception_work_High	1954	0.029	1.94E-01	1951	0.024	2.95E-01	1954	0.053	1.87E-02
16	Risk perception_work_medium	1954	-0.070	2.08E-03	1951	-0.029	2.01E-01	1954	-0.114	4.76E-07
17	Risk perception_work_Low	1954	0.045	4.62E-02	1951	0.008	7.27E-01	1954	0.069	2.37E-03
18	Risk perception_school_High	1960	0.071	1.60E-03	1958	0.093	3.56E-05	1960	0.020	3.73E-01
19	Risk perception_school_medium	1960	-0.089	7.96E-05	1958	-0.095	2.33E-05	1960	-0.078	5.82E-04
20	Risk perception_school_Low	1960	0.010	6.55E-01	1958	-0.008	7.09E-01	1960	0.057	1.20E-02
21	Risk perception_daycare_High	1924	0.050	2.90E-02	1922	0.075	9.50E-04	1924	0.008	7.27E-01
22	Risk perception_daycare_medium	1924	-0.065	4.31E-03	1922	-0.073	1.30E-03	1924	-0.046	4.54E-02

23	Risk perception_daycare_Low	1924	0.006	7.94E-01	1922	-0.015	5.23E-01	1924	0.034	1.36E-01
24	Risk perception_stores_High	2023	0.139	3.43E-10	2021	0.134	1.67E-09	2023	0.123	3.22E-08
25	Risk perception_stores_medium	2023	-0.056	1.21E-02	2021	-0.035	1.13E-01	2023	-0.054	1.57E-02
26	Risk perception_stores_Low	2023	-0.085	1.29E-04	2021	-0.105	2.50E-06	2023	-0.069	1.81E-03
27	Risk perception_restaurant_High	2027	0.157	1.03E-12	2025	0.119	8.33E-08	2027	0.125	1.45E-08
28	Risk perception_restaurant_medium	2027	-0.055	1.40E-02	2025	-0.017	4.47E-01	2027	-0.045	4.35E-02
29	Risk perception_restaurant_Low	2027	-0.096	1.37E-05	2025	-0.102	4.28E-06	2027	-0.075	7.03E-04
30	Risk perception_library_High	1967	0.107	2.10E-06	1965	0.082	2.65E-04	1967	0.082	2.78E-04
31	Risk perception_library_medium	1967	-0.011	6.27E-01	1965	-0.002	9.38E-01	1967	-0.025	2.63E-01
32	Risk perception_library_Low	1967	-0.077	6.23E-04	1965	-0.066	3.25E-03	1967	-0.042	6.49E-02
33	Risk perception_hospital_High	2015	0.087	9.95E-05	2012	0.088	7.15E-05	2015	0.035	1.16E-01
34	Risk perception_hospital_medium	2015	-0.066	3.09E-03	2012	-0.054	1.52E-02	2015	-0.034	1.24E-01
35	Risk perception_hospital_Low	2015	-0.032	1.56E-01	2012	-0.048	3.04E-02	2015	-0.004	8.73E-01
36	Risk perception_doctor's office_High	2026	0.084	1.56E-04	2024	0.095	1.96E-05	2026	0.026	2.34E-01
37	Risk perception_doctor's office_medium	2026	-0.076	6.23E-04	2024	-0.062	5.02E-03	2026	-0.020	3.68E-01
38	Risk perception_doctor's office_Low	2026	-0.015	4.91E-01	2024	-0.049	2.87E-02	2026	-0.010	6.49E-01
39	Risk perception_public transit_High	1988	0.124	3.08E-08	1986	0.185	1.05E-16	1988	0.060	7.23E-03
40	Risk perception_public transit_medium	1988	-0.133	2.70E-09	1986	-0.203	5.40E-20	1988	-0.097	1.46E-05
41	Risk perception_public transit_Low	1988	-0.006	7.93E-01	1986	-0.003	8.92E-01	1988	0.035	1.18E-01
42	Risk perception_friend's or family's place_High	2017	0.062	5.16E-03	2014	0.020	3.74E-01	2017	0.077	5.63E-04
43	Risk perception_friend's or family's place_medium	2017	-0.023	3.04E-01	2014	0.011	6.22E-01	2017	-0.062	5.53E-03
44	Risk perception_friend's or family's place_Low	2017	-0.038	9.02E-02	2014	-0.033	1.34E-01	2017	-0.007	7.45E-01
45	Do you have health insurance	2126	0.032	1.40E-01	2123	0.067	1.95E-03	2126	-0.009	6.66E-01
46	If the respondent has influenza vaccine	2127	0.039	6.86E-02	2125	0.060	5.77E-03	2127	0.020	3.65E-01
47	Squared Age of the participant	2135	0.089	4.01E-05	2132	0.166	1.28E-14	2135	0.084	1.01E-04

48	Income per household member	2135	-0.096	9.71E-06	2132	-0.034	1.19E-01	2135	-0.179	9.56E-17
49	Region 1	2135	-0.037	8.47E-02	2132	-0.057	8.04E-03	2135	-0.041	6.01E-02
50	Region 2	2135	-0.020	3.45E-01	2132	-0.063	3.55E-03	2135	-0.051	1.94E-02
51	Region 3	2135	-0.014	5.24E-01	2132	0.005	8.08E-01	2135	0.022	3.17E-01
52	Region 4	2135	-0.022	3.19E-01	2132	-0.014	5.19E-01	2135	-0.014	5.17E-01
53	Region 5	2135	0.020	3.48E-01	2132	0.014	5.33E-01	2135	0.016	4.68E-01
54	Region 6	2135	0.037	8.46E-02	2132	0.051	1.76E-02	2135	0.047	2.86E-02
55	Region 7	2135	0.037	8.62E-02	2132	0.019	3.71E-01	2135	0.022	3.01E-01
56	Region 8	2135	-0.013	5.38E-01	2132	0.019	3.68E-01	2135	0.003	8.72E-01
57	Region 9	2135	0.006	7.82E-01	2132	0.024	2.58E-01	2135	-0.005	8.26E-01
58	Income greater than 50k	2135	-0.085	8.08E-05	2132	-0.030	1.63E-01	2135	-0.145	1.64E-11
59	Kids less than 12 years	2135	-0.072	8.77E-04	2132	-0.053	1.46E-02	2135	-0.026	2.24E-01
60	Kids less than 5 years	2135	-0.066	2.42E-03	2132	-0.062	3.92E-03	2135	-0.021	3.41E-01
61	race_white	2135	-0.028	1.96E-01	2132	0.045	3.98E-02	2135	-0.070	1.17E-03
62	marital_married	2135	0.012	5.65E-01	2132	0.075	5.07E-04	2135	-0.027	2.19E-01
63	Expensive_state_Metro	2135	-0.020	3.45E-01	2132	-0.037	8.62E-02	2135	-0.045	3.69E-02